Essays in Empirical Industrial Organization

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Abstract

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While the tools in empirical industrial organization allow structural analysis for competitions, it is less applied to study the competition between sellers in housing market, which is a crucial market for almost every economy. This dissertation structurally estimates the dynamic competition between real estate developers, analyses the pricing in primary real estimate market, and reviews the literature on the dynamic game estimation and other structural estimation in housing market.

Chapter 1 studies the dynamic competition between real estate developers and the policy outcome of counter-cyclical measures. In the face of transient shocks in an economy, cyclical or counter-cyclical policy tends to be prescribed, as opposed to universal/acyclical policy[1], due to the smaller implementation scale of the former. However, once competition over time is taken into consideration, whether the former policy implies smaller impacts than the latter becomes unclear. 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. Peripheral data, including satellite images, are used to support the assumptions required for the structural model. 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

[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.

55. The counterfactual analysis shows that counter-cycle policy indeed introduces an impact more extensive than acyclical policy in this market. Unlike acyclical policy that delays the listing universally, counter-cycle policy delays only in some periods, which creates congestion of apartments in other periods. The congestion leads to slower sales, and hence more apartments left unsold overall. This finding calls for caution against a common perception that a counter-cycle measure necessarily causes less distortion than a full-scale acyclical measure.

Chapter 2 studies in details of the pricing behaviors among Hong Kong real estate developers. It reveals various aspect of real estate pricing including floor level, price list order, individual developer behavior, discount, and competition. Furthermore, I utilized my high frequency daily data to construct a daily price index to reflect changes by date. The index has controlled for influences from apartment heterogeneity and other intentional pricing practices and hence a better alternative in reflecting the daily changes in real estate prices. Assisted by the index, I illustrated the convoluted relationship between real estate pricing and the stock market performance, in Hong Kong and in mainland China. I also demonstrated the sophistication of responses in the real estate pricing. When previous price list does not sell well, developers respond by lowering the price in later price list. However, when the low demand is driven by peripheral factors only (e.g. flu prevalence-induced absence), I found that they do not lower the price, and even raise the price significantly, potentially to counter any negative comments from the media or the public.

Chapter 3 reviews multiple strands of literature that pertain to dynamic competition and real estate market, particularly for Hong Kong. The review serves to highlight the achievements of the existing literature and illustrates the contribution of my research in expanding our understanding of dynamic competition estimation and real estate market. This review covers the estimation of dynamic game and its later development for competition with many firms, in terms of both theoretical works and empirical works. After that, current structural estimation in housing is discussed. The typical structural estimation includes dynamic models from single agent perspective and search models. Researches focusing on the local market in Hong Kong are also reviewed.

Acknowledgements

I would like to express my gratitude towards my committee chair, Professor Yuya Takahashi, who is a truly supportive and caring mentor. Without his insightful guidance, it would be much harder for me to navigate as a researcher. This is of immense value in a sub-field of significant technicality. His experience and knowledge of the field has doubtlessly inspired me to learn more from him. When I faced various bottlenecks during my dissertation, he frequently provided timely comments to get me through the bottlenecks. Beyond academics, he is also very supportive in my career plan and offers his advice accumulated from years of experience. Whether it is a critical issue or a minor request, he is always there to offer help that he can provide. He does not take care of me just on academics and my careeer, but also for my personal life. The different occasions that he intentionally cared for my needs would be a warmth that I bring to my next stage in life.

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Lastly, I would like to thank my wife and the One. Upon the selfless sacrifice of my wife, my Ph.D. adventure becomes a joyful hike. And to the One, who turned profound difficulties into unspeakable blessings.

DEDICATION

To those who love me more than I do:

Kam-Shing Wong, who teaches me reality over ideal

Hoi-Ying Kwok, who bears (with) me to dream high

Tung-Yu Wong, who imparts me crazy ideas

Wing-Yan Chan, who accepts me as who I am

The One, who is behind all these

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Chapter 1

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

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 et al. [2014], Aghion and Roulet [2014], and Aghion et al. [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 oligopoly competition. 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 chapter, 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 counterfactual.

Housing market is one of the markets that often consider (counter-)cyclical policy in response to transient 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. The result from this work is relevant to competition beyond oligopoly. 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 subject to common shocks. Using pseudo likelihood maximization, 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. 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 the estimator 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. The intuition is clear once the dynamic consideration is taken into account. In the acyclical regime, sellers delay their listings universally. In the counter-cyclical regime, sellers delay their listings only in seasons with a raised entry cost (i.e. high season), and hence apartments tend to be listed in periods outside of high seasons. This intertemporal differential creates congestion in apartments in the non-high seasons, which slows down sales and hence leaves more apartments unsold overall. These show that a counter-cycle policy, of a smaller implementation scale than an acyclical policy, can indeed trigger a more extensive impact on the market. This finding calls for caution against the common perception of using cyclical policy in addressing transient shocks. Cyclical policy can result in a long-lasting and more extensive impact when dynamic competition is considered. In addition, 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. Also, a counterfactual with vacancy tax is 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 and Ramey [1995], Aghion et al. [2010], Aghion et al. [2014], and Aghion et al. [2019]) where cyclical fiscal policy is recommended to nurture long-term growth. My work contributes by providing micro-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 et al. [2010], and Murphy [2018]) or from a search model perspective (e.g. Liberati and Loberto [2019], Huang et al. [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 and Pakes [1995], Pakes and McGuire [1994], and Doraszelski and 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 et al. [2008], Weintraub et al. [2010b], Weintraub et al. [2010a], and Benkard et al. [2015]) proposed to approximate MPE when there are many firms in the market. In addition to the empirical works by Qi [2013] and **?**, my work extends the empirical work to a prominent industry of economy and is the first work to study OE under common shock (i.e. EOE).

Section 1.1 discusses the transaction-level data and other industry details. With which, I explore some model-free empirical observation in section 1.2. Section 1.3 constructs a dynamic competition model with

EOE. Its estimation result, as well as some robustness checks, are discussed in section 1.4. Section 1.5 evaluates the counterfactual policies and demonstrates the interesting contrast between acyclical and countercyclical policy. Section 1.6 concludes.

1.1 Data

1.1.1 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[1], 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.

[1] 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.

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.

1.1.2 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[2], when real estate developers were required to provide the documents to the government[3]. 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 sale and purchase within 24 hours of

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

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

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[4]. 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).

1.1.3 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 1.1, 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

[4]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.

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 1.1: 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 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 1.2 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 1.1 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 1.2, the median

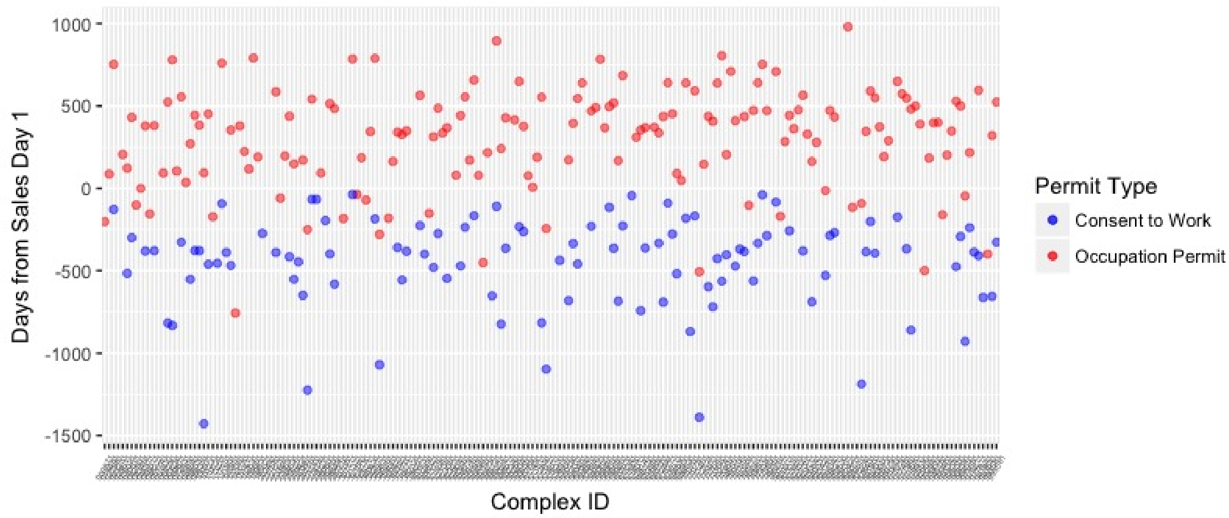


Figure 1.1: Difference between Sales Date and CW/OP Date

difference of CW days and OP days is about 760[5]. 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 1.2: 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 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 im-

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

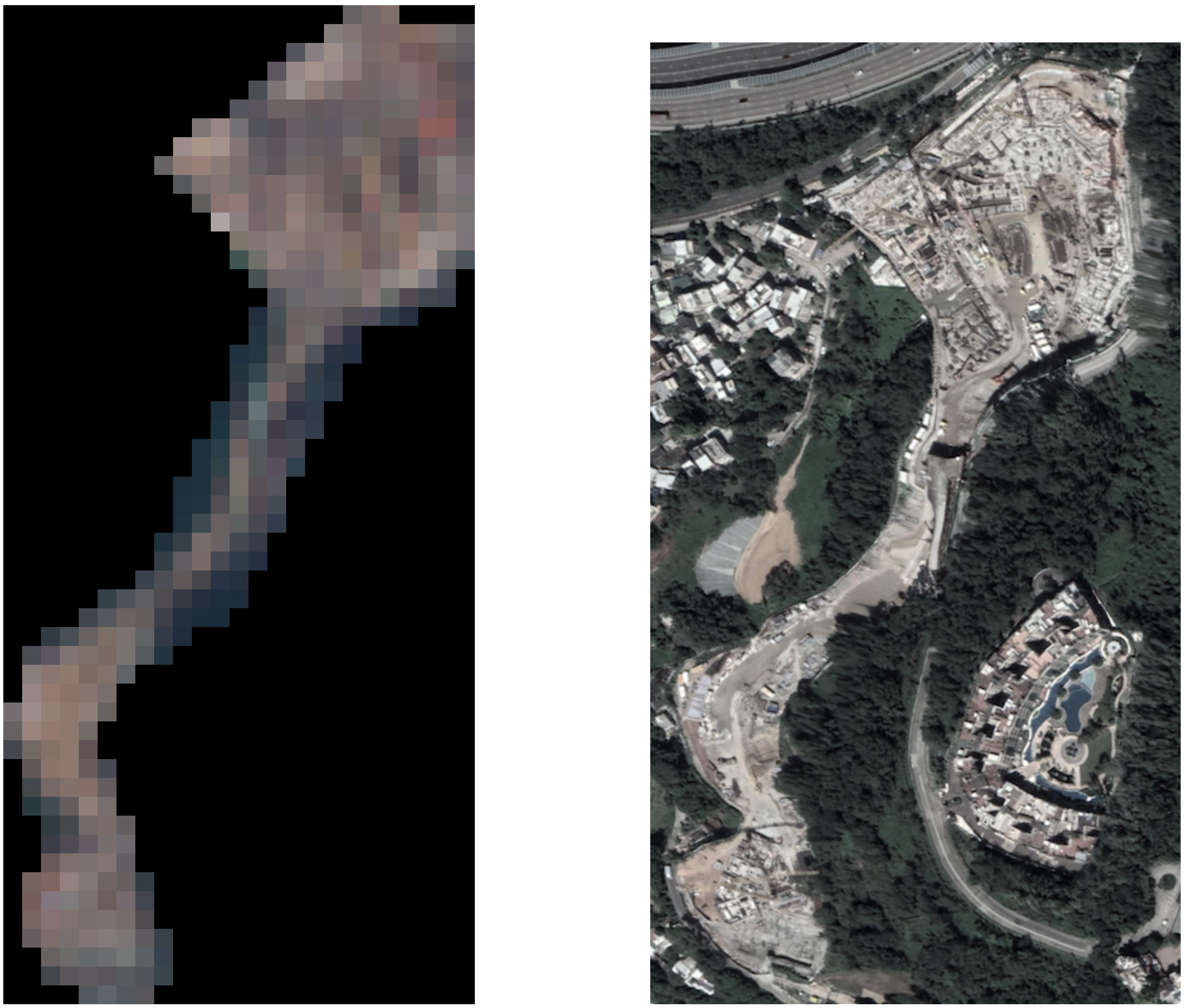
age resolution as one can see in figure 1.2. The only public data is from the Sentinel 2 project, where the satellite visits the same place every few days which provides a continuous stream of information about the construction site. Although the resolution is relatively low to bare eyes per our use 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[6]. 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.

Given the date of emergence, one can see how the competition presents itself over time. Figure 1.3 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 1.4 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)[7] 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

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

[7] 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



(a) Sentinel 2 on 2018-11-06

(b) Google Earth on 2018-10

Figure 1.2: Sources of Satellite Images at Varying Resolution

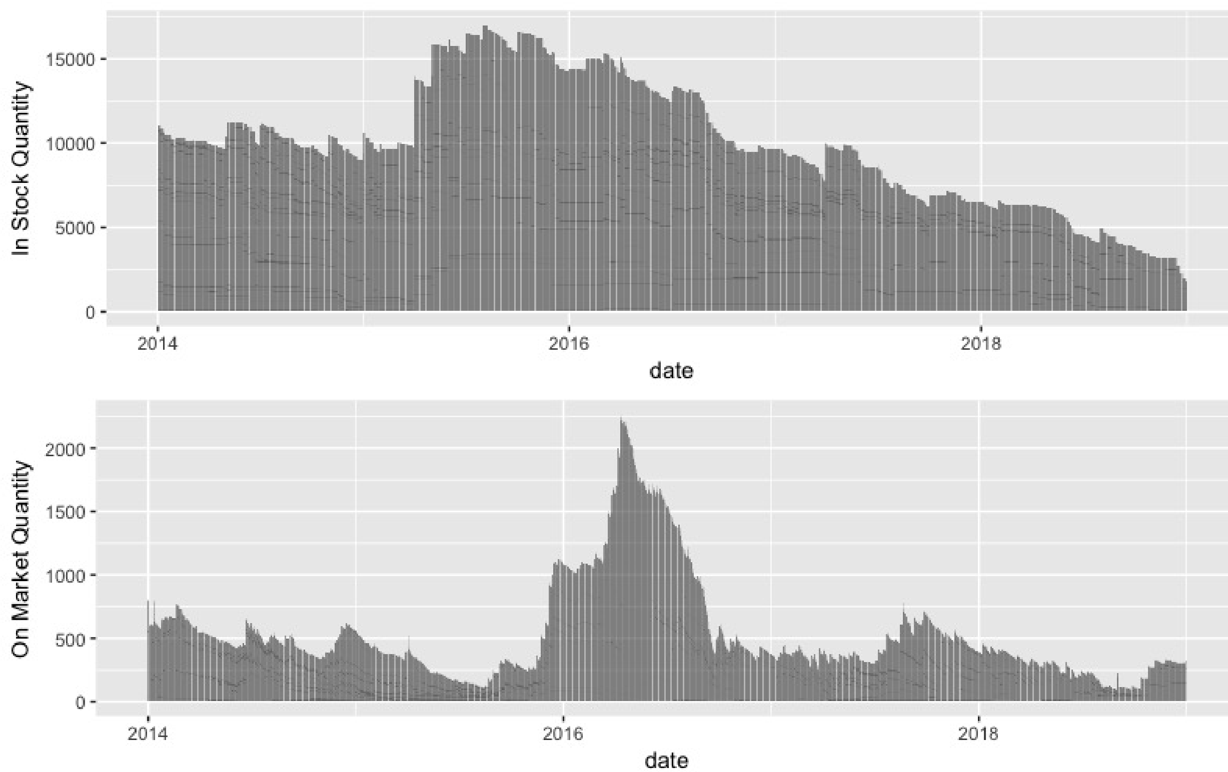


Figure 1.3: Raw quantities in-stock and on-market over time

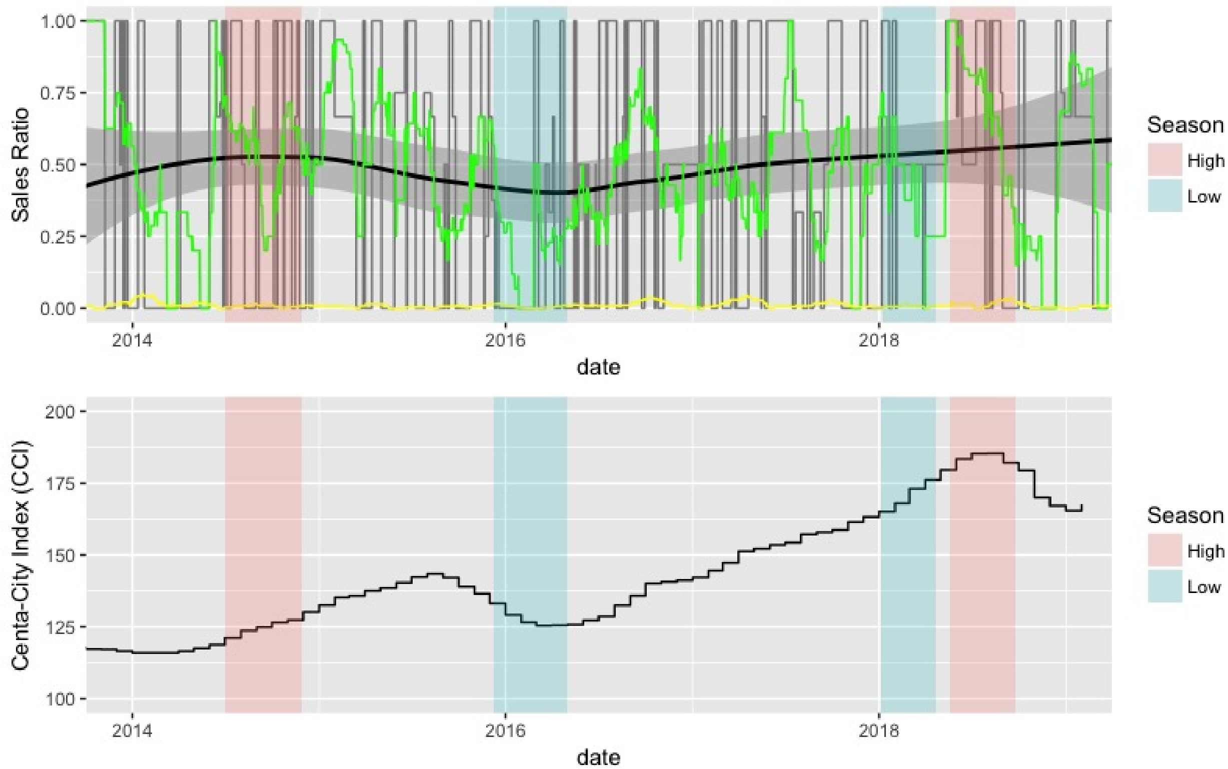


Figure 1.4: Seasonality in Housing Market

- 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.

1.2 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

1.3 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.

Table 1.3: 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)
	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

When the pricing residuals from table 1.3 are analysed further, one can see that there is a clear trend the price increases as the price list releases in order. Figure 1.5 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[8] 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

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

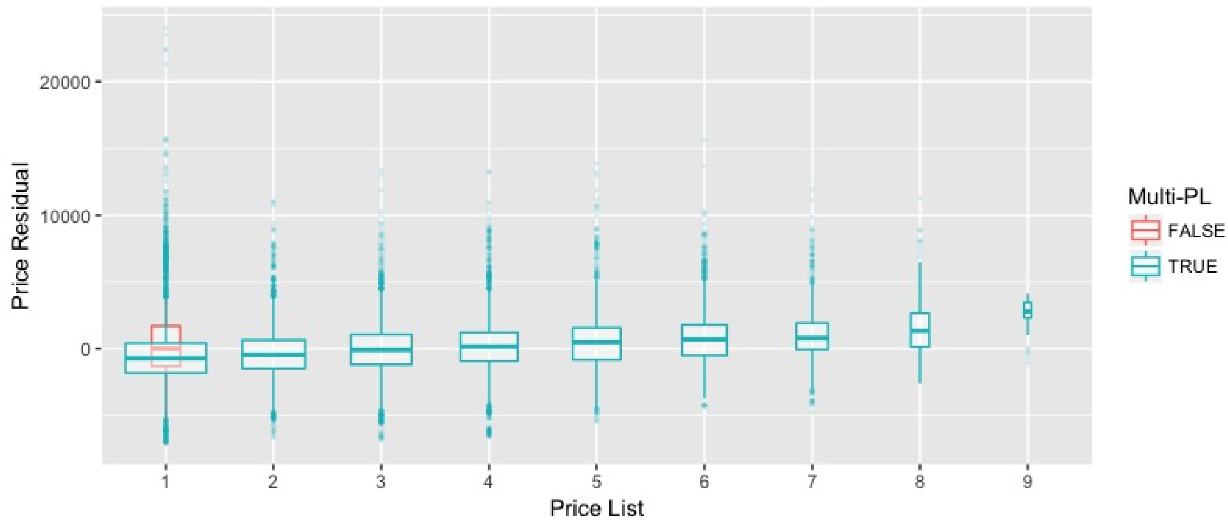


Figure 1.5: Price Residual across Price Lists

increasing prices in multi-PL complex.

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 1.4 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 1.4 shows the price is lower when it has more in-stock or on-market, but no statistical significant impact from any competition measures.

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

Table 1.4: 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

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

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[9]. 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 1.5 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.

1.3 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

[9]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 1.4 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.

Table 1.5: 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

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

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

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[10]. 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 1.6 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[11]. Individual state of sellers are then updated and 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 1.6 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).

[10] Estimation uses the emergence sequence in reality.

[11] 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.
Complex in Non-Listing Days: $\alpha = 3.85640^{*}$ and $\gamma = -0.48900^{***}$
Complex in Listing Days: $\alpha = 1.71702$ and $\gamma = -0.19410^{*}$

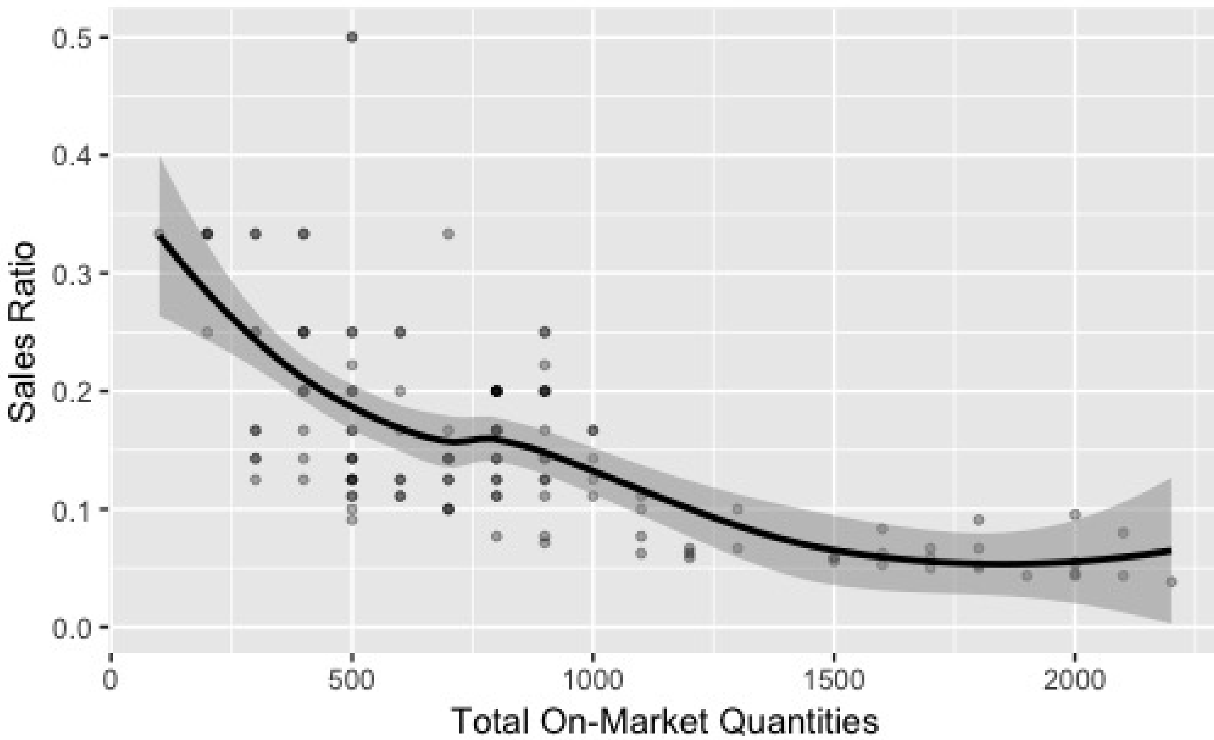


Figure 1.6: Competition Impact on Sales in Non-Listing Days

Table 1.6: Seasonality transit

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

Note: Each row sums to 1.

1.3.1 Payoff

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

$$\begin{aligned}\pi(a_{jt}, a_{-jt}, s_{jt}, s_{-jt}) = pq(a_{jt}, a_{-jt}, s_{jt}, s_{-jt}) - c_e I(a_{jt} > 0|k = 0) \\ - c_r I(a_{jt} > 0|k > 0) - c_h h_{jt} - c_o o_{jt} + \epsilon_{ajt}\end{aligned} \tag{1.1}$$

where p is price[12], 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 :

$$V(s_t, \epsilon_{ajt}) = \max_{a_{jt}} \pi(a_{jt}, a_{-jt}, s_t) + \beta \sum_{s_{t+1}} \bar{V}(s_{t+1}) G(s_{t+1}|s_t, a_t) \tag{1.2}$$

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 and 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.

1.3.2 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

[12] Since this chapter 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

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[13].

Oblivious Equilibrium (OE), proposed by Weintraub et al. [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 et al. [2008] shows that satisfying a "light-tail" condition[14] 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.[15] 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 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 et al. [2010b], 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

[13]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.

[14]"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 et al. [2008] for the formal definition of "light-tail" condition.

[15]Note that the impact on payoff increases with rival's state (that is rival's quality level) in Weintraub et al. [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.

by all sellers. Formally, payoff becomes

$$\begin{aligned} \pi(a_{jt}, s_{jt}, \tilde{s}_\sigma) = pq(a_{jt}, s_{jt}, \tilde{s}_\sigma) - c_e I(a_{jt} > 0 | k = 0) \\ - c_r I(a_{jt} > 0 | k > 0) - c_h h_{jt} - c_o o_{jt} + \epsilon_{ajt} \end{aligned} \tag{1.3}$$

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

$$V(s_{jt}, \epsilon_{ajt}, \tilde{s}_\sigma) = \max_{a_{jt}} \pi(a_{jt}, s_{jt}, \tilde{s}_\sigma) + \beta \sum_{s_{t+1}} \bar{V}(s_{j(t+1)}, \tilde{s}_\sigma) G(s_{j(t+1)} | s_{jt}, a_{jt}, \tilde{s}_\sigma) \tag{1.4}$$

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

$$\tilde{s}_\sigma \equiv \sum_{t=0}^{\infty} P_\sigma(s_t) \tag{1.5}$$

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

1.4 Estimation

1.4.1 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.

1.4.2 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.

$$logit(P(q_{jt} < q|a_{jt} = 0)) = \eta_0 + \eta_1 o_{jt} + \eta_2 k_{jt} + \eta_3 z_{jt} \tag{1.6}$$

$$logit(P(q_{jt} < q|a_{jt} > 0)) = \xi_0 + \xi_1 a_{jt} o_{jt} + \xi_2 k_{jt} + \xi_3 I(k = 0) + \xi_4 z_{jt} \tag{1.7}$$

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

Table 1.7 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 1.8, 1.9 and 1.10) 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 1.11) 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 1.12 shows an excerpt of the full transition matrix, accommodating season transit at once.

Table 1.7: 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 2 is for non-listing listing days respectively.

Table 1.8: Transition matrix excerpt when a = 0

t $\backslash t+1$	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 1.9: Transition matrix excerpt when a = 100 across PLs

t $\backslash t+1$	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 1.10: Transition matrix excerpt when a = 100 at different Season

t $\backslash t+1$	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 1.11: 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 1.12: Full transition matrix excerpt (with season change)

t $\backslash t+1$	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 1.13 presents the result for the estimated choice probability.

Table 1.13: 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)
McFadden R^2			0.12		

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

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 1.14 shows the estimation result of a linear regression on the price per sq. ft. residual.

Table 1.14: 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 1.15 and 1.16) of the $1773 * 6$ matrix are shown below.

Some features of the pricing are worth mentioning. It has an increasing trend as later PLs post (table 1.15). 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

Table 1.15: 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

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 1.16: 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

1.4.3 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 1.7 shows that the EOE recovers the simulated data generated by the empiri-

Table 1.17: Parameters of choice

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

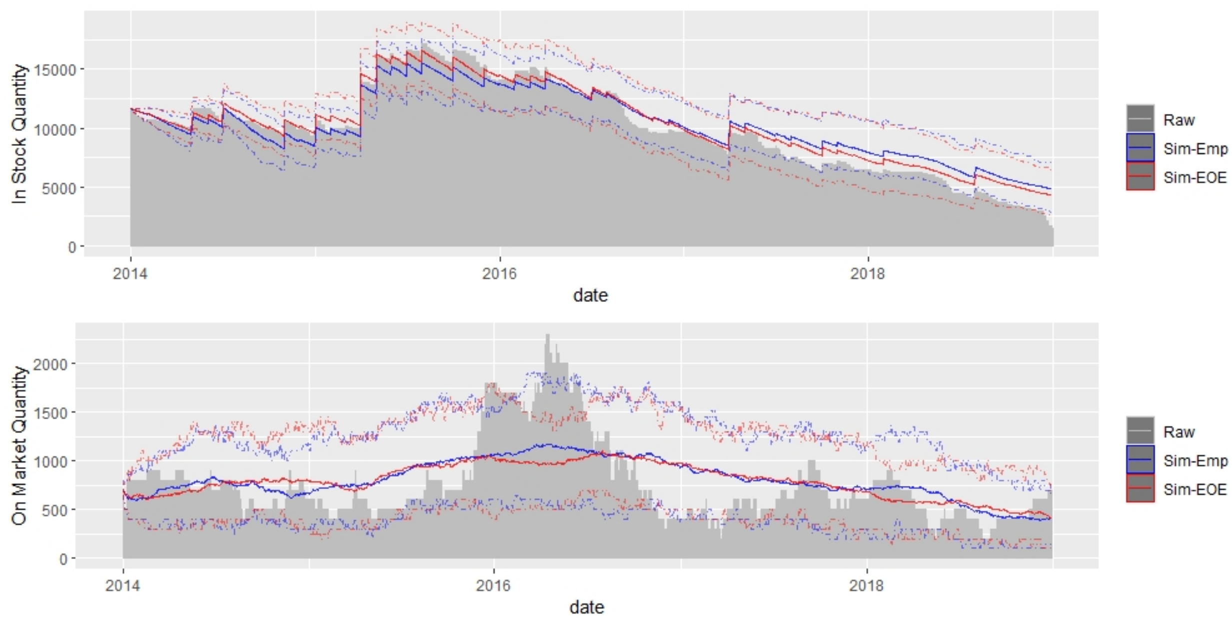


Figure 1.7: Simulations of Estimated EOE

cal 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 1.7, 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 1.18 & 1.19), the EOE entry probabilities for 500 or less apartments in-stock, across all seasons, are quite close. As for table 1.20 & 1.21, 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.

Table 1.18: 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 1.19: 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

Cost estimates show that seasonality does matter. Table 1.22 shows an excerpt of entry cost across

Table 1.20: 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 1.21: 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

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 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.

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 1.23. 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

Table 1.22: 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 1.23: 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

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[16]. 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.

1.4.4 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 1.13 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[17] with a median $2.761e^{-4}$. The 1^{st} quartile and the 3^{rd} quartile of their differences

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

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

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 specification changed. Table 1.24 shows that the difference for each potential action has a median difference[18] to be in the order of -3 to -7, with the 1^{st} quartile and 3^{rd} quartile less than 0.1.

Table 1.24: 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 1.14, I attempt to estimate by considering the second order.

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

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

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 1.14.

1.5 Counterfactual Policy

1.5.1 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.

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. 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 1.25: 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 1.26: 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.

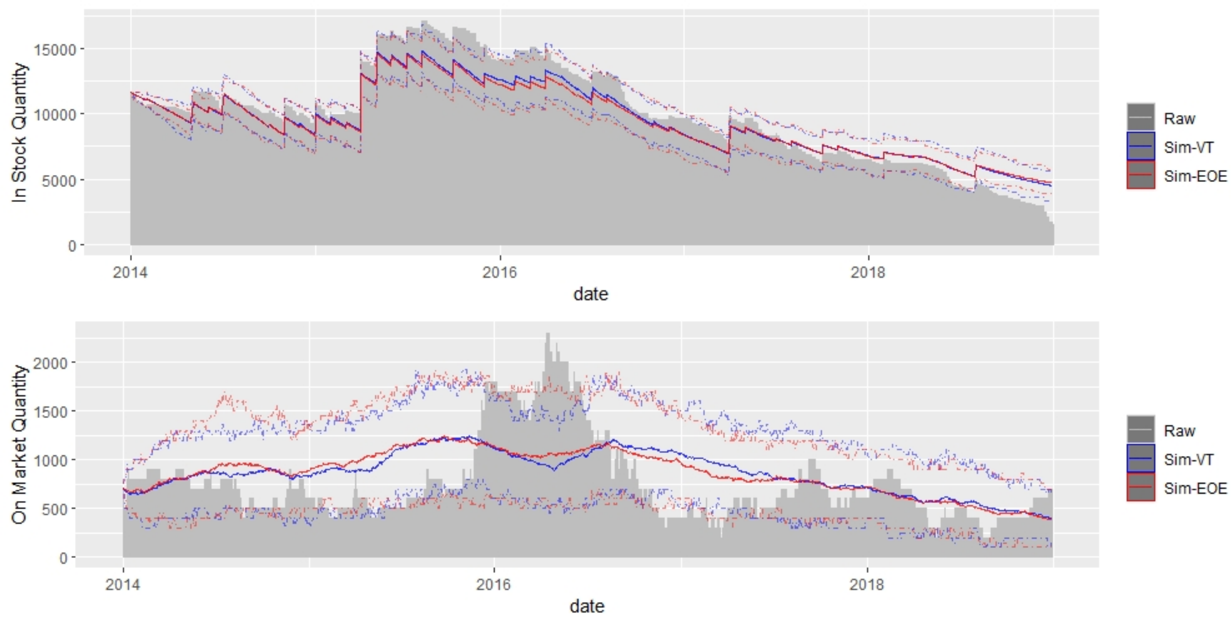


Figure 1.8: Simulations of Counterfactual EOE under Vacancy Tax

Counterfactual Equilibrium

Table 1.25 and 1.26 showed the excerpts of updated equilibrium, as compared to the original equilibrium in table 1.22. 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 1.8 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 competition is insensitive to imposing vacancy tax[19]. In light of the competition model in EOE, the proposed vacancy tax has minimal impact to the behaviors of sellers.

[19] 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.

1.5.2 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.

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 1.27) and reentry (Table 1.28) strategy show the 10% penalty deter them from entering with small batches. For example, Table 1.28 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 1.27 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 1.27: 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

Table 1.28: 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

By simulating the market with the new strategy, Figure 1.9 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

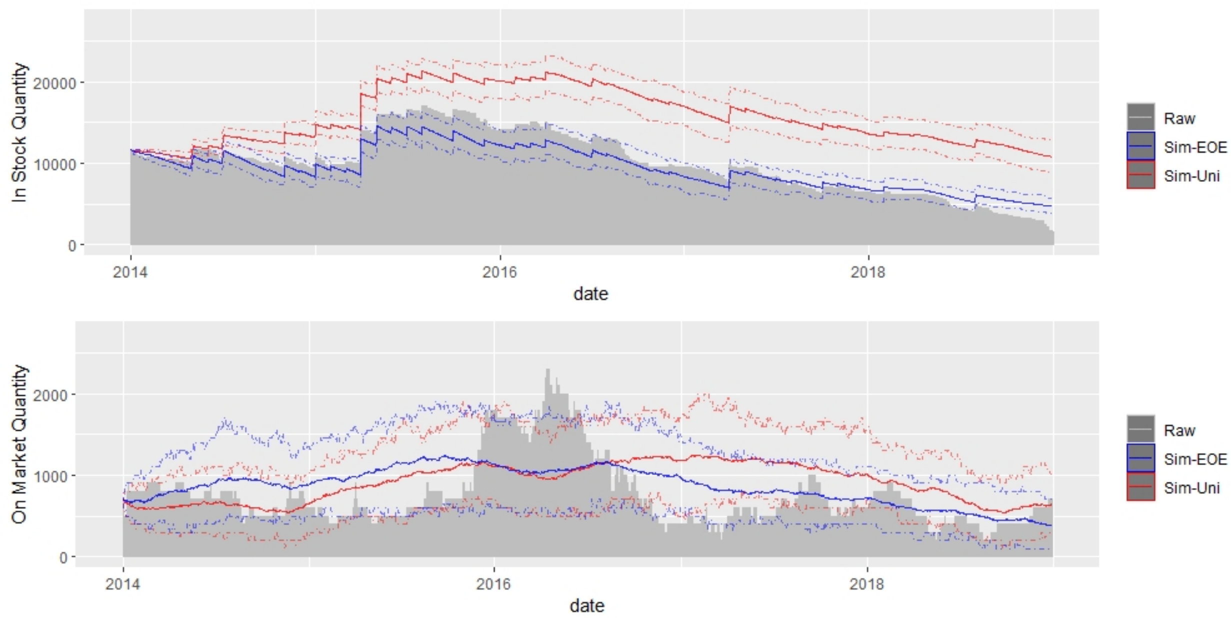


Figure 1.9: Simulations under Acyclical Phased Sales Penalty

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 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.

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 1.29 & 1.30 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 1.29 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 1.27 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.

A more comprehensive picture of the changed strategy can be demonstrated in simulations. Figure 1.10 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

Table 1.29: 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

Table 1.30: 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

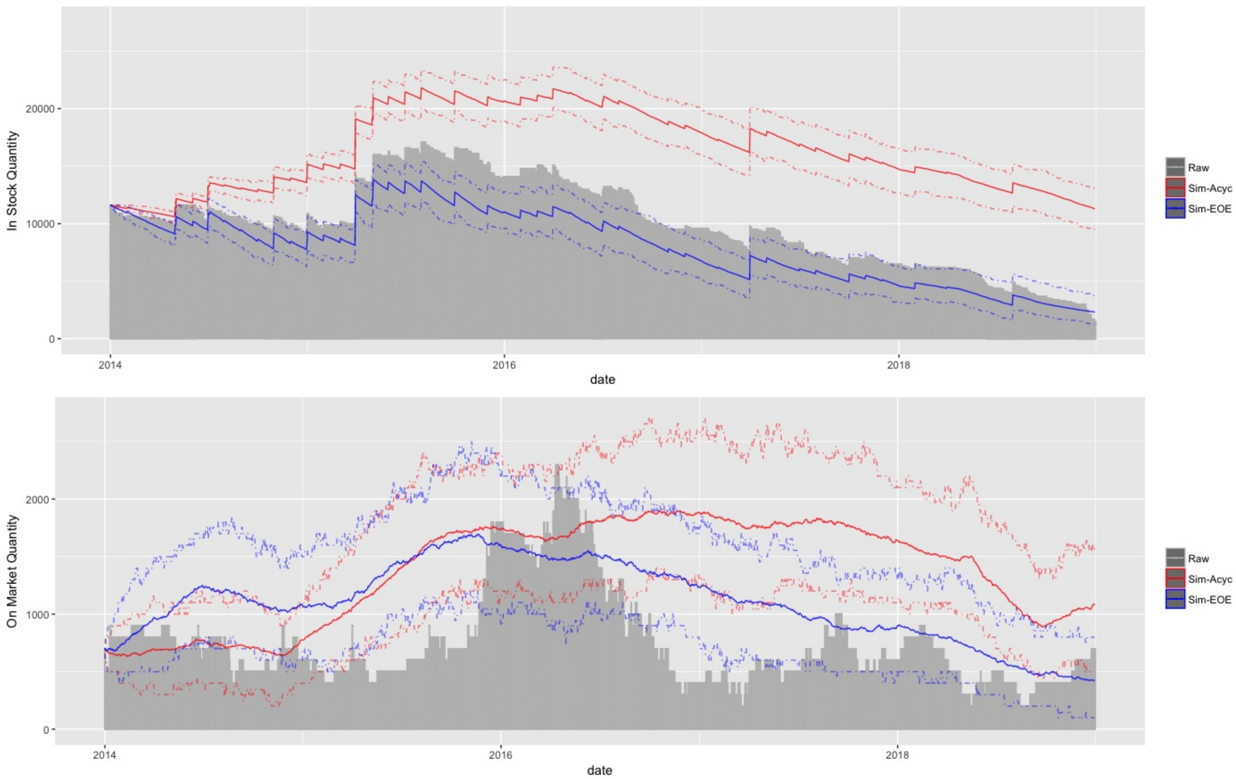


Figure 1.10: Simulations under Counter-cyclical Phased Sales Penalty

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 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.

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.

1.5.3 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

Figure 1.11: Simulations of Counterfactual under Vacancy Tax: EOE vs OE

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 1.11 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 1.12 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 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.

1.6 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[20], OE approximates MPE by tracking

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

Figure 1.12: Simulations of Counterfactual under Vacancy Tax: EOE vs OE

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 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.

Chapter 2

Daily Pricing in Primary Real Estate Market

Price is a tremendously important measurement in understanding any market. Pricing behavior is no doubt a crucial aspect for all sellers. While many real estate researches may simplify pricing for the sake of model sophistication, this chapter studies in details of the pricing behaviors among Hong Kong real estate developers. In particular, I utilized the high frequency daily data to construct a daily price index to reflect changes by date. The index has controlled influences from apartment heterogeneity and other intentional pricing practices and hence a better alternative in reflecting the daily changes in real estate prices.

For this chapter, I start by describing the data further from the pricing perspective. Then, I investigate how the fundamental features affects pricing. I discuss the pricing differences across developers. Other market-specific pricing details such as discount, difference for apartments larger than 600 sq. ft. and competitive pressure are then investigated. With these, the daily price index can be constructed utilizing the fixed effect by date. External environment such as secondary market and stock market are studied. In response to demand shift due to flu prevalance, I find evidence that pricing is sophisticated enough to discern the lower transactions of flu prevalance from other cases of actual low demand. Rather, the developers raise the price significantly in such case, apparently to clarify against any potential negative comments about sales performance from the media or the public.

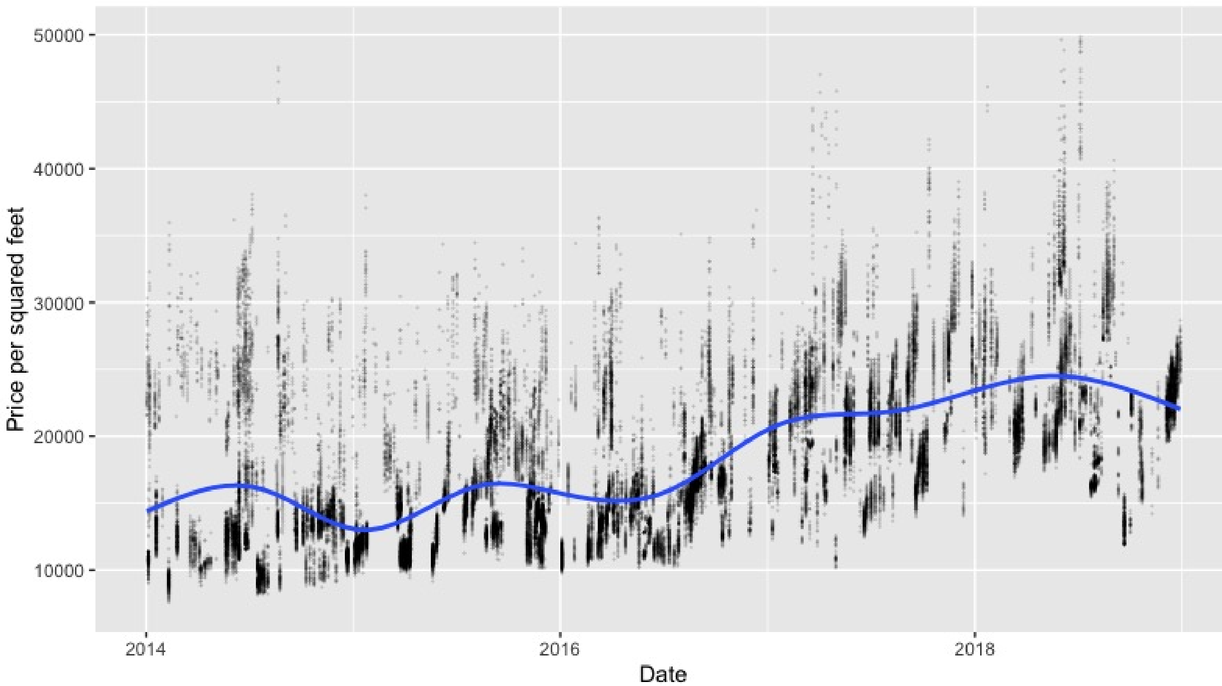


Figure 2.1: Listed Price per squared feet over Time

2.1 Data

As described in the previous chapter, during the data period from 2014 to 2018, I have the full coverage of primary market pricing of real estate in Hong Kong. This implies the daily changes in price are all reflected in the data. Despite the heterogeneity across apartments, figure 2.1 illustrates at a high level how the price per squared feet changes over time. From 2014 to 2016, average price fluctuates around HKD 15,000 per sq.ft.[1] with HKD 10,000 and HKD 25,600 as 5-th and 95-th percentile respectively. After the prices trend down twice in late 2014 and early 2016, it raises gradually since the late 2016. From 2017 to 2018, the average price raises from HKD 15,000 to about HKD 25,000. The average price in this period is HKD 23,000 with HKD 15,000 and HKD 32,000 as 5-th and 95-th percentile.

2.1.1 Descriptive Statistics for Pricing

Table 2.1 provides an overview of data from the apartment pricing perspective. Listed price of all apartments averages at around HKD 18,000 with a standard deviation at around HKD 6,000. An average apartment is

[1] Hong Kong Dollars per squared feet is presumed hereafter as the default measuring unit of price, unless it is specified otherwise.

Table 2.1: Descriptive Statistics for Pricing

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
Price/sq. ft. (HKD)	43,980	18,190.550	5,991.351	7,583.000	13,264.000	16,917.500	22,289.740	49,849.000
Size (sq. ft.)	40,257	565.833	243.715	161	396	519	705	2,019
Floor	43,965	18.412	12.703	0	8	16	26	76
Price list	43,882	3.101	1.945	1	1	3	4	9
Close Price/sq. ft. (HKD)	40,064	15,615.040	4,951.288	6,951.049	11,712.380	14,823.580	18,626.900	46,081.180
Discount	43,980	0.873	0.058	0.700	0.825	0.865	0.910	1.199

sized at 570 sq. ft., ranging from 161 to above 2,000 sq. ft. Apartments in Hong Kong can get as high as 76^{th} floor and the median is 16^{th} floor. This consistent with most apartments in Hong Kong are usually in building with 20+ floors. Apartment listing can spread into as many as 9 price lists while many are sold by 3 or 4 price lists. When the apartments close on transaction, the closing price is typically HKD 2,000-3,000 lower, which implies around 15% off compared to the listed price.

2.2 Fundamental Features

2.2.1 Size

To account for the heterogeneity in prices, I first look at the difference in the physical attributes of the apartments. Figure 2.2 provides a detailed distribution of apartment size by every 10 sq. ft. One can see the mode is around 500 sq. ft. Around 750 sq.ft., there are also quite apartments. Beyond 1,000 sq. ft., there are limited apartments in the range. Comparing to the price across apartment size, figure 2.3 show the box plot after discretizing the apartment size into 100 sq. ft. For the apartments smaller than 700 sq. ft., there is a trend of lower price when the apartment size increases. However, there is no monotonic trend overall. Price gets higher after 700 sq. ft., but it gets lower when the size gets even larger. Apparently, this basic feature is limited in explaining the price variations. More factors need to be considered.

2.2.2 Floor Level

Similar to many metropolis in the world, Hong Kong is dense with skyscrapers. It is rare to have apartment building of 10 floors or less. In my data, buildings of 15 floors is at the 1st quartile already. More than half of buildings are of at least 25 floor levels and it goes as many as 80 floors.

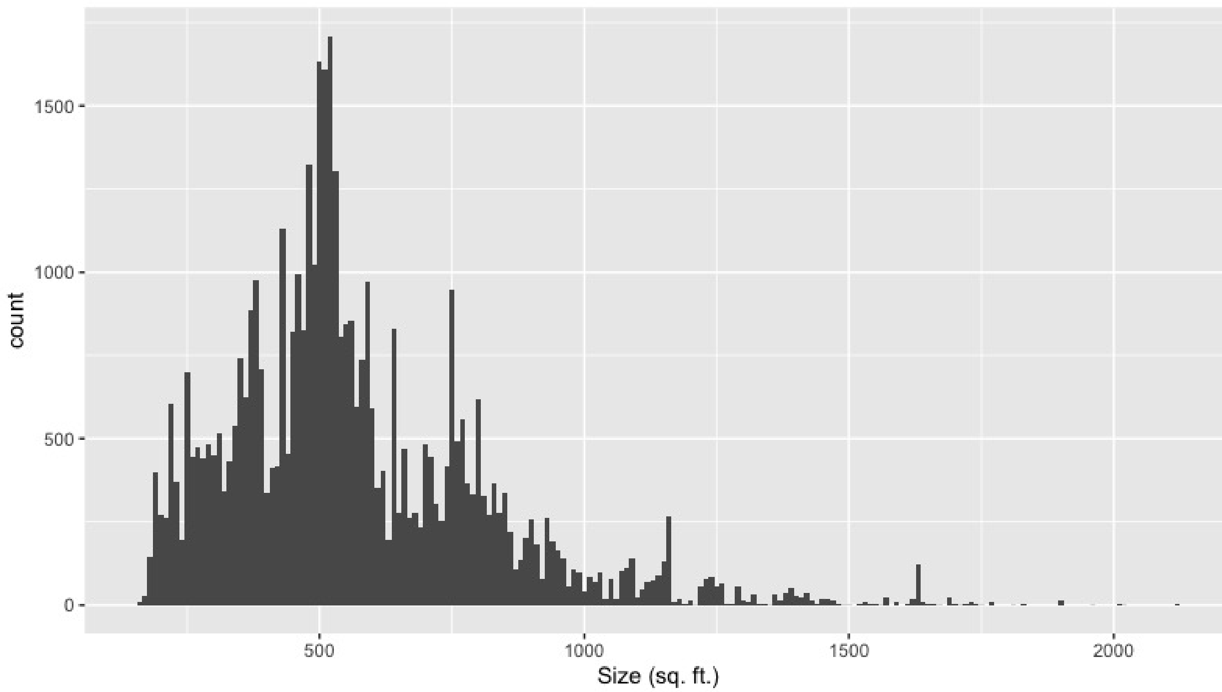


Figure 2.2: Size Distribution across Apartments

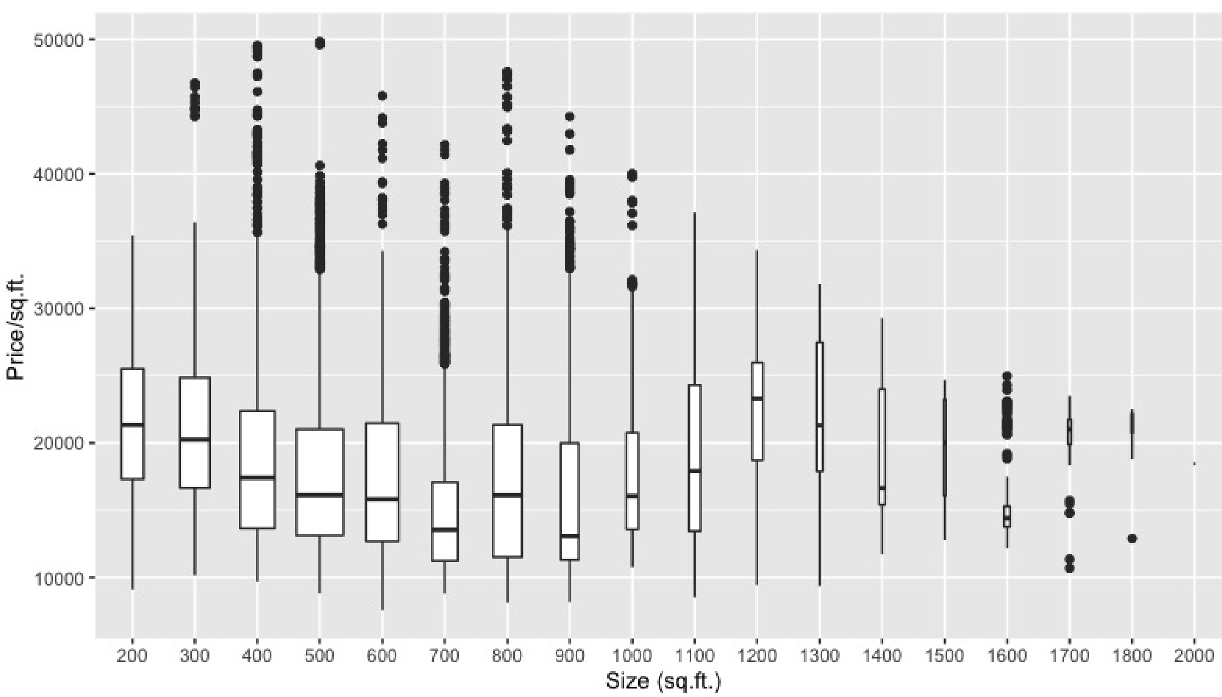


Figure 2.3: Listed Price per squared feet across Apartment Size

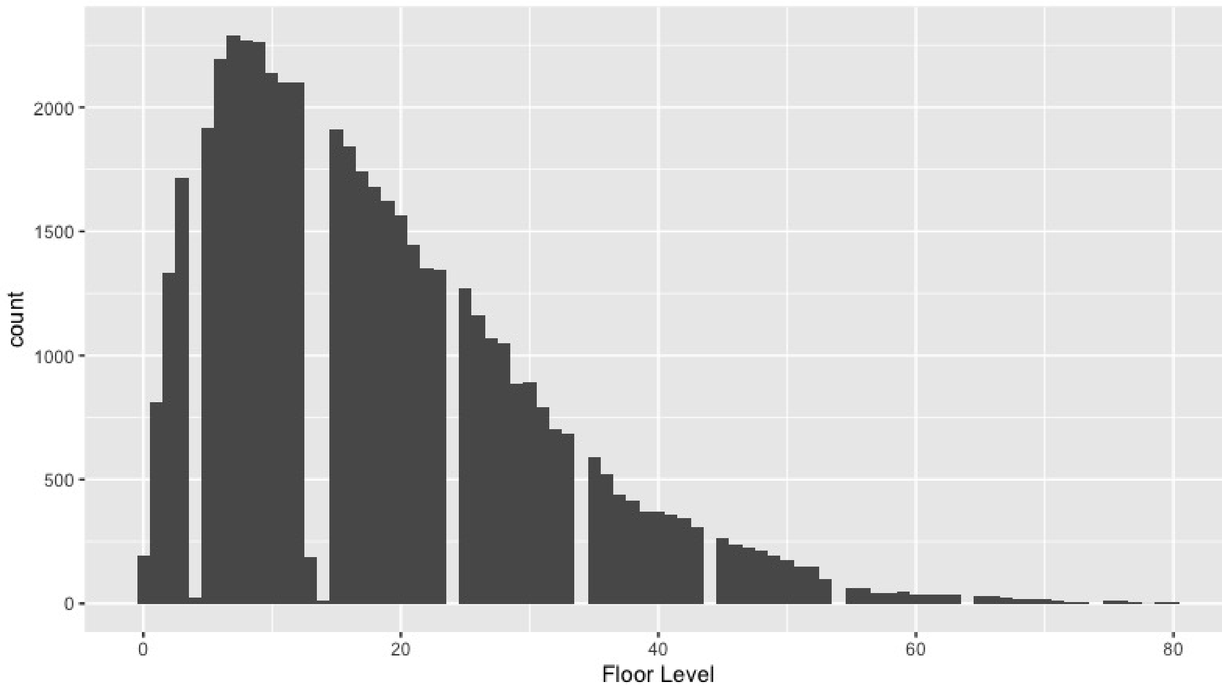


Figure 2.4: Floor Distribution across Apartments

Figure 2.4 shows the distribution of floor levels. In addition to the expected left-skewing due to the accumulating nature of floors, many buildings clearly skip a level or two in every 10 floors. These are the floors ending with 4, which is regarded ominous due its close pronunciation with "death" in local language. Given the western culture in Hong Kong, it is not surprising that floor 13 is also widely skipped.

By comparing the floor level and the price, figure 2.5 demonstrates an increasing trend of price when the floor level increases. This is consistent with the phenomenon that the marketing of various apartments emphasizing it as "high level". Given the density in Hong Kong, higher in the building implies a wider view and less noise from the streets. It is confirmed in the data that floor is a valid pricing basis. Furthermore, while the definition of "high level" is rather vague and easily manipulated depending on the apartment to promote, my data summarizes some objective information. For apartments below floor 8, price medians are around HKD 15,000. From floor 8 until 20, medians are about HKD 17,000. Beyond floor 20, price medians are going to around 19,000 and above. This information suggests "high level" to be above floor 20, where "low level" refers to floors below the 8-th.

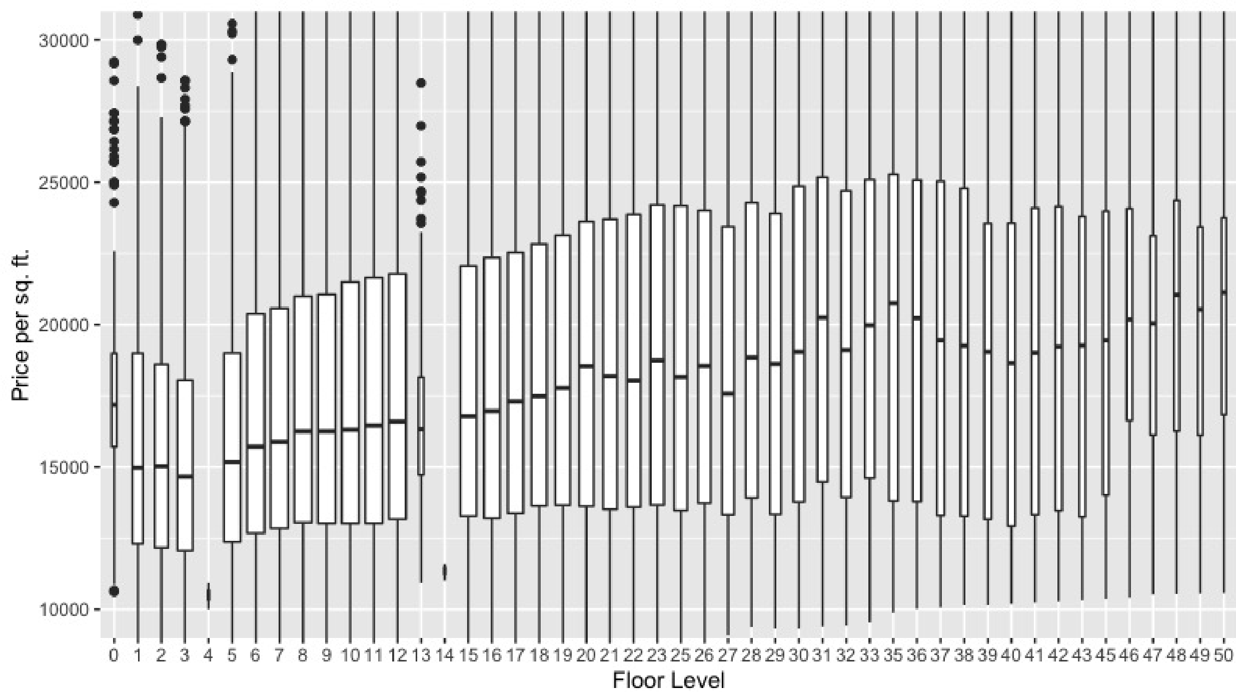


Figure 2.5: Listed Price per squared feet across Floor levels

2.2.3 Price List

As described previously, primary real estate market in Hong Kong sells apartments batch by batch through phased sales. One batch is referred as one price list. There can be as many as 9 price lists for one development site, but many would have about 4 or 5 price lists. Figure 2.6 shows the distribution of price list in the data.

On the surface, it is ambiguous whether price list has any influence to the prices. As figure 2.7 shows, there is no significant price trend.However, once you take into consideration of the differences in apartment attributes, the price residuals demonstrate a clear increasing trend for the later price list. This is consistent with my interviews with industry insiders. Many pointed out an industry norm of raising the price gradually after intentionally setting a lower price at the beginning. Figure 2.8 shows an example when other apartment attributes are controlled for. The increasing trend is evident.

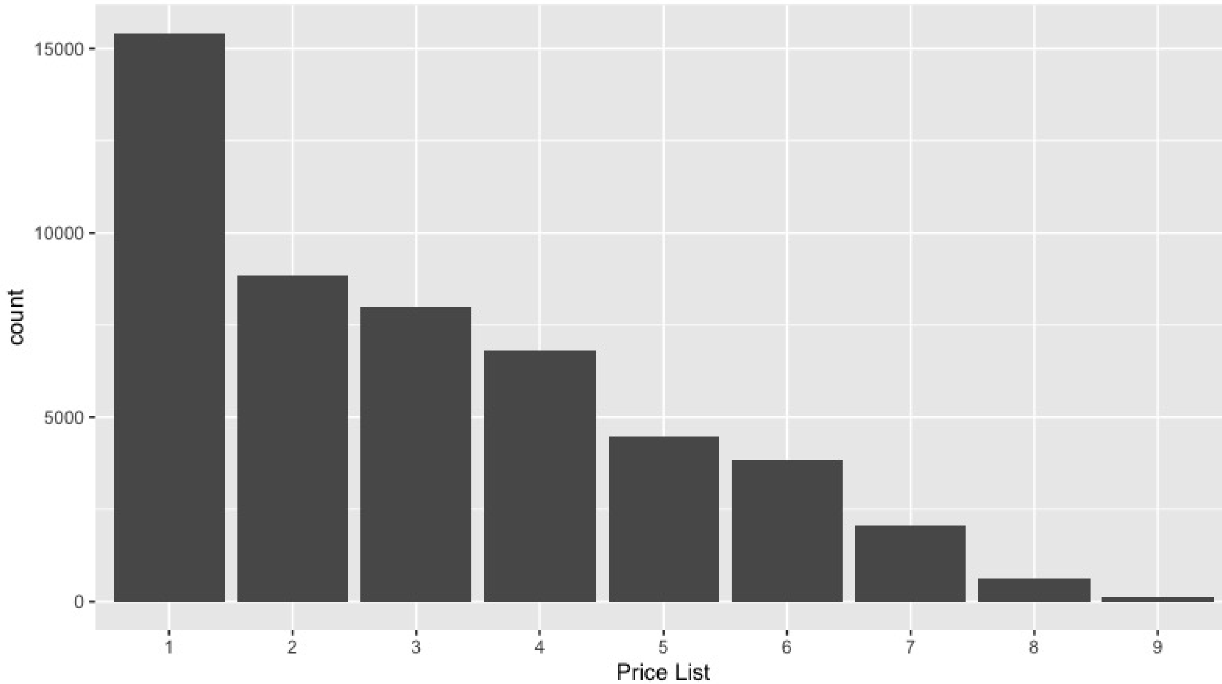


Figure 2.6: Price List Distribution

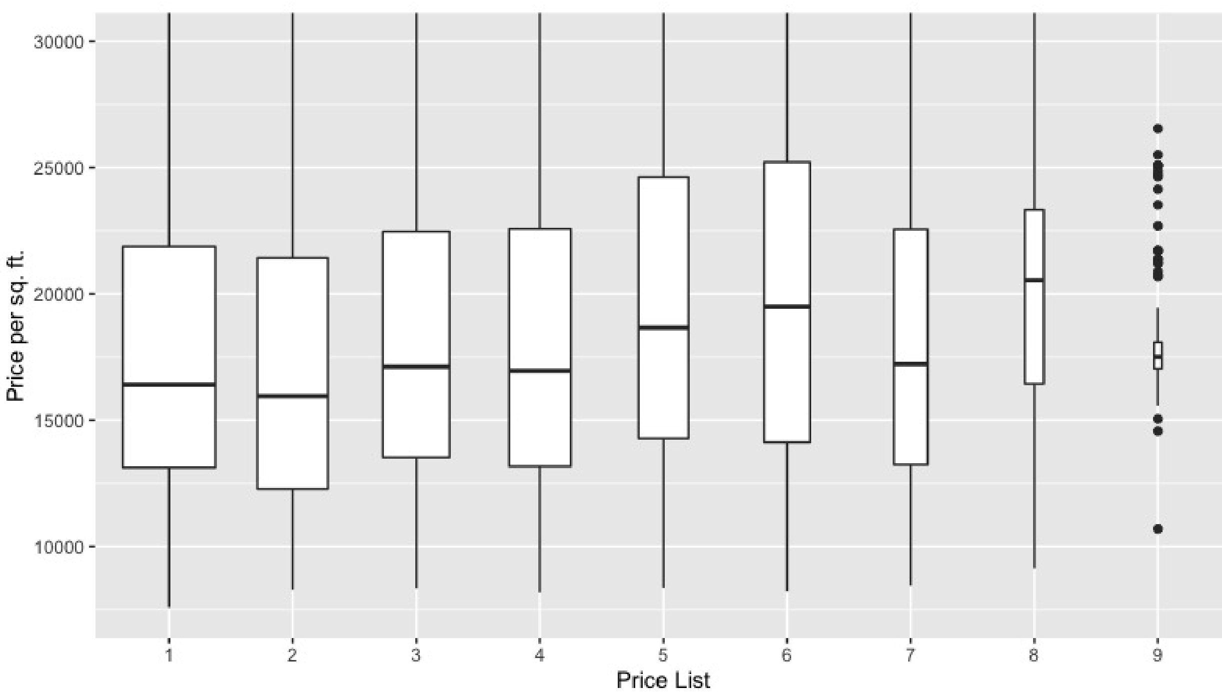


Figure 2.7: Listed Price per squared feet across Price List

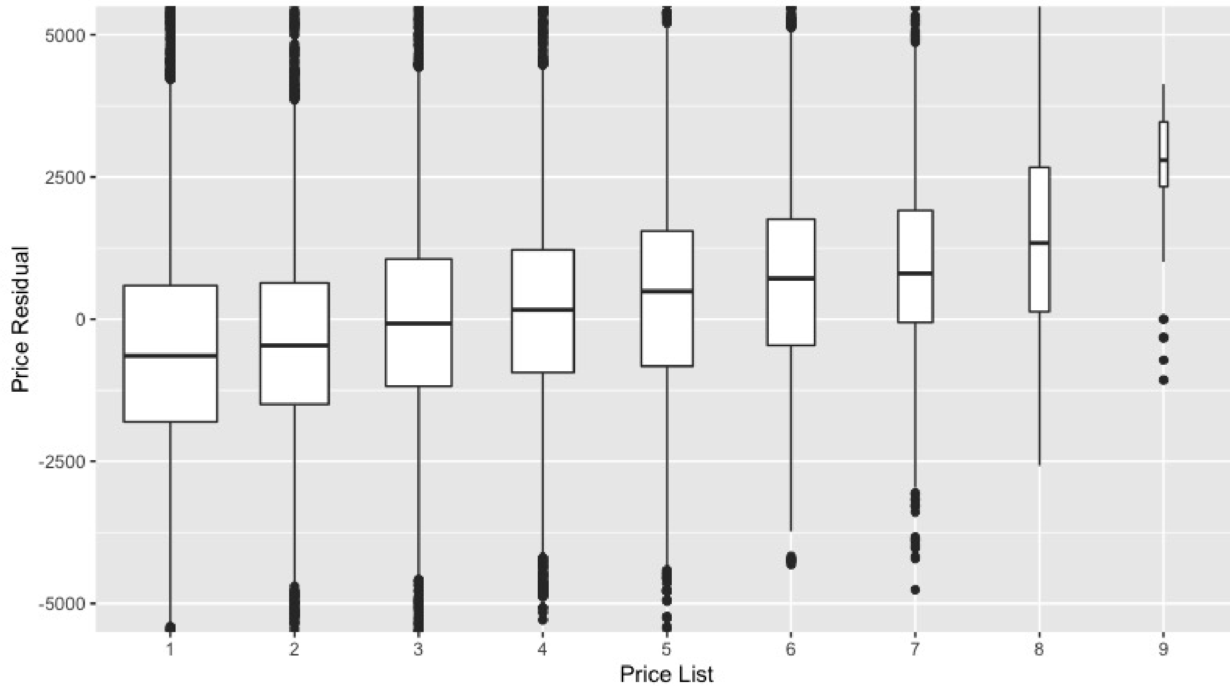


Figure 2.8: Price residual across Price List

2.2.4 Regression on Fundamental Attributes

To quantify the overall impact of fundamental attributes, I estimated the ordinary least square regression of the fundamental attributes on prices. In the column 1 of 2.2, both price list and the floor level both have significant positive statistical impact. For 1 price list later, the price increase by about HKD 250. The price raise is on average HKD 100 per floor. As more variables are contolled for (e.g. geographic location, the imapcts remain the same direction but with a different magnitude. For example when geographical location is considered in column 2, the impact from price list raises to HKD 415 per PL and that from floor reduces to HKD 41 per floor.

Regarding the geographical location, the pricing is consistent with expectation. Hong Kon can be split into 3 regions - Hong Kong Island, Kowloon and New Territories. Hong Kong Island is frequently regarded as more expensive than the other two and Kowloon forms the downtown area (with Hong Kong Island). Therefore, relative to Hong Kong Island, New Territories has the lowest price and Kowloon is in the middle. Furthermore, since lands in Hong Kong Islands and Kowloon are much more limited than New Territories due to earlier development in history, the price contrast in primary real estate market would be even steeper.

Column 2 shows that new apartments in Kowloon are HKD 5,000 lower and those in New Territories are HKD 12,000 lower on average, compared to Hong Kong Islands.

Breaking down further to look at the distribution across District - s, I used Sha Tin District - that is in New Territories and the closest to the downtown area as the reference District - . Central and Western District - and Easter District - , both on the Hong Kong Island, have the highest price, more than HKD 10,000 higher relative to apartments in Sha Tin District - . Islands District - and North District - are the lowest in price, HKD 4,000 and HKD 2,000 cheaper respectively. Islands District - essentially necessitates ferry to travel to the rest of Hong Kong. North District - is the furthermost District - from downtown by distance and indeed the District - bordering mainland China in the north. Therefore, the differences are reasonable due to the severe commute difficulties.

2.2.5 Differences across Developers

While the pricing based on the fundamental attributes has been analysed, developers might indeed adopt different pricing approach based on the attributes. During my data period, the leading developers[2] are Henderson, Sun Hung Kai, MTR and Cheung Kong. Table 2.3 presents their pricing varies in face of same set of attributes. Taking all developers other than these 4 developers as the reference level, the regression result highlights how the 4 firms differ across size, floors and price lists. While the effect of floor and price list remains significant and of the same sign, the apartment size has insignificant effect once developers are controlled for.

In terms of brand premium, Sun Hung Kai has the highest, above HKD 800, while Henderson also has about HKD 500. Apartments by Cheung Kong are priced almost HKD 2,500 less relative to other smaller developers. While this might appear surprising to some, Cheung Kong indeed has a reputation of less comfortable provision in terms of apartment floor plan design, quality of interiors and other qualities. The lower pricing would be a natural offering for the tradeoff in quality. Regarding the apartment size, all 4 except Cheung Kong offer a lower per sq. ft. price for larger apartments. For price raise in higher level, Henderson and MTR are more aggressive in raising their price at around HKD 35 per floor on average. While Sun Hung Kai and Cheung Kong have the same price raise practice, it is statistically less so at around HKD

[2]URA has the same number of developments with MTR, but it has an additional public service objective of re-developing urban area. Hence, it is less interesting an comparison for its intrinsic difference in nature.

Table 2.2: Price Regression of Fundamental Featrues

	Dependent variable:		
	Price/Sq. ft. (HKD)		
	(1)	(2)	(3)
Size(sq. ft.)	-3.993^{***}	-1.445^{***}	-0.624^{***}
	(0.107)	(0.083)	(0.077)
Floor	101.618^{***}	41.333^{***}	55.466^{***}
	(2.045)	(1.588)	(1.485)
Price List	234.511^{***}	415.480^{***}	469.435^{***}
	(13.645)	(10.352)	(9.280)
Region - Kowloon		$-5,144.703^{***}$	
		(83.319)	
Region - New Territories		$-11,536.820^{***}$	
		(81.506)	
District - Central and Western			$11,560.940^{***}$
			(129.595)
District - Eastern			$10,021.330^{***}$
			(133.289)
District - Islands			$-4,347.046^{***}$
			(98.672)
District - Kowloon City			$5,962.348^{***}$
			(77.358)
District - Kwun Tong			$5,684.938^{***}$
			(105.116)
District - North			$-2,361.168^{***}$
			(168.896)
District - Sai Kung			$-1,251.289^{***}$
			(77.514)
District - Sham Shui Po			4.110
			(157.320)
District - Southern			$6,995.173^{***}$
			(236.473)
District - Tai Po			354.251^{***}
			(87.832)
District - Tsuen Wan			$1,413.472^{***}$
			(90.113)
District - Tuen Mun			$-2,249.649^{***}$
			(94.329)
District - Wan Chai			$9,025.322^{***}$
			(128.860)
District - Wong Tai Sin			$3,382.897^{***}$
			(539.307)
District - Yau Tsim Mong			$8,892.057^{***}$
			(98.734)
District - Yuen Long			$-1,804.966^{***}$
			(80.176)
Constant	$17,562.950^{***}$	$25,183.280^{***}$	$14,027.750^{***}$
	(83.847)	(91.306)	(84.371)
Observations	45,128	45,128	45,128
R^2	0.087	0.479	0.594
Adjusted R^2	0.087	0.479	0.594
Residual Std. Error	5,559.546 (df = 45124)	4,198.895 (df = 45122)	3,706.867 (df = 45108)
F Statistic	$1,427.475^{***}$ (df = 3; 45124)	$8,298.559^{***}$ (df = 5; 45122)	$3,475.070^{***}$ (df = 19; 45108)

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

Table 2.3: Price Regression with Leading Developers

	Dependent variable:
	Price/Sq. ft. (HKD)
Size(sq. ft.)	0.021
	(0.112)
Floor	37.422***
	(2.832)
Price List	627.354***
	(14.865)
Henderson	489.321***
	(189.593)
SHK	814.356***
	(175.446)
CK	−2,463.183***
	(265.252)
MTR	−499.582***
	(170.244)
Henderson:Price List	−537.595***
	(33.327)
SHK:Price List	−319.500***
	(23.888)
CK:Price List	−511.496***
	(34.852)
MTR:Price List	53.741**
	(23.551)
Henderson:Size(sq. ft.)	−2.729***
	(0.230)
SHK:Size(sq. ft.)	−0.448*
	(0.238)
CK:Size(sq. ft.)	0.503*
	(0.297)
MTR:Size(sq. ft.)	−1.189***
	(0.202)
Henderson:Floor	35.353***
	(6.417)
SHK:Floor	25.870***
	(4.836)
CK:Floor	22.091***
	(6.394)
MTR:Floor	34.665***
	(3.672)
Constant	14,835.940***
	(103.953)
District - FE	Yes
Observations	45,128
R^2	0.626
Adjusted R^2	0.626
Residual Std. Error	3,556.604 (df = 45092)
F Statistic	2,160.895*** (df = 35; 45092)

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

Note: Some abbreviations are used for the leading developers: Sung Hung Kai - SHK and Cheung Kong - CK.

25 per floor with a standard deviation of 5. As for the progressive price by price list, the traditional family tycoons, Henderson, Sun Hung Kai and Cheung Kong, all raise several hundreds HKD less for each price list relative to other smaller developers. Only MTR raises about HKD 50 per price list. This is potentially because of the concern for public image. Price raise per price list is one of the most scrutinized feature of real estate market in Hong Kong. As the tycoon families for decades in the city, the public relation concern can rationally justify the lower than competitor price raise. After all, they are still raising around HKD 100 per batch at least.

2.3 Market-specific Pricing Behaviors

In addition to the product attributes, pricing is also optimized for the market situation. Real estate market in Hong Kong sophisticates over decades. This section discusses how pricing takes into account of the market specificity, in particular the discount, market boundary and pricing under competition.

2.3.1 Discount

Figure 2.1 shows the listed price for each apartment when it opens for sales. When it proceeds to transaction, the registered closing price is typically lower than what is listed at the beginning. This is due to the discount provided by the developers when the buyers commit to some payment plans favorable to sellers. Therefore, other than the listed price, the closing price is also of market interest. Figure 2.9 supplemented the closing price in red. One can see the lower price with a tracking trend.

Figure 2.10 shows that the majority of apartments is discounted to about 85% (i.e. 15% off) although there is also a certain portion receiving no discount. Table 2.4 column 1 shows that discount percentage is deeper when the size is larger, the floor is higher and the price list is later. Instead of looking at the derived percentage, one can also look at the closing price regression while controlling the listed price. This specification in Column 2 yields that both size and floor have the same statistically significant negative sign for lower closing price. However, this specification does not show statistical support for later price list implying lower closing price.

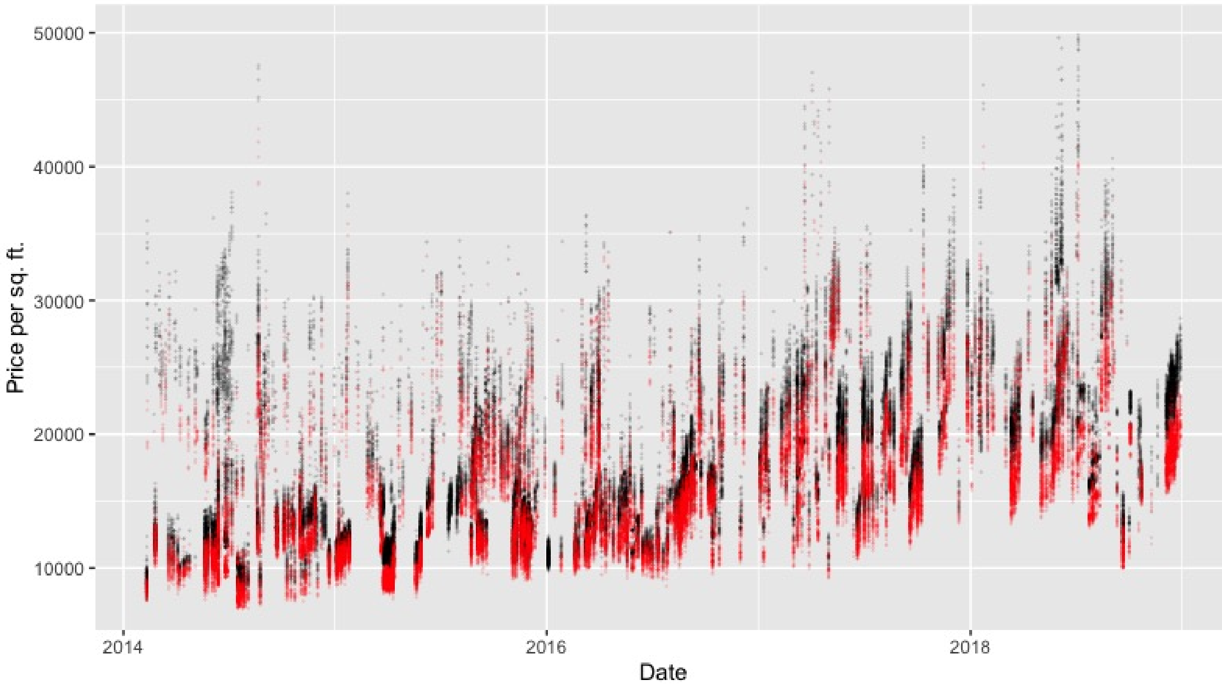


Figure 2.9: Closing Price per sq. ft. (in red) over Time

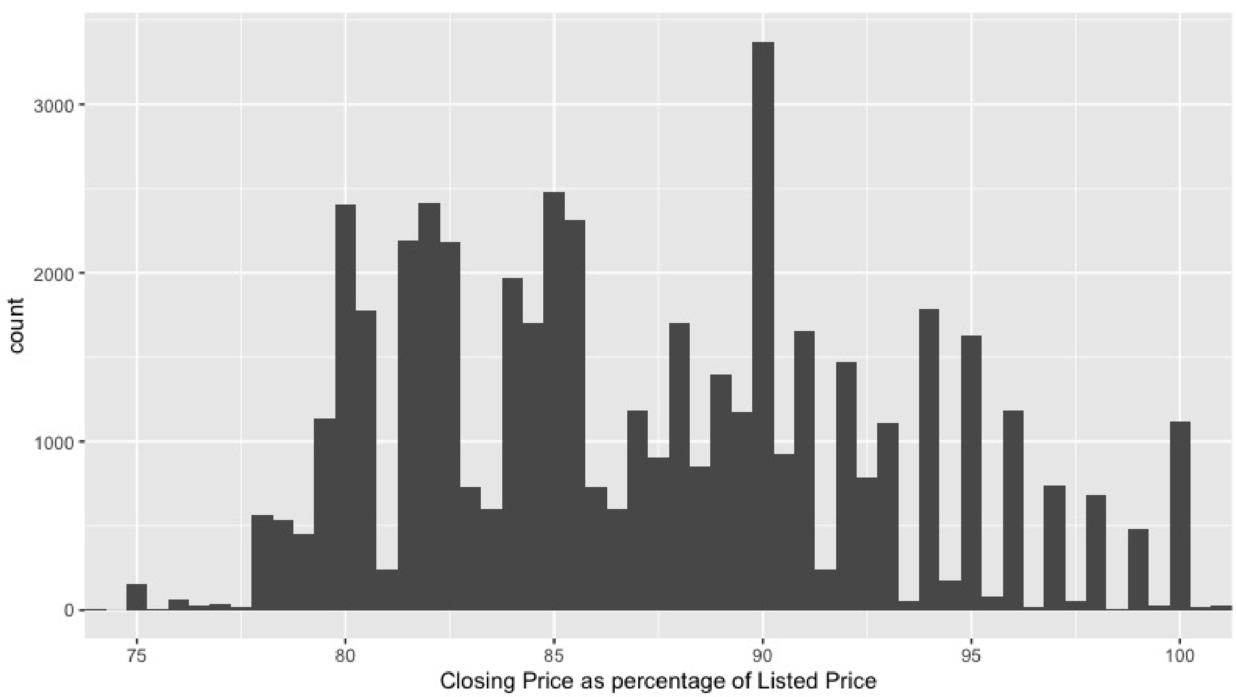


Figure 2.10: Distribution of Pricing Discount

Table 2.4: Discount and Closing Price Regression

	Dependent variable:	
	(disc $*$100)	Closing Price/Sq. ft. (HKD)
	(1)	(2)
Size(sq. ft.)	-0.001^{***}	-0.173^{***}
	(0.0001)	(0.020)
Floor	-0.034^{***}	-2.825^{***}
	(0.002)	(0.392)
Price List	-0.098^{***}	-0.723
	(0.012)	(2.485)
Price/Sq. ft. (HKD)		0.811^{***}
		(0.001)
District - Central and Western	1.198^{***}	$1{,}556.021^{***}$
	(0.164)	(36.619)
District - Eastern	-0.656^{***}	991.635^{***}
	(0.169)	(36.880)
District - Islands	-1.072^{***}	-514.591^{***}
	(0.125)	(26.225)
District - Kowloon City	-4.259^{***}	-322.357^{***}
	(0.098)	(21.476)
District - Kwun Tong	-9.552^{***}	$-1{,}473.201^{***}$
	(0.133)	(28.229)
District - North	1.897^{***}	41.891
	(0.214)	(43.939)
District - Sai Kung	-6.686^{***}	$-1{,}097.815^{***}$
	(0.098)	(20.273)
District - Sham Shui Po	0.567^{***}	177.347^{***}
	(0.200)	(41.302)
District - Southern	1.579^{***}	$1{,}170.285^{***}$
	(0.300)	(62.164)
District - Tai Po	-7.064^{***}	$-1{,}087.574^{***}$
	(0.111)	(22.932)
District - Tsuen Wan	-9.032^{***}	$-1{,}521.717^{***}$
	(0.114)	(23.540)
District - Tuen Mun	-2.752^{***}	-686.456^{***}
	(0.120)	(24.876)
District - Wan Chai	-7.606^{***}	-892.106^{***}
	(0.164)	(35.292)
District - Wong Tai Sin	-0.326	269.666^{*}
	(0.684)	(146.075)
District - Yau Tsim Mong	-4.064^{***}	2.274
	(0.125)	(27.956)
District - Yuen Long	-1.771^{***}	-455.224^{***}
	(0.102)	(21.078)
Constant	93.088^{***}	$1{,}810.968^{***}$
	(0.107)	(27.917)
Observations	45,128	44,729
R^2	0.335	0.964
Adjusted R^2	0.335	0.964
Residual Std. Error	4.704 (df = 45108)	961.255 (df = 44708)
F Statistic	$1{,}195.986^{***}$ (df = 19; 45108)	$59{,}263.420^{***}$ (df = 20; 44708)

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

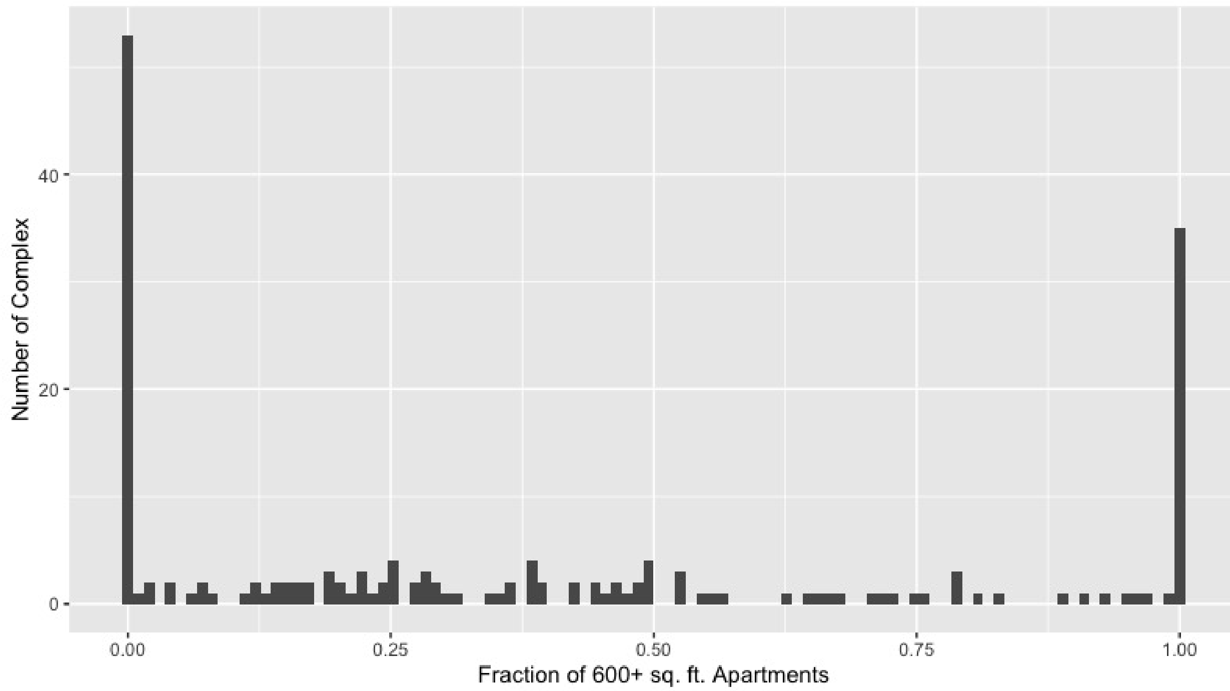


Figure 2.11: Distribution of Complex Fractions of Apartments sized above 600 sq. ft.

2.3.2 Market Boundary

As Hong Kong is a relatively small and contained administrative region, one market basically spans the whole Hong Kong geographically. However, the housing goods can differ substantially. While many are designed to satisfy the majority need, some apartments are much larger and hence potentially forming another market of housing goods. Considering the bi-modal size distribution of apartments, figure 2.11 shows the fraction of apartments sized above 600 sq. ft. for each development complex. It is clear that most complexes have either zero apartments larget than 600 sq. ft. or all apartments being large, very few fractions are between 0 and 1. Since developers have the autonomy in construction design, it is rather evident that the supply side perceives the complex as binary type, mass market and luxury market.

Given the observation, I dissect the apartments into two markets, mass and luxury, based on their complex. The threshold is whether the complex fraction of apartments above 600 sq. ft. is more than 0.5 or not. Figure 2.12 shows that such partition separates the bi-modal distribution into 2 uni-modal distributions cleanly, few apartments overlapping the other distribution.

Analysing the pricing behavior of the mass complexes and the luxury complexes separately, table 2.5

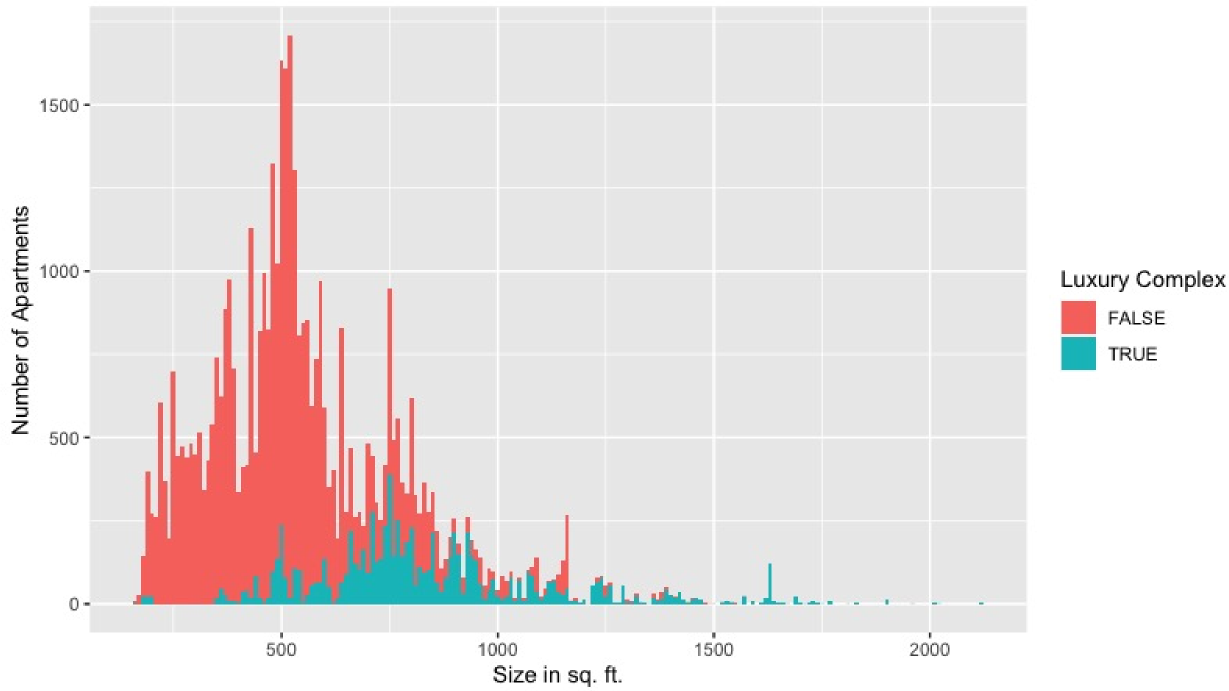


Figure 2.12: Distribution of Apartment Size in the Mass and the Luxury Complex

yields better fit than combined and than those separating at apartment level. While column 1 replicates the previous result in table 2.2, column 2 and 3 estimate the same regression on solely the mass complexes and solely the luxury complexes respectively. Regarding the price raise by price list, while both mass and luxury complexes have these practices, the mass complexes raise more aggressively at about HKD 500 and the luxury complexes raise only HKD 200 per price list. As for the raise by floor, only the mass complexes raise HKD 70 per floor. It is reasonable as luxury complexes also have much fewer floors to achieve the leisure atmosphere. The difference between those few floors would not be much. For the price influence of apartment size, mass complexes no longer see statistical significant relationship. It is probably because other variables can control better when the goods are now more homogeneous. Luxury complexes, in contrast, has a higher price when the size is larger at HKD 2.8 more per sq.ft.

2.3.3 Competitive Pricing

Market competition would no doubt be one important consideration for pricing. Although it has been discussed in the previous chapter, I would also discuss briefly here for a comprehensive pricing picture. From

Table 2.5: Price Regression for Mass and Luxury Complexes

	Dependent variable:		
	Price/Sq. ft. (HKD)		
	(1)	(2)	(3)
Size(sq. ft.)	-0.624^{***}	0.057	2.828^{***}
	(0.077)	(0.100)	(0.130)
Floor	55.466^{***}	71.124^{***}	1.600
	(1.485)	(1.533)	(2.425)
Price List	469.435^{***}	523.914^{***}	202.273^{***}
	(9.280)	(9.246)	(18.772)
District - Central and Western	$11{,}560.940^{***}$	$11{,}157.530^{***}$	$15{,}876.460^{***}$
	(129.595)	(124.863)	(272.589)
District - Eastern	$10{,}021.330^{***}$	$9{,}823.455^{***}$	$15{,}710.860^{***}$
	(133.289)	(125.624)	(371.384)
District - Islands	$-4{,}347.046^{***}$	$-4{,}338.627^{***}$	$-4{,}723.567^{***}$
	(98.672)	(96.268)	(204.792)
District - Kowloon City	$5{,}962.348^{***}$	$5{,}895.469^{***}$	$7{,}359.250^{***}$
	(77.358)	(76.452)	(159.557)
District - Kwun Tong	$5{,}684.938^{***}$	$5{,}519.113^{***}$	
	(105.116)	(100.810)	
District - North	$-2{,}361.168^{***}$	$-1{,}298.134^{***}$	$-4{,}506.310^{***}$
	(168.896)	(172.308)	(268.298)
District - Sai Kung	$-1{,}251.289^{***}$	-467.288^{***}	$-2{,}829.212^{***}$
	(77.514)	(80.042)	(126.492)
District - Sham Shui Po	4.110	$2{,}581.059^{***}$	$-2{,}908.366^{***}$
	(157.320)	(171.949)	(216.583)
District - Southern	$6{,}995.173^{***}$	$7{,}239.960^{***}$	
	(236.473)	(212.514)	
District - Tai Po	354.251^{***}	$4{,}074.764^{***}$	$-3{,}157.732^{***}$
	(87.832)	(99.969)	(120.504)
District - Tsuen Wan	$1{,}413.472^{***}$	$3{,}502.361^{***}$	$-2{,}387.156^{***}$
	(90.113)	(95.983)	(144.758)
District - Tuen Mun	$-2{,}249.649^{***}$	$-2{,}199.079^{***}$	-23.479
	(94.329)	(90.054)	(552.170)
District - Wan Chai	$9{,}025.322^{***}$	$8{,}989.549^{***}$	
	(128.860)	(118.839)	
District - Wong Tai Sin	$3{,}382.897^{***}$	$2{,}121.073^{***}$	$4{,}576.791^{***}$
	(539.307)	(706.207)	(572.345)
District - Yau Tsim Mong	$8{,}892.057^{***}$	$8{,}457.625^{***}$	$13{,}547.570^{***}$
	(98.734)	(95.864)	(205.644)
District - Yuen Long	$-1{,}804.966^{***}$	$-1{,}458.528^{***}$	$-2{,}483.508^{***}$
	(80.176)	(80.566)	(142.872)
Constant	$14{,}027.750^{***}$	$13{,}217.620^{***}$	$12{,}209.290^{***}$
	(84.371)	(85.161)	(173.518)
Observations	45,128	36,930	8,198
R^2	0.594	0.646	0.741
Adjusted R^2	0.594	0.646	0.740
Residual Std. Error	3,706.867 (df = 45108)	3,297.897 (df = 36910)	2,863.370 (df = 8181)
F Statistic	$3{,}475.070^{***}$ (df = 19; 45108)	$3{,}541.395^{***}$ (df = 19; 36910)	$1{,}461.155^{***}$ (df = 16; 8181)

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

a reduced form perspective, competition can be gauged by the aggregate measures of the number of competitors and the number of apartments available. Table 2.6 presents the pricing under competition. There are two measures of the number of competitors. Player concerns the total number of active complexes at the time. Entrant measures the number of complexes listing a new price list at the day. Since the two variables are closely related, I estimated the interaction of two variables also. The sole impact of having 1 more player is about HKD 500 lower in price, where 1 more entrant further lowers HKD 20 through the interaction. The sole impact of entrant, however, might appear surprising. Note that it is rare to have an entry by competitor as developers tend to avoid clashing together. The positive sign likely proxy for the good market for sales, rather than the actual competitive effect. As for the number of apartments available on the market, for 1 more apartment on market, price is set HKD 2 less. Therefore, competition does exert downward pressure on the price through the number of active selling complexes and the number of selling apartments.

2.4 Response to External Environment

Real estate has two distinct features that differentiates the pricing consideration from many other goods. First, real estate is a decades-long durable good. This allows a significant secondary market. Unlike many other goods, even for goods with some secondary market like automobile, the pricing in primary real estate market needs to pay attention to the secondary market condition. Second, real estate is an investment asset. This makes the pricing sensitive to the return from other asset markets.

2.4.1 Secondary Market Indices

To gauge the atmosphere in the secondary market, indices provided by Centaline Property Agency are the reputable indicators and frequently reported by the media. I use Centa-City index and Centa-City leading index to analyse its influence on pricing. Centa-City index is a monthly price index based on the registered transaction in Land Registry of Hong Kong Government. While the government department takes time to process and publish, the agency provides Centa-City leading index that is a weekly price index based on the preliminary agreements under the agency. Since the agency accounts for above 20% market share, this leading index provides reliable weekly information.

To estimate the current pricing based on the past secondary market condition, I used the two indices

Table 2.6: Price Regression with Aggregate Measurements of Competition

	Dependent variable:
	Price/Sq. ft. (HKD)
Size(sq. ft.)	1.373***
	(0.068)
Floor	63.654***
	(1.284)
Price List	448.862***
	(8.033)
Number of Active Sellers	−497.256***
	(4.709)
Number of Entrants	429.778***
	(72.941)
Number of Active Sellers:Number of Entrants	−21.474***
	(6.125)
Apartments on Market	−2.414***
	(0.040)
District - Central and Western	10,536.380***
	(111.062)
District - Eastern	8,726.548***
	(114.374)
District - Islands	−5,209.948***
	(85.285)
District - Kowloon City	4,926.028***
	(66.936)
District - Kwun Tong	2,456.295***
	(93.331)
District - North	−3,178.157***
	(153.044)
District - Sai Kung	−1,724.539***
	(66.621)
District - Sham Shui Po	−590.418***
	(139.254)
District - Southern	6,529.597***
	(202.349)
District - Tai Po	−1,989.719***
	(77.299)
District - Tsuen Wan	−775.747***
	(78.899)
District - Tuen Mun	−2,071.118***
	(80.780)
District - Wan Chai	11,773.510***
	(112.676)
District - Wong Tai Sin	1,567.434***
	(461.183)
District - Yau Tsim Mong	7,372.272***
	(85.936)
District - Yuen Long	−2,784.099***
	(69.901)
Constant	20,360.430***
	(91.245)
Observations	44,795
R^2	0.705
Adjusted R^2	0.705
Residual Std. Error	3,166.667 (df = 44771)
F Statistic	4,645.200*** (df = 23; 44771)

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

Table 2.7: Price Regression with Lagged Secondary Market Price Index

	Dependent variable:	
	Price/Sq. ft. (HKD)	
	(1)	(2)
Size(sq. ft.)	2.499***	2.508***
	(0.060)	(0.060)
Floor	55.494***	55.502***
	(1.110)	(1.110)
Price List	311.077***	311.199***
	(6.975)	(6.975)
Lagged CCI	35.018***	50.649***
	(9.780)	(13.619)
Lagged CCL	108.362***	113.176***
	(9.517)	(9.954)
Lagged CCI:Lagged CCL		−0.068*
		(0.041)
District - Central and Western	10,743.870***	10,742.370***
	(97.119)	(97.121)
District - Eastern	8,135.195***	8,137.380***
	(104.882)	(104.888)
District - Islands	−4,161.759***	−4,170.274***
	(74.196)	(74.374)
District - Kowloon City	4,837.879***	4,826.148***
	(58.742)	(59.170)
District - Kwun Tong	496.492***	508.723***
	(83.433)	(83.760)
District - North	−1,933.208***	−1,928.627***
	(126.365)	(126.393)
District - Sai Kung	−2,369.888***	−2,379.103***
	(58.971)	(59.234)
District - Sham Shui Po	1,003.721***	1,016.515***
	(138.265)	(138.479)
District - Southern	5,065.026***	5,065.881***
	(176.323)	(176.320)
District - Tai Po	−2,162.293***	−2,141.232***
	(67.695)	(68.887)
District - Tsuen Wan	−100.313	−97.145
	(68.710)	(68.736)
District - Tuen Mun	−3,309.904***	−3,293.295***
	(71.275)	(71.981)
District - Wan Chai	11,287.170***	11,317.390***
	(97.317)	(99.024)
District - Wong Tai Sin	3,128.739***	3,126.876***
	(401.118)	(401.111)
District - Yau Tsim Mong	6,549.823***	6,564.873***
	(75.985)	(76.530)
District - Yuen Long	−2,422.361***	−2,421.722***
	(60.882)	(60.882)
Constant	−6,731.451***	−8,225.411***
	(127.308)	(914.698)
Observations	44,605	44,605
R^2	0.775	0.775
Adjusted R^2	0.775	0.775
Residual Std. Error	2,753.632 (df = 44583)	2,753.579 (df = 44582)
F Statistic	7,320.916*** (df = 21; 44583)	6,988.540*** (df = 22; 44582)

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

from 1 month and 1 week earlier respectively. This avoids measure solely the contemporaneous correlation between the primary and secondary markets. Table 2.7 shows both indices increase with the price. Centa-City leading index has more than double of impact on the primary market price than the traditional Centa-City index. When both of them increase, however, the raise in price tames as the interaction term on column 2 indicates.

2.4.2 Influence from Stock Markets

For the role as investment asset, real estate is subject to the performance of other asset classes. I investigate its relationship with stock market. Unlike other asset class, stock has the widest reach to all investors given its familiarity to the public. This is the most typical asset for any investor to consider, just like real estate. In particular, I look into the main index of Hong Kong stock market, Hang Seng index and the indices of China stock market, China Securities Index 300, Shanghai Composite Index and Shenzhen Composite Index. Hang Sang Index includes the largest and most liquid stocks listed on the main board of the Hong Kong stock exchange. China Securities Index 300 consists of the 300 largest and most liquid A-share stocks in the Shanghai and Shenzhen stock exchange. It aims to reflec the overall performance of China A-share market. Shanghai Composite Index includes all stock (both A-share and B-share) of the Shanghai Stock Exchange. Shenzhen Cmposite Index includes all stocks at the Shenzhen Stock Exchange. Therefore, these indices cover the performance in Hong Kong stock market and China stock market.

Table 2.8 shows the relationship between price and the stock market indices. Column 1 looks at the level of Hang Seng index on the previous day. The higher the level, the lower the pricing. Developers are cautious when Hang Seng index went high the day before. From column 2 to 4, I consider not just the gross level, but the percentage change over a 90-day period.[3] This represents the return from the Hang Seng index. Estimation result shows that for 1 percent higher in return, pricing of real estate increase by at least HKD 95. When China index is included in column 3, the impact is opposite where the price is HKD 43 lower with 1 percent higher from the 90-day change of China Securities Index 300. Further inclusion of Shanghai Composite index and Shenzhen Composite index in column 4 shows that the lower price comes from both the overall China stock performance and more so from the Shenzhen stock performance. The

[3]Multiple duration (i.e. 1, 5, 30, 90, 180 and 360) are considered and they are qualitatively similar. 90-day represents a more reasonable investment timeframe.

Table 2.8: Price Regression with Lagged Stock Market Variables

	Dependent variable:			
	Price/Sq. ft. (HKD)			
	(1)	(2)	(3)	(4)
Size(sq. ft.)	2.550***	2.412***	2.408***	2.347***
	(0.062)	(0.063)	(0.062)	(0.062)
Floor	59.441***	60.910***	58.790***	57.343***
	(1.174)	(1.178)	(1.174)	(1.165)
Price List	313.900***	272.943***	257.834***	231.843***
	(7.124)	(7.225)	(7.192)	(7.213)
Lagged Hang Seng Index (HSI)	−0.030***	−0.386***	−0.218***	−0.142***
	(0.008)	(0.012)	(0.013)	(0.013)
HSI 90-day %change		94.981***	118.875***	110.781***
		(2.436)	(2.496)	(2.500)
CSI300 90-day %change			−43.187***	−20.477***
			(1.055)	(6.959)
SH Composite 90-day %change				4.726
				(8.038)
SZ Composite 90-day %change				−32.095***
				(1.716)
Lagged CCI	73.684***	194.928***	243.462***	285.967***
	(14.184)	(14.726)	(14.583)	(14.761)
Lagged CCL	119.423***	−85.069***	21.448*	−3.317
	(9.880)	(11.058)	(11.273)	(11.761)
Lagged CCI:Lagged CCL	−0.156***	0.293***	−0.296***	−0.402***
	(0.043)	(0.045)	(0.046)	(0.050)
District - Central and Western	10,825.620***	10,560.120***	10,491.140***	10,415.940***
	(97.007)	(101.263)	(100.008)	(99.202)
District - Eastern	8,183.125***	7,958.875***	7,725.739***	7,681.782***
	(103.815)	(104.973)	(104.957)	(104.092)
District - Islands	−4,116.342***	−3,211.123***	−2,127.410***	−2,648.843***
	(75.303)	(78.902)	(84.684)	(87.176)
District - Kowloon City	4,829.548***	4,785.577***	4,594.174***	4,543.380***
	(60.149)	(60.756)	(61.029)	(60.761)
District - Kwun Tong	457.237***	456.895***	733.382***	781.825***
	(86.295)	(86.019)	(86.947)	(86.825)
District - North	−2,029.506***	−2,121.038***	−2,148.599***	−2,208.778***
	(132.698)	(139.501)	(143.407)	(142.213)
District - Sai Kung	−2,198.908***	−2,120.093***	−1,862.665***	−1,689.629***
	(59.597)	(59.771)	(60.707)	(60.862)
District - Sham Shui Po	1,625.520***	1,114.918***	1,239.588***	1,328.269***
	(147.573)	(154.923)	(162.455)	(161.145)
District - Southern	5,266.176***	5,833.107***	5,631.505***	5,444.080***
	(176.100)	(174.740)	(171.081)	(169.779)
District - Tai Po	−2,066.397***	−1,858.490***	−1,965.963***	−2,053.050***
	(68.717)	(68.756)	(68.571)	(68.895)
District - Tsuen Wan	47.088	−217.030***	−481.088***	−628.078***
	(69.060)	(69.879)	(69.921)	(69.738)
District - Tuen Mun	−3,367.890***	−3,414.217***	−3,553.119***	−3,617.749***
	(75.560)	(75.642)	(75.089)	(74.546)
District - Wan Chai	11,485.440***	11,417.650***	11,566.740***	11,468.180***
	(98.835)	(98.600)	(98.293)	(97.564)
District - Wong Tai Sin	1,098.925*	2,165.090***	1,935.961***	2,090.096***
	(588.622)	(581.609)	(567.100)	(562.781)
District - Yau Tsim Mong	6,670.348***	6,619.972***	5,923.244***	5,831.961***
	(76.496)	(76.645)	(77.569)	(76.989)
District - Yuen Long	−2,469.462***	−2,577.921***	−2,591.508***	−2,475.263***
	(62.276)	(63.296)	(63.816)	(64.271)
Constant	−9,930.711***	1,983.348*	−11,974.780***	−13,833.610***
	(974.630)	(1,014.287)	(1,043.323)	(1,143.056)
Observations	42,199	40,583	39,284	39,284
R^2	0.776	0.784	0.794	0.797
Adjusted R^2	0.776	0.784	0.794	0.797
Residual Std. Error	2,748.351 (df = 42175)	2,712.072 (df = 40558)	2,643.449 (df = 39258)	2,620.970 (df = 39256)
F Statistic	6,365.963*** (df = 23; 42175)	6,125.396*** (df = 24; 40558)	6,047.649*** (df = 25; 39258)	5,721.261*** (df = 27; 39256)

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

contrasting response to Hong Kong and China stock market likely suggests the different roles in each stock market. Higher return from Hong Kong stocks gives the buyer more capital to afford a higher real estate price. Higher return from China stocks, however, attracts more capital back to the China market and hence real estate needs to lower the price.

Other than looking at the price directly, I also study how the price residual is affected by the stock performance. Table 2.9 shows a consistent picture. While pricing becomes cautious in face of a high level of Hang Seng index in previous day, the percentage change in 90-day of Hang Seng index raises the price. The overall impact from China stock market is negative on pricing. When individual Shanghai and Shenzhen stock markets are considered, the estimation result shows that return from the larger companies allows higher pricing even though each of Shanghai and Shenzhen would lower the price.

Table 2.9: Stock Market Regression on Price Residual

	Dependent variable:			
	Price Residual			
	(1)	(2)	(3)	(4)
Lagged Hang Seng Index (HSI)	0.081***	−0.199***	−0.094***	−0.043***
	(0.008)	(0.012)	(0.013)	(0.013)
HSI 90-day %change		77.792***	82.305***	73.652***
		(2.422)	(2.460)	(2.485)
CSI300 90-day %change			−22.071***	76.644***
			(1.061)	(7.183)
SH Composite 90-day %change				−83.702***
				(8.131)
SZ Composite 90-day %change				−20.817***
				(1.652)
Lagged CCI	122.967***	220.695***	225.581***	246.384***
	(14.107)	(14.724)	(14.892)	(15.274)
Lagged CCL	71.265***	−88.574***	−3.596	−68.673***
	(10.152)	(11.427)	(12.121)	(12.503)
Lagged CCI:Lagged CCL	−0.322***	0.017	−0.328***	−0.222***
	(0.041)	(0.043)	(0.046)	(0.051)
Constant	−22,968.930***	−13,899.590***	−22,236.940***	−19,248.690***
	(928.236)	(974.704)	(1,051.080)	(1,163.509)
Observations	42,199	40,583	39,284	39,284
R^2	0.329	0.341	0.358	0.371
Adjusted R^2	0.329	0.341	0.358	0.371
Residual Std. Error	3,018.428 (df = 42194)	3,000.960 (df = 40577)	2,988.161 (df = 39277)	2,958.836 (df = 39275)
F Statistic	5,165.761*** (df = 4; 42194)	4,198.829*** (df = 5; 40577)	3,651.705*** (df = 6; 39277)	2,891.388*** (df = 8; 39275)

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

Note: Dependent variable is the residual from the pricing regression with apartment size, number of price list, number of floor and District - s.

In addition to the apartment level perspective, my daily frequency data allows a micro-level pricing index. On top of the hedonic regression using apartment size, floor, price list and District - , I can estimate the date fixed effect. The coefficients for each date is essentially a daily price index. It is superior to the aggregate price index because raw price, as analysed above, has incorporated many considerations such

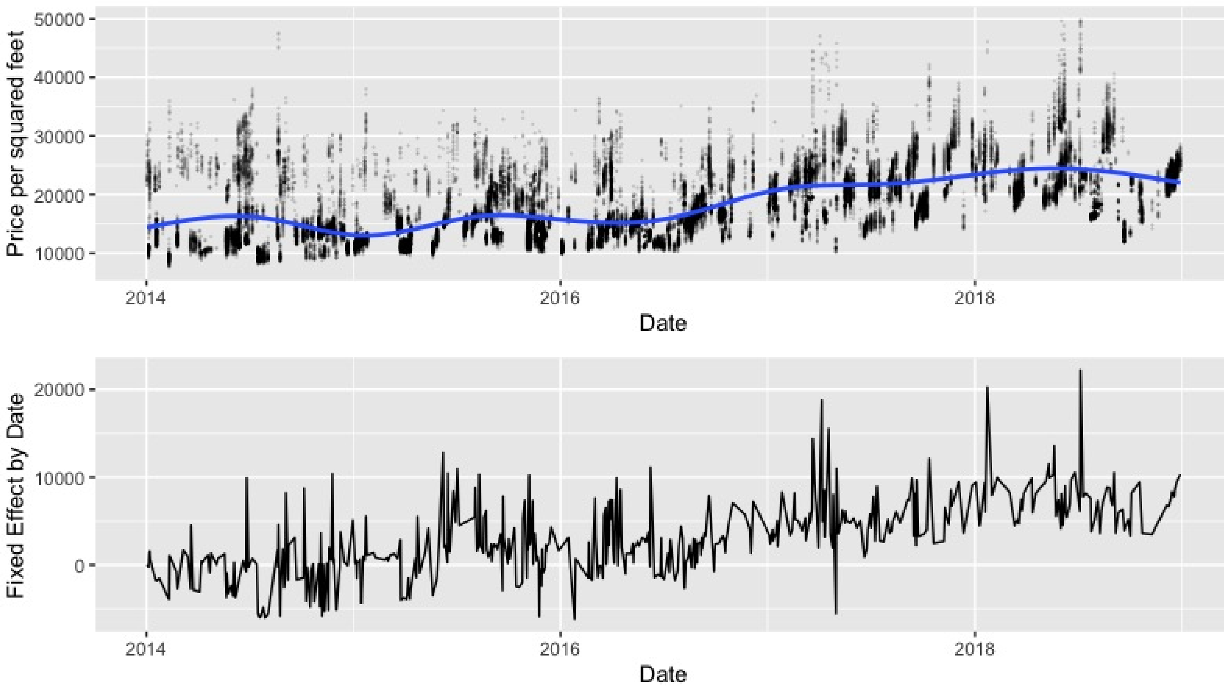


Figure 2.13: Price per sq. ft. and Date Fixed Effect over Time

as the District - , the floor and the price list. Figure 2.13 plots the date fixed effect, in comparison with the original prices. This time series of date fixed effect, in contrast, removes the influence from these considerations at once. Also, this daily index is more appropriate for analysing its relationship with the stock market because it matches the frequency with the stock market time series.

Table 2.10 presents the estimation result of the daily index. Even though data have condensed to a much lower number of observation, the estimation shows the same picture. Percentage change in 90-day of Hang Seng index increases by 1 leads to about HKD 80 increase in price. Higher percentage change in China index, especially the change in Shenzhen Composite index, lowers the price.

2.5 Response to Demand Shift

Other than the external environment, pricing also faces various changes over time. Sometimes the change is permanent, while the other time a shift is simply temporary. Knowing how the developers respond to change gives us a deeper understanding behind pricing. In this section, I particularly study a scenario of temporary shift in demand.

Table 2.10: Stock Market Regression on Date Fixed Effects

	Dependent variable:			
	Date Fixed Effect			
	(1)	(2)	(3)	(4)
Lagged Hang Seng Index (HSI)	0.091	-0.183	-0.021	0.019
	(0.077)	(0.112)	(0.122)	(0.124)
HSI 90-day %change		72.650^{***}	88.596^{***}	91.727^{***}
		(23.584)	(24.171)	(24.595)
CSI300 90-day %change			-38.203^{***}	-94.401
			(10.914)	(70.953)
SH Composite 90-day %change				84.115
				(80.240)
SZ Composite 90-day %change				-30.343^{*}
				(16.829)
Lagged CCI	282.785^{**}	362.481^{**}	410.317^{***}	456.914^{***}
	(137.474)	(145.200)	(145.094)	(148.141)
Lagged CCL	211.593^{**}	59.184	162.117	165.953
	(103.193)	(116.761)	(119.805)	(121.434)
Lagged CCI:Lagged CCL	-1.228^{***}	-0.854^{**}	-1.435^{***}	-1.624^{***}
	(0.401)	(0.425)	(0.450)	(0.475)
Constant	$-44{,}375.980^{***}$	$-34{,}707.130^{***}$	$-48{,}183.450^{***}$	$-52{,}267.410^{***}$
	(9,010.347)	(9,600.474)	(10,184.210)	(10,804.470)
Observations	503	478	463	463
R^2	0.407	0.417	0.435	0.440
Adjusted R^2	0.402	0.411	0.428	0.430
Residual Std. Error	3,303.680 (df = 498)	3,301.061 (df = 472)	3,268.205 (df = 456)	3,263.604 (df = 454)
F Statistic	85.293^{***} (df = 4; 498)	67.554^{***} (df = 5; 472)	58.622^{***} (df = 6; 456)	44.501^{***} (df = 8; 454)

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

2.5.1 Demand Shift when Flu Prevails

Since developers raise the price for each new price list, the previous sales performance would affect how the price is raised in the next price list. Table 2.11 column 1 shows that when the fraction of apartments sold on the day they open increases by 1 percent, price increases by about HKD 26. Therefore, stronger the demand for previous price list, developers raise the price more in this price list.

However, do the developers still raise the price if the demand shift is only temporary? Since real estate is a durable goods, if the temporary demand shift does not change the fundamental needs, it would be optimal not to change the price mechanically for merely superficial shift. Yet, whether the developers can distinguish a shift in the fundamental needs or not is ambiguis ex ante. Therefore, I study a scenario of superficial temporary shift where sales speed is reduced due to the prevalence of flu.

I utilize the weekly influenza report by the Centre for Health Protection in Hong Kong for the measurement of flu prevalence. Flu consultation measures the count of consultations on influenza-like illness per 1,000 consultations. Column 3 of table 2.11 shows that 1 more flu-like consultation out of 1,000 leads to 0.6% decrease in the day-0 sales rate.

In order to investigate the demand shift due to the flu prevalence, I am only interested in the variation in day-0 sales rate due to changes in flu consultation. Therefore, although I am not concerned with the endogeneity in the previous day-0 sales rate, I am implementing a two-stage least square (2SLS) method to instrument for the day-0 sales rate to investigate only its variation due to flue prevalence.[4] Column 3 of table 2.11 shows the first stage result and the large F-statistic clears of weak instrument concern. Column 2 reports the 2SLS result which states that lower day-0 sales rate actually increases price. For 1% decrease in day-0 sales, the price increases by HKD 40. While the opposite sign might surprise some, it indeed points out that developers do know the difference between an actual demand shift and a superficial demand shift due to flu prevalence only. For the latter, the lower sales speed is only phenomenal and poses no threats in selling the apartments eventually.

Furthermore, the countering price raise appears to demonstrate seller confidence against the superficially weaker sales record. The day-0 sales rate in Hong Kong is indeed closely monitored by the media as one of the indicators for how attractive the complex is. Typically, when the media report negatively or even just

[4] Month dummy is included as flu tends to be season-specific. Such specification ensures the estimation picks up only variation in flu prevalence, not the monthly difference.

Table 2.11: Price Regression of Sales Speed on Day 1 instrumented with Lagged Flu-like Consultations

	Dependent variable:		
	Price/Sq. ft. (HKD)		Lagged Day 1 Sales%
	OLS	*instrumental variable*	*first stage*
	(1)	(2)	(3)
Size(sq. ft.)	-1.629^{***}	-1.755^{***}	0.0003
	(0.116)	(0.131)	(0.001)
Floor	49.182^{***}	68.024^{***}	0.231^{***}
	(2.218)	(2.892)	(0.017)
Price List	678.266^{***}	310.232^{***}	-5.060^{***}
	(18.808)	(35.339)	(0.140)
Lagged Day 1 Sales%	25.666^{***}	-40.756^{***}	
	(0.978)	(5.216)	
Lagged Flu-like Consultation			-0.565^{***}
			(0.020)
District - Central and Western	$9{,}425.919^{***}$	$8{,}566.217^{***}$	-6.287^{***}
	(226.297)	(263.905)	(1.759)
District - Eastern	$9{,}681.449^{***}$	$7{,}408.727^{***}$	-35.925^{***}
	(261.374)	(342.823)	(2.001)
District - Islands	$-6{,}584.360^{***}$	$-5{,}560.514^{***}$	18.042^{***}
	(156.840)	(193.747)	(1.208)
District - Kowloon City	$5{,}999.377^{***}$	$5{,}919.107^{***}$	2.073^{**}
	(134.669)	(152.186)	(1.046)
District - Kwun Tong	951.552^{***}	$5{,}116.047^{***}$	58.359^{***}
	(201.440)	(392.291)	(1.489)
District - North	$-1{,}665.646^{***}$	$-2{,}563.794^{***}$	-11.737^{***}
	(258.846)	(300.295)	(1.996)
District - Sai Kung	$-3{,}864.829^{***}$	$-1{,}523.775^{***}$	34.358^{***}
	(144.940)	(243.036)	(1.087)
District - Sham Shui Po	$-3{,}386.948^{***}$	$-1{,}065.319^{***}$	32.228^{***}
	(250.782)	(334.566)	(1.919)
District - Southern	$7{,}381.770^{***}$	$10{,}380.350^{***}$	35.572^{***}
	(435.426)	(542.858)	(3.360)
District - Tai Po	$-1{,}082.695^{***}$	-932.864^{***}	-2.219^{**}
	(144.215)	(163.246)	(1.124)
District - Tsuen Wan	834.499^{***}	793.436^{***}	7.732^{***}
	(157.499)	(177.868)	(1.251)
District - Tuen Mun	$-2{,}934.710^{***}$	$-4{,}320.740^{***}$	-20.671^{***}
	(171.653)	(221.094)	(1.315)
District - Wan Chai	$8{,}849.723^{***}$	$5{,}861.412^{***}$	-44.569^{***}
	(390.334)	(496.848)	(2.993)
District - Yau Tsim Mong	$7{,}926.618^{***}$	$9{,}606.845^{***}$	22.573^{***}
	(192.586)	(252.820)	(1.477)
District - Yuen Long	$-3{,}180.233^{***}$	$-3{,}686.572^{***}$	-2.898^{**}
	(153.794)	(177.952)	(1.197)
Constant	$12{,}406.650^{***}$	$19{,}023.520^{***}$	126.900^{***}
	(196.948)	(554.392)	(1.640)
Month FE	Yes	Yes	Yes
Observations	16,802	16,802	16,802
R^2	0.704	0.623	0.469
Adjusted R^2	0.704	0.622	0.468
Residual Std. Error (df = 16771)	3,318.092	3,746.632	25.602
F Statistic (df = 30; 16771)	$1{,}331.905^{***}$		494.303^{***}

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Note: Lagged Day 1 Sales% measures the percentage of apartments sold on the first day when the price list opens for transaction.

mildly, the reputation of this new complex is hurt and the sales suffers. Therefore, when the developers know the sales record is superficially misleading, there is incentive for them to intentionally raise the price as a counter signal to avoid reputation hurt.

2.5.2 Robustness Check - Alternative Measurements

To check for the robustness of the result, I added another instrument - the weekly number of severe influenza cases in the age group of 18 - 49 years old. This captures better the illness severe enough to affect daily activities, including real estate transaction. Table 2.12 column 2 shows that this indicator does have a stronger impact to day-0 sales rate. With both flu measurements used, column 1 states that 1 percent lower in day-0 sales rate induces an increase of HKD 37 in price.

As for the sales performance measurement, I also checked an alternative computation - the average number of available days before an apartment sold. Column 4 of table 2.12 confirms both measurement still statistically significant to the available days. Column 3 yields that 1 day longer for the average available days results in HKD 31 price increase.

The various specification and measurements point to the same conclusion that developers do not reduce price when demand superficially lowers due to flu prevalence. Apparently, they do distinguish whether the demand shift alters the fundamental needs. Furthermore, they tend to make a price raise against a misleading low recorded demand, likely to counter unfavorable comments from the media and the public.

2.6 Conclusion

Pricing of real estate draws much interest from the public, the government and the researchers. My high frequency daily data of all primary market housing transactions allows an in-depth discussion on the pricing behavior of developers. In terms of the fundamental features of the apartments, I analysed the implication of apartment size, floor level and price list on the apartment price. I found that higher the floor level, the higher the apartment price. In particular, floors lower than the 8^{th} and for floors above 20^{th} clearly have lower and higher price, respectively, than the floors in between. As for the price list, once the apartment attributes are controlled, it is obvious that later price list has a higher price, which is consistent with the market wisdom of gauging the buyer interest with lower price in the early price lists. Regarding pricing for some individual

Table 2.12: Price Regression of Sales Speed instrumented with Lagged Flu-like Consultations and Lagged Severe Cases

	Dependent variable:			
	Price/Sq. ft. (HKD)	Lagged Day 1 Sales%	Price/Sq. ft. (HKD)	Lagged Average Days Open
	instrumental variable	*first stage*	*instrumental variable*	*first stage*
	(1)	(2)	(3)	(4)
Size(sq. ft.)	-1.748^{***}	0.001	-1.837^{***}	0.001
	(0.130)	(0.001)	(0.127)	(0.001)
Floor	66.897^{***}	0.209^{***}	60.228^{***}	-0.034^{**}
	(2.770)	(0.017)	(2.430)	(0.016)
Price List	332.242^{***}	-5.541^{***}	539.164^{***}	0.076
	(32.140)	(0.143)	(19.522)	(0.134)
Lagged Day 1 Sales%	-36.784^{***}			
	(4.529)			
Lagged Flu-like Consultation		-0.369^{***}		0.311^{***}
		(0.024)		(0.022)
Lagged Severe Cases (aged 18-49)		-2.175^{***}		3.042^{***}
		(0.142)		(0.134)
Lagged Average Days Open			31.443^{***}	
			(3.904)	
District - Central and Western	$8,617.632^{***}$	-7.115^{***}	$8,626.126^{***}$	9.140^{***}
	(258.642)	(1.748)	(251.651)	(1.647)
District - Eastern	$7,544.647^{***}$	-34.631^{***}	$8,534.261^{***}$	8.514^{***}
	(327.941)	(1.989)	(282.908)	(1.874)
District - Islands	$-5,621.745^{***}$	16.066^{***}	$-6,352.472^{***}$	5.252^{***}
	(187.535)	(1.207)	(170.403)	(1.137)
District - Kowloon City	$5,923.908^{***}$	2.438^{**}	$6,028.932^{***}$	-5.833^{***}
	(150.241)	(1.039)	(146.134)	(0.978)
District - Kwun Tong	$4,866.991^{***}$	56.838^{***}	$4,229.627^{***}$	-46.459^{***}
	(355.526)	(1.482)	(293.556)	(1.396)
District - North	$-2,510.080^{***}$	-12.613^{***}	$-2,352.150^{***}$	10.174^{***}
	(294.654)	(1.983)	(283.307)	(1.868)
District - Sai Kung	$-1,663.781^{***}$	37.020^{***}	$-2,022.520^{***}$	-32.627^{***}
	(223.869)	(1.093)	(191.917)	(1.030)
District - Sham Shui Po	$-1,204.164^{***}$	34.649^{***}	$-1,660.186^{***}$	-26.952^{***}
	(319.039)	(1.913)	(288.277)	(1.802)
District - Southern	$10,201.020^{***}$	39.075^{***}	$9,671.035^{***}$	-30.948^{***}
	(524.464)	(3.344)	(489.992)	(3.150)
District - Tai Po	-941.824^{***}	0.942	-841.945^{***}	-5.605^{***}
	(161.096)	(1.135)	(157.914)	(1.069)
District - Tsuen Wan	795.892^{***}	9.262^{***}	$1,285.958^{***}$	-25.644^{***}
	(175.622)	(1.247)	(180.278)	(1.174)
District - Tuen Mun	$-4,237.848^{***}$	-19.807^{***}	$-3,344.919^{***}$	-5.398^{***}
	(212.228)	(1.307)	(185.361)	(1.231)
District - Wan Chai	$6,040.127^{***}$	-41.563^{***}	$6,807.315^{***}$	23.593^{***}
	(478.024)	(2.979)	(434.533)	(2.806)
District - Yau Tsim Mong	$9,506.359^{***}$	25.419^{***}	$9,357.903^{***}$	-26.033^{***}
	(241.805)	(1.478)	(228.625)	(1.393)
District - Yuen Long	$-3,656.290^{***}$	-0.199	$-3,477.438^{***}$	-5.435^{***}
	(174.714)	(1.202)	(166.953)	(1.132)
Constant	$18,627.800^{***}$	125.275^{***}	$14,866.820^{***}$	-22.888^{***}
	(489.871)	(1.632)	(185.877)	(1.537)
Month FE	Yes	Yes	Yes	
Observations	16,802	16,802	16,802	16,802
R^2	0.632	0.477	0.653	0.402
Adjusted R^2	0.632	0.476	0.652	0.401
Residual Std. Error	3,699.454 (df = 16771)	25.426 (df = 16770)	3,595.940 (df = 16771)	23.951 (df = 16770)
F Statistic (df = 31; 16770)		492.553^{***}		364.218^{***}

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

Note: Lagged Day 1 Sales% measures the percentage of apartments sold on the first day when the previous price list opens for transaction. Lagged Average Days Open measures the average of days open among apartments in previous price list.

developers, the leading developers do have some differences in pricing, compared to other developers. Sun Hung Kai and Henderson are similar in pricing lower for larger apartments and raising price less in later price lists, on top of their brand premium in price.

On top of the typical pricing based on the fundamental features, there are other aspects specific to the Hong Kong primary housing market. Apartments in Hong Kong usually offer discounts to about 15% off. The discount percentage is deeper when the size is larger and the floor is higher. Given the small apartment size in Hong Kong, data showed that the residential complex with high fraction of apartments above 600 sq. ft. have clear difference from those mostly 600 sq. ft. or less. The former complexes raise the price less aggressive in later price lists than the latter complexes. And those large apartment complexes price higher for larger apartment size. As for competition, it does exert downward pressure on the price. The more active selling complexes and apartments, the lower the price developers would choose.

With the understanding of prices, I used my daily data to form a daily price index using the fixed effect for each date of price listing. By the regression controlling for the impact of floor, price list, and other impact, this index removed the influence from factors due to strategy or heterogeneous attributes, but solely reflecting the pricing of the day. This gives a deeper consideration than simply aggregating all the publish price. This daily index would be suitable for analysing the influence from external environment.

Environment external to the primary housing market also plays a crucial role in price. Secondary market price indices from the previous period (month or week) yield a higher price in the primary market. This suggests the substitutability between primary and secondary market in real estate. As for stock market, while the gross level of stock index actually has negative impact to housing price, the 90-day return increases with the price. The larger capital gained appears to afford more expensive houses. Nonetheless, when I consider the stock market in mainland China also, the higher return in mainland stock market, the price actually goes lower. This is likely the capital flow back to mainland for better investment opportunities.

I also discuss the response of pricing. Considering the demand shift due to flu prevalence, the response in pricing was investigated. While the more severe flu prevalence, as measured by medical consultation and severe cases, delays the transaction with an increased days on market, developers do not respond by lowering the price as in other cases. This suggests the pricing is not a mechanical response to some statistics only, but a careful decision considering what is driving the low transactions. On the contrary, developers raise the price significantly in this case, apparently to counter potential negative comments from the media.

This chapter reveals various aspect of real estate pricing. It illustrates the sophisticated response and convoluted relationship in the real estate pricing, even including the specificity of Hong Kong. This serves as a good foundation for future research in the real estate pricing.

Chapter 3

Literature Review

This chapter reviews multiple strands of literature that pertain to dynamic competition and real estate market, particularly for Hong Kong. The review serves to highlight the achievements of the existing literature and illustrates the contribution of my research in expanding our understanding of dynamic competition estimation and real estate market. This review covers the estimation of dynamic game and its later development for competition with many firms, in terms of both theoretical works and empirical works. After that, current structural estimation in housing is discussed. The typical structural estimation includes dynamic models from single agent perspective and search models. Researches focusing on the local market in Hong Kong are also reviewed before conclusion.

3.1 Dynamic Game Estimation

The dynamic game estimation literature is no doubt an important strand for modeling tool. While the literature in dynamic game has formalized many insightful scenarios in theory, its estimation has long been a hurdle for any empirical work. This section discusses the estimation literature of dynamic game, in terms of both its theoretical framework and the applied empirical works.

3.1.1 Theory Works

Before 1990s, even though the theories in dynamic game thrived, the estimation on the dynamic strategic interaction was lacking, both for its complexity in model and its associated computational burden. With a goal to understand the developments inside industry over time, Ericson and Pakes [1995] proposed a framework with entry, exit and investment where Markov Perfect Equilibrium (MPE) can be computed to generate dynamics in an oligopolistic industry. In their framework, all firm are competing by selling a homogeneous good only differing by the marginal costs that depends on the technology of each firm. By assuming this cost-saving technology can be discretized, the payoff for each firm would then be affected by this discrete technology level variable through its impact on marginal cost. In each period, the technology can be improved by level with probability that increases with investment, a continuous choice. Simultaneously, technology can also degrade by 1 level with an exogenous constant probability. In other words, technology for one firm can at most increase or decrease by 1 level per period. Note that investment is a continuous decision by the firm. This set-up of technology progression has implicitly translated a continuous choice into a discrete state. The payoff change due to technology is not linked directly to a continuous choice, but mediated and hence partitioned by a discrete state variable of technology level. Other than the key technology progression mechanism, payoff for firms is influenced by the competition at sales. Ericson and Pakes [1995] models the competition as a quantity competition and allows the firms enter or exit. Note that the optimal solution for quantity competition can be pinned down given the number of firms and their cost-saving technology. Hence, the payoff depends on the number of firm, which results from entry and exit. This framework of discrete technology state, together with the number of firm, entry and exit that are intrinsically discrete ensures the per period payoff and the life time value to be based on a discrete state space. The evaluation of payoff and value is much easier handle. Markov Perfect Equilibrium (MPE) can then computationally feasible to compute. Therefore, they managed to rely on MPE to generate simulations to discuss the development of industry over time.

Around a similar time, Pakes and McGuire [1994] adopted a similar framework of discretized progression in technology to discuss a simple algorithm for computing MPE. Instead of a cost-saving technology, the technology in Pakes and McGuire [1994] affects the quality of goods that directly increase consumption utility. The mechanism, however, is still the discrete level improved with probability affected by continuous investment decision, although potentially degraded by an exogenous probability. The competition is a price competition with a standard assumption that consumer can only buy one good. Therefore, a logistic market share results and pricing decision can then be determined in the static spot market. This is essentially a differentiated product version of Ericson-Pakes model. Given the model set-up, the paper computed the MPE with a simpler algorithm at the time. Even though it is a specific framework, its generality leads to high flexibility for estimating any competition that is crucial on technology or other competition dimension with accumulative nature. Such framework is later proven applicable to many competition and provides more realistic setting in investigat the dynamic development than other technique. Therefore, dynamic game estimation literature has since developed and implicitly taken this framework by Ericson and Pakes [1995] and Pakes and McGuire [1994], typically referred as EP framework, to be the workhorse model.

For the algorithms to estimate MPE, a pure entry/exit strategy is required. Doraszelski and Satterthwaite [2010] further strengthened the theoretical foundation by providing conditions that ensures the existence of symmetric pure strategy equilibrium in the EP framework. While the complete information game initially suggested in the EP framework needs to admit mixed entry/exit strategy equilibrium, this renders the existing algorithm in capable of estimating. Doraszelski and Satterthwaite [2010] used the perspective of incomplete information game which introduces private scrap value (collected on exit) or private entry cost (paid on entry). By changing these from common value/cost to private, a pure strategy in entry/exit can always be obtained. Furthermore, if the transition probability is only affected by investment through a first order polynomial term with diminishing marginal effect, pure strategy in investment can also be obtained. Given these pure strategies in entry/exit and investment, the desired symmetric equilibrium exists as long as everything else in the model is symmetric. Intuitively, when a firm observes rival firms to take different action given the exam same state, it is no longer necessary to regard the rival firms as taking a mixed strategy as the complete information game requires. The fact that a firm does not know the private scrap value or entry cost of rival firms implies the different action of same state can simply come from different private information. In other words, the conditions ensure the potential need of probabilistic action at equilibrium to be satisfied by the unknown private information, rather than mixed strategy that cannot be observed without repeated realization.

Given the theoretical work, different estimation approaches were proposed. Bajari et al. [2007] proposed a two-step algorithm to estimate the MPE. In the first step, the conditional choice probability and the transition matrix are first estimated flexibly. Therefore, the value function can be obtained by simulating forward with the estimated optimal decision policy. Simultaneously, the policy is perturbed many times to make many sub-optimal policies, which are then used to simulate for obtaining the sub-optimal value functions. By the rationality of agents, the values directly from first stage is larger than the values from the perturbed decisions. Therefore, many inequalities are obtained via perturbation. In the second stage, a simple simulated minimum distance estimator is applied on these inequalities to find the dynamic parameters that best justify the inequalities. This two-step approach avoids the actual computation of an equilibrium as in nested fixed point approach and hence lighten the computation burden significantly.

Aguirregabiria and Mira [2007] proposed a class of pseudo maximum likelihood estimators and it showed that the recursive extension of two-step pseudo maximum likelihood further addresses the small sample bias and asymptotic efficiency. First, the conditional choice probability and transition matrix are flexibly estimated. With the estimated functions, Aguirregabiria and Mira [2007] pointed out that the value functions can be directly obtained through inverting. Given the value, choice probability and transition matrix, dynamic parameter can be obtained by maximizing the likelihood of observing the data on hand. Given this two-step pseudo maximum likelihood procedure, the recursive extension use the likelihood to update as the choice probability as they are conceptually equivalent. Then another likelihood and dynamic parameters can be obtained by repeating the two-step procedure. The dynamic parameters from this recursive approach are the one yield the largest likelihood.

In addition, one major difficulty for implementation is the computational burden associated in the discrete space size. Since the state space is growing exponentially with the number of firms and the number of technology level, an apparently simple competition with several firms can involve prohibitive amount of resources on memory and computation. Noticing that state space required for dynamic game are typically not hypercube, Gowrisankaran [1999] illustrated an efficient representation that significantly reduce the computational burden. For example, in a competition with 10 firms and 10 discrete technology level, the efficient encoding reduces the state size from 10 billion down to less than 50 thousands. Since Ericson and Pakes [1995] and Pakes and McGuire [1994] had utilized the exchangeability assumption (also known as symmetry assumption), that is firm identity does not matter other than their technology level and other state variables, encoding by Gowrisankaran [1999] further unleashed the application potential of the framework given the same computational resources.

3.1.2 Empirical Works

As for empirical application, Ryan [2012] estimated the underlying entry cost of cement industry. By adopting the EP framework, it setup a model with state variable as capacity. Capacity is continuous, but under a (S, s) framework with investment. Deviating from the EP framework, the investment in Ryan [2012] is deterministic and it abstracts away from any potential exogenous reduction of capacity, which greatly reduces computational complexity. In each period, a firm needs to make entry, exit, production, and investment decision. For each period, sales are made in the static quantity competition where demand and production cost are first estimated. Using the estimates, the cost of investment, divestment and exit are estimated and then the entry cost is estimated with 500 discretized capacity states. Ryan [2012] used a moment inequality method proposed in Bajari et al. [2007], also known as BBL, for estimating the dynamic parameters. By perturbing for more than a thousand sub-optimal policies, a se of inequalities are generated to find out the dynamic parameters that rationalize the observed policies that are optimal. In terms of the empirical result, it shows a significant increase in entry cost in the cement industry after an amendment to the Clean Air Act, which leads to a significant loss in product market surplus ranging from 810 million to 3.2 billion dollars.

Another empirical application is Collard-Wexler [2013] on ready-mix concrete industry. Following the EP framework, it used current plant size (large, medium and small) and the maximum plant size in the past of a firm. With 7 potential states and firm number truncated to 10 at most, it managed to estimate the MPE. Collard-Wexler [2013] used conditional choice probability (CCP) indirect inference to obtain the estimates. After estimating CCP and the transition matrix, with market size discretized into 10 levels, it computes the choice-specific value through discrete action stochastic algorithm by Pakes and McGuire [2001] while incoporating the separable dynamic parameters insight from Bajari et al. [2007]. With the choice-specific value, the predicted optimal choice probability can be obtained. Two set of coefficients can be obtained after regressing firm and competition features on both observed and predicted choice probability. Since the coefficients of predicted choice are conditional on the unknown dynamic parameters, minimizing the distance between coefficients for observed and coefficients for predicted can solve for dynamic parameters. The result is calibrated to the medium plant entry cost according to insider interview. Through this indirect inference method using CCP, Collard-Wexler [2013] showed that a demand smoothing policy leads to more plants, larger plant and lower entry and exit. With these two early examples, empirical works in various competitions ranging from CPU, hard-drive to shipbuilding grows in the literature. While the literature using MPE formalized dynamic games with theoretical robustness, the current computation power limits its application mostly to industries with less than 10 firms in empirical model. Many industries, however, have more than 10 firms involved in relevant competition. In particular, the real estate primary market in Hong Kong with 20-60 firms is computationally infeasible to estimate MPE.

3.2 Dynamic Competition with Many Firms

3.2.1 Theory Works

A recent development in dynamic game/competition estimation literature addresses the feasible estimation with many firms. Weintraub et al. [2008] proposed an equilibrium concept, Oblivious Equilibrium (OE), to approximate MPE when there are many firms in the market. In the EP framework, the number of firms exponentially increases the dimensionality when we consider MPE instead of others. While MPE is clearly a relatively comprehensive equilibrium concept in considering strategic interaction, the dimensionality implication motivates the search for a proper substitute in those computationally infeasible cases such as cases with many firms. By observing that the strategic interaction in EP framework roots in the number of firms in each state (e.g. technology level), Weintraub et al. [2008] points out that, when there are many firms, the exits and entries cancel out and leave the firm distribution largely unchanged over time. Therefore, when OE conditions on long run average of firm distibution in state, it approximates the MPE in cases that are computationally infeasible to recover, in addition to the immediate behavioral appeal of OE. In other words, instead of tracking the current state of each rival in MPE, OE assumes that firms only keep track of the long run average of the state distribution of the rivals. Since the number of firms exponentially increases the dimensionality of MPE, adopting OE can greatly reduce the difficulties in calculating an equilibrium. For the approximation by OE to perform well, a critical assumption "light tail condition" is required. Intuitively, "light-tail condition" states that when the long run average firm state distribution is different, the maximum change to payoff is minimal, even for states (e.g. technology level) that is very large as they are unlikely.[1]

[1] In the EP framework, larger state means higher technology which implies larger competitive pressure to the payoff of other firms. For the model illustrated in Weintraub et al. [2008], large state means a higher quality of the goods.

Therefore, since the state distribution of firms would not change much in competition with many firms, "light tail condition" ensures that the payoff due to the state distribution of firms in MPE in every period would not differ much from the payoff due to the long run average state distribution and hence the close firm behaviors. By the observation of cancel out effect among many firms, Weintraub et al. [2008] showed that as long as the firm distribution satisfies "light tail condition", OE can approximate MPE well.

Since Weintraub et al. [2008], there is a series of works further developing the use of OE in the dynamic game estimation with more firms. Weintraub et al. [2010b], after elaborated on the algorithm and computation of OE, introduced Extended OE (EOE). The original OE only conditions on the state of self every period and the long run average of rival stat distribution, but it cannot accommodate shocks that are common across firms. Common shock, however, is often an important feature in various competitions as business cycles or aggregate uncertainties. EOE relaxes this assumption and allows for aggregate shock to be tracked when firms optimizing for the best action. This is achieved at the expense of greater modelling and computational complexity. Weintraub et al. [2010a] extends OE in another direction. Motivated by understanding the short-run dynamics following a policy change or other sudden change, Weintraub et al. [2010a] develops the concept of nonstationary OE. Unlike OE, nonstationary OE models that the state distribution of every firm at the initial period is known by all, but there is no update after this period. Therefore, firms behave based on their expectation of how the rival state distribution shall evolve. Nonstationary OE hence allows one to estimate the short-run dynamic in the industry following a policy change. In many industries, the competition in reality is neither pure oligopoly with only several firms, nor many firm of similar size. Rather, many competitions are concentrated in the sense that several firms are dominant in the competition while many much smaller firms are also part of the competition. Therefore, Benkard et al. [2015] considers this case of concentrated competition and proposed partially OE. Partially OE modifies OE to include a set of strategically important firms, together with many other firms described a fringe firms. The states of those dominant firms are tracked by every firm, both fringe firms and other dominant firms, in the market. A new feature that was not in the original OE stems from this information structure. The dominant firms can deter investment or entry of fringe firms but not vice versa even when they all have the same profit cost parameters. One assumption worth noting in partially OE is that the status of dominant or fringe cannot be changed throughout the competition in the modeling framework. Benkard et al. [2015] showed that partially

OE generally performs well in highly concentrated markets, compared to both OE and MPE. In summary, the theoretical works developing OE managed to provide framework for estimating competition of many firms with aggregate market shock, concentrated competition and short-run dynamics of competition after policy change.

3.2.2 Empirical Works

Chen and Xu [2018] applied the OE estimation Korean electric motor industry with hundreds of firms to study relationship between individual RD and industry productivity and hence study the R&D spill-overs. Following EP framework, each firm chooses R&D investment to affect the knowledge, which is a discrete level. Other than entry and exit, there is also physical capital investment which requires an adjustment cost to change. Both knowledge and physical capital affects the production efficiency by their distance relative to the frontier. This relationship gives rise to the R&D spill-overs in the model. Given the 180 firms on average every year, Chen and Xu [2018] used OE to circumvent the computational burden of MPE. Using a simulated method of moments, it aims to estimate the equilibrium in the data. It found out that increasing the elasticity of substitution between products raises plant innovation incentives and the plant turnover. Lower entry cost, however, does not affect industry productivity. And higher firm turnover increases market selection effect, but reduces plant's incentive for R&D at once.

In another application, Qi [2013] studied the impact of advertising regulation in 1970s cigarette industry with nonstationary OE. Following the advertising ban of 1971, the industry advertising sharply dropped, but it recovered and exceeded the pre-ban level within 5 years. Following the EP framework, each firm chooses an advertising investment, which affects the discretized brand goodwill level, just like technology level in other EP models. The higher goodwill, the larger consumption value. Given the 137 brands in data, Qi [2013] considers OE. Given the focus of study the imapct in industry after a policy of advertising ban, nonstationary OE is used. Its estimation adopted general method of moment to match the sales growth regression and the industry advertisement expenditure for each period. First, it estimates the initial state distribution using market share. Then, the nonstationary OE is estimated using nested fixed point method as the data does not support the use of BBL. At the final step, general method of moment is estimated by simulating 1,000 error draws. The estimation result showed that 74% of the puzzling trend can be explained by industry dynamics while the rest by learning. The nonstationary OE handle the intractable state space and acceleration the equilibrium computation.

The development in OE addresses the need of the real estate primary market in my previous chapter, which has 20+ active competitors at any point in time. In particular, the apparent cyclical pattern in the real estate market renders the plain OE to be an unsuitable concept. Extended OE that accommodate market cycle would be a proper equilibrium for the market. My previous chapter is also the first paper to apply EOE empirically.

3.3 Structural Estimation in Housing

3.3.1 Dynamic Single Agent Model

There is a growing literature on dynamic structural analysis for housing market. Bayer et al. [2016] developed a dynamic model of housing and neighborhood demand. Although previous housing literature has estimated various static models due to computational and data limitation, it might not be appropriate for location decision that is inherently dynamic in nature. The dynamics come naturally from the large transaction costs that make moves relatively rare, changing household tastes and needs over the life-cycle, and evolving local amenities and housing prices. Bayer et al. [2016] combines the demographic information from mortgage applications and the universe of housing transaction in the San Francisco Bay Area during 1994 - 2004. The neighborhood choices and the timing of moves recover the preferences for housing and neighborhood attributes, housing demand aspect given its performance as asset (e.g. appreciation, volatility), and moving costs. Building upon the durable demand literature, Bayer et al. [2016] explicitly model housing as asset and allow wealth to change endogenously. It also used uniform realtor fees to identify the marginal utility of consumption in estimating move-stay decision. Instead of using logit inclusive value as sufficient for continuation value, the value is constructed from predicted future utilities. It estimated the marginal willingness to pay for some non-marketed amenities (e.g. air pollution, violent crime, racial composition). In comparison with a static model, the static model understates the marginal willingness to pay to avoid pollution and crime. It overstates the marginal willingness to pay for low-income household and understates for high-income household on racial composition. The dynamic structural model highlights several important biases when dynamic consideration is ignored.

In addition to the demand side, Epple et al. [2010] provided a new flexible approach to estimate the housing production function using micro data. Production function abstracts housing as just the quantity of housing services per dwelling, which combines with the price per unit of housing service forms the housing price. Although both the quantity and the price are unobserved, Epple et al. [2010] uses a new technique to estimate. It showed price per housing service is monotonically increasing with housing value observed. And exploiting a zero profit condition that follows constant return to scale assumption helps pin down a supply function that can be consistently estimated by researchers. Production function can then derived from it.Using a data of all housing units in Allegheny County in the Pittsburgh Metropolitan Area, the approach yields a plausible and robust estimates of the underlying production function.

Murphy [2018] estimated the fixed and variable cost in a dynamic housing supply model, using the lot size, house size, development time etc. Given the irreversible nature of construction, forward-looking is an important feature in construction. In the dynamic housing supply model, landowners choose both the timing and the size of construction, which allows separating the effect of current profit from the effect of expected future profits. Using data of individual parcels of land in San Francisco Bay Area over the period 1988-2004, it showed variation in costs are key to understanding construction and those landowners actively choosing the right timing to build, rather than whether to build. It found the increase in the location-price premium but not construction cost is the primary determinant of increase in house price. Variable costs vary pro-cyclically over the time period. And the fixed costs vary considerably over both geography and time.

Although structural estimation for housing market emerges, the literature thus far discussed from a dynamic single agent perspective. While competition is a crucial component in affecting the market outcome, literature is in lack for studies considering strategic interactions between real estate sellers in primary market.

3.3.2 Search Model

Search literature is also frequently applied to housing market, other than labour market. Directed search and random search are two typical modeling framework to analyse search. Liberati and Loberto [2019] applied search model to analyse property tax. In their model, each family receives a flow utility from living in the house. Subject to an idiosyncratic preference shock, one becomes uncomfortable and adopt a costly search. Once the dwelling is found, household move in and put the previous house for sale with a price determined by Nash bargaining. While this is following Wheaton [1990], Liberati and Loberto [2019] incorporates a rental market with endogenous rent price and tenure choices. Using the calibrated search and match model for Italian housing market during 2007-2012, it showed that an increase of property taxes on owner-occupied dwellings decrease both housing demand and prices. However, for an increase of property taxes on secondary dwellings, the tax results in higher demand and prices. This is because the landlords shift part of the tax burden to the tenants through higher rents, which makes homeownership relatively more convenient.

Huang et al. [2018] applied a random search model to show low rent-to-price ratio and high turnover rate are associated in equilibrium. It developed a search and match model that enables owners to choose whether to sell or to rent their properties. Hence, the rental yield and turnover can be derived endogenously. Using secondary market data of 130 estates in Hong Kong during November 2011 - October 2012, it confirmed a higher turnover rate is associated with a lower rental yield. The higher popularity leads to a lower rental yield as well. Also, it found an empirical "dichotomy" that demographic structure and past returns of an estate tend to affect its turnover rate, while popularity, human capital, mortgage, and long-run rent growth influence the rental yield more.

Blending in price posting component, Zhu et al. [2017] used both random search and directed search to show price stickiness and dispersion can emerge without assumptions like menu cost, regret theory etc. Using English housing data, it assumed heterogeneous buyers and homogeneous buyers regarding the residuals after hedonic pricing regression. Based on the pricing equation and a typical discount rate, the value function of seller and posting cost can be estimated. Using the days on market and across sub-market, parametric matching function such as urn ball can be estimated. During which, buyers to house stock ratio is assumed to allow a flexible parameter on the matching function. With the seller value function, the seller to buyer ratio and matching function, Zhu et al. [2017] showed that the distribution of utility can be estimated nonparametrically. Regarding the price stickiness, it roots in the homogeneous seller assumption where all sellers receive the same utility within a certain price range. Therefore, for anyone within the price range, there is no incentive in deviating from the price and hence sticky price emerges.

While it is common to apply search model on housing market, the focus of search is on interaction between buyers and sellers. Dynamic competition between firms would be less of a focus. Therefore, while there is much to learn from applying search model, it is not the most suitable for analysing dynamic competition between sellers.

3.4 Real Estate in Hong Kong

Since the empirical application is on Hong Kong real estate market, literature related to this market should also be discussed. While researches particularly related the real estate market in Hong Kong are rather limited in more popular journals of Economics, there are many researches in the real estate journal discuss the market in Hong Kong. Using data from 1995 to 2015, Li and Chau [2019] discuss what motivates developers to sell before completing construction. By regressing on the presale apartments as a percentage of all apartments under construction, they found that the financing incentive is not important as industry wisdom suggests. At least for the listed developers, it does not matter as the listed companies have stronger financial ability. It only matters to the unlisted. Rather, hedging again future price fluctuation appears to raise the presale percentage. Other than these, more supply by the developer relative to the market supply and the construction project relative to the market capitalization of developers increase with the persale percentage, potentially because those projects are too large to handle if kept unsold till construction completion. The presence of consent scheme on the construction also lowers the presale percentage as affected by the regulation.

Based on data from 2013 to 2017,Liang et al. [2018] discussed a policy of new residential stamp duty using a spatial-temporal model. Starting from 2010, Hong Kong government has imposed various demand-side measures to calm the market. Special stamp duty since 2010 collects duties from property helf less than 2-3 years. Buyer's stamp duty since 2012 levies on non permanent residents of Hong Kong. Double ad valorem stamp duty since 2013 raised the old duty to roughly double of before. The focus of Liang et al. [2018], new residential stamp duty since 2016, charge 15% for any non permanent residents or buyer with existing property. Instrumented with the apartment size and the number of transactions within 500 meters in the last month, it implemented a 2SLS model and a spatial autoregressive model. Since the new residential stamp duty limits the options of buyers, the time-on-market (TOM) is found to be reduced. It implied that buyers intend to suffer high transaction tax of the property once the new duty is enforced. Apparently, the underlying belief is that property asset still outperforms other investment asset in Hong Kong.

Hui and Yu [2012] discussed how price adjustments affect the time-on-market under various economic conditions, in the secondary market in Hong Kong. It used a cox survival model to analyse two separate periods, an economic downturns in 2003 and an economic recovery in 2004-2006. It showed the effectiveness of raising list price before transactions does not always optimize seller's returns and TOM. With the data of about 4,000 transactions, Hui and Yu [2012] found that during crisis or initial recovery, people are uncertain about the future and the house price is much cheaper than the initial purchase, the supply is lower. Buyers also, expecting a downward price trend in near future, postpone their decision. The best strategy for sellers become selling the flat fast by lower listing price. Contrasting the period with gradual recovery, when prices soar, buyers hasten their purchase and hence the seller strategy becomes raising the listing price to maximize the return.

3.5 Conclusion

This chapter reviews various strands of literature in relation to my work in dynamic competition in Hong Kong real estate market. Dynamic game estimation literature laid the theoretical foundation for many empirical estimations of market competition. In particular, the EP framework with discretized technology level or other state variable serves as the workhorse model in the literature. Many empirical works applied the framework to analyse oligopoly competition. They managed to recover the dynamic parameters from the panel data that would not be feasible otherwise.

As the literature develops further, the limitation to competition with several firms becomes obvious given the constraint of computational burden. Oblivious equilibrium is then proposed to allow estimating dynamic competition with many firms while approximating the traditional Markov perfect equilibrium. In addition to the original setup, the model extends to covers various modification. Nonstationary OE estimates the short-run dynamic after a policy change. Extended OE estimate the dynamic competition that accommodates common market shocks. Partially OE bridges between MPE and OE by including dominant firms that are closely tracked and fringe firms that are tracked for the long run average distribution, although the firm status cannot be changed throughout. The empirical literature of using OE is at its early stage where there are only

2 works as of today, one on cigarette industry and the other one on motor industry. Both demonstrate the significant computation savings that afford the estimation on competition with many firms.

Other than the strategic perspective, housing market also has other forms of structural estimation. With the development in the theoretical tools, empirical analysis can estimate various aspects of the market (e.g. demand, production function) from a dynamic perspective. This helps to remove the bias introduced by static models, especially when the dynamic aspect of real estate is evident given its durable good and investment asset nature. Search model is frequently applied to housing market. With random search and directed search, analysis through search model focuses on the interaction between buyers and sellers. It helps to analyse how these interactions lead to the market outcomes (e.g. price, turnover rate, rent to price ratio), sometimes affected by policy. While these literature are fruitful tools for housing market analysis, their focus is less on the competition among sellers to understand their long term decisions.

For the researches focusing on the local market, they studied different facets pertaining to the Hong Kong real estate market. The majority form of sales practice in Hong Kong, presale, was studied and shown to be related to hedging against future volatility. A special demand-side measure used by Hong Kong government led to a shorter time on market. The listing prices by sellers were shown to be the optimizing strategy that changes under different economic conditions.

With the rich literature available, my work on estimating dynamic competition with many developers stands to expand our understanding on dynamic competition and the real estate market. It contributes by realizing the extended OE framework in the first practical estimation and bringing the dynamic competition tools to real estate market for deeper analysis of developer behaviors.

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