Initial Property Offering: Underpricing and Learning Behavior in the Presale Housing Market

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Abstract: Utilizing a transaction-level dataset of presale private properties in Singapore over 20 years (2000-2020), this paper investigates the property price dynamics following a project launch. We show that for a newly launched residential project, presale prices increase by approximately 1% every 100 days from the launch date, indicating an IPO underpricing price pattern. By matching transaction data with developer information, we demonstrate that developers tend to underprice their first two presale projects, and then adjust pricing strategies in subsequent projects by learning from experience and adjacent peers. Our study discloses developers' underpricing and learning behavior in the presale housing market.

Keywords: underpricing; learning; property price; developer; presale

1 Introduction

Product pricing is one of the most challenging decisions producers and marketers make. Producers' pricing strategies are not fully understood, including the pricing of sequentially sold products with dynamic prices. Previous studies propose theoretical or optimal pricing models under demand uncertainty (Baron, 1971; Besbes & Zeevi, 2009; Harris & Raviv, 1981; Holthausen, 1976, 1979). Among pricing issues, IPO underpricing is one of the focuses of finance scholars. When a company goes public, we often see an underpriced initial price and an ascendant price trend starting from the first day of trading, i.e., leaving money on the table. IPO researchers provide explanations such as information asymmetry (Baron, 1982; Baron & Holmström, 1980; Benveniste & Spindt, 1989;

Khurshed, Paleari, Pande, & Vismara, 2014; Muscarella & Vetsuypens, 1989; Neupane & Poshakwale, 2012; Rock, 1986; Welch, 1989), signaling (Allen & Faulhaber, 1989; Grinblatt & Hwang, 1989; Ibbotson, 1975; Ritter, 1984; Welch, 1989), issue mechanism (Derrien & Womack, 2003; Sherman, 2005), and behavioral explanations (Loughran & Ritter, 2002; Ritter, 1991; Welch, 1992), among others. We shed light on a market similar to IPOs, the presale residential real estate market. Presale, or sale before completion, is the prevailing selling model in real estate markets, especially in Asian areas such as mainland China, Hong Kong, Singapore, South Korea, etc. Like an IPO, a developer sets launch prices for a project based on its demand projection and then adjusts the prices during sequential sales after the launch. There is some literature that investigates pricing schemes under uncertainty in land or housing markets (Holland, Ott, & Riddiough, 2000; Lin & Vandell, 2007; Titman, 1985). Other studies investigate price anomalies (Munneke, Ooi, Sirmans, & Turnbull, 2019), transaction volume (Yiu, Wong, & Chau, 2009), housing quality (Chau, Wong, & Yiu, 2007), speculation in the presale housing market (Fu, Qian, & Yeung, 2016), the roles of the presale housing system in risk sharing (Lai, Wang, & Zhou, 2004), and price stabilization (Wong, Yiu, Tse, & Chau, 2006), among others. However, there is little empirical evidence investigating presale property underpricing and how developers learn to adjust their pricing strategies to reduce the money on the table for purchasers. Our paper fills this gap.

We employ empirical models to examine developers' pricing and learning patterns based on Singapore's presale residential real estate market. Utilizing more than 65,000 transactions of presale private properties in Singapore over 20 years (2000-2020), we find that the selling prices of the presale residential projects show rising trends from the launch date. For a newly developed and sold residential project, presale prices could increase by approximately 1% every 100 days from its launch. Our results also indicate that more recently established developers are more likely to exhibit the presale underpricing pattern.

We then uncover why and how presale housing prices show similarities to the IPO underpricing trend. We find that lower launch price behavior stems from developers' inexperience; that is, developers tend to initially underprice properties at the project launch, especially for their first few projects. Moreover, we rule out the deliberate discounting hypothesis where developers deliberately offer lower prices at the initial stage for marketing or signaling.

Finally, we show that developers adjust their pricing strategies through learning to avoid leaving too much on the table. This finding is related to studies about learning in pricing (Benveniste, Ljungqvist, Wilhelm Jr, & Yu, 2003; Besanko, Doraszelski, & Kryukov, 2014; Colaco, Ghosh, Knopf, & Teall, 2009; Willems, 2017) in the stock market, but we provide new empirical evidence to show that real estate developers also learn from their experience and their competing peers to adjust their pricing strategies.

2 Background

Singapore is an island country in Southeast Asia with a small area of 728.6 square kilometers and a high-density population of nearly 5.7 million. The housing system in Singapore has three separate sectors: the private sector, the public sector, and the public-private hybrid sector. We focus only on the presale of non-landed private properties, including condominiums and apartments, which account for the largest proportion of Singapore's private housing market. We exclude other property types for two reasons. First, the public and hybrid sectors have strict price controls and eligibility restrictions for newly launched projects. In contrast, in the private market, developers directly sell private properties, which means that price dynamics can reflect potential pricing decisions. Second, in the private sector, we exclude landed properties[1] because landed properties mainly target wealthy purchasers with lower transaction frequency.

In Singapore, licensed real estate developers can commence construction and launch sales of projects by law. A developer can launch presales before completion or even before starting construction of the project. Prospective buyers visit the project's show flats approximately 1-2 weeks before the official launch. At this point, developers only disclose flat models' estimated price ranges, or indicative prices, instead of providing exact prices. Keen purchasers may submit their Expression of Interest (EOI) and participate in the ballot system on the launch date when developers reveal actual prices. After the launch date, purchasers can also walk in to select and pay for chosen flats without submitting an EOI. After deciding on the flat option, the purchaser will receive a Sales and Purchase Agreement (S&PA) delivered from the developer, and then the purchaser will sign the S&PA and make payments. For uncompleted flats, payments are made progressively until the Temporary Occupation Permit (TOP) date, when the purchaser can move into the completed flat and pay at least 40% of the purchase price. For a developer, presale transactions can occur from the launch date until the completion date. Our sample of non-landed private property transactions contains the property type, i.e., completed or not, when purchasers' complete deals. We define presale purchases as transactions taking place before the completion of projects. Hence, we employ regression models to investigate the price dynamics after the launch and to analyze developers' learning processes when launching later projects.

3 Data and empirical design

[1] Landed property is one property type in Singapore. When a purchaser buys a landed property, she gets the property ownership together with the land ownership. Land properties account for approximately 5% in the residential real estate market in Singapore.

3.1 Property transactions

We collect non-landed transactions from the Real Estate Information System (REALIS), an official online data portal operated by Singapore Urban Redevelopment Authority (URA). The raw dataset includes countrywide transactions between 2000 and 2020. We then conduct data cleaning procedures as follows. First, we drop completed flats transactions at purchase, ensuring that our sample only includes presale purchases. Second, we delete observations with missing, incomplete, or incorrect property attributes (including flat area, flat floor, address information, property type, and tenure of ownership), purchaser type, project name, and developer name. We also exclude projects with less than 20 transactions recorded. Finally, we cut the sample by trimming transactions outside the 1% and the 99% thresholds of unit price and flat area.

In our empirical models, the dependent variable is the unit price in log-form. We also construct and include hedonic factors (e.g., property attributes, purchaser type, locational attributes, etc.) as control variables. We select the flat area (square meter, in log-form) and floor level as property attributes.[2] We also include a dummy of purchaser type, which takes value one if the purchaser's address is private property and takes value 0 for HDB. For locational attributes, we derive each flat's distances to its nearest Mass Rapid Transit (MRT, Singapore urban transit system) station, bus stop, top 30 primary schools, and the CBD (defined as the location of the City Hall MRT station) using GIS tools.[3] We convert these four locational attributes into log-forms and include them in regression models.

While the transaction date for each home transaction in included in the dataset, it does not contain the exact launch dates of projects. Therefore, we identify the launch date as the earliest transaction date of

[2] We do not include other property attributes such as tenure of ownership because they would be absorbed by fixed effects in our specifications.

[3] In Singapore, each postal code represents a single building. Since the address information includes the postal code in the sample, we geocode the address and obtain coordinates of each building. Each flat in the same building has the same coordinates.

flats in each project. Since developers usually receive EOIs before the launch date, and transactions at the launch date account for a major proportion of the whole sale cycle, it makes sense for the earliest transaction date to represent the project's launch date. We code the launch date as day 1 and restrict our sample to transactions within 365 days following the launch date. Approximately 80% of transactions occur during this time.

3.2 Developer information

Since the transaction data only contains project names, we match it with developer names using information listed on REALIS. However, REALIS does not disclose developer information other than their names and projects. Therefore, we also use another data source, Orbis, a database with information on more than 400 million companies (publicly listed or not) worldwide. We gather developer information, including name, registration date, and the global ultimate owner (GUO), then we match it to the transaction data using developer names. We remove developers registered before 2000 to be consistent with the transaction data starting from 2000.

3.3 Summary statistics

After conducting the data cleaning procedures discussed above, our sample has 65,142 presale non-landed private property transactions. We show their spatial distribution in Figure 1 and summary statistics in Table 1. The average unit price is 13,574 Singapore dollars per square meter (approximately 9,757 USD/m^2), and the average number of days since launch is 76 days. These transactions belong to 474 projects, 438 developers, and 1,352 buildings. We plot bin-scattered trends of unit price, flat area, and flat level within 365 days of the launch, as shown in Figure 2. Most flats were sold within 100 days. The average unit price drops from a higher level at the launch and gradually grows approximately 50 days after launch. Average flat area and flat level exhibit upward trends during the one-year period.

These trends are consistent with what we can observe in the market, i.e., popular flats (usually one-bedroom or two-bedroom flats at higher levels) with lower unit prices transacted earlier after the project launch, while remaining flats take longer to be sold or are unmarketable.

[Figure 1 about here]

[Table 1 about here]

[Figure 2 about here]

3.4 Empirical design

We seek to investigate the price dynamics in the presale housing market. By employing transaction-level pooled cross-sectional data, we can examine the trend of property prices following the launch date. Then we run the model as equation (1), where the dependent variable is the flat unit price (S$/m^2) in log-form of flat i in project j at time (year-month). The key variable of interest is $daysincelaunch_{ij}$ defined as the number of days since the launch of project j to the transaction date of flat i. Considering that the magnitude of daily price appreciation or depreciation percentage is small, we convert the unit of $daysincelaunch_{ij}$ into 100 days when running regressions. Therefore, the coefficient β measures the price appreciation or depreciation every 100 days. The vector $\boldsymbol{X}$ contains controls of property attributes (flat area and flat level), purchaser type, and locational characteristics (distances to nearest subway station, bus stop, top 30 primary schools, and the CBD). ε_{ijt} is the error term.

One of the empirical challenges is that popular flat types (e.g., smaller areas, fewer rooms, higher floor levels) are usually sold first, and their unit prices are relatively higher. Our model specifications are designed to absorb variations of property attributes, to purely capture the relationship between transaction sequence and prices. Even though we include flat area and flat level to control for housing attributes, other characteristics such as number of rooms and facing cannot be absorbed. Therefore, we try to capture more property type information from the address, including postal code, stack number, and storey range. A unique postal code represents one single building in Singapore. Considering stacks are continuously coded with no duplicate numbers in each project, we can reasonably assume that flats in the same stack have the same facing and housing type, including flat area and number of rooms. As for the storey range, we classify flats in our sample into three groups: level <= 10, 10 < level <= 20, and level > 20. To sum up, in our regression analysis, we include four sets of fixed effects τ_t and μ_p: (1) year-month FE and project FE; (2) year-month FE and postal code FE; (3) year-month FE and project-stack FE; and (4) year-month FE and project-stack-storey range FE, to control for different levels of transaction time and property types, respectively. Robust standard errors are clustered at the postal code level.

$$ln(unit\ price)_{ijt} = \alpha + \beta daysincelaunch_{ij} + \boldsymbol{X}'\Gamma + \tau_t + \mu_p + \varepsilon_{ijt} \quad (1)$$

We further test the trend of selling prices by dividing the sample into six groups, i.e., transactions at the launch date (day 1), transactions during day 2 - day 25, day 26 - day 50, day 51 - day 75, day 76 - day 100, and day 101 - day 365 since project launch. We include five dummy variables $D_{ij,2-25}$, $D_{ij,26-50}$, $D_{ij,51-75}$, $D_{ij,76-100}$, and $D_{ij,101-365}$ to represent the last five periods, respectively, while the launch date (day 1) is set as the benchmark. Equation (2) shows model specifications, coefficients β_1, β_2, β_3, β_4, and β_5 indicate the price appreciation or depreciation at each period relative to the launch date, while other model details are the same as equation (1).

$$ln(unit\ price)_{ijt} = \alpha + \beta_1 D_{ij,2-25} + \beta_2 D_{ij,26-50} + \beta_3 D_{ij,51-75} + \beta_4 D_{ij,76-100} + \beta_5 D_{ij,101-365} +$$

$\boldsymbol{X}'\Gamma + \tau_t + \mu_p + \varepsilon_{ijt}$ (2)

4 Results

4.1 Presale underpricing

We start from the baseline results of the price trends of presale properties after launch. Table 2 shows the estimating equation (1) results. The coefficients of $daysincelaunch_{ij}$ (100 days) indicate that the unit prices of presale properties increase by approximately 0.6% to more than 1% every 100 days after the project launch. This is where we find evidence of the underpricing behavior of developers. From our sample, we know that the average unit price of presale non-landed private properties in 2020 is 18.6 thousand S$/m^2, and the average flat area is 74.5 m^2. If we assume that the price increases by 1% 100 days after launching, for each flat, the presale underpricing leaves 13,900 S$ on the table every 100 days.

[Table 2 about here]

We further conduct robustness checks on the underpricing behavior of developers. First, we remove the restriction of 365 days since launch. Table A1 in Appendix shows consistent results with our baseline findings. Second, private properties in Singapore have two tenure types: leasehold properties with 99 years or 999 years of initial tenure and freehold properties with perpetual tenure. One concern is that freehold properties account for a low market share and are aimed at the wealthy upper class. Therefore, we exclude freehold properties from the sample, and the results in Table A2 are consistent with the baseline results. Third, we conduct a robustness check by controlling for the demand side, measured by the relative change in Google Trends. We collected the Google Trends index[4] (week-level) of all project

[4] Google Trends index represents search interest of the given keyword relative to the highest point on the chart for the given

names, given the search region as Singapore and the search period as the selling period of projects. We then calculate the percentage change in the index for each project in each week relative to the index in the launch week. Table A3 shows the results with the demand side indicator incorporated in the model, and the presale underpricing pattern is consistent with the baseline analysis. Finally, for each project, we derive its average listing days (defined as the total sale days divided by the transaction volume) to measure its popularity. Then we drop projects with average listing days less than 0.5 days or over four days (each account for approximately 10% of observations) and estimate equation (1) based on the remaining transactions to further mitigate the concern that demand could influence developers' pricing strategies. Results in Table A4 still show the rising price trend following the project launch.

We then divide the sample period into six periods and test the price dynamics by estimating equation (2). As shown in Figure 3, there is a clear upward trend during the 365-day period following the project launch. Starting from day 51 to day 75, the prices are significantly higher than the price at launch, and this significant difference persists from day 101 to day 365. We show the regression results in Table A5 in the Appendix.

[Figure 3 about here]

4.2 Heterogeneous tests

Furthermore, we want to investigate who is leaving money on the table selling their presale projects. Therefore, we conduct the heterogeneous test based on the developer registration year. We sort developers by their registration date and identify relatively mature developers whose registrations were earlier than the average registration date. We generate a dummy variable $maturefirm_d$ to represent

region and time after 2004. A value of 100 is the peak popularity for the term. A value of 50 means that the term is half as popular. We collected the index of projects (there are 200 projects that can be matched with the index) during their selling periods. For each project, we use the index in the launch week as the base, then we calculate the relative change in the index in the subsequent weeks. For example, the index of a project is 100 in the launch week and 80 in the second week, so the value of the relative change in the second week is -0.2.

mature developers and interact it with $daysincelaunch_{ij}$, while other specifications are the same as those in equation (1). Results in Table 3 indicate that mature developers underprice at launch and offer increasing sequential prices with higher slopes relative to later established developers. A possible explanation is that developers who entered the market earlier were not familiar with the market, and there was not much experience to learn from.

[Table 3 about here]

4.3 Learning in pricing

We propose a learning hypothesis to explain developers' presale underpricing. IPO literature tells us that attempting IPO has information externalities on the issuer itself and its peers or rivals (Benveniste, Busaba, & Wilhelm Jr, 2002; Lowry & Schwert, 2002). Firms may make IPO decisions by learning from the experience of their contemporaries (Benveniste et al., 2003; Colaco et al., 2009). In the presale property market, we hypothesize that developers learn from their own experience and their adjacent competing peers to adjust their pricing strategies.

We start by testing developers' self-learning behavior. Different from public firms, developers may launch multiple projects simultaneously or sequentially. A developer may market its first project with a conservative strategy and initially set relatively lower prices while leaving too much money on the table for purchasers. When the developer realizes this, it may set higher launch prices in subsequent projects, and following projects' prices would not rise as significantly following the initial launch.

One concern is that developers with different names may belong to the same parent company, or one is the parent company of the others. It is reasonable to surmise that information and experience sharing exist among associated companies. Therefore, we use the common words in companies' names to manually classify them as the same developer.[5] We take the associated companies' earliest registration date as their common registration date. There remain 263 developers after combination. Among them, 188 developers have one project, 40 have two projects, and the others developed three or more projects. We then identify each developer's first, second, and subsequent projects based on the sale dates. By doing this, we can examine if developers learn from their experience to adjust pricing strategies.

We employ the following model to examine developers' learning process over projects. As equation (3) shows, we generate interaction terms of five period dummies ($D_{ij,2-25}$, $D_{ij,26-50}$, $D_{ij,51-75}$, $D_{ij,76-100}$, $D_{ij,101-365}$) and three project sequence dummies that represent the project sequence among all projects of this developer. Dummy variable $sequence_{j,1}$ takes value one if project j is the first project of this developer, and otherwise, 0, and similarly, $sequence_{j,2}$ indicates the second project, while $sequence_{j,3}$ indicates the third and subsequent projects. In this model setting, the project launch date is the benchmark.

$$ln(unit\ price)_{ijt} = \alpha + \sum_{k=1}^{3}[sequence_{j,k} \times (\delta_{k1}D_{ij,2-25} + \delta_{k2}D_{ij,26-50} + \delta_{k3}D_{ij,51-75} + \delta_{k4}D_{ij,76-100} + \delta_{k5}D_{ij,101-365})] + \boldsymbol{X}'\Gamma + \tau_t + \mu_p + \varepsilon_{ijt} \qquad (3)$$

The regression results of equation (3) are reported in the Appendix Table A6, and we also plot estimated coefficients and their confidence intervals in Figure 4. Relative to the launch date, developers' first projects experience significant price growth in the following dates. Specifically, the unit price could rise by up to approximately 2% from the project's launch. Prices of developers' second projects also show similar upward trends. However, we could not find such a pattern in developers' third and

[5] For example, "CES Land Pte Ltd", "CES-Balmoral Pte Ltd", "CES-Shanghai Pte Ltd", and "CES-West Coast Pte Ltd" are classified as the same developer and encoded with the same developer ID.

subsequent projects. In other words, our results indicate that developers only leave money for purchasers in their first two projects. They learn and adjust their pricing strategies in their following projects.

[Figure 4 about here]

Another channel is that developers may observe existing projects launched earlier and adjust pricing strategies based on the experience of peers and competitors. To test this channel, we identify the project sequence within its 2 km radius (i.e., the number of projects launched earlier than it + 1), generate five dummies indicating this sequence (<=5 (the benchmark), 6-10, 11-20, 21-30, >=31), and interact them with $daysincelaunch_{ij}$. We show estimation results in Table A7 and draw estimated coefficients of interaction terms in Figure 5. For a project, if there were more than 10 projects launched before it within its 2 km radius, we find that this project has a significantly milder price appreciation trend after its launch. Therefore, we could argue that developers can learn from their adjacent projects.

[Figure 5 about here]

4.4 Deliberate discounting

One concern is whether developers deliberately set lower prices at launch for marketing to attract more purchasers instead of a lack of experience leading to money being inadvertently left on the table due to market uncertainty or unfamiliarity. To mitigate this concern, we restrict the sample to two periods of housing booms in Singapore, i.e., 2005-2007 and 2010-2012 (we show Singapore's non-landed private property price index in Appendix Figure A1). If developers intentionally set lower prices, we should not observe this rising trend following a project launch during housing market booms, when discounting for marketing is unnecessary. Results shown in Table 4 still disclose increasing price trends since launch during both housing boom waves, which rules out the explanation of intentional discounting. This finding also echoes the IPO underpricing literature (Loughran & Ritter, 2002).

[Table 4 about here]

5 Conclusion

Utilizing a transaction-level dataset in Singapore, we focus on the price dynamics of presale private properties. We find that the selling prices of residential real estate projects have an upward trend following the launch date. In other words, the initial presale prices are underpriced. To be specific, for a newly developed and transacted residential project, its presale price can rise by approximately 1% every 100 days since the launch date. This presale underpricing is similar to IPO underpricing in the stock market. We borrow IPO underpricing theories to investigate developers' learning in presale property pricing. By comparing developers' first and subsequent projects, our empirical results indicate that developers tend to leave less money on the table for purchasers starting from their third projects. We also show heterogeneities in the presale underpricing and rule out the deliberate discounting hypothesis.

This paper has limitations. First, we mainly investigate the price trend from the supply side. Even if we run a robustness check by including a demand index, we do not have more information on the demand side. Second, we did not directly test the inexperience mechanism which drives presale underpricing. We wait for future studies to discuss this question.

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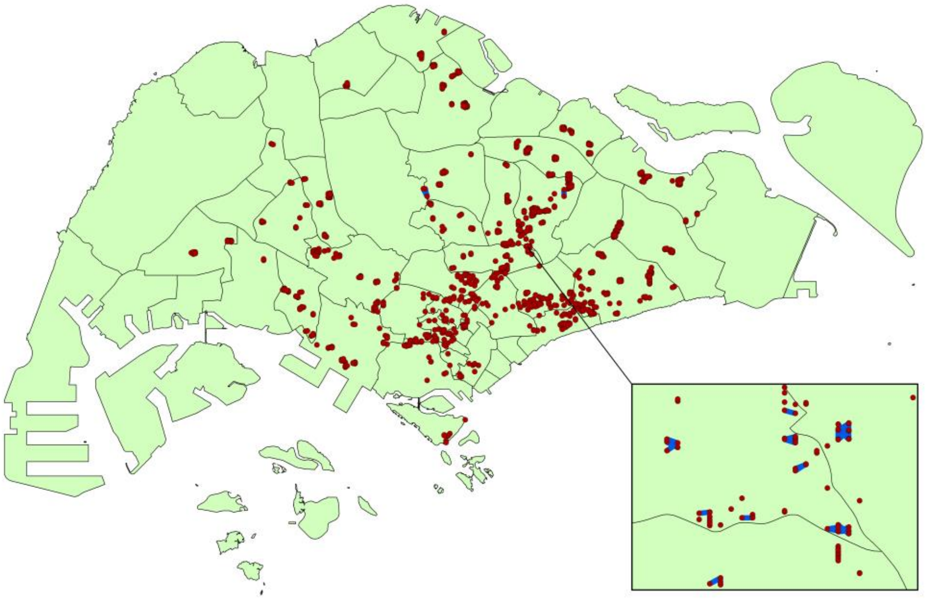
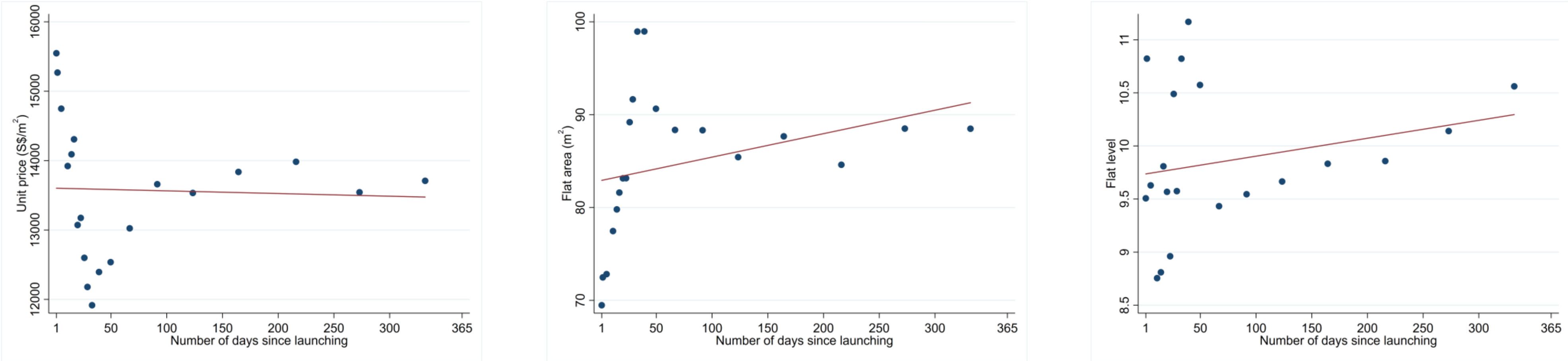


Figure 1 Distribution of presale private properties

Notes: This figure shows the distribution of presale non-landed properties in our sample. Each dot indicates one block with multiple flats and transactions. We also connect blocks within the same projects using blue lines.



Panel A Unit price

Panel B Flat area

Panel C Flat level

Figure 2 Trends of property attributes since the project launch

Notes: We aggregate the sample by the number of days since project launch and display trends of average unit price, flat area, and flat level from the launch date to 365 days post-launch. The number of equal-sized bins is 20 for each panel.

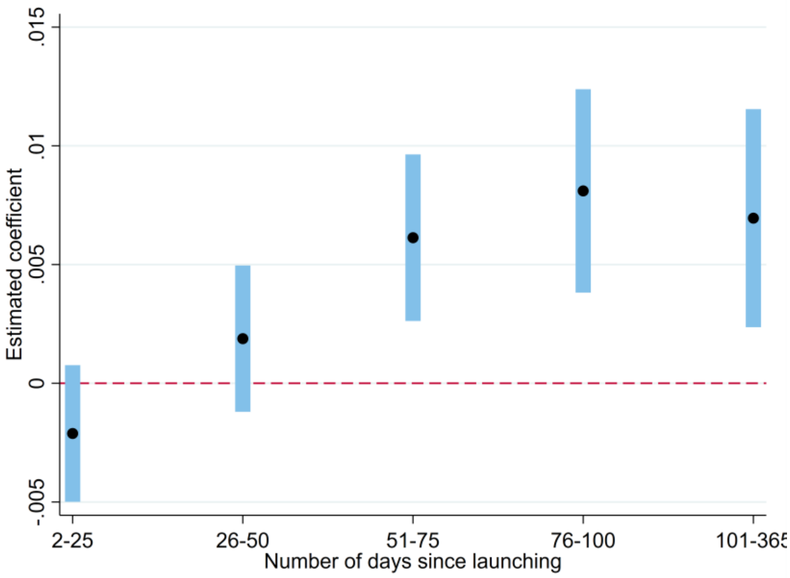


Figure 3 Price trends of presale properties since launching

Notes: This figure shows price trends in groups of days after launch, with the launch date as the benchmark. The dots indicate the coefficients of each dummy, and the shaded bars represent 95% confidence intervals. We control for property attributes, locational characteristics, year-month fixed effects, and project-stack-storey range fixed effects. Robust standard errors are clustered at the postal code level.

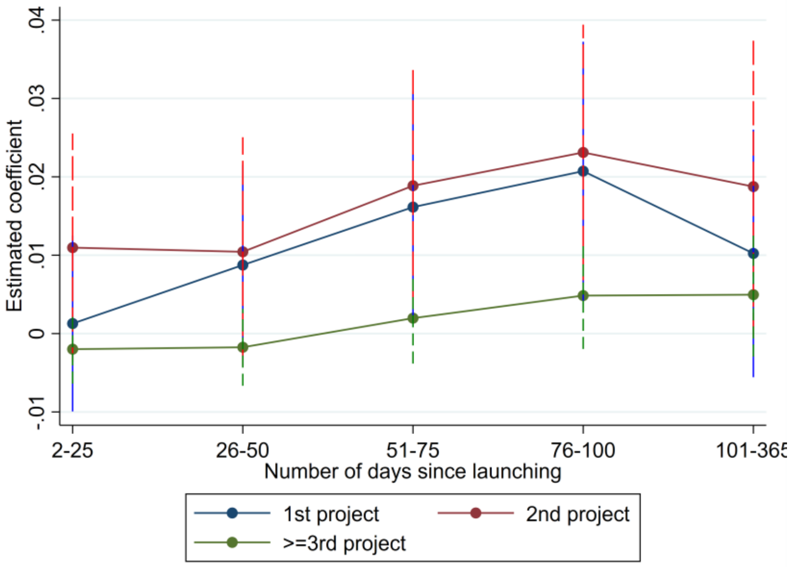


Figure 4 Evidence of learning in pricing sequential projects of developers

Notes: We regress the unit price of presale private properties (in log-form) on period dummies and project sequence dummies and take the launch date as the benchmark. The dots indicate the coefficients of each interaction, and the shaded lines represent 95% confidence intervals. We control for property attributes, locational characteristics, year-month fixed effects, and project-stack-storey range fixed effects. Robust standard errors are clustered at the postal code level.

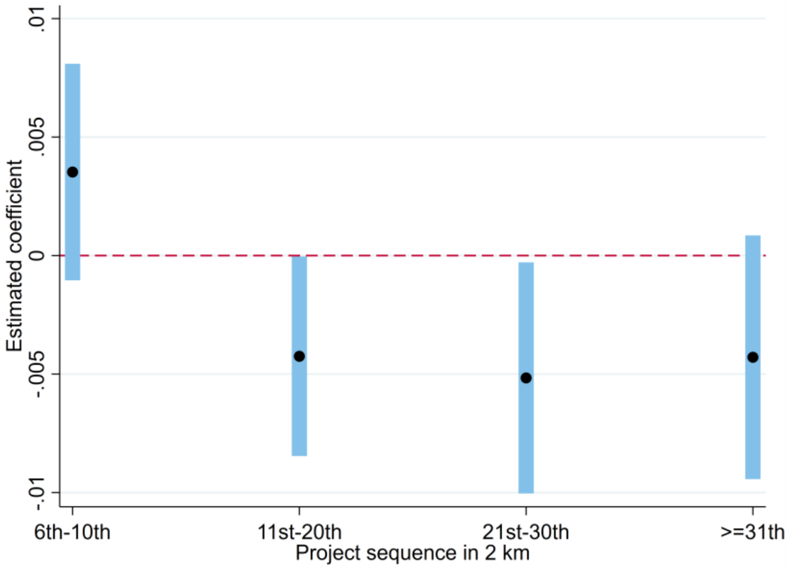


Figure 5 Price appreciation after launch and project sequence within 2 km

Notes: We identify the sequence of each project within its 2 km radius. This figure shows the presale property price appreciation after launching over project sequence. The dots indicate the coefficients of interaction terms (sequence dummy × $daysincelaunch_{ij}$), and the shaded bars represent 95% confidence intervals. We control for property attributes, locational characteristics, year-month fixed effects, and project-stack-storey range fixed effects. Robust standard errors are clustered at the postal code level.

Table 1 Summary statistics

Variable	Unit	N	Mean	SD	Min	Max
unit price	S$/m^2	65,142	13,573.590	4,598.869	5,208.000	32,524.000
number of days since launch	/	65,142	76.385	94.319	1.000	365.000
flat area	m^2	65,142	84.829	37.613	36.000	259.000
flat level	/	65,142	9.864	7.895	1.000	67.000
purchaser type	/	65,142	0.490	0.500	0.000	1.000
distance to nearest MRT station	km	65,142	0.642	0.489	0.028	3.438
distance to nearest bus stop	km	65,142	0.135	0.122	0.005	2.401
distance to nearest top 30 primary school	km	65,142	1.537	0.898	0.047	5.071
distance to CBD	km	65,142	8.338	4.176	0.953	18.195

Notes: This table shows the variables for estimations and their units. This table also summarizes the number of observations, mean, standard deviation, minimum value, and maximum value of these variables. We restrict the sample to transactions of non-landed private properties within 365 days since their corresponding launch dates. We convert unit price, flat area, distance to nearest MRT station, distance to the nearest bus stop, distance to the nearest top 30 primary school, and distance to CBD to log-form when running regressions.

Table 2 Presale price trends since launch

	(1)	(2)	(3)	(4)
	ln (unit price)	ln (unit price)	ln (unit price)	ln (unit price)
$daysincelaunch_{ij}$ (100 days)	0.013***	0.009**	0.009***	0.006**
	(0.004)	(0.004)	(0.003)	(0.003)
Controls	√	√	√	√
Year-month FE	√	√	√	√
Project FE	√			
Postal code FE		√		
Project-stack FE			√	
Project-stack-storey range FE				√
Observations	65,138	65,123	64,262	63,244
R-squared	0.968	0.972	0.989	0.991

Notes: This table shows presale price trends since project launch within 365 days, based on transactions between 2000 and 2020. The dependent variable is unit price in log-form. The variable $daysincelaunch_{ij}$ measures the number of days since project launch (unit: 100 days). We include control variables and fixed effects in regressions. Robust standard errors are clustered at the postal code level. *** p<0.01, ** p<0.05, * p<0.1.

Table 3 Heterogeneity by developer's registration date

	(1)	(2)	(3)	(4)
	ln (unit price)	ln (unit price)	ln (unit price)	ln (unit price)
$daysincelaunch_{ij}$ (100 days)				
$\times maturefirm_d$	0.007**	0.008**	0.009***	0.006**
	(0.003)	(0.003)	(0.003)	(0.003)
$daysincelaunch_{ij}$ (100 days)	0.011**	0.006	0.006**	0.004
	(0.004)	(0.004)	(0.003)	(0.003)
Controls	√	√	√	√
Year-month FE	√	√	√	√
Project FE	√			
Postal code FE		√		
Project-stack FE			√	
Project-stack-storey range FE				√
Observations	65,138	65,123	64,262	63,244
R-squared	0.968	0.972	0.989	0.991

Notes: This table shows presale price trends since project launch within 365 days, based on transactions between 2000 and 2020. The dependent variable is unit price in log-form. The variable $daysincelaunch_{ij}$ measures the number of days since project launch (unit: 100 days). Dummy variable $maturefirm_d$ represents developers who were registered before the average registration date in our sample. We include control variables and fixed effects in regressions. Robust standard errors are clustered at the postal code level. *** p<0.01, ** p<0.05, * p<0.1.

Table 4 Presale price trends since launch (housing boom years)

	(1)	(2)	(3)	(4)
	ln (unit price)	ln (unit price)	ln (unit price)	ln (unit price)
Panel A: 2005-2007				
$daysincelaunch_{ij}$ (100 days)	0.048***	0.034**	0.034***	0.030***
	(0.014)	(0.014)	(0.010)	(0.010)
Observations	8,164	8,163	8,050	7,876
R-squared	0.964	0.969	0.985	0.989
Panel B: 2010-2012				
$daysincelaunch_{ij}$ (100 days)	0.010*	0.007	0.010**	0.008**
	(0.006)	(0.005)	(0.004)	(0.004)
Observations	24,463	24,461	24,194	23,943
R-squared	0.960	0.966	0.986	0.988
Controls	√	√	√	√
Year-month FE	√	√	√	√
Project FE	√			
Postal code FE		√		
Project-stack FE			√	
Project-stack-storey range FE				√

Notes: This table shows presale price trends since project launch within 365 days. We restrict the sample to two housing boom waves: 2005-2007 (Panel A) and 2010-2012 (Panel B). The dependent variable is unit price in log-form. The variable $daysincelaunch_{ij}$ measures the number of days since project launch (unit: 100 days). We include control variables and fixed effects in regressions. Robust standard errors are clustered at the postal code level. *** p<0.01, ** p<0.05, * p<0.1.