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Working Paper 1502

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March 2015

Abstract. *Examining the sequential sale of new condominium units in a setting in which both consumption risk and completion risk are minimized and where production agglomeration does not pertain, this paper provides new evidence on the sales price-sales sequence pattern for real estate. The empirical results show that the anomalies of declining price "afternoon effect" or rising price from increasing relative demand documented in the auction literature do not extend to real estate markets. We thus conclude that the law of one price appears to hold for real estate assets sold in open (non-auction) markets. Nevertheless, the presence of a quality-sales sequence phenomenon suggests that earlier buyers in a multiple-unit development have and do exercise their option to select the more desirable unit.*

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1. Introduction

Sequential sales of similar assets occur regularly in real estate, for example, in new residential subdivisions, industrial parks, and condominium developments. It is not surprising then, that there is a modest but growing literature testing the law of one price for real estate in such situations. Simply stated, the law of one price holds that identical assets sold sequentially sell at the same equilibrium price. Otherwise, it is argued, speculators could buy in the low-price period and arbitrage potential gains. Nonetheless, the literature offers examples of price-sales sequence anomalies that appear to contradict the law of one price. This paper offers new empirical evidence on the price-sales sequence relationship and tests for development scale and selection bias effects.

The auction literature provides much of the early motivation for studying price-sales sequence anomalies. Ashenfelter (1989) first observed the so-called "afternoon effect" of declining prices over the sequence of sales in wine and art auctions. He attributes departure from the law of one price to risk-averse buyers who are willing to pay a higher price in early periods because the opportunity to buy later is increasingly uncertain as the sales sequence proceeds (Ashenfelter, 1989; McAfee and Vincent, 1993). On the other hand, prices may rise over the sales sequence because relative demand increases when sold units and the buyers of those units are no longer potential participants as the sequence of auctions proceeds (Van den Berg, Van Ours and Pradhan 2001). In a different vein, Milgrom and Weber (1982) show that later buyers in the sequence of sales can draw information from earlier sales to reduce their valuation risk, leading to different bidding strategies as the sales sequence progresses.

While the auction literature provides early examples and motivation for studying price-sales sequence relationships, most real estate in the U.S. is sold in open (non-auction) markets.

But even in these settings, there is evidence of afternoon effects or other patterns that contrast with the law of one price. Theoretical explanations for the apparent anomalies emphasize the role of prices capitalizing the declining consumption risk as new residential developments are completed or the increasing agglomeration economies as new industrial parks or commercial developments fill in (Rauch 1993, Sirmans, Turnbull and Dombrow 1996). The empirical study by Fu and Qian (2014) concludes that speculators do not stabilize prices but instead reinforce momentum effects driving prices from fundamental values. Munneke, Ooi, Sirmans and Turnbull (hereafter, MOST) (2011) find statistically significant increases in selling price over the sales sequence in a low consumption risk environment, although the magnitude of the increases is economically insignificant. The pattern persists even when controlling for differences in sales momentum across development projects.

This paper provides new evidence on the sales price-sales sequence pattern for real estate, controlling for two possible price anomaly sources largely ignored thus far in the real estate literature, namely development scale effects and self-selection bias. The data cover market transactions for new condominiums in Singapore. The Singapore condo market has several advantages for studying the relationship between selling price and sales sequence. It is standard for developers to offer condo units on the open market (i.e., non-auction) before the development project is completed. The government regulates developers and their handling of buyers' payments in order to minimize the risk of project failure and to ensure that projects fulfill all of the detailed requirements spelled out in the approved development plan, from development amenities and architectural features to individual unit floor plans. The regulations mean that consumers should not to be subject to the types of consumption risk that Sirmans, Turnbull and

Dombrow (1996) argue explains rising prices over the sequence of sales observed for single family houses in new developments in the U.S.

The condominium product sold under these regulatory constraints more closely resembles a commodity than do heterogeneous units of detached single family housing. The sale of new condominiums in Singapore therefore yields an excellent opportunity to examine whether the phenomenon of increasing prices observed for single family homes in the literature also holds when housing consumption risk is minimal and invariant through the entire sequence of individual condo unit sales for each development. Applying the theory offered by Sirmans, Turnbull and Dombrow (1996), developers need not sell the first units at a discount to compensate for greater consumption risk in the Singapore market because consumption risk is unlikely to vary over the sales period. Thus, an afternoon effect or any other price-sequence anomaly in this market is not likely driven by consumption risk effects.

The sample of transactions covers about 20,000 new condominium units sold in Singapore over 1996-2005. The hedonic models include the usual characteristics, controlling for differences in observable features across development projects and individual units as well as broader real estate market conditions. The models include an additional variable indicating the order in which individual units sell within each development. The OLS estimates reveal a negative relationship between sales sequence and price that, although statistically significant, is economically insignificant. The OLS results qualitatively resemble MOST (2011) for a different sample of development projects. Our analysis shows that development scale influences the price-sequence relationship. While the pooled sample and low rise developments show similar afternoon effects of declining price over the sales sequence, high rise developments show the opposite pattern of rising prices over the sales sequence. Once again, though, the magnitude of the price effects is economically insignificant.

In any case, the OLS estimates do not account for one possible explanation of the afternoon effect or other price anomalies, that buyers respond to subtle differences in quality across condo units that are not observed in the data. The auction literature provides the rationale for selection effects that may drive observed price-sales sequence relationships (Ashenfelter and Genesove, 1991; Beggs and Graddy, 1997; Burguet 2005). Hollins, Martin and Munneke (2013) find stable prices over a long part of the sales sequence but falling prices near the end and attribute the discounts to lower quality lots being developed last. They leave rigorous testing for selection effects to future work.

Therefore, we also introduce a multinomial selection correction to control for price effects that arise because choice units tend to sell earlier than less desired units in the sales sequence. The selection-corrected results indicate that the negative price-sales sequence effect observed in our initial OLS estimates are indeed systematically biased as suspected. Selection corrected pooled sample estimates show declining prices in the early part of the sales sequence, followed by rising prices up to project completion. Prices of sales after project completion continue rising, but at a more modest pace. The high rise and low rise subsamples yield very different patterns. The high rise subsample exhibits rising prices in both the early and middle phases of the sales sequence with declining prices for the sequence of units sold after project completion. The low rise sample exhibits no price movement over the sales sequence in the early part of the sales sequence and declining prices thereafter. Nonetheless, all of the selection-corrected estimates of the sequence effect remain economically insignificant, accounting for only hundreds of dollars on units selling for hundreds of thousands of dollars. We conclude that this offers no strong evidence of a sequential pricing anomaly resembling either the declining price "afternoon effect" documented in the auction literature or the rising price from increasing relative demand in the auction literature or declining consumption risk in the land development literature (Sirmans, Turnbull and Dombrow, 1997; Hollan, Martin, and Munneke, 2013). Our data pertain to the sale of condominium units with full market exposure, so the results clearly show that the afternoon effect and other price-sales sequence anomalies appear to be artifacts of auctions and do not represent a general real estate market price anomaly.

2. The Data

Our study focuses on condominiums in Singapore. We first describe the key institutional features of the market which make it a good setting to study the price sequence effect in the presence of selection. Consistent with the practice in many Asian markets, such as Mainland China, Hong Kong, Malaysia, Singapore, South Korea, and Taiwan, new condominiums are mostly sold before project completion (see Chang and Ward, 1993; Fu and Qian, 2014; Lai, Wang and Zhou, 2004). On average, the time interval from site acquisition to initial marketing of the condominiums in Singapore is two years, and from initial marketing to physical completion and handover of the units is around three years (Ooi and Le, 2013).[1] Since additional costs will be incurred to hold condominium units that remain unsold after the development is completed, the optimal strategy for developers is to sell as many units as possible prior to project completion. On the demand side, the majority of the market participants in the presale market in Singapore are individual investors, who together account for 96% of trading volume in the sample in Fu and Qian (2014).

[1] In Singapore developers can begin preselling as soon as the construction permit is obtained; in contrast, developers in other presale markets such as Hong Kong can only start selling when construction is close to completion (Fu and Qian, 2014).

A Housing Developer Sale License, which is only granted to developers with good track records, is required before any residential units can be offered for sale in Singapore. Under the Project Account Scheme (PAS), which was introduced in 1981, buyers pay the purchase price progressively according to defined stages of the construction process. To protect homebuyers from errant developers siphoning off monies received from the progress payments to use for other speculative projects, all sale proceeds from the project must be paid into a project account with a bank, the withdrawal of which can only be for disbursements related to the project. The surplus monies from the account can only be withdrawn by the developer after the project is completed. By ring-fencing the progress payments, the PAS protects buyers from the risk of losing their monies in the unlikely event of the developer entering into bankruptcy before the project is completed. In contrast to other presale markets such as China or Malaysia, Singapore developers almost never default or abandon a development project prematurely (Fu and Qian, 2014).

The main source of our data is the Real Estate Information System (REALIS), which is maintained by the Urban Redevelopment Authority (URA), the de facto land use planning and development control authority in Singapore. Our sample comprises a total of 19,831 new residential units within 69 developments in Singapore between 1996 and 2005. The average number of observations in each sampled development is 287. Figure 1 charts the performance of the private housing market in Singapore over the study period. In the first six quarters starting from 1995Q1, the residential price index rose steadily to peak at 169.1 in 1996Q2. Following the introduction of anti-speculation measures[2] in 1996 and the Asian Financial Crisis which hit the

[2] The anti-speculation measures announced on May 15, 1996 include a tax of 100%, 66%, and 33% on the gains from disposal if the property is sold within the first, second, and third year of purchase, respectively. In addition, buyers of residential properties are required to pay 20% of the purchase price in cash. They are also not allowed to use their pension fund to cover stamp duties related to property transactions.

region in 1997, the housing market in Singapore went into a recession as the private property index hit a low of 100 in 1998Q4. The housing market sentiment improved between 1999Q1 and 2000Q2, but the recovery was checked by three external events which reversed the market sentiment, namely the terrorist attack on the U.S. (September 11, 2001), the Bali bombings in Indonesia (October 12, 2002), and the Severe Acute Respiratory Syndrome (SARS) epidemic which hit the region in first half of 2003. The residential price index declined gradually until 2004Q3, when it started to show a marginal improvement.

For each transaction, we collect the following information from REALIS: sale price, date of sale, floor area, and floor level of the individual units. The sale price is the agreed purchase price of the property between the developer and a purchaser. It excludes stamp duties, legal and agency fees, and other professional fees. We supplement this information with the internal spatial attributes of each unit with respect to its orientation towards morning sun, evening sun, swimming pool, and exposure to traffic noise from the main road by painstakingly examining the site layout, orientation, amenities and detailed floor plans of the developments. For each of the developments in our sample, we also measure their distance from the CBD and the closest subway station.

The number of units sold is calculated from the date a project is first launched until all units are sold or until the end of the sample period, December 2005, whichever is earlier. After arranging the transactions sequentially by contract date, there are two ways to measure the sequential sale effect. A natural way would be to denote the order of sale for each unit incrementally. Alternatively, we could use the number of days that have lapsed between the current sale and the first unit sold in the same development. We adopt the second approach because it captures any time lapse for information from the early transactions to flow to subsequent buyers. This is particularly relevant to situations in which more than one unit is sold in a given day, which is frequently the case during the launch of a condominium project. Moreover, information on earlier sales may not be revealed to subsequent buyers on the same day because the new units are sold by private negotiation (rather than public auction). In this sense, our measure allows for the possibility that, in the very short run, price information transmission may take longer for open market sales than for auction sales.[3]

Table 1 presents the variable definitions and descriptive statistics of the sample and subsamples used in the analysis. The average price of the units in the entire sample is S$751,630. The average unit is located on the eighth floor and has a floor area of 1,308 sq ft. We expect that the sale price will be related positively with the unit floor area and floor level. On the basis that apartments located on the higher floors tend to have better view, be more airy and be exposed to less visual intrusion from neighboring buildings, flats located on higher floors are expected to be more desirable and command a price premium (Ong and Koh, 2000; Tse, 2002). In addition, 8.0% of the units in our sample are located on "lucky" floors, which we define as those ending with number eight, namely 8th floor, 18th floor, and 28th floor, whilst 12.4% are located on "unlucky" floors, defined as those ending with the number four, namely 4th floor, 14th floor, and 24th floor.[4] We predict that units located on "lucky" floors will command a price premium while

[3] Our measurement of the sequential sale effect can also account for possible missing observations due to incomplete transaction data. The transaction database is based on caveats lodged by the purchasers to protect their interest soon after an option to purchase a property is exercised. Essentially, caveats are legal documents lodged by home purchasers through their lawyers with the Singapore Land Authority to register their legal interest in the property. Typically, caveats are lodged two to three weeks after a purchaser signs an option to purchase at the show flat. Since it is not mandatory to lodge a caveat, it is technically possible that the transaction database does not include all the units sold directly by the developers. However, any omission is likely to be small in practice since most home purchases involved mortgage loans, in which case the solicitors acting on behalf of the banks would insist on lodging a caveat to protect their clients' interest in the property.

[4] The number eight is considered a lucky number because it sounds like "prosperity" in Chinese. Conversely, the number four is considered an unlucky number because it sounds like the word "death".

units located on “unlucky’ falls will be priced at a discount. We based on our prediction on the findings of prior studies which have found that, in areas with a relatively high concentration of Chinese households, superstitions play a significant role in determining house prices. For example, Chau, Ma and Ho (2001) and MOST (2011) observed that flats located on “lucky” floors in Hong Kong and Singapore command price premiums of 2.8% and 1.0%, respectively.

Thirty eight percent of the sample enjoys swimming pool views and 20.3% front an arterial road. A number of prior studies, such as Benson et. al (1998), Bond, Seiler and Seiler (2002), Chau, Ma and Ho (2001) and Tse (2002), have found that houses with views of a water body command a price premium. The Chinese community also commonly associates water with wealth, and accordingly, a view of a water body would be a desirable feature. Since not every unit in a condominium can be orientated to face the swimming pool, we predict that units facing the swimming pool should command a price premium. Units facing busy roads will be discounted if traffic noise is sufficiently loud and priced at a premium if the value of a permanently unobstructed view is sufficiently great. In particular, we predict the negative externality of facing a busy road may be greater for units located on the lower floors. With regards to units’ orientation to the sun, 28.4% of the units face the morning sun, and 30.1% face the evening sun. Fanning, Grissom and Pearson (1995: 38-39) provide anecdotal evidence and MOST (2011) provide econometric evidence that orientation to the sun at different times during the day matter. In the tropics, in particular, homes with an afternoon or evening sun exposure suffer bright glare and solar heating that increases cooling costs. MOST (2011) find that morning and evening exposure price effects differ, with units with west exposure experiencing greater price discounts.

As mentioned earlier, our sample comprises 19,831 new residential units within 69 developments in Singapore sold between 1996 and 2005. To control for variations in the market conditions over time, we include the residential property price index in the hedonic price function. Furthermore, to control for building heterogeneity, we also include a group of variables to pick up the effects of site-specific characteristics, namely site tenure, site location, distance from the Central Business District (CBD) and distance from the nearest metro station. In Singapore, private residential properties can be built on sites with either freehold or leasehold tenure. About 64 of the sample have 99-year leasehold tenure and 36% have freehold or leasehold tenure of 999 years. Freehold properties are usually more expensive because the interest is owned by the owners in perpetuity (Tu and Bao, 2009). Slightly more than 8% of the sample transactions are in the residential district traditionally considered the prime district, which are expected to fetch a higher price. Table 1 indicates that the average distance of the developments to a metro station is only 1.2 km and from the CBD is 10.8 km. The short commuting distance is due to Singapore occupying a small physical land area of only 714 square km.[5]

While the relationship of these variables with house prices has been documented in the literature, their effect on housing choice is less studied. In particular, the locational attributes of the developments may influence the speed of sale of the new units. For example, if condominiums that are located in prime residential districts or near the city center are more desirable, it may take a shorter time for units in these developments to be sold; thus, they are more likely to be sold in the early phase of the marketing. Conversely, if leasehold property is less desirable than freehold property, they may take a longer time to be sold, leading to a higher

[5] The mainland of Singapore measures 50 km from east to west and 26 km from north to south.

concentration of leasehold units to be sold in the later phase of the development, all else being equal. Similarly, a unit's internal spatial attributes may also influence buyers' choice decisions. For example, units facing the pool, have "lucky" numbers, or on the top floor are more popular with potential homebuyers, and hence, they may be sold out first. Conversely, units facing the west, or with "unlucky" numbers may be less popular, and may only be sold in the later phase of marketing. From the perspective of price affordability, smaller units may sell faster because they are cheaper than larger-sized units. Fu and Yu (2015) also note that short-term speculators also prefer flipping smaller units in the condominium projects because they are less costly and hence, more liquid. Our estimation of the selectivity model on the choice sequence of the buyers will also yield additional insights on the most desirable attributes of the units and developments.

In the empirical tests, we also examine whether the price evolution for presold units is any different from the price evolution for completed units. The presold units are further partitioned into those that are sold in the early stage of the marketing campaign and those sold in the mid-stage of the marketing process. Panel B in table 1 reports descriptive statistics for subsamples partitioned according to when the units are sold within the sale sequence. The data show that 90.6% of the observations in our sample are sold before the condominium developments are physically completed, which is not surprising since the developers will be incurring additional costs to hold the unsold completed condominium units. Out of those that are sold before completion, over three quarters of the units are sold within the early range. This reflects the practice of developers timing their new launches to coincide with favorable market conditions. To examine the extent to which development scale influences the sales price sequence, we also partition the sample into low rise (10 and fewer stories) and high rise (greater than 10 stories) subsamples. Panel C presents the summary statistics for the high rise subsample while panel D presents the sample statistics for the low rise subsample. As in the pooled sample description in panel B, the subsample partitions for high rise and low rise samples are determined in the estimation procedure as explained below.

3. Empirical Model and Results

A. OLS Results

In order to explore how the timing/sequencing of sales affects price, we begin by estimating a standard hedonic price model with an additional variable measuring the sales sequence. In general, the price model is

$$P_i = \pi \; x_i + \nu_i \tag{1}$$

where P_i is the natural log of the selling price of the *i*th property, X_i is a vector of explanatory variables containing physical and location characteristics, development specific attributes, and the number of days between the contract date of the transaction and the date of the first sale for the development, our sales sequence measure. The error term, ν_i, is assumed to be normally distributed with mean zero and variance σ_ν^2. Table 2 reports the OLS estimates of the price function for the full sample and the high-rise and low-rise subsamples.

Overall, the estimate models are significant and explain over 83% of the price variation. Many of the explanatory variables exhibit the expected effects on price. Freehold units in prime locations command a significant price premium. As expected, the distance to CBD coefficient is negative and significant in all the models. The *MRT* coefficient, however, is positive and significant, which suggests that the negative externality from pedestrian congestion, noise or other negative externalities from the metro station is stronger than the countervailing positive externality of easy access to mass transportation. The *RPI* coefficient, as expected, is positive and strongly significant.

There are some important differences between the pooled, high-rise, and low-rise estimates. For example, the effect of *AREA* on sales price is positive as expected and robust across subsamples. The effect of floor *LEVEL*, on the other hand, is generally positive for both pooled and high-rise samples. In contrast, the low rise sample price declines for the first three floors and then rises thereafter. Units on the top floor or ground floor of buildings sell at a discount but the interaction variables indicate that the top floor discount is greater for low rise buildings and more modest for high rise buildings. Most developers in Singapore also sell undeveloped space on the ground and roof levels. These private enclosed spaces, which are usually converted to private gardens, are bundled and sold as part of the floor area of the adjacent residential units. This practice reduces the price per unit area. The sales data, however, do not classify the area of a unit into improved or unimproved space, which makes it impossible to adjust the reported price of a unit for this effect.

The *LUCKY* floor effect is significantly positive while the *UNLUCKY* floor effect is significantly negative for the pooled and high-rise samples, the pattern also found by Chau, Ma and Ho (2001). In contrast, there are no significant *LUCKY* or *UNLUCKY* floor effects in the low-rise sample. Finally, morning sun exposure (*AM*) increases selling price while afternoon sun exposure (*PM*) lowers the selling price for the pooled sample. The differences between the high-rise and low-rise results for these variables are interesting: morning exposure increases price in high-rise units and decreases price in low-rise units; afternoon exposure does not affect price in high-rise units but it does reduce price in low-rise units. It turns out that this difference in high rise and low rise results, however, is driven by the selection bias, as demonstrated below.

The main variable of interest, *DAYS*, exhibits statistically significant negative marginal effects for the pooled sample and the high-rise sample, but is positive in the low-rise sample. The marginal effects on price, however, range from about S$11 to S$39 on an average S$729,000 unit—an economically insignificant effect. The OLS estimates offer no convincing evidence of a meaningful effect of sales sequence on the price of condominiums in our sample. Nonetheless, these results should not be taken as the last word, as we show in the next step of our analysis.

B. The Sample Selection Problem

Ashenfelter and Genesove (1991), Beggs and Graddy (1997) and Burguet (2005) argue that price can decline over the sales sequence when buyers chose the most desirable units first in an auction. This is relevant to our open market (non-auction) sales context to the extent that individual condominiums are not entirely homogeneous so that early buyers can obtain choice units with positive attributes, such as a view of the pool. The remaining units, which have fewer superior attributes, will subsequently be sold at a lower price. This line of reasoning implies that the transaction decision and the market price are not independent and the higher prices paid for earlier choices in the sequence reflect, at least in part, a selection bias arising from being able to select one of the higher quality condominium units remaining.

In order to account for this type of selection process, we model the transaction decision as a timing decision rather than the decision to purchase or not. The equation describing the *phase of development in which to purchase* can be written as:

$$I_{si}^{*} = \omega_s z_{si} - \eta_{si} \qquad (3)$$

where I_{si}^{*} is the underlying response variable (an index of the choices made), ω_s are the estimated parameters for development phase *s*, z_{si} is a vector of explanatory variables containing physical and location characteristics that influence the sale of the property, and η_{si} is the error term. Equation (3) can be thought of as a reduced-form choice equation where z_{si} includes x_{si} and the error term (η_{si}) includes the errors of the offering and reservation prices.

We use a two-stage approach outlined in Lee (1982) to control for possible sample selection bias. The correction procedure calls for the introduction of a selection variable, an inverse Mills ratio, to each of the price equations as an explanatory variable. The price equation for a transaction in the sequence subsample *s* can be written as

$$P_{si} = \pi_s x_{si} - \sigma_{\eta \nu_s} W_{si} + \mu_{si} \tag{4}$$

where W_{si} is the inverse Mills ratio, the selection variable, and $\sigma_{\eta\nu}$ is the covariance between η and ν_s. The selection variable is constructed from the maximum likelihood estimation of the choice equation (3). The specific maximum likelihood method and the definition of the selection variable depend on the number of response levels represented by the dependent variable in equation (3). The traditional selection approach is cast in a setting where the choice equation is dichotomous and the Mills ratios are based on the estimates of a probit model. In a model with a polychotomous choice variable, the error term in (3) is assumed to follow an extreme value distribution and the equation is estimated using a multinomial logistic (MNL) procedure or unordered logit. Following Lee (1982, 1983), the error from the MNL is transformed to a standard normal random variable using the *J* factor which results in an inverse Mills ratio equal to

$$-\sigma_s \frac{\phi(J_s(\omega_s z_z))}{F_s(\omega_s z_z)} \tag{5}$$

where F_s and ϕ denote the cumulative and marginal densities of regime *s*, respectively. Introducing the selection variable into the price equation produces consistent coefficient estimates and also provides a test for the presence of sample selection bias. A significant coefficient on the selection variable indicates that selection bias is present in the model.

Thus, to estimate the price equations, we construct the selection variables using the parameter estimates from the maximum likelihood estimation of the choice equation (3). Our application requires that the dependent variable in (3) represents three phases of development in which to purchase: early, middle, and late (i.e., post completion).[6] In a model with a polychotomous choice variable, the error term in (3) is assumed to follow an extreme value distribution and the equation is estimated using a multinomial logit procedure (MNL). We then estimate the price equation over each of the individual subsamples, including the selection variables with the independent variables. Maddala (1983) notes that it is possible to estimate the total price equations simultaneously through the construction of an unconditional expected total price equation. To find the unconditional total price equation, the probability of event *s* is multiplied by the price equation for *s* and then added over all *s*. The resulting total price equations, under the assumption that the explanatory variables in the separate price equations are the same ($x_i = x_1 = x_2 = x_3$), can be written as

$$\begin{aligned} E(P_i) = {} & \alpha_3 + \beta_3 x_i + (\alpha_1 - \alpha_3)F_1 + (\beta_1 - \beta_3)x_i F_1 + (\alpha_2 - \alpha_3)F_2 + (\beta_2 - \beta_3)x_{1i} F_2 \\ & - \rho_1 \phi(J_1) - \rho_2 \phi(J_2) - \rho_3 \phi(J_3) \end{aligned} \tag{6}$$

which provides the estimable form of the price equation reported in table 4. As a final step, we employ a variation of the procedure implemented by Lee (1982) and reiterated by

[6] The partitions of the sample into these sequence subsamples are the partitions that maximize second stage model fit. Of course, this requires re-estimating the MNL model and second stage price equations for all feasible partitions and then optimizing over goodness-of-fit in the selection-corrected price function.

Maddala (1983) to obtain a corrected asymptotic covariance matrix for each of the price equations.

Table 3 reports the estimation results for the MNL regression. The independent variables explain why a unit would be sold in the mid-range and post-completion in the sale sequence, respectively. A negative sign shows that a greater likelihood that the unit possessing the particular attribute will be sold in the early-range. Conversely, a positive sign indicates a greater likelihood that the unit possessing the particular attribute will be sold in the mid-range or after completion. The independent variables include the unit and project characteristics in the price equation as well as additional variables to help identify the sales phase selection equation. These additional variables capture development characteristics (standard deviation of unit area within development and height of building) and relative competition from other developments (unsold units from other developments that overlap the midpoint of this development's sales).

The coefficient estimates for the unit characteristics generally confirm that choice units, such as those located on the higher or "lucky number" floors, that have a pool view, or do not face the east-west orientation, are more likely to be sold in the earlier sequence of the sale process. Thus, it appears that the quality-sales sequence phenomenon is relevant to our case, too.

Table 4 reports the sample selection corrected hedonic price function estimates. As in the OLS models, the dependent variable is the natural logarithm of sale price for individual units. The second stage introduces additional variables derived from the MNL to correct for the sample selectivity bias in the price equation, which are reported at the end of the list of independent variables. We note that the sample selection coefficients are highly significant in all of the models. The hedonic estimates show that the property attributes shown to be significant in the choice equation also have a positive effect on price.

The coefficients on most of the property and unit characteristics are significant and have the expected signs. While most have the same sign and significance as the uncorrected OLS results reported in table 2, the morning and afternoon exposure results found in the OLS models are no longer puzzling. Once corrected for the underlying selection process, the *AM* coefficients now indicate a significant discount for morning exposure in the low rise sample. The *PM* coefficients now reveal a discount for afternoon exposure in both high-rise and low-rise developments. Further, the afternoon exposure generates a greater discount than does morning exposure for the low-rise developments—a result consistent with our expectations. In addition, while units fronting a main road sell at a discount in low-rise buildings in the uncorrected OLS results in table 2, the coefficients on *ROAD* reported in table 4 show that these units sell at a premium in both high-rise and low-rise developments, although the premium in the low-rise sample is less than one third (in percentage terms) the premium in the high-rise sample. This suggests that the negative externality from traffic noise is felt more by units facing the road that are located on lower floors.

The point estimates show that after controlling for unit size, floor level, and orientation, units situated on the top most level of a residential block sell at a discount, but the estimates are not significant. On the other hand, ground floor units are consistently discounted between 9.1 and 12.7%. These discounts, however, do not mean that units located on the ground floor and top floors are unpopular. Indeed, results of the earlier MNL model shows that units located on the ground level and top most level tend to be sold earlier in the sale sequence. The apparent contradiction between price and popularity can be attributed to the fact explained earlier, that units on the ground and top floors are usually sold with private enclosed space, a practice that reduces the measured price per square foot.

Turning to the main question, we allow for different sales sequence marginal effects in early sequence, mid-sequence, and post completion samples by including in the model the variable *DAYS* and its interaction with the endogenous early and mid-sequence dummy variables. For this model, the *DAYS* coefficient captures the marginal effect of sales sequence for units sold after completion. The sum of *DAYS* and the interaction with the early sequence dummy together capture the marginal effect of sales sequence for the early period and the sum of *DAYS* and the interaction with the mid-sequence dummy together capture the sales sequence effect for the mid-period.

Looking at the estimates on these variables, we observe statistically significant coefficients on *DAYS* and the interactive terms for the sequence subsamples. For the pooled model, units sold in the early sales subsample exhibit a statistically significant negative sales sequence effect while units sold in the mid-subsample exhibit a significantly positive sales sequence effect on price. Prices decline for sales after project completion. The pooled model estimates indicate that the fact that choice units are sold first does not fully explain the effect of sales sequence on price observed in the OLS estimates. The sequence effects, however, are not economically significant; the marginal effects are a discount of S$116 and a premium of S$182 for the two sequence period subsamples, respectively, when evaluated at the mean selling price S$729,000.

The high-rise and low-rise sample results, however, differ from the pooled results in this regard. The *DAYS* effect is significant and negative for both high- and low-rise projects. For low-rise developments, the early sales sequence exhibits a statistically significant but economically insignificant *DAYS* effect. The mid-sequence subsample, however, reveals a negative *DAYS* effect on price that, while statistically significant, is economically insignificant with a marginal effect of S$277 on a S$729,000 unit. The high-rise price-sales sequence relationship differs from the low-rise pattern. Sales in the early and middle periods of the sales sequence exhibit rising prices while sales after project completion exhibit falling prices, as noted earlier. Nonetheless, none of the magnitudes is economically significant. Thus, in this sense, once we allow for differences between high-rise and low-rise buildings and correct for selectivity, we again find no appreciable sales sequence effect on price in either sample. This evidence is consistent with Mayer (1998) who also finds no evidence of the declining price anomaly for condominium sales in Los Angeles from 1970 to 1991 and for both condominium and single-family home sales in Dallas from 1970 to 1991.

5. Conclusions

It is not unusual in real estate markets to observe similar assets being sold in sequence. The literature identifies several rationales for sales sequence effects on prices in open (non-auction) markets: consumption risk when units are heterogeneous and the built-out characteristics of the development are uncertain until completion; the risk that the development will not be completed successfully; the benefit of agglomeration economies do not accrue until a critical mass is reached in the development; and the notion that choice units tend to sell early in the sequence. The existing literature does not yet offer sufficient evidence on whether or not the law of one price holds in the absence of such effects.

This paper offers an empirical test for development scale effects and selection effects driven by unobserved differences in unit quality. We examine the sequential sales of new condominiums in a setting in which it appears that both consumption risk and completion risk are minimized and where production agglomeration economies do not pertain. We control for development scale effects by splitting the sample into high rise and low rise developments and control each model for possible selection bias in the estimated sequence-price relationship with a selection correction procedure. The results reveal significant development scale effects. In addition, choice condominium units do tend to sell earlier in the sequence and this effect does bias the OLS estimates. Once these factors are controlled, however, we find no strong empirical support for the type of pricing anomalies observed in the auction literature. The afternoon effect observed for the pooled sample does not hold once we control for scale and selection effects. In all cases, though, all price-sales sequence relationships are economically insignificant even when statistically significant. In sum, the pricing anomalies identified in the literature do not extend to real estate markets; the law of one price appears to hold for real estate assets sold in open markets.

Nevertheless, the presence of a quality-sales sequence phenomenon suggests that earlier buyers in a multiple-unit development have and do exercise their option to select the more desirable units. From the perspective of a developer with multiple units to sell, the results show that, in this market, developer wealth is not affected by the sequence of specific units sold.

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Table 1
Descriptive Statistics Singapore Condo Market

Panel A: Descriptive Statistics

		Full Sample	High-Rise Sample	Low-Rise Sample
$LNPRICE_i$	Mean	13.530	13.479	13.622
Natural logarithm of selling price	s.d.	0.325	0.346	0.259
$AREA_i$	Mean	1307.670	1292.580	1334.480
Floor area (sq ft) of the unit.	s.d.	339.970	333.274	349.971
$LEVEL_i$	Mean	8.317	10.592	4.278
Floor level of the unit	s.d.	6.145	6.416	2.496
$POOL_i$	Mean	0.380	0.408	0.330
Binary variable equals one if unit has pool view	s.d.	0.485	0.492	0.470
$ROAD_i$	Mean	0.203	0.222	0.169
Binary variable equals one if unit faces major roads	s.d.	0.402	0.416	0.375
AM_i	Mean	0.284	0.299	0.259
Binary variable equals one if unit faces morning sun	s.d.	0.451	0.458	0.438
PM_i	Mean	0.301	0.272	0.353
Binary variable equals one if unit faces evening sun	s.d.	0.459	0.445	0.478
TOP_F_i	Mean	0.065	0.031	0.126
Binary variable equals one if unit is located on the top most floor	s.d.	0.247	0.173	0.332
TOP_H_i	Mean	0.670	0.590	0.813
*Interaction term: TOP_F_i * DEV_HEIGHT_i*	s.d.	3.071	3.425	2.307
GRD_F_i	Mean	0.071	0.033	0.139
Binary var. equals one if unit is located on the ground lvl.	s.d.	0.257	0.178	0.346
RPI_i	Mean	128.069	123.943	135.397
Residential price index	s.d.	20.345	17.486	22.851
$LUCKY_i$	Mean	0.080	0.089	0.063
Binary var. equals one if unit is located on a floor ending with the number 8.	s.d.	0.271	0.285	0.244
$UNLUCKY_i$	Mean	0.124	0.107	0.154
Binary var. equals one if unit is located on a floor ending with the number 4.	s.d.	0.330	0.309	0.361
$FREEHOLD_i$	Mean	0.364	0.182	0.687
Binary var. indicating freehold tenure	s.d.	0.481	0.386	0.464
$PRIME_i$	Mean	0.081	0.069	0.102
Binary var. equals one if unit is located in prime location	s.d.	0.273	0.254	0.303
$UCBD_i$	Mean	10.812	10.530	11.314
Distance to CBD (km)	s.d.	4.266	4.462	3.841
$UMRT_i$	Mean	1.162	0.900	1.626
Distance to the nearest metro station (km)	s.d.	0.733	0.619	0.687
$DEV\_AREA\_STD_i$	Mean	270.631	264.169	282.110
Standard Deviation of unit area within development	s.d.	100.478	89.011	117.266
DEV_HEIGHT_i	Mean	15.911	20.551	7.668
Height of development in stories	s.d.	7.761	5.577	2.407
DEV_SZ_i	Mean	446.333	513.6921	326.6832
Number of units in development	s.d.	186.556	173.941	143.2055
$UNSOLD\_HS_i$	Mean	4436.220	4446.47	4418
Total number of new units launched but not sold in Singapore when the sale of the project reached its mid-point (50%).	s.d.	1212.050	1288.94	1061.65
Sample Size		19831	12688	7143

Panel B: Full Sample Grouped by Sales Sequence

		Early %SEQ < .51	**Mid** .51<%SEQ<1	**Post-completion** %SEQ>1
$LNPRICE_i$	Mean	13.536	13.498	13.560
Natural logarithm of selling price	s.d.	0.293	0.318	0.507
$AREA_i$	Mean	1286.990	1329.510	1414.070
Floor area (sq ft) of the unit.	s.d.	318.013	331.248	469.936
$LEVEL_i$	Mean	8.198	9.097	7.497
Floor level of the unit	s.d.	6.022	6.530	6.021
$POOL_i$	Mean	0.391	0.389	0.277
Binary variable equals one if unit has pool view	s.d.	0.488	0.488	0.448
$ROAD_i$	Mean	0.207	0.183	0.222
Binary variable equals one if unit faces major roads	s.d.	0.405	0.387	0.416
AM_i	Mean	0.287	0.315	0.199
Binary variable equals one if unit faces morning sun	s.d.	0.452	0.465	0.399
PM_i	Mean	0.286	0.360	0.285
Binary variable equals one if unit faces evening sun	s.d.	0.452	0.480	0.452
TOP_F_i	Mean	0.067	0.049	0.090
Binary variable equals one if unit is located on the top most floor	s.d.	0.249	0.216	0.287
TOP_H_i	Mean	0.674	0.547	0.914
*Interaction term: TOP_F_i * DEV_HEIGHT_i*	s.d.	3.075	2.886	3.403
GRD_F_i	Mean	0.070	0.059	0.106
Binary var. equals one if unit is located on the ground lvl.	s.d.	0.255	0.235	0.308
RPI_i	Mean	133.035	115.899	117.712
Residential price index	s.d.	21.420	11.377	9.332
$LUCKY_i$	Mean	0.086	0.071	0.057
Binary var. equals one if unit is located on a floor ending with the number 8.	s.d.	0.280	0.257	0.232
$UNLUCKY_i$	Mean	0.117	0.130	0.169
Binary var. equals one if unit is located a floor ending with the number 4.	s.d.	0.321	0.336	0.375
$FREEHOLD_i$	Mean	0.365	0.374	0.330
Binary var. indicating freehold tenure	s.d.	0.482	0.484	0.470
$PRIME_i$	Mean	0.056	0.107	0.212
Binary var. equals one if unit is located in prime location	s.d.	0.230	0.309	0.409
$UCBD_i$	Mean	11.199	9.754	10.246
Distance to CBD (km)	s.d.	4.313	3.849	4.330
$UMRT_i$	Mean	1.176	1.178	1.018
Distance to the nearest metro station (km)	s.d.	0.755	0.709	0.585
$DEV\_AREA\_STD_i$	Mean	273.507	259.618	273.338
Standard Deviation of unit area within development	s.d.	95.245	106.982	120.236
DEV_HEIGHT_i	Mean	15.516	17.720	14.888
Height of development in stories	s.d.	7.840	7.632	6.784
DEV_SZ_i	Mean	452.441	448.061	396.959
Number of units in development	s.d.	183.111	192.308	191.939
$UNSOLD\_HS_i$	Mean	4482.350	4299.200	4392.560
Total number of new units launched but not sold in Singapore when the sale of the project reached its mid-point (50%).	s.d.	1083.110	1448.830	1496.050
Sample Size		13887	4083	1861

Note: The variable %SEQ is defined as the number of days from the date of first sale divided by the total number of days from the first sale until the date a temporary occupation permit was obtained.

Panel C: High-Rise Sample Grouped by Sales Sequence

		Early %SEQ < .12	**Mid** .12<%SEQ<1	**Post-completion** %SEQ>1
$LNPRICE_i$	Mean	13.485	13.449	13.574
Natural logarithm of selling price	s.d.	0.276	0.333	0.584
$AREA_i$	Mean	1256.020	1304.980	1405.130
Floor area (sq ft) of the unit.	s.d.	305.162	304.812	500.758
$LEVEL_i$	Mean	10.811	10.669	9.266
Floor level of the unit	s.d.	6.565	6.255	6.262
$POOL_i$	Mean	0.454	0.383	0.307
Binary variable equals one if unit has pool view	s.d.	0.498	0.486	0.462
$ROAD_i$	Mean	0.258	0.192	0.192
Binary variable equals one if unit faces major roads	s.d.	0.438	0.394	0.394
AM_i	Mean	0.311	0.303	0.222
Binary variable equals one if unit faces morning sun	s.d.	0.463	0.460	0.416
PM_i	Mean	0.222	0.317	0.309
Binary variable equals one if unit faces evening sun	s.d.	0.416	0.465	0.462
TOP_F_i	Mean	0.031	0.026	0.052
Binary variable equals one if unit is located on the top most floor	s.d.	0.173	0.159	0.222
TOP_H_i	Mean	0.625	0.489	0.860
*Interaction term: TOP_F_i * DEV_HEIGHT_i*	s.d.	3.633	3.100	3.743
GRD_F_i	Mean	0.036	0.026	0.048
Binary var. equals one if unit is located on the ground lvl.	s.d.	0.186	0.160	0.214
RPI_i	Mean	131.187	117.289	119.551
Residential price index	s.d.	18.578	14.597	8.812
$LUCKY_i$	Mean	0.103	0.081	0.060
Binary var. equals one if unit is located a floor ending with the number 8.	s.d.	0.304	0.273	0.238
$UNLUCKY_i$	Mean	0.088	0.118	0.147
Binary var. equals one if unit is located a floor ending with the number 4.	s.d.	0.284	0.323	0.354
$FREEHOLD_i$	Mean	0.152	0.198	0.245
Binary var. indicating freehold tenure	s.d.	0.359	0.399	0.430
$PRIME_i$	Mean	0.026	0.074	0.246
Binary var. equals one if unit is located in prime location	s.d.	0.159	0.261	0.431
$UCBD_i$	Mean	11.312	9.877	9.777
Distance to CBD (km)	s.d.	5.006	3.659	4.401
$UMRT_i$	Mean	0.872	0.914	0.972
Distance to the nearest metro station (km)	s.d.	0.691	0.541	0.578
$DEV\_AREA\_STD_i$	Mean	267.314	261.666	260.618
Standard Deviation of unit area within development	s.d.	82.407	91.260	106.055
DEV_HEIGHT_i	Mean	20.893	20.673	18.487
Height of development in stories	s.d.	6.150	5.033	4.522
DEV_SZ_i	Mean	523.309	513.989	468.877
Number of units in development	s.d.	169.283	176.705	175.999
$UNSOLD\_HS_i$	Mean	4655.350	4319.560	4042.480
Total number of new units launched but not sold in Singapore when the sale of the project reached its mid-point (50%).	s.d.	1087.240	1437.790	1293.010
Sample Size		5864	5529	1295

Note: The variable %SEQ is defined as the number of days from the date of first sale divided by the total number of days from the first sale until the date a temporary occupation permit was obtained.

Panel D: Low-Rise Sample Grouped by Sales Sequence

		Early %SEQ < .8	Mid .8<%SEQ<1	Post-completion %SEQ>1
LNPRICE$_i$	Mean	13.632	13.613	13.525
Natural logarithm of selling price	s.d.	0.260	0.232	0.253
AREA$_i$	Mean	1326.400	1317.450	1434.530
Floor area (sq ft) of the unit.	s.d.	346.293	323.834	390.010
LEVEL$_i$	Mean	4.348	4.373	3.447
Floor level of the unit	s.d.	2.474	2.706	2.436
POOL$_i$	Mean	0.346	0.247	0.208
Binary variable equals one if unit has pool view	s.d.	0.476	0.432	0.407
ROAD$_i$	Mean	0.159	0.162	0.290
Binary variable equals one if unit faces major roads	s.d.	0.365	0.369	0.454
AM$_i$	Mean	0.270	0.252	0.145
Binary variable equals one if unit faces morning sun	s.d.	0.444	0.435	0.352
PM$_i$	Mean	0.362	0.383	0.231
Binary variable equals one if unit faces evening sun	s.d.	0.481	0.487	0.422
TOP_F$_i$	Mean	0.123	0.100	0.178
Binary variable equals one if unit is located on the top most floor	s.d.	0.329	0.301	0.383
TOP_H$_i$	Mean	0.792	0.828	1.037
*Interaction term: TOP_F$_i$ * DEV_HEIGHT$_i$*	s.d.	2.273	2.591	2.450
GRD_F$_i$	Mean	0.129	0.149	0.239
Binary var. equals one if unit is located on the ground lvl.	s.d.	0.335	0.357	0.427
RPI$_i$	Mean	138.514	117.666	113.505
Residential price index	s.d.	22.737	8.806	9.129
LUCKY$_i$	Mean	0.065	0.054	0.049
Binary var. equals one if unit is located a floor ending with the number 8.	s.d.	0.247	0.226	0.217
UNLUCKY$_i$	Mean	0.149	0.134	0.221
Binary var. equals one if unit is located a floor ending with the number 4.	s.d.	0.357	0.341	0.415
FREEHOLD$_i$	Mean	0.695	0.799	0.525
Binary var. indicating freehold tenure	s.d.	0.460	0.401	0.500
PRIME$_i$	Mean	0.102	0.051	0.134
Binary var. equals one if unit is located in prime location	s.d.	0.303	0.221	0.341
UCBD$_i$	Mean	11.408	9.804	11.320
Distance to CBD (km)	s.d.	3.818	3.721	3.962
UMRT$_i$	Mean	1.668	1.689	1.124
Distance to the nearest metro station (km)	s.d.	0.673	0.754	0.589
DEV_AREA_STD$_i$	Mean	281.272	265.851	302.441
Standard Deviation of unit area within development	s.d.	115.308	101.054	143.572
DEV_HEIGHT$_i$	Mean	7.675	9.044	6.652
Height of development in stories	s.d.	2.371	1.838	2.654
DEV_SZ$_i$	Mean	332.154	376.823	232.410
Number of units in development	s.d.	142.784	141.051	106.575
UNSOLD_HS$_i$	Mean	4337.620	4568.170	5193.540
Total number of new units launched but not sold in Singapore when the sale of the project reached its mid-point (50%).	s.d.	989.724	561.557	1617.260
Sample Size		6188	389	566

Note: The variable %SEQ is defined as the number of days from the date of first sale divided by the total number of days from the first sale until the date a temporary occupation permit was obtained.

Table 2:
Estimation Results of (uncorrected) Condo Price Equation

	Full Sample	**High-rise Sample**	**Low-rise Sample**
Intercept	11.6352	11.5734	11.8118
	(977.27)	(766.13)	(635.2)
$AREA_i$	0.0011	0.0011	0.0011
Floor area (sq ft) of the unit.	(109.36)	(91.39)	(72.82)
$AREA\_SQ_i$	-1.4E-07	-1.3E-07	-1.7E-07
Floor area (sq ft) of the unit squared	(54.71)	(42.04)	(43.22)
$LEVEL_i$	0.0071	0.0070	-0.0192
Floor level of the unit	(13.59)	(10.67)	(5.43)
$LEVEL\_SQ_i$	-1.7E-05	-2.8E-05	2.7E-03
Floor level of the unit squared	(0.86)	(1.18)	(8.03)
$POOL_i$	0.0361	0.0383	0.0470
Binary variable equals one if unit has pool view	(17.73)	(14.93)	(16.96)
$ROAD_i$	0.0167	0.0238	-0.0013
Binary variable equals one if unit faces major roads	(6.91)	(7.93)	(0.38)
AM_i	0.0125	0.0292	-0.0244
Binary variable equals one if unit faces morning sun	(5.85)	(10.83)	(8.45)
PM_i	-0.0145	0.0016	-0.0430
Binary variable equals one if unit faces evening sun	(6.88)	(0.58)	(16.18)
TOP_F_i	-0.0945	-0.1432	-0.0408
Binary variable equals one if unit is located on the top most floor	(13.36)	(5.43)	(3.03)
TOP_H_i	0.0015	0.0013	-0.0024
Interaction term: $TOP\_F_i * DEV\_HEIGHT_i$	(2.56)	(0.94)	(1.17)
GRD_F_i	-0.0691	-0.0854	-0.0753
Binary variable equals one if unit is located on the ground level	(16.17)	(11.57)	(12.67)
RPI_i	0.0059	0.0062	0.0053
Residential price index	(112.52)	(86.83)	(72.38)
$LUCKY_i$	0.0116	0.0110	-0.0076
Binary var. equals one if unit is located a floor ending with the number 8.	(3.34)	(2.66)	(1.37)
$UNLUCKY_i$	-0.0063	-0.0056	0.0049
Binary var. equals one if unit is located a floor ending with the number 4.	(2.18)	(1.48)	(1.27)
$FREEHOLD_i$	0.1818	0.1563	0.1741
Binary var. indicating freehold tenure	(79.8)	(43.46)	(51.43)
$PRIME_i$	0.2829	0.3762	0.1963
Binary var. equals one if unit is located in prime location	(70.59)	(68.82)	(37.05)
$UCBD_i$	-0.0162	-0.0179	-0.0125
Distance to CBD (km)	(67.17)	(59.00)	(32.68)
$UMRT_i$	0.0308	0.0353	0.0357
Distance to the nearest metro station (km)	(22.05)	(17.73)	(18.56)
$DAYS_i$	-1.7E-05	-5.3E-05	1.5E-05
The number of days between the contract date and the date of the first sale	(5.83)	(15.36)	(3.33)
Adj R-Sq	0.8397	0.8568	0.8414

* Dependent variable natural log of selling price and t-values are reported in parentheses.

Table 3

Development Phase Equation Estimation Results: Multinomial Logit Estimates

	Full-Sample		**High Rise-Sample**		**Low-rise Sample**	
	Mid	Post-Top	Mid	Post-Top	Mid	Post-Top
Intercept	6.5581	5.3931	7.8263	8.096	3.9395	10.7018
	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)
$AREA_i$	0.0017	0.0017	0.0022	0.0014	-0.0004	0.0024
Floor area (sq ft) of the unit.	(<.001)	(<.001)	(<.001)	(<.001)	(0.573)	(<.001)
$AREA\_SQ_i$	-3.2E-07	-2.1E-07	-4.6E-07	-1.1E-07	2.6E-07	-4.8E-07
Floor area (sq ft) of the unit squared	(<.001)	(<.001)	(<.001)	(0.093)	(0.217)	(0.003)
$LEVEL_i$	-0.0064	-0.0460	0.0091	-0.1557	-0.2652	-1.008
Floor level of the unit	(0.558)	(0.003)	(0.448)	(<.001)	(0.127)	(<.001)
$LEVEL\_SQ_i$	-0.0001	0.0008	-0.0005	0.00602	0.0108	0.0733
Floor level of the unit squared	(0.850)	(0.209)	(0.229)	(<.001)	(0.516)	(<.001)
$POOL_i$	-0.3405	-0.8849	-0.7429	-1.4202	-0.4546	-1.0863
Binary variable equals one if unit has pool view	(<.001)	(<.001)	(<.001)	(<.001)	(0.002)	(<.001)
$ROAD_i$	-0.3494	-0.2854	-0.7435	-0.9659	-0.1292	-0.1224
Binary variable equals one if unit faces major roads	(<.001)	(<.001)	(<.001)	(<.001)	(0.456)	(0.361)
AM_i	0.2541	-0.5461	0.0926	-0.4018	-0.0147	-1.1653
Binary variable equals one if unit faces morning sun	(<.001)	(<.001)	(0.062)	(<.001)	(0.923)	(<.001)
PM_i	0.3295	-0.1790	0.3993	0.2402	0.2633	-1.0803
Binary variable equals one if unit faces evening sun	(<.001)	(0.003)	(<.001)	(0.003)	(0.058)	(<.001)
TOP_F_i	-0.4955	-0.8020	0.1163	3.8171	-0.8379	-0.9438
Binary var. equals one if unit is located on the top most floor	(0.003)	(<.001)	(0.815)	(<.001)	(0.313)	(0.109)
TOP_H_i	0.0068	0.0583	-0.0288	-0.2305	0.1586	0.1654
Interaction term: $TOP\_F_i * DEV\_HEIGHT_i$	(0.598)	(<.001)	(0.257)	(<.001)	(0.153)	(0.082)
GRD_F_i	-0.1731	-0.0476	-0.6254	-0.9466	-0.2084	-0.8170
Binary var. equals one if unit is located on the ground lvl.	(0.071)	(0.662)	(<.001)	(<.001)	(0.476)	(0.002)
RPI_i	-0.0674	-0.0472	-0.0595	-0.0434	-0.0856	-0.1122
Residential price index	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)
$LUCKY_i$	-0.1666	-0.1994	-0.2324	-0.5233	-0.0754	1.1703
Binary var. equals one if unit is located a floor ending with the number 8.	(0.031)	(0.079)	(0.002)	(<.001)	(0.787)	(<.001)
$UNLUCKY_i$	0.1535	0.4496	0.3062	0.6199	0.1637	0.9155
Binary var. equals one if unit is located a floor ending with the number 4.	(0.012)	(<.001)	(<.001)	(<.001)	(0.413)	(<.001)
$FREEHOLD_i$	0.6061	-0.5033	0.0191	-2.0800	2.3045	0.7070
Binary var. indicating freehold tenure	(<.001)	(<.001)	(0.813)	(<.001)	(<.001)	(<.001)
$PRIME_i$	-0.1927	1.4200	0.2526	3.2821	-3.8632	0.2727
Binary var. equals one if unit is located in prime location	(0.020)	(<.001)	(0.030)	(<.001)	(<.001)	(0.303)
$UCBD_i$	-0.0730	0.0032	-0.1471	0.0129	-0.2880	0.1838
Distance to CBD (km)	(<.001)	(0.673)	(<.001)	(0.260)	(<.001)	(<.001)
$UMRT_i$	0.3308	-0.2419	-0.0956	0.6398	-0.2941	-0.9119
Distance to the nearest metro station (km)	(<.001)	(<.001)	(0.034)	(<.001)	(0.045)	(<.001)
$DEV\_AREA\_STD_i$	-0.0044	-0.0034	-0.0021	0.0011	-0.0003	-0.0022
Standard Deviation of unit area within development	(<.001)	(<.001)	(<.001)	(0.015)	(0.768)	(<.001)
DEV_HEIGHT_i	0.0418	-0.0155	-0.0151	-0.1460	0.2643	0.2807
Height of development in stories	(<.001)	(0.007)	(0.002)	(<.001)	(<.001)	(<.001)
DEV_SZ_i	0.0003	-0.0011	0.0024	-0.0014	0.0036	-0.0099
Number of units in development	(0.047)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)
$UNSOLD\_HS_i$	-0.0001	-0.0002	-0.0002	-0.0004	0.0009	0.0003
Total number of new units launched but not sold in Singapore when the sale of the project reached its mid-point (50%).	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)
Likelihood Ratio	5483.92		4680.65		2791.38	

*Note: p-values are reported in parentheses.

Table 4
Estimation Results of Corrected Condo Price Equation

	Full Sample	**High-rise Sample**	**Low-rise Sample**
Intercept	10.7596	11.5347	11.2670
	(214.74)	(156.82)	(307.53)
$AREA_i$	0.0010	0.0010	0.0011
Floor area (sq ft) of the unit.	(27.57)	(32.70)	(61.33)
$AREA\_SQ_i$	-1.5E-07	-1.1E-07	-1.7E-07
Floor area (sq ft) of the unit squared	(12.43)	(12.01)	(32.11)
$LEVEL_i$	0.0062	0.0048	-0.0055
Floor level of the unit	(9.95)	(6.63)	(1.67)
$LEVEL\_SQ_i$	-2.2E-05	4.5E-05	1.4E-03
Floor level of the unit squared	(0.97)	(1.60)	(4.50)
$POOL_i$	0.0334	0.0279	0.0676
Binary variable equals one if unit has pool view	(11.02)	(8.88)	(23.69)
$ROAD_i$	0.0335	0.0300	0.0079
Binary variable equals one if unit faces major roads	(12.96)	(8.38)	(2.47)
AM_i	-0.0224	-0.0014	-0.0123
Binary variable equals one if unit faces morning sun	(6.90)	(0.41)	(4.71)
PM_i	-0.0297	-0.0231	-0.0296
Binary variable equals one if unit faces evening sun	(12.27)	(7.20)	(11.95)
TOP_F_i	-0.0691	-0.0577	-0.0145
Binary variable equals one if unit is located on the top most floor	(7.20)	(1.31)	(1.02)
TOP_H_i	0.0023	-0.0031	-0.0049
*Interaction term: TOP_F_i * DEV_HEIGHT_i*	(2.54)	(1.25)	(2.32)
GRD_F_i	-0.0664	-0.0841	-0.0681
Binary variable equals one if unit is located on the ground level	(16.32)	(11.52)	(12.67)
RPI_i	0.0084	0.0075	0.0074
Residential price index	(49.68)	(43.46)	(48.30)
$LUCKY_i$	0.0141	0.0052	-0.0020
Binary var. equals one if unit is located a floor ending with the number 8.	(4.09)	(1.24)	(0.40)
$UNLUCKY_i$	-0.0081	-0.0013	-0.0027
Binary var. equals one if unit is located a floor ending with the number 4.	(2.92)	(0.38)	(0.74)
$FREEHOLD_i$	0.1657	0.1375	0.1370
Binary var. indicating freehold tenure	(53.73)	(33.76)	(22.27)
$PRIME_i$	0.2962	0.4256	0.2224
Binary var. equals one if unit is located in prime location	(38.02)	(40.74)	(22.9)
$UCBD_i$	-0.0148	-0.0143	-0.0128
Distance to CBD (km)	(46.14)	(26.86)	(19.73)
$UMRT_i$	0.0169	0.0737	0.0506
Distance to the nearest metro station (km)	(11.14)	(23.22)	(18.37)

Table 4 (continued)

Estimation Results of Corrected Condo Price Equation

	Full Sample	High-rise Sample	Low-rise Sample
Φ_{0i} *Probability of early sale*	0.8572 (16.73)	0.4849 (6.22)	0.2098 (6.55)
Φ_{1i} *Probability of sale in mid-range of sales*	-0.6453 (10.31)	-0.9842 (11.74)	0.6145 (10.83)
$DAYS_i$ *The number of days between the contract date and the date of the first sale*	1.6E-04 (3.51)	-1.3E-04 (3.85)	-1.1E-04 (3.90)
$DAYS_i\ \Phi_{0i}$ *Interaction term*	-3.2E-04 (6.41)	3.2E-05 (0.87)	1.2E-04 (4.11)
$DAYS_i\ \Phi_{1i}$ *Interaction term*	9.1E-05 (1.59)	1.2E-04 (2.82)	-2.7E-04 (4.53)
ϕ_{0i} *Early sales selection variable*	-0.7512 (39.26)	-0.2750 (10.69)	-0.1753 (23.70)
ϕ_{1i} *Mid-range sales selection variable*	-0.2030 (16.33)	0.2351 (9.17)	-0.0797 (14.05)
ϕ_{2i} *Post-top sales selection variable*	-0.2972 (22.80)	-0.0897 (14.02)	-0.0494 (14.22)
Adj R-Sq	0.8619	0.8758	0.8777

*Note: The dependent variable is the log of sales price. Asymptotic t-statistics, reported in parentheses, were calculated from a heteroscedasticity consistent covariance matrix.

Figure 1: Performance of the Property Market (1995-2005)