A Real-Option Based Dynamic Model to Simulate Real Estate Developer Behavior

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Abstract

Real estate developers are facing a dynamic and volatile market when making their investment decisions. In this study, a real option-based adaptive formulation is adopted so as to incorporate market uncertainties in simulating developer behaviors such as when, where, what type, and how much built space to build within an agent based, integrated land use and transportation simulation framework. This study extends the traditional discrete choice model based modeling approach by adding an explicit probabilistic representation of development templates available to developers to take into account both developers' option to hold the land undeveloped and the market volatility of different development types. Model components addressing future revenue prediction, construction cost estimation, market volatility measurement, development template definition, and development template choice are presented. The proposed simulation framework is applied to the private residential housing supply in Singapore as a demonstration.

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1. Introduction

The spatial and temporal distribution of built space supply plays an important role in shaping urban form and thus the general travel pattern in an urban area. Real estate developers are facing a dynamic and volatile market when making their investment decisions. Most projects typically involve large investments and take a few years to construct and finally launch into market. The market conditions, such as economic growth, population growth, and social and cultural evolution, are subject to uncertainty over the investment period. And they could have direct impacts on construction cost and future revenue of any development. Therefore, developers shall make decisions on not only the optimal combination of development type but also the best investment timing so as to maximize their estimated profit.

The impacts of market uncertainty on development have been explored by a number of studies using various methodologies such as dynamic programming and real option theory. The idea of dynamic programming intends to incorporate the likely future scenarios in a probabilistic manner into the formulation, so that the decision will be clearer for them at the early state of implementation (Bertsekas, 1995; Ukkusuri and Patil, 2009; Ma and Lo, forthcoming). Ukkusuri and Patil (2009) developed a multi-period transportation network design problem under demand uncertainty via a flexible network design formulation (FNDP). The solution takes the form of an open-loop control, resulting in a deterministic time-dependent investment plan. Ma and Lo (forthcoming) developed a framework to formulate adaptive transport supply and demand management (TS-DM) strategies over time under demand uncertainty. The resultant optimal policy takes the form of a closed-loop decision, which has flexibility to make adjustment on whether to defer a highway expansion or not, as the population growth is revealed along the planning horizon. On the other hand, real option theory considers a vacant land as a "call option". Under market uncertainty, it gives its owner the right, without obligation to build a rent-producing structure upon the payment of the construction cost. Therefore, land (or the development project) may be worth more than the difference between the value of the best project that could currently be built on the land and the construction cost of that project. The greater the uncertainty, the greater the value of the options to invest, and the greater the incentive to keep these options open. Chow and Regan (2011) proposed a real option model to quantify the value of flexibility for deferring and/or adjusting network investments with demand uncertainty for the long term network design problem.

The developer model is one central component of an integrated land use and transportation simulation, which focuses on modeling the decisions of real estate developers in terms of when, where, what type, and how much built space to build. In the micro-simulation literature, the developer decision is usually modeled in a static nature, either as a site looking for its best use or a use looking for its best site, within a multinomial logit modeling framework. Market uncertainty is generally overlooked by previous micro-simulation models. This study extends the traditional discrete choice model based approach in simulating developer behavior by taking in account both the developer's option to hold the land undeveloped and the market volatility of different development types.

The proposed simulation framework for developer behavior is applied to the developer module of SimMobility, an agent-based micro-simulation framework as part of the Future Urban Mobility project in the Singapore-MIT Alliance for Research and Technology (SMART). SimMobility integrates and links together various state-of-the-art behavioral models to predict the impacts of future mobility demand on the built environment system and to simulate the effects of a portfolio of policy and infrastructure investments under alternative scenarios. The agents include individuals, households, firms, and developers, each of whom have their inherent characteristics and distinctive choices/decisions to make. The developer module is a sub-module in the SimMobility long-term modeling framework, which simulates the decision making process of real estate developers on the amount, type and timing of built space supply. Specifically, a real option-based adaptive formulation is adopted so as to incorporate market uncertainties in simulating developer behavior. The private housing supply of Singapore is used as an example to showcase the application of this approach in real-world settings.

The remaining part of the paper is organized as follows: Section 2 describes the general model formulation. Section 3 demonstrates some preliminary estimation results for the supply of new private residential housing units in Singapore. Section 4 presents concluding remarks.

2. Formulation

In this section, we describe the formulation of the proposed simulation model for private real estate developers, including the behavioral framework and model components.

2.1 Behavioral Framework

In general, the whole investment process for a property by private developers could be divided into three periods: bidding for land/parcels in the land market, investment including determining development templates and constructing, and finally launching the property for sale into the housing market, as shown in Figure 1. In this formulation, only the investment process is simulated in the developer model. The land sale process is not included at this stage. The proposed model treats future economic conditions probabilistically, allowing for the implementation of land development adaptively over time as the uncertainty is gradually revealed. In this context, as shown in Figure 1, the whole investment horizon $n^i$for location i is divided into two periods, expressed as:

$$n^i = n_1^i + nr_d^i \tag{2.1}$$

where n_1^i is the time period in which the developer holds the land undeveloped and nr_d^i is the construction/demolition time at location i by developer d. Note that, the time for a specific development template v, $nr_d^{v,i}$, only depends on the developer's technology constraint, which is exogenously given in the model.

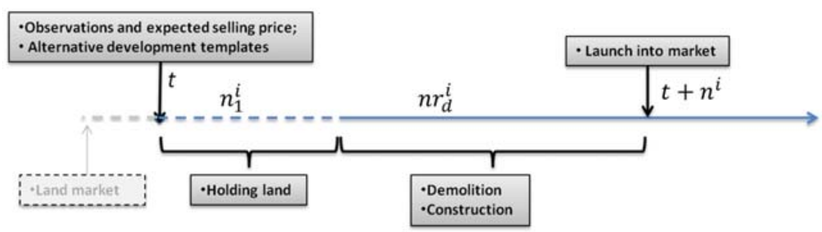

Figure 1. The decision making process of a private developer

Other assumptions made in this paper include:

- Developers' decisions are bounded by planning regulations that are attached to each parcel, e.g. gross plot ratio, the upper/lower bounds of the percentage of different land use types, and the time constraint that the development should be completed.
- There is no budget constraint. In other words, the developer always has enough budgets or he can borrow money from banks to invest on any development template that maximizes his profit. In future extensions, the budget constraint could be included as a consideration of land auction in the land market model.
- Within the time constraint, as shown in Figure 1, each developer has the flexibility to choose when to start construction according to their estimation of profit and option value. After the construction is completed,

the project will be launched into the market, while developers have very similar behaviors as that of sellers in the housing market, e.g. determining reservation prices and asking prices based on the investment cost and the estimation of market demand. Therefore, these behaviors will be modeled by other SimMobility modules.

2.2 Model Component

In our proposed simulation framework, a developer making investment decisions for a parcel faces a set of alternative development templates in a market with uncertainty. At each time period, the developer estimates future revenue and construction cost of feasible development templates under planning constraints and related real option values. It chooses the template based on the principle of profit maximization, but only does so if the return of the development template is greater than a threshold level (value of the call option), which is a function of the market volatility of the built property as suggested by the real option theory, otherwise, keeps status quo. In this section, we present model components related to the decision making process of developers, including revenue projection and market uncertainty measurement, construction cost estimation, development template definition, and development template choice model.

2.2.1 Revenue Projection and Market Uncertainty Measurement

In this study, a set of hedonic price models are calibrated in order to: 1) predict the future revenue of a proposed development project based on available amenities and historical market dynamics; and 2) compute the market uncertainty of different property types, such as apartment, condominium, etc. For each property type *j*, the hedonic price model is expressed as:

$$P^{gj(t)} = \varphi_0^j + \sum_{m=1}^{M} \phi^{mj} H^{mgj(t)} + \sum_{n=1}^{N} \chi^{nj} L^{ngj(t)} + \sum_{t=1}^{T} \tau^{j(t)} D^{gj(t)} + \varepsilon^{gj(t)} \tag{2.2}$$

where $P^{gj(t)}$ is log of transaction price of property g in property type j at time *t*, $H^{mgj(t)}$ is property specific attributes, $L^{ngj(t)}$ is location specific attributes, $D^{gj(t)}$ is a set of time dummy variables to capture the overall market condition over time, which takes the value of 1 if the transaction occurred at time t and 0 other wise, $\varepsilon^{gj(t)}$ is an error term. φ_0^j, ϕ^{mj}, χ^{nj} and $\tau^{j(t)}$ are coefficients to be estimated.

We assume that the willingness-to-pay for structural attributes and location amenities are constant over time. Hence, for a property with constant structural characteristics, the price evolution is the result of changes in location amenities over time and the dynamics of the overall housing market as captured by $\tau^{j(t)}$. When making their investment decisions, developers need to predict the future revenue once the proposed project is completed. In addition to the price for structural and locational attributes, developers also need a forecast of future housing market. If the construction time is T_0 and the estimated coefficient of $D^{gj(t)}$ from Equation 2.2 is $\hat{\tau}^{j(t)}$, we calibrate a housing market forecast model which predicts the future market situation using historical market information and macroeconomic factors. The model can be expressed as:

$$\hat{\tau}^{j(t)} = \alpha_0^{j(t)} + \sum_{l=1}^{L} \beta_l^{j(t)}\, \hat{\tau}^{j(t-T_0-l+1)} + \sum_{k=1}^{K} r_k^{j(t)} Macro_k^{(t)} + e^{j(t)} \qquad (2.3)$$

Where $\hat{\tau}^{j(t-T_0-l+1)}$ is a set of L lagged terms of $\hat{\tau}^{j(t)}$ that starts from time $t - T_0 - L + 1$ to time $t - T_0$. L is determined based on the dataset used to calibrate the model. $Macro_k^{(t)}$ is a set of *K* macroeconomic factors at time *t*, such as population, GDP, interest rate, etc. $\alpha_0^{j(t)}$, $\beta_l^{j(t)}$, and $r_k^{j(t)}$ are coefficients to be estimated.

The SimMobility platform has developed a dynamic model of the housing market to simulate the bargaining process between individual buyers and sellers. The seller generates expectations for the property and publishes an asking price for the property. The bidder observes the attributes of the property and the asking price and decides whether to submit a bid considering the likelihood of winning. This entails a bargaining dynamic with endogenously changing asking prices and bids and subsequent housing transactions. Assuming that there are *G* simulated transactions with known structural and location attributes for property type *j* in time *t* of the simulation, $\hat{\tau}^{j(t)}$ can be computed as:

$$\hat{\tau}^{j(t)} = \frac{1}{G} \sum_{g=1}^{G} \left(P^{gj(t)} - \hat{\varphi}_0^{j} - \sum_{m=1}^{M} \hat{\phi}^{mj}\, H^{mgj(t)} - \sum_{n=1}^{N} \hat{\chi}^{nj} L^{ngj(t)}\right) \qquad (2.4)$$

where $P^{gj(t)}$ is log of simulated transaction price of property g in property type j at time t, $H^{mgj(t)}$ is property specific attributes, $L^{ngj(t)}$ is location specific attributes, $\hat{\varphi}_0^{j}$, $\hat{\phi}^{mj}$ and $\hat{\chi}^{nj}$ are estimated coefficients from the hedonic price model. In this way, the market dynamics can be updated continuously based on simulated transactions in the market over the entire simulation time period.

A housing price index (HPI) of property type *j* can be obtained using Equation 2.5. The market uncertainty of property type *j* can be then computed as the standard deviation of HPI.

$$HPI^{j(t)} = \exp(\hat{\tau}^{j(t)}) \tag{2.5}$$

2.2.2 Construction Cost Estimation

In this study, we assume that developers can fix the construction cost for the entire development project when the project gets stared. Therefore, construction cost estimation is different from project revenue estimation that requires developers' forecast on future market situation. To obtain the construction cost of a development project at a point of time *t* in the simulation, we propose an approach to estimate the unit construction cost for property type *j* at time *t* based on historical construction cost and macroeconomic factors, as expressed in Equation 2.6.

$$C^{j(t)} = \alpha_0^{j(t)} + \sum_{l=1}^{L} \beta_l^{j(t)} C^{j(t-l)} + \sum_{m=1}^{M} r_k^{j(t)} Macro_k^{(t)} + e^{j(t)} \tag{2.6}$$

where $C^{j(t-l)}$ is a set of L lagged terms of $C^{j(t)}$ that starts from time $t-L$ to time $t-1$. L is determined based on the dataset used to calibrate the model. $\alpha_0^{j(t)}$, $\beta_l^{j(t)}$, and $r_k^{j(t)}$ are coefficients to be estimated.

2.2.3 Development Template Definition

Development template *v* is characterized by a unique combination of property types, unit type mixture, and density, which are exogenously determined. Also, these characteristics specify a development scenario that can be deployed to parcels, depending on development constraints on the parcel. Private developers may face a set of alternative development templates given their own technology constraints. The development template can be generalized by applying a cluster analysis using characteristics of existing development projects.

2.2.4 Development Template Choice Model

In the proposed modeling framework, the decision process of developers is modeled as a two-step choice model following Ben-Akiva and Boccara (1995): a probabilistic choice set generation model, which generate the choice set of development templates with investment returns higher than the minimum return level; and a probabilistic development template choice model conditioned on the choice set, which selects the optimal development type to maximize profit.

A development template is considered deterministically feasible if it meets all the planning regulations. $M_d^{i(t)}$ denotes the set of deterministically feasible development templates for developer *d* at location *i* and time *t*. The probability of developer *d* chooses development template *v* at location *i* at time *t*, $\Pr(v|i,t,d)$ is:

$$\Pr(v|i,t,d) = \sum_{C \in G_d^{i(t)}} \Pr(v|C) \Pr(C|i,t,d) \tag{2.7}$$

where $G_d^{i(t)}$ is the set of all non-empty subsets of $M_d^{i(t)}$. $\Pr(v|C)$ is the probability of developer *d* chooses development template *v* given that the choice set is *C*. $\Pr(C|i,t,d)$ is the probability that a developer *d* considers choice set *C* given at location *i* and time *t*.

For each alternative v, its availability depends on the value of a latent binary variable $A_d^{v,i(t)}$. $A_d^{v,i(t)}$ takes the value 1, if development template *v* is available to or considered by developer *d* at location *i* and time *t*; and 0 otherwise. We denote it as

$$A_d^{v,i(t)} = 1[\mathit{if\ v\ is\ available\ to\ developer\ d\ at\ location\ i\ and\ time\ t}] \tag{2.8}$$

In this study, we adopt a constraint based approach to choice set generation, which considers a development type to be available at a point of time *t* if a set of relevant constraints specific to that alternative are met. The developer excludes from any further consideration all alternatives that do not meet certain criteria (denoted by $H_d^{v,i(t)} \geq 0$), no matter what the values of other attributes and criteria are. The constraints are unobservable, hence latent, and vary across alternatives due to the different characteristics of development types. Thus, they should be considered as random variables.

$$\Pr\left(A_d^{v,i(t)} = 1\right) = \Pr(H_d^{v,i(t)} \geq 0) \tag{2.9}$$

The probability that *C*, where $C \in G_d$, is developer *d*'s choice set can be computed as:

$$\Pr(C|i,t,d) = \frac{\Pr(\{A_d^{v,i(t)}=1, \forall v \in C\} \cap \{A_d^{u,i(t)}=0, \forall u \in M_d^{i(t)} \setminus C\})}{1-\Pr(A_d^{w,i(t)}=0, \forall w \in M_d^{i(t)})} \tag{2.10}$$

where $M_d^{i(t)} \setminus C$ denotes the complement of $M_d^{i(t)} \cap C$. The above probability is conditional on the event that the choice set is non-empty.

If we assume that the random components of the elimination criteria across alternatives are independent, the choice set probability are given by:

$$\Pr(C|i,t,d) = \frac{\prod_{v \in C} \Pr(A_d^{v,i(t)}=1) \prod_{u \in M_d^{i(t)} \setminus C} \Pr(A_d^{u,i(t)}=0)}{1-\prod_{w \in M_d^{i(t)}} \Pr(A_d^{w,i(t)}=0)} \tag{2.11}$$

Here we suggest a parametric form for $\Pr(A_d^{v,i(t)} = 1)$ based on the real option theory. The availability latent criterion for development type *v* can be specified as

$$\alpha^v \frac{R_d^{v,i(t)}}{B_d^{v,i(t)}} - \beta^v V^{v^*} - \mu_d^{v,i(t)} \geq 0 \tag{2.12}$$

where $R_d^{v,i(t)}(B_d^{v,i(t)})$ is the projected revenue (cost) to develop location *i* with type *v* at time *t*; V^{v^*} is the hurdle ratio of development type *v*, which is positively associated with market volatility of development type *v*. α^v and β^v are unknown parameters; and $\mu_d^{v,i(t)}$ is a random disturbance. Assume $\mu_d^{v,i(t)}$ to be a logistic random variable (with location parameter 0 and scale parameter 1), then

$$\begin{aligned}\Pr\left(A_d^{v,i(t)} = 1\right) &= \Pr(\alpha^v \frac{R_d^{v,i(t)}}{B_d^{v,i(t)}} - \beta^v V^{v^*} - \mu_d^{v,i(t)} \geq 0\ ) \\ &= \Pr(\mu_d^{v,i(t)} \leq \alpha^v \frac{R_d^{v,i(t)}}{B_d^{v,i(t)}} - \beta^v V^{v^*}\ ) \\ &= 1/(1 + \exp(-\alpha^v \frac{R_d^{v,i(t)}}{B_d^{v,i(t)}} + \beta^v V^{v^*}))\end{aligned} \tag{2.13}$$

Conditional on the choice set $C \in G_d^{i(t)}$, a developer is assumed to choose an alternative from the choice set *C* according to a multinomial logit model. The utility function of a development alternative is expressed as:

$$U_d^{v,i(t)} = \lambda^v R_d^{v,i(t)} - \eta^v B_d^{v,i(t)} + \varepsilon_d^{v,i(t)} \tag{2.14}$$

where $R_d^{v,i(t)}$ is the projected revenue (cost) to develop location *i* with type *v* at time *t*; $\varepsilon_d^{v,i(t)}$ is an error term with i.i.d. extreme value distribution. Therefore, the probability of developer *d* chooses development template *v* given the choice set *C* at location *i* and time *t* is expressed as:

$$\Pr(v|C) = \frac{\exp(\lambda^v R_d^{v,i(t)} - \eta^v B_d^{v,i(t)})}{\sum_u \exp(\lambda^u R_d^{u,i(t)} - \eta^u B_d^{u,i(t)})}$$

3. Model Estimation

In the SimMobility project, we apply the proposed simulation framework on developers' investment behavior to the private housing market in Singapore. The private residential real estate system in Singapore functions like most places in the world, although some restrictions apply. There are six types of private housing in Singapore: apartment, condominium, semi-detached house, detached house, terrace house and executive condominium. This section presents the estimation results of the proposed model components using data on private housing in Singapore, including the hedonic price model, housing market forecast model, construction cost model and cluster analysis. These models enable us to define development template, quantify market uncertainty, and compute future revenue and construction cost of development projects, thus providing a basis for developers' development decisions. Due to the lack of data on project development, we have not been able to calibrate the development template choice model as proposed in Section 2.2.4 at this stage.

3.1 Hedonic Price Model

In this study, one hedonic price model is calibrated for each property type to capture the differences in the valuation of amenities and market dynamics across property types. The dependent variable of the hedonic price model is the log of inflation-adjusted transaction price. The independent variables include structure attributes such as floor area (in log form) and lease type, location attributes such as distance to CBD, job accessibility, accessibility to top primary school, and distance to MRT stations, expressway and bus stops, and a set of transaction quarter dummy variables which take the value of 1 if the transaction occurred in the quarter and 0 otherwise. The estimation results for the structural and location variables are listed in Table 1. The estimated coefficients vary across property type, but generally fit our expectations.

Based on the estimated coefficients of transaction quarter dummy variables, we compute the HPI by property type in Singapore over time, as plotted in Figure 2. The co-movement of HPIs can be observed, but they also display notable differences. The markets for expensive high-end properties such as detached and semi-detached houses are the most volatile while the low-end property types such as executive condominium market is more stable. To quantify the market uncertainty of different property types and capture its impact on developers' development decision, we compute the standard deviation of HPI as a measure of market uncertainty. Figure 3 shows the HPI volatility by property type in Singapore. The most expensive detached houses have a volatility of 40.6, while executive condominiums only has a volatility of 15.7. The significant difference in market uncertainty could influence the option value of different development projects and subsequent development decisions.

Table 1: Value of Amenities by Property Type

	Apartment		Condo		Detached		Semi-detached		Terrace		Executive Condo	
	Coeff.	**t-stats.**	**Coeff.**	**t-stats.**	**Coeff.**	**t-stats.**	**Coeff.**	**t-stats.**	**Coeff.**	**t-stats.**	**Coeff.**	**t-stats.**
Constant	9.059	423.74 ***	9.524	883.89 ***	9.874	129.32 ***	11.770	219.88 ***	11.350	343.04 ***	10.020	646.96 ***
Log(area)	0.814	384.75 ***	0.909	648.97 ***	0.807	107.71 ***	0.440	60.74 ***	0.477	109.20 ***	0.732	254.69 ***
Freehold	0.151	62.37 ***	0.169	149.84 ***	-0.008	-0.77	0.106	23.01 ***	0.091	28.82 ***		
Distance to CBD (km)	0.012	18.09 ***	-0.031	-151.04 ***	-0.038	-19.34 ***	-0.015	-13.73 ***	0.003	5.24 ***	-0.014	-47.91 ***
Accessibility to jobs by car (10^6)	1.355	87.53 ***	0.609	96.75 ***	1.095	17.51 ***	1.337	34.55 ***	0.000	43.31 ***	0.008	0.52
Within 1km of a top primary school	0.091	40.51 ***	0.063	58.40 ***	0.029	3.56 ***	0.033	7.14 ***	0.030	9.52 ***	-0.020	-15.21 ***
Distance to major shopping mall (km)	-0.063	-47.96 ***	-0.031	-56.07 ***	0.043	10.12 ***	0.010	4.27 ***	0.005	3.57 ***	-0.014	-13.27 ***
Within 200m of a MRT station	0.011	2.44 *	-0.003	-1.39	0.009	0.10	-0.210	-7.17 ***	-0.047	-1.50		
Within 200-400m of a MRT station	0.150	54.23 ***	0.043	27.16 ***	-0.043	-2.06 *	-0.033	-2.95 **	0.001	0.20	0.029	9.40 ***
Within 200m of expressway	-0.095	-31.81 ***	-0.063	-45.08 ***	-0.118	-8.00 ***	-0.191	-22.24 ***	-0.028	-5.25 ***	-0.030	-15.01 ***
Within 200 of a bus stop	-0.247	-30.81 ***	-0.273	-90.19 ***	-0.170	-15.11 ***	-0.125	-16.49 ***	-0.190	-29.79 ***	0.035	10.77 ***
Within 200-400m of a bus stop	-0.170	-20.61 ***	-0.215	-69.11 ***	-0.084	-7.42 ***	-0.100	-12.87 ***	-0.158	-24.02 ***	0.027	8.01 ***
Observations	99,450		219,796		7,208		15,141		32,207		23,102	
Adjusted R2	0.701		0.817		0.794		0.634		0.565		0.867	

Significance codes: *** 0.001; ** 0.01; * 0.05

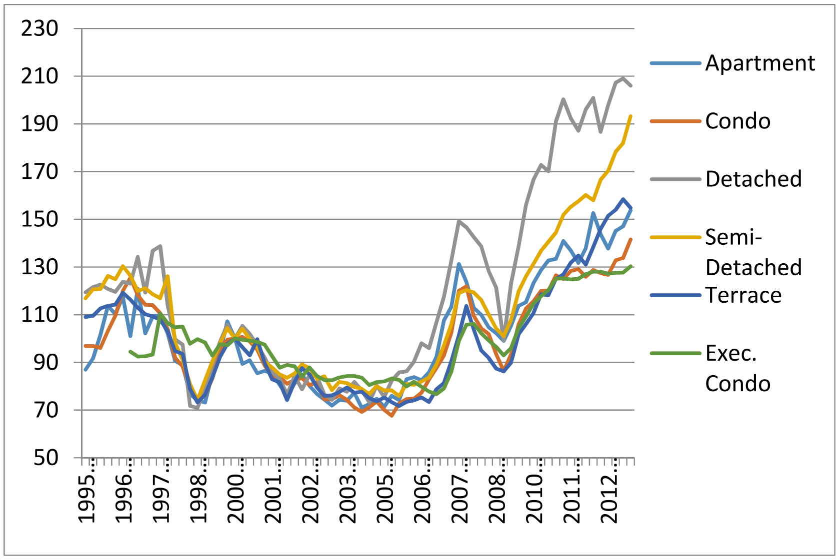

Figure 1: House Price Index (HPI) by property type in Singapore

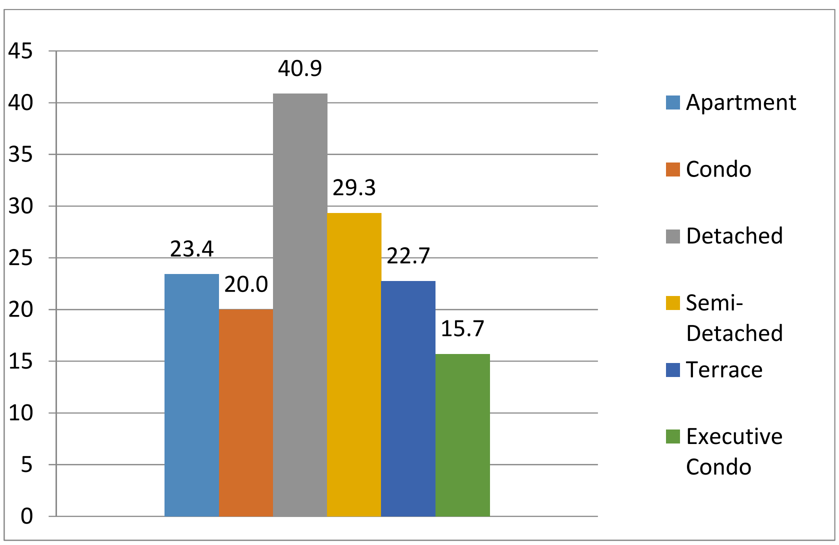

Figure 2: Volatility of House Price Index (HPI) by property type in Singapore

3.2 Housing Market Forecast Model

In this study, we assume that structural and locational attributes of properties in a new development project is known to developers and the willingness-to-pay for these attributes are constant overtime, therefore the value of structural and locational attributes of properties is deterministic to developers. Developers only need to forecast the general housing market situation (represented by $\tau^{j(t)}$) in order to predict future revenue of the proposed development project once it is completed. We propose an approach that can forecast future market conditions based on the housing market dynamics in recent years. In this specification, assuming that the construction time of a development project is 1 year, we regress $\hat{\tau}^{j(t)}$ (estimated from the hedonic price model) on its lagged terms. Using condominiums in Singapore as an example, the calibration results can be translated into Equation 3.1.

$$\hat{\tau}^{j(t)} = 0.029 + 1.799 * \hat{\tau}^{j(t-4)} - 0.911 * \hat{\tau}^{j(t-5)} - 0.465 * \hat{\tau}^{j(t-6)} + 0.491 * \hat{\tau}^{j(t-7)} \quad (3.1)$$

Where $\hat{\tau}^{j(t)}$ is the market situation for condominium in quarter *t*; $\hat{\tau}^{j(t-4)}$, $\hat{\tau}^{j(t-5)}$, $\hat{\tau}^{j(t-6)}$, and $\hat{\tau}^{j(t-7)}$ are lagged terms of $\hat{\tau}^{j(t)}$, which are 4-7 quarters prior to quarter *t*, respectively.

3.3 Construction Cost Model

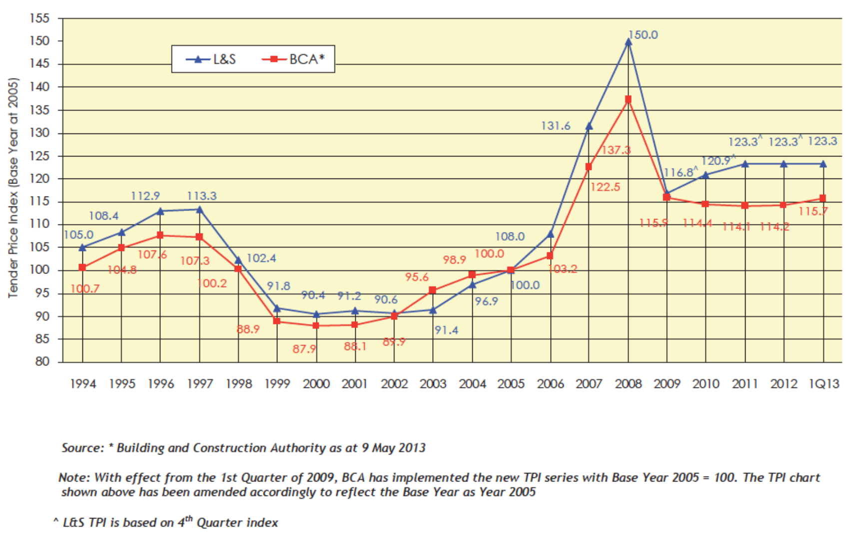

Figure 4: Temporal change of average construction cost in Singapore

The average construction cost in Singapore is measured by the Tender Price Index (TPI). Figure 4 from the Building and Construction Authority (BCA) of Singapore shows the evolution of two TPIs compiled by the BCA and a construction consultancy firm Langdon and Seah, respectively. It can be observed that the average construction cost in Singapore changes significantly over time, although not as much as the change of property values as shown in Figure 2. To take into account the temporal dynamics of construction cost in the simulation, a TPI prediction model is developed to generate future TPI based on current TPI and future economic conditions, which is exogenously determined. It should be noted that, in this study, developers make development decisions based on their "current" construction cost, implying that any changes of construction cost after the project starts will not be considered. The construction costs of different property types is computed based on the predicted TPI and their respective values in the base period (base value), assuming that construction costs of all property types have the same growth rate as the TPI.

In this study, we use the time series of TPI to calibrate a simple regression model that predicts the TPI with its one-quarter lagged term and the GDP in the current quarter. The calibration results are shown in Table 2:

Table 2: Estimation Results of the TPI Prediction Model

Variables	Estimate	Std.	T-stats	
Intercept	25.07	15.98	1.569	
TPI_lag1	0.6486	0.1824	3.555	**
GDP	0.06025	0.0412	1.463	
R square	0.668			
Adj. R	0.623			

** Significant at the 0.01 level

Therefore, in the simulation, the TPI in quarter t can be computed as:

$$TPI^{(t)} = 25.07 + 0.6486 * TPI^{(t-1)} + 0.06025 * GDP^{(t)} \quad (3.2)$$

The construction cost in the base period (1st quarter 2011, TPI = 113.9) by property type are listed in Table 3.

Table 3: Unit Construction Cost by Property Type in the Base period (2011Q1)

Property Type	Construction cost ($/caf)
Terraced Houses	2,525
Semi-Detached Houses	2,775
Detached Houses	3,500
Average Standard Condominium	1,975
Above Average Standard Condominium	2,450
Luxury Condominium	3,500

3.4 Cluster analysis

Developers make development decisions at the project level. A project is the combination of a development template and a land parcel. A development template is defined by property type, density and mix of different unit types. In the Singapore context, it is common practice for developers to build to the maximum density allowed by zoning. Accordingly, in the SimMoiblity project, the development template is defined based on property type and unite type mix. We apply a K-means cluster analysis to existing development project and use the centroid of each cluster to define development templates.

We use the condominium projects in Singapore as an example to demonstrate this approach. Based on the floor area of condominium transactions, we identify 5 types of condominium units, as shown in Table 4. A representative unit for each condominium type with a typical floor area (column 4 in Table 4) is set so that the supply of condominium projects in the simulation is a mix of "standard" condominium units as defined in Table 4. We compute the proportions of different types of condominium units within existing condominium projects and apply K-means clustering to partition these projects into groups based on the proportions.

Table 4: Condominium unit types in Singapore

Type	Description	Area Range (sqm)	Typical Area (sqm)
1	2-Room	<60	55
2	3-Room	60-80	70
3	4-Room	80-100	90
4	5-Room	100-135	115
5	Luxury	>=135	160

Cluster analysis requires the analyst to specify the number of clusters to extract. Figure 5 plots the relationship between number of clusters and the within group sum of squares. The within-group difference decreases as the number of clusters increase. It is observed that when the number of clusters is above 4, the curve becomes relatively flat. Therefore, we choose to partition the condominium projects in Singapore into 4 clusters, and use the mean values of each cluster as a template for condominium projects, as shown in Table 6.

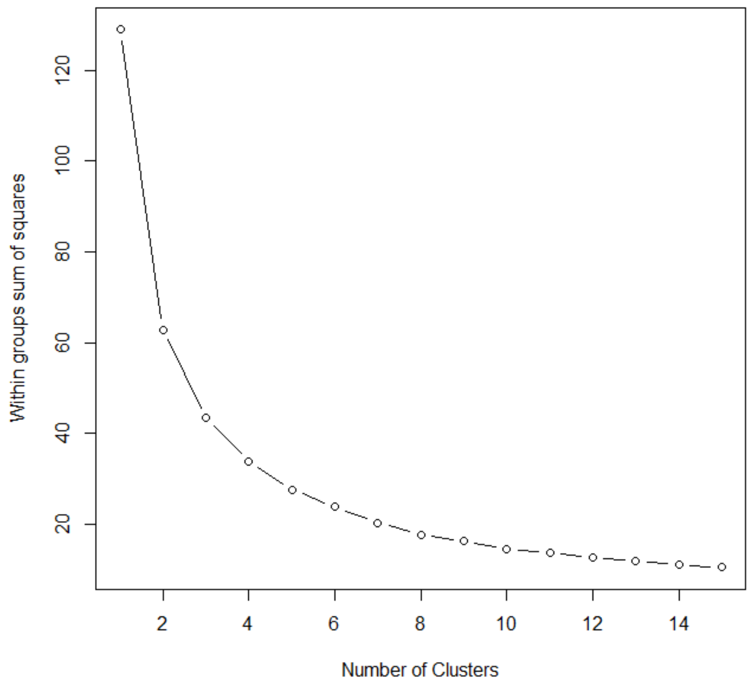

Figure 5: Number of clusters

Table 5: Development template configuration

Template	Condominium Unit Types				
	Type 1	Type 2	Type 3	Type 4	Type 5
1	1.7%	3.1%	11.3%	40.0%	43.9%
2	15.1%	17.6%	30.3%	27.3%	9.7%
3	0.6%	1.2%	14.6%	72.1%	11.4%
4	0.0%	0.5%	3.3%	5.7%	90.4%

4. Conclusion

In summary, we propose a real option-based adaptive formulation to simulate the investment behavior of developers. Our simulation framework contributes to the microsimulation literature by proposing a new approach which takes into account the dynamic and volatile nature of the real estate market. The model components in the proposed simulation framework are calibrated with private housing data in Singapore as a demonstration. The results indicate (1) significant volatility in housing prices and construction costs, (2) meaningful differences in volatility across housing types, and (3) good explanatory power in the hedonic model of near term market prices and construction costs. As a result, we expect that the proposed developer model can capture key aspects of the configuration and timing of decisions to initiate, and then launch for sale, residential housing development. We have coded the developer model as part of the land use change portion of our SimMobility platform for micro-simulation of daily housing market dynamics in Singapore.

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