REFINING THE EFFECTS OF LOCATION IN COMPUTER-ASSISTED RATING VALUATION

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ABSTRACT

In Hong Kong, the rating and valuation authority uses computer-assisted mass appraisal (CAMA) in the yearly reassessment of each property's annual rental value. In particular, the multiple regression analysis (MRA) technique has been applied to the valuation of domestic, office, industrial and some commercial properties. Tax appraisers adopt the traditional method of geographical stratification to examine the effect of location on property values in the MRA models and encounter problems such as value inconsistency at neighbourhood boundaries. This paper introduces Location Value Response Surface (LVRS) modelling, which has been used to appraise single-family houses in the United States and Britain. The paper further develops a constant quality approach, based on the standardisation method, to derive the location factor and illustrates in a case study, how this technique can be used to value high-rise office units for rating purposes in Hong Kong. As a result, the prediction of property values is improved using the model.

Keywords: Rating, mass appraisal, location value response surface modeling, regression, location.

INTRODUCTION

Computer-assisted mass appraisal (CAMA) is a valuable device to tax assessment agencies and authorities. A good mass appraisal system produces equitable values for many properties effectively (Eckert, 1990). In Hong Kong, a well-established CAMA system using multiple regression analysis (MRA) is used by the Rating & Valuation Department (RVD) of the Hong Kong Special Administrative Region (HKSAR) Government to value properties for taxation purposes. One of the main responsibilities of appraisers in this assessment authority is to estimate the net annual rental value, or the "rateable value" of the properties, as this rateable value forms the basis of charging the amount due for rates and Government Rent, which are both property-related taxes and levies. The effectiveness of CAMA modeling permits the Government to perform an annual reassessment of rateable values at a given historical date of valuation.

While tax appraisers rely more on CAMA in their property valuations, they encounter a problem with respect to the analysis of location influence in property values. This occurs when they segregate the jurisdiction into various neighborhoods and specify a localized MRA model to value properties within a neighborhood. It implies that similar properties located on either side of a neighborhood boundary are appraised by completely different models, often producing substantial disparities in valuations across the boundary.

To improve the value measurement of location in CAMA, a technique called "Location Value Response Surface (LVRS) Analysis" has been applied in the U.S. (O'Connor, 1982) to eradicate the value inconsistency problem. While the LVRS analysis has successfully been put into use for the mass appraisal of private single-family houses in selected cities and counties in the U.S. (Eichenbaum, 1989, 1995; Ward et al., 1999), its present applications are still limited, as the technique has not yet been fully tested for other property sub-classes, such as apartments, commercial or industrial properties. It has not been applied outside North America, Britain or Northern Ireland.

This paper gives an overview of the computer-assisted rating valuation system used in the annual reassessment exercise in Hong Kong, and then examines the possible applications of the LVRS analysis in the valuation system. A case study on office properties is carried out to illustrate how such an analysis may be incorporated in the mass appraisal process.

Hong Kong is a small city with a population of 6.7 million. The mountainous landscape further intensifies the land constraint, and thus high-rise living is predominant. This poses a problem in determining the location values or location adjustments of the building blocks from the rental evidence of individual units. Besides, land use in Hong Kong is compact and often mixed, and location values can vary on a building-by-building basis, rather than a "grid" or street/city block basis as in the U.S. There is therefore arguably a greater need for a more refined location analytical tool, such as the LVRS.

RATING IN HONG KONG

In Hong Kong, rates are collected by the HKSAR Government as a form of indirect tax, levied on the occupation of real properties. The Government's RVD is the rating authority responsible to assess all properties in Hong Kong.

Rates[1] of a particular property are charged as a percentage[2] of its rateable value, which is defined as the reasonable net annual value expected to be fetched, should the property, including land and building structures, be let in an open market at a designated historical (reference) date. Under this hypothetical tenancy, the tenant is responsible for all the usual tenant's rates and taxes; while the landlord is responsible for Government rent, maintenance, repairs, insurance and other outgoings necessary to maintain the property in a state to command that rent.

Since the reversion of Hong Kong to mainland China in 1997, a Government Rent was introduced as a rent payable to the Government in return for a lease extension of those non-renewable land leases (including all leases in New Kowloon, the New Territories and outlying islands, and a few in Hong Kong Island and Kowloon), which would have been expired before 1997.[3] The rateable value of a property again assumes a dual role as the basis of charging the Government Rent.[4]

Reassessment of rateable values (with reference to a new designated valuation date) has been carried out annually since 1999 by tax appraisers at the RVD. The main purpose of introducing this annual exercise is to better reflect changes in rateable values and to bring them more in line with market rentals.

COMPUTER-ASSISTED RATING VALUATION SYSTEM

CAMA has been utilised by the rating authority in Hong Kong for more than 20 years. It has become indispensable to tax appraisers at RVD for performing the following functions:

- *Valuation*- involved mainly in the annual reassessment of rateable values;
- *Data management* - collecting, editing and storing information on attributes of properties, details of sales and rental transactions;

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[1] The statutory provisions governing aspects in rating, such as the valuation basis, assessable property, basis of liability, exemptions and objections provisos, can be found in the Rating Ordinance and its subsidiary by-laws.

[2] The rates percentage is determined by the Legislative Council of Hong Kong, at 5% of the rateable value of the property for both Financial Years of 1999/2000 and 2000/01.

[3] Almost all privately owned land in Hong Kong is held by way of a Government Lease (previously known as "Crown Lease") under which a rent is payable. In order to ease the financial burden of lessees of those non-renewable leases that expired before 30 June 1997 (including all leases in the New Territories and New Kowloon north of Boundary Street), the Annex III to the Sino-British Joint Declaration and the Basic Law provided that these land leases were automatically extended up to 30 June 2047 without a premium payment, but subject to payment of a Government Rent from the date of extension. In addition, all land leases in Hong Kong that have been granted since 27 May 1985 (the date from which the Joint Declaration took effect) are also liable for a similar Government Rent from 1 July 1997. The Rating & Valuation Department publishes a booklet titled *Government Rent (under the Government Rent (Assessment & Collection) Ordinance)*, which prescribes the applicable land leases, basis of liability, concession and objections provisos.

[4] The percentage charged for Government Rent is fixed at 3%, as per the Sino-British Joint Declaration.

- *Sales and rental analysis* - selecting and screening comparables for analysis and providing valuations; and
- *Administrative functions* - for purposes such as the preparation of assessment lists, notices and bills, enquiry and reporting of information, objection and appeals.

CAMA is especially important in the annual reassessment exercise, as it is capable of appraising a large number (about two million assessments in Hong Kong) of properties efficiently.

MULTIPLE REGRESSION ANALYSIS

Property assessments in Hong Kong consist of different types of properties, such as flats, houses, offices, shops, factories, vacant land, car parks, special properties, etc. Tax appraisers in Hong Kong apply MRA techniques and build hedonic regression models to value properties of a comparatively homogeneous nature, such as residential flats, apartments, houses, and offices. MRA is also applied to assess industrial premises, warehouses, and commercial properties, such as shops and shopping arcades.

Data used in the regression analysis includes property attributes, rental transaction details and previous rateable values. The RVD gathers property and rental data from various sources on a periodic basis: floor plans of buildings from the Buildings Authority[5] and architects; property inspections; actual on-site measurements and information supplied by property developers, owners, tenants and occupiers. Property data kept by the RVD is comprehensive, and has captured a large quantity of property attributes and characteristics, thus facilitating the use of regression models, and deriving reliable and consistent results. The data has also been well maintained and updated periodically by the RVD, and it has reflected the latest conditions of the properties and taken into account any physical or environmental changes that affect property values.

In view of the availability of market evidence of rental transactions, tax appraisers in Hong Kong adopt the sales comparison approach in the MRA. In general, these "market" valuation models attempt to disaggregate the rental values into various "contributing" components or property characteristics for analysis of the supply and demand forces operating in the rental market. A previous study of CAMA in the Hong Kong market (Stevenson, 1996) has shown that an additive hybrid log-linear regression model is most suitable in the appraisal process.

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5 The Buildings Authority is a Government body that scrutinizes, monitors and approves all building works, including constructions, demolitions, structural alterations and additions, so that they comply with the statutory requirements under the Buildings Ordinance.

A typical regression model used in Hong Kong is as follows:

$$LnV_p = \beta_0 + \sum_{i=1}^{M} \beta_i LnX_{ip} + \sum_{j=1}^{N} \alpha_j Y_{jp} + \sum_{d=1}^{T} \gamma_d Z_{dp} + \varepsilon_p \qquad (1)$$

where: LnV_p is the log of the rental value of the p^{th} property.

β_0 is a constant value.

β_i are coefficients of the ith property attributes X, where $i = 1, 2, \ldots M$.

α_j are coefficients of the jth rental attributes Y, where $j = 1, 2, \ldots N$.

γ_d are coefficients of the dummy variables Z, where $d = 1, 2, \ldots T$.

ε_p is the error term of the p^{th} property.

Taking domestic flats as an example, property attributes may comprise the floor area, floor level, view and orientation, number of bedrooms/bathrooms, type of construction, building age, communal facilities, etc., while rental data may consist of the effective monthly rents, lease commencement date, lease terms, rent free periods, etc.

The valuation model specified and the coefficients obtained are then used to predict the rateable values. The values for the variables used in the model are either the properties' attributes or those values accorded with the hypothetical tenancy on which the rateable value is based.

The prediction of rateable values is further assisted by the application of a reference tenement approach for relatively homogeneous properties with similar characteristics, such as flats and offices, in multi-story buildings. It involves selecting a typical unit from a building block or estate development, and introducing a relativity factor for every other property within the same building/development. The relativity factor of the benchmarked property is taken to be 1.00, while those of other properties vary according to their differences in physical attributes, such as size, number of bedrooms, view and orientation, floor level, etc. against the benchmark. The reference tenement approach is based on the assumption that the relativity within a building/development is generally constant over a period of time. This technique in Hong Kong is similar with the sub-market classes (SMC) approach practiced in Singapore (Leung & Usilappan, 1997).

By adopting the reference tenement approach, the predicted rateable values of similar properties within a building will not be too out of line with one another. As a result, valuation consistency and uniform relativity are maintained, so is the tone of the valuation list (Cruden, 1986). This practice is able to produce valuations that are fairer to the taxpayers.

Before finalising the estimated rateable values, tax appraisers in Hong Kong review the results from the MRA, and perform appraisals on a building, district/neighbourhood, and property type basis, to identify those anomalies where exceptional high or low valuations are noted, and make appropriate adjustments, if necessary.

Effect of location on values

Among the various property attributes considered in the MRA models, location is often regarded as the most important, especially in international cosmopolitan cities where some sharp variations of property values are noted (Thrall, 1979a, b). The value of a residential property could drop drastically in the next street because it is located at the beginning of a slum area (Eichenbaum, 1995). Similarly, shops could have substantial value differences round a street corner; and offices are worth more if located in the central business area than in decentralised districts.

As mentioned earlier, tax appraisers in Hong Kong examine the effect of location on property values in the MRA models by stratifying the jurisdiction into neighborhoods and appraising each with a distinct model for a particular property type. In this way, it is assumed that properties within a neighborhood have the same location value, which is that of the average typical property. In general, some subjective location qualifiers are also specified to indicate whether certain properties are at a comparatively better or worse location than other properties within the neighborhood.

The use of multiple valuation models has the advantage of reflecting more accurately the local characteristics within the neighborhood, and thus more supportable results may be produced. However, the main disadvantage of this stratification method is that it cannot properly account for the sudden and sharp value changes for similar properties right on different sides of a neighborhood boundary, simply because the neighborhoods are valued by different models or assigned different location factors. In view of this possible inconsistency, manual overrides are often necessary to adjust for variations of location values within the neighborhoods or along the boundaries.

LOCATION VALUE RESPONSE SURFACE MODELLING

The LVRS technique endeavors to better analyse the effect of location on property values in CAMA, through the integration of Geographical Information Systems (GIS).

Almost all past studies of the LVRS model were carried out in the U.S, Canada, and more recently England (Gallimore et al., 1996) and Northern Ireland (McCluskey et al, 2000). It was first introduced by O'Connor (1982) for the appraisal of single-family houses in Lucas County, Ohio. The technique was first comprehensively documented by Cook (1988) and O'Connor and Eichenbaum (1988). In their paper, O'Connor and Eichenbaum concluded that the LVRS technique is superior and more sophisticated than traditional ones such as the fixed neighborhood approach, localised models (as in Hong Kong) or cluster analysis.

These traditional approaches basically demarcate the jurisdiction on a geographical basis or stratify the properties into clusters. Each neighborhood/ cluster or stratum either (i) has its own valuation model to analyse the location influence (as in Hong Kong) or (ii) has a separate location adjustment factor in a single model for the whole jurisdiction. When used appropriately, these traditional approaches may produce overall effective results (Eckert, 1990).

In addition to the value inconsistency problem at neighborhood boundaries, O'Connor and Eichenbaum further criticised these approaches for their inherent vulnerability to environment changes, the difficulty in explaining to taxpayers, and the considerable resource required in building and maintaining the models.

On the contrary, the LVRS analysis is able to overcome these problems by interpolating or "smoothing out" a response surface as a function of location adjustment and thus eliminating value inconsistencies. The applications of LVRS analysis in the CAMA of residential properties in New York City (Eichenbaum, 1989, 1995) have demonstrated that the technique may also be suitable for large cosmopolitan cities.

At the same time, several counties in the U.S. started to utilise the technique to appraise single-family domestic units. Some forms of GIS were first used to interpolate property values in Quebec, Canada (Des Rosiers and Theriault, 1992), while Ward et al (1999) of the Lucas County further incorporated tools of commercially available GIS to analyse the location adjustment and effectively merged these with the CAMA process.

Mechanism of LVRS analysis

The key objective of the LVRS model is to establish the relationship between location and its corresponding value. It analyses the location adjustment, in value or relative terms, of every rental observation, and then approximates this location value for the rest of the properties, as a function of a response over a spatially continuous geographical region comprising the properties' x- and y-coordinates.

This is achieved by using a three-dimensional space, or two-dimensional contour plot, and utilising the spatial analyst tool in ArcView (a GIS package) to interpolate the response surface (Ward et al., 1999; McCluskey et al., 2000). The spatial interpolation in this paper adopts the Inverse Distance Weighting (IDW) approach, which computes the property's location value as a calculated/optimal weighted average of those of the sales/rents within a certain distance, or from a specified number of nearest sales/rents. Other interpolation methods available are kriging (McCluskey et al, 2000), Triangulated Irregular Network (TIN), locally adaptive gridding, geo-statistical and variational approaches such as splines.

These procedures vary according to the method in determining and calculating the weighted average. For example, the weights assigned in the IDW approach are inversely proportional to a power of the distance between the subject and its neighbouring properties.

During the process, Value Influence Centres (VIC) and value breaklines are identified (O'Connor and Eichenbaum, 1988). It follows a notion that a VIC may affect the value of adjacent properties, and this influence varies according to the distance from the VIC and the VIC's type. The existence of value barriers or breaklines, e.g. topographical, socioeconomic or political discontinuities such as highways or railway tracks, may also curtail the VIC's influence.

The interpolated response surface using the observations, visualised as a terrain of the Earth's surface, provides a location value adjustment for each property, which in turn is treated as one of the variables, among other attributes in any CAMA model. It is assumed that one universal valuation model is used for appraising all properties in the jurisdiction, and thus no district boundaries are set up within.

Derivation of location value adjustment

The crux of the matter is how to ascertain the location adjustment factor for surface interpolation from the rental observations. Two methods were suggested, namely, the residual regression method and the standardisation method (O'Connor and Eichenbaum, 1988).

(a) Residual regression method
The residual regression method specifies a cost approach (Eckert, 1990) for the regression model to predict the sales price[6], and comprises both the building costs,

[6] CAMA is used in many locations in the U.S. to appraise real estate for property tax purposes. The tax chargeable is based on the capital values of the properties. This differs from Hong Kong where rates are calculated with reference to the annual rental value of the properties.

cost of improvement and basic land cost, without any location qualifiers such as convenience, environment, proximity to city centre, etc.

The residuals of the model thus represent the location effect and the unexplained effects. The location factor of a property can then be derived by dividing its sales price with the estimated capital value from the MRA model.

This method can produce consistent results for single-family landed properties in the U.S., since the cost model is a good location comparison independent of the sales price. In our study, it is however not applicable because of the difficulty to apportion the building cost, and more significantly, the land value component of individual office units, especially in mixed-use developments comprising offices and shops.

(b) Standardisation method
A typical property with the most common features is chosen within a jurisdiction. Its sales price acts as a proxy for location. The estimated location factor of any property is then derived by dividing its sales price with this proxy. Another similar approach is to adopt the average sales price of all observations as the proxy (Ward et al., 1999).

As this method disregards differences in the other attributes such as size and quality of construction, it is only suitable in jurisdictions comprising homogeneous properties. It is therefore inadequate to apply this method in this study, where individual units of multi-story buildings vary in size amongst other attributes, and may even have different values within the same building block.

Constant quality approach to derive location adjustment

The "constant quality" approach is devised in this study to supplement the standardisation method described above. In addition to assigning a typical, standard property as the proxy, a multiple regression analysis without any location variables is also undertaken. Referring to the hybrid log-linear regression specification at equation (1), any location variables are excluded from the model specification. The model used in our study is as follows:

$$LnVnl_p = \beta_0 + \sum_{g=1}^{K} \beta_g LnX_{gp} + \sum_{h=1}^{L} \alpha_h Y_{hp} + \sum_{c=1}^{P} \gamma_c Z_{cp} + r \qquad (2)$$

where: $LnVnl_p$ is the log of the rental value of the p^{th} property, without location variables.

β_0 is a constant value.

β_g are coefficients of the gth property/rental attributes X (excluding location variables), where g = 1,2,…K.

α_h are coefficients of the hth property/rental attributes Y (excluding location variables), where h = 1,2,…L.

γ_c are coefficients of the dummy variables Z (excluding location variables), where c = 1,2,…P.

r is residual of the model.

With the coefficients estimated in equation (2), the difference in the log of the values δ_p of the property attributes between a property p and the typical standard property s can be estimated as:

$$\delta_p = \sum_{g=1}^{K} \beta_g \left(LnX_{gp} - LnX_{gs} \right) + \sum_{h=1}^{L} \alpha_h \left(Y_{hp} - Y_{hs} \right) + \sum_{c=1}^{P} \gamma_c \left(Z_{cp} - Z_{cs} \right) \quad (3)$$

where: X_{gp}, Y_{hp}, Z_{cp} are values of the property p's attributes X_g, Y_h, and dummy variables Z_c respectively.

X_{gs}, Y_{hs}, Z_{cs} are values of the property / rental attributes X_g, Y_h, and dummy variables Z_c respectively of typical property s.

An adjusted rent for p is:

$$Adj.R_p = Exp\left(LnR_p - \delta_p \right) \quad (4)$$

where R_p is the actual rent of the property

This $Adj.R_p$ represents the rent of a typical unit as if it is situated at the current location of p. Adopting the average rent of the typical property(s) from all observations in a sample, or using equation (2) above to estimate the rental value of the typical property V_s, the location factor for property p is as follows:

$$LC_p = \frac{Adj.R_p}{V_s} \quad (5)$$

As there may be a number of rental transactions in the same building block, an appropriate method is to take the mean of the location factors of all rents in this building:

$$LC_{block} = \frac{\sum_{p=1}^{Q} LC_p}{Q} \tag{6}$$

where Q is the number of rents in the block

The averaged LC_{block} is then plotted in the LVRS model and interpolated to form a response surface using the IDW approach as described in the above sub-section. This location factor is then put back into the regression model as one of the variables.

DATA AND METHODOLOGY

The case study makes use of private office properties in the district of Causeway Bay on Hong Kong Island. The district is the regional shopping and commercial centre for all Hong Kong. It has also emerged as a prominent decentralised business district over the past 20 years. The area consists mainly of multi-use buildings, typically with shopping complexes on lower floors, and offices, hotels and/or residential properties on upper floors of the buildings.

Altogether 1,212 rental transactions of office units with commencement dates in 1998 and 1999 were obtained from the RVD of the HKSAR Government. The rents were screened for their validity and completeness of data. After discarding missing data cases, transactions between related parties and other outliers, a total of 1,022 rents from 49 office developments were used for analysis in this study.

These data are representative of the spectrum of office properties in Hong Kong; there are small (about 15 – 30 sq. meter) units, as well as whole floor and multiple floor properties, of superior (grade A) quality in terms of scale, construction, facilities, etc. to poorer (grade C or D) ones, on low, medium or high floor levels, and scattered in the entire district.

The information available includes the rental details and property attributes of each of the office units. Rental data consists of the rent in HK$, lease commencement date, term of the lease, rent-free periods, fresh letting or renewals, rates and Government rent liabilities by landlords or tenants, etc. Property attributes are the previous year rateable value (reference date as at 1 October 1998), floor area, floor level, lift access, year of completion of building, provision of central air-conditioning, grade/quality, view/orientation, provision of facilities, e.g. clubhouses.

Hedonic MRA models are used in the CAMA process to predict the rateable values of the offices, with a reference valuation date of 1 October 1999. The statistical package SPSS 10.0 is used. Selected rental data and property attributes described in the above section become independent variables in the regression model, after data transformation of some variables is taken heuristically.

The corresponding digital base maps are also gathered from RVD. Each parcel is grouped to a spatially unique building or development level, which is then linked to the rental data by the building locator in the form of a geocode. The spatial analyst module of ArcView 3.2 is utilised to map the data, perform surface modeling and interpolation in this study.

ANALYSIS AND RESULTS

The results and analyses of the case study are given in the following three sub-sections: the MRA model (without location variables), the LVRS model, and lastly, the MRA model (with location variables).

Multiple regression model (without location variables)

In our study, the net rent is analysed on a per unit area basis and this *Ln_R* is adopted as the dependent variable. After exploratory data analysis, the definitions and descriptive statistics of the variables subsequently adopted in the analysis are given in Tables 1 & 2. A Pearson's correlation matrix is also given in Table 3 to show the co-linearity amongst the variables.

A forward stepwise MRA is then carried out to help derive the location factor. Of the variables listed in Table 1, the previous rateable value *Ln_PRV* has already reflected the value of the office units attributed to its location, and is therefore excluded from the model specification. The rest of the independent variables in Table 1 (unless otherwise noted) are entered iteratively into the analysis until every significant one has been included in the regression model. Table 4 gives the summary and coefficients of the best-fit model adopted, together with the corresponding statistics of the model at each step. The variables are displayed according to the sequence of their selection into the model.

Table 1: Definition of variables

Variable Name	Type	Valid Values	Description	See Note
***Ln_R* (Dependent)**	Numeric	Continuous	Log of Net Rents on a sq. meter basis	
Ln_Area	Numeric	Continuous	Log of Floor Area	
Datedif	Numeric	-21 to 2 (i.e. Jan 98 to Dec 99)	Difference of Lease Commencement Date and Valuation Date (1 Oct 99), in number of months	(1)
Ln_Flr	Numeric	Continuous	Log of Floor Level	
View	Dummy	0 = Average 1 = Good	View or Orientation	
Lift	Dummy	0 = No; 1 = Yes	Lift Access	
AC	Dummy	0 = No; 1 = Yes	Central Air-conditioning	
GradeA	Dummy	0 = No; 1 = Yes	Grade A office	
GradeB	Dummy	0 = No; 1 = Yes	Grade B office	
GradeC	Dummy	0 = No; 1 = Yes	Grade C office	
GradeD	Dummy	0 = No; 1 = Yes	Grade D office	(2)
Anc	Dummy	0 = No; 1 = Yes	Ancillary Accommodation for the Office. Examples are flat roof, balcony, and other structures not part of the building	
Ln_YoC	Numeric	Continuous	Log of the Building's Actual Year of Completion	
HdrmL	Dummy	0 = No; 1 = Yes	Low Floor to Ceiling Height (< 2.9 meters)	(2)
HdrmO	Dummy	0 = No; 1 = Yes	Ordinary Floor to Ceiling Height (between 2.9 and 3.5 meters)	
HdrmH	Dummy	0 = No; 1 = Yes	High Floor to Ceiling Height (> 3.5 meters)	
Term00	Dummy	0 = No; 1 = Yes	No Fixed Lease or Flexible Lease Term	
Term06	Dummy	0 = No; 1 = Yes	Lease Term (between 1 and 6 months)	
Term12	Dummy	0 = No; 1 = Yes	Lease Term (between 7 and 18 months)	
Term24	Dummy	0 = No; 1 = Yes	Lease Term (between 19 and 30 months)	(2)
Term30	Dummy	0 = No; 1 = Yes	Lease Term (> 30 months)	
StatusF	Dummy	0 = No; 1 = Yes	Fresh Letting	
StatusR	Dummy	0 = No; 1 = Yes	Lease Renewal	
StatusX	Dummy	0 = No; 1 = Yes	Other Status not reported, or lease with rising rent, etc.	(2)
Premat	Dummy	0 = No; 1 = Yes	Lease Terminated or Lease Terms revised before end of the Lease Term	
Rate_I	Dummy	0 = No; 1 = Yes	Rates Liability by Tenant, inclusive in rent	

Variable Name	Type	Valid Values	Description	See Note
Rate_E	Dummy	0 = No; 1 = Yes	Rates Liability by Tenant, exclusive of rent	(2)
Rate_X	Dummy	0 = No; 1 = Yes	Other Rates Liability arrangements	
A3Rent_I	Dummy	0 = No; 1 = Yes	Government Rent Liability by Tenant and included in rent	
A3Rent_L	Dummy	0 = No; 1 = Yes	Government Rent Liability by Landlord	
A3Rent_X	Dummy	0 = No; 1 = Yes	Other Government Rent Liability arrangements	(2)
Furn_F	Dummy	0 = No; 1 = Yes	Furnished	
Furn_N	Dummy	0 = No; 1 = Yes	Unfurnished	(2)
Ln_PRV	Numeric	Continuous	Log of Previous Rateable Value as at 1 Oct 98 on a sq. meter basis	(3)

Notes: (1) The office leasing market was depressed from 1998 to 2000 following the Asian financial crisis in 1997. According to the office rental indices compiled by the RVD of HKSAR Government, the office rents declined from Jan 98 to Dec 99, and such decrease appears to be a linear relationship from 1998 to late-1999.

(2) Dummy variables are created for each of the categories for their respective variables, for instance, *GradeA*, *GradeB*, etc. are converted for Building Grades A to D respectively. The indicated dummy variables are excluded from the regression analysis.

(3) Previous study in Hong Kong (Stevenson, 1996) has indicated that the inclusion of Previous Year Rateable Values in the MRA model improves valuation accuracy.

The first variable to enter the regression and the most significant is *Datedif*, explaining about 26.8% of the variance in *Ln_R*. The negative coefficient reflects the bearish office leasing market from Jan 1998. The variables *GradeA, GradeB* and *Ln_YoC* show positive coefficients, supporting the general view that prospective office tenants favor newer and higher-quality buildings and are prepared to pay a premium for these property attributes. The coefficients for *Ln_Area* and *Anc* are less than zero, indicating the existence of quantum allowance to the per sq. meter rate, as the size of the office increases.

The coefficient for *StatusF* is lower than that of *StatusR,* suggesting in our sample that existing tenants are likely to pay a higher rent on renewal than a fresh tenant, possibly due to the existing tenant's "lock-in" effect, such as removal costs. In a highly competitive office leasing market, landlords also often offer incentives to new tenants, such as rent-free periods. Besides, short-term tenants of lease term less than 6 months are also expected to pay more than yearly or two-yearly lessees, as denoted by the positive coefficients for *Term00* and *Term06.*

Table 2: Descriptive statistics of variables

Variable Name	No.	Minimum	Maximum	Mean	Std. Deviation	Variance
Ln_R	1,022	4.860	6.698	5.734	0.323	0.104
Ln_Area	1,022	2.674	7.399	4.176	0.874	0.764
Datedif	1,022	-21	2	-10.203	6.122	37.484
Ln_Flr	1,022	0	3.714	2.566	0.543	0.295
View	1,022	0	1	0.160	0.367	0.135
Lift	1,022	1	1	1.000	0	0
AC	1,022	0	1	0.0538	0.226	0.0510
GradeA	1,022	0	1	0.238	0.426	0.181
GradeB	1,022	0	1	0.450	0.498	0.248
GradeC	1,022	0	1	0.306	0.461	0.213
GradeD	1,022	0	1	5.87E-03	0.0764	5.84E-03
Anc	1,022	0	1	0.0235	0.152	0.0230
Ln_YoC	1,022	4.317	4.585	4.478	0.0843	7.11E-03
HdrmL	1,022	0	1	0.0450	0.207	0.0430
HdrmO	1,022	0	1	0.864	0.343	0.118
HdrmH	1,022	0	1	0.0910	0.288	0.0828
Term00	1,022	0	1	0.0362	0.187	0.0349
Term06	1,022	0	1	0.0254	0.158	0.0248
Term12	1,022	0	1	0.171	0.377	0.142
Term24	1,022	0	1	0.632	0.482	0.233
Term30	1,022	0	1	0.135	0.342	0.117
StatusF	1,022	0	1	0.496	0.500	0.250
StatusR	1,022	0	1	0.459	0.499	0.249
StatusX	1,022	0	1	0.0450	0.207	0.0430
Premat	1,022	0	1	0.0215	0.145	0.0211
Rate_I	1,022	0	1	0.0391	0.194	0.0376
Rate_E	1,022	0	1	0.954	0.210	0.0439
Rate_X	1,022	0	1	6.85E-03	0.0825	6.81E-03
A3Rent_I	1,022	0	1	0.123	0.329	0.108
A3Rent_L	1,022	0	1	0.306	0.461	0.213
A3Rent_X	1,022	0	1	0.570	0.495	0.245
Furn_F	1,022	0	1	9.78E-03	0.0985	9.70E-03
Furn_N	1,022	0	1	0.990	0.0985	9.70E-03
Ln_PRV	1,022	5.295	6.434	5.702	0.206	0.0425

Table 3: Pearson's correlation matrix for variables

	Ln_R	Ln_Area	Datedif	Ln_Flr	View	AC	GradeA	GradeB	GradeC	Anc	Ln_YoC	HdrmO	Hdrm H	Term0 0	Term0 6	Term1 2	Term3 0	Status F	Status R	Premat	Rate_I	Rate_X	A3Rent _I	A3Rent _L	Furn_F	Ln_PR V
Ln_R	1	0.051	-0.518*	0.059#	0.126*	-0.115*	0.425*	-0.205*	-0.162*	-0.037	-0.115*	-0.149*	0.153*	-0.018	0.100*	-0.052#	-0.024	-0.241*	0.077*	0.097*	-0.145*	-0.050	-0.041	-0.312*	-0.032	0.658*
Ln_Area	0.051	1	0.093#	0.186*	0.408*	0.011	0.466*	-0.115*	-0.295*	0.172*	-0.181*	-0.114*	0.307*	-0.065#	0.084*	-0.182*	0.431*	-0.042	0.062#	-0.031	-0.039	0.009	0.178*	-0.132*	-0.042	0.172*
Datedif	-0.518*	0.093*	1	0.039	0.098*	-0.004	-0.036	0.138*	-0.111*	-0.031	0.038	-0.055#	0.093*	0.078*	0.005	0.024	0.069#	-0.059#	0.125*	-0.051	0.013	-0.005	0.183*	0.312*	0.008	-0.061#
Ln_Flr	0.059#	0.186*	0.039	1	0.243*	-0.061#	0.219*	-0.048	-0.138*	-0.064#	0.012	-0.056#	0.123*	-0.002	-0.122*	-0.015	0.016	0.150*	-0.157*	0.005	-0.053#	0.007	0.109*	-0.139*	-0.039	0.134*
View	0.126*	0.408*	0.098*	0.243*	1	0.144*	0.401*	-0.165*	-0.186*	0.055#	0.073#	-0.324*	0.455*	-0.070#	0.048	-0.043	0.139*	0.003	0.031	0.027	-0.074*	-0.004	0.355*	-0.204*	-0.043	0.284*
AC	-0.115*	0.011	-0.004	-0.061#	0.144*	1	-0.082*	-0.033	0.114*	0.020	0.109*	0.095*	-0.075*	0.000	-0.011	0.064#	-0.056#	-0.072#	0.094*	-0.005	-0.026	-0.020	0.003	-0.064#	0.020	-0.198*
GradeA	0.425*	0.466*	-0.036	0.219*	0.401*	-0.082*	1	-0.505*	-0.371*	0.096*	-0.401*	-0.315*	0.463*	-0.084*	-0.017	-0.107*	0.290*	-0.016	-0.127*	-0.083*	-0.077*	-0.019	0.224*	-0.226*	-0.056#	0.702*
GradeB	-0.205*	-0.115*	0.138*	-0.048	-0.165*	-0.033	-0.505*	1	-0.601*	-0.101*	0.208*	0.290*	-0.204*	-0.017	0.054#	0.038	-0.098*	-0.013	0.079*	0.015	-0.061#	-0.004	-0.130*	0.282*	-0.050	-0.243*
GradeC	-0.162*	-0.295*	-0.111*	-0.138*	-0.186*	0.114*	-0.371*	-0.601*	1	0.023	0.160*	-0.027	-0.203*	0.087*	-0.040	0.064#	-0.169*	0.024	0.036	0.062#	0.129*	0.022	-0.068#	-0.087*	0.106*	-0.368*
Anc	-0.037	0.172*	-0.031	-0.064#	0.055#	0.020	0.096*	-0.101*	0.023	1	-0.019	-0.089*	0.041	-0.030	0.098*	-0.002	0.109*	-0.025	0.039	-0.023	-0.031	-0.013	0.020	0.023	-0.015	-0.001
Ln_YoC	-0.115*	-0.181*	0.038	0.012	0.073#	0.109*	-0.401*	0.208*	0.160*	-0.019	1	-0.182*	0.157*	-0.013	0.028	0.069#	-0.114*	0.225*	-0.069#	0.047	-0.053#	-0.038	0.116*	0.084*	-0.079*	-0.275*
HdrmO	-0.149*	-0.114*	-0.055#	-0.056#	-0.324*	0.095*	-0.315*	0.290*	-0.027	-0.089*	-0.182*	1	-0.797*	-0.015	-0.081*	-0.002	-0.085*	-0.046	0.010	0.059#	0.080*	0.033	-0.407*	0.041	0.010	-0.310*
HdrmH	0.153*	0.307*	0.093*	0.123*	0.455*	-0.075*	0.463*	-0.204*	-0.203*	0.041	0.157*	-0.797*	1	-0.007	0.057#	0.001	0.154*	0.081*	-0.052#	-0.047	-0.064#	-0.026	0.544*	-0.122*	-0.031	0.372*
Term00	-0.018	-0.065#	0.078*	-0.002	-0.070#	0.000	-0.084*	-0.017	0.087*	-0.030	-0.013	-0.015	-0.007	1	-0.031	-0.088*	-0.077*	-0.077*	0.095*	-0.029	0.150*	-0.016	0.007	0.064#	-0.019	-0.079*
Term06	0.100*	0.084*	0.005	-0.122*	0.048	-0.011	-0.017	0.054#	-0.040	0.098*	0.028	-0.081*	0.057#	-0.031	1	-0.073*	-0.064#	-0.160*	0.175*	0.190*	0.031	-0.013	-0.042	-0.040	0.047	-0.001
Term12	-0.052#	-0.182*	0.024	-0.015	-0.043	0.064#	-0.107*	0.038	0.064#	-0.002	0.069#	-0.002	0.001	-0.088*	-0.073*	1	-0.180*	-0.144*	0.170*	0.004	0.149*	-0.006	0.027	0.042	0.060#	-0.111*
Term30	-0.024	0.431*	0.069#	0.016	0.139*	-0.056#	0.290*	-0.098*	-0.169*	0.109*	-0.114*	-0.085*	0.154*	-0.077*	-0.064#	-0.180*	1	0.083*	-0.054#	-0.039	-0.021	0.002	0.104*	-0.026	-0.039	0.102*
StatusF	-0.241*	-0.042	-0.059#	0.150*	0.003	-0.072#	-0.016	-0.013	0.024	-0.025	0.225*	-0.046	0.081*	-0.077*	-0.160*	-0.144*	0.083*	1	-0.914*	0.001	-0.059#	-0.011	0.098*	-0.073*	-0.019	-0.087*
StatusR	0.077*	0.062#	0.125*	-0.157*	0.031	0.094*	-0.127*	0.079*	0.036	0.039	-0.069#	0.010	-0.052#	0.095*	0.175*	0.170*	-0.054#	-0.914*	1	0.012	0.077*	0.019	-0.071#	0.134*	0.028	-0.113*
Premat	0.097*	-0.031	-0.051	0.005	0.027	-0.005	-0.083*	0.015	0.062#	-0.023	0.047	0.059#	-0.047	-0.029	0.190*	0.004	-0.039	0.001	0.012	1	-0.030	-0.012	-0.056#	-0.084*	-0.015	-0.038
Rate_I	-0.145*	-0.039	0.013	-0.053#	-0.074*	-0.026	-0.077*	-0.061#	0.129*	-0.031	-0.053#	0.080*	-0.064#	0.150*	0.031	0.149*	-0.021	-0.059#	0.077*	-0.030	1	-0.017	-0.060#	-0.014	0.134*	-0.114*
Rate_X	-0.050	0.009	-0.005	0.007	-0.004	-0.020	-0.019	-0.004	0.022	-0.013	-0.038	0.033	-0.026	-0.016	-0.013	-0.006	0.002	-0.011	0.019	-0.012	-0.017	1	-0.031	-0.004	-0.008	-0.024
A3Rent_I	-0.041	0.178*	0.183*	0.109*	0.355*	0.003	0.224*	-0.130*	-0.068#	0.020	0.116*	-0.407*	0.544*	0.007	-0.042	0.027	0.104*	0.098*	-0.071#	-0.056#	-0.060#	-0.031	1	-0.249*	-0.037	0.206*
A3Rent_L	-0.312*	-0.132*	0.312*	-0.139*	-0.204*	-0.064#	-0.226*	0.282*	-0.087*	0.023	0.084*	0.041	-0.122*	0.064#	-0.040	0.042	-0.026	-0.073*	0.134*	-0.084*	-0.014	-0.004	-0.249*	1	-0.066#	-0.208*
Furn_F	-0.032	-0.042	0.008	-0.039	-0.043	0.020	-0.056#	-0.050	0.106*	-0.015	-0.079*	0.010	-0.031	-0.019	0.047	0.060#	-0.039	-0.019	0.028	-0.015	0.134*	-0.008	-0.037	-0.066	1	-0.052#
n_PRV	0.658*	0.172*	-0.061#	0.134*	0.284*	-0.198*	0.702*	-0.243*	-0.368*	-0.001	-0.275*	-0.310*	0.372*	-0.079*	-0.001	-0.111*	0.102*	-0.087*	-0.113*	-0.038	-0.114*	-0.024	0.206*	-0.208*	-0.052#	1

* Significance level at 0.01 (1-tailed)
# Significance level at 0.05 (1-tailed)

Note: Variable "***Lift***" is excluded from the correlation matrix and subsequent analyses as all 1,022 observations have lift access.

The variable *Premat* has a positive coefficient, since it is likely that a high contracted rent would lead to the premature termination of the lease. The negative coefficients for *A3Rent_I* and *A3Rent_L* could be explained by the assumption that the hypothetical landlord is responsible for paying Government Rent in the calculation of ratable values. The negative coefficient observed for *Rate_I* seems to imply that rates-inclusive rents are likely to be lower than similar ones that are rates-exclusive. However, since the rateable value is estimated on the assumption that the tenant pays the rates, rates-inclusive rents should be higher than rates-exclusive rents. It is probable that landlords in the sample may not have factored in the effect of their rates liability on an inclusive basis, as this issue is often considered as a landlord's "final" concession during rental negotiations.

Residual analysis is used to test non-linearity, independence and heteroscedasticity for the best-fit model accordingly. This regression model without location variables has a coefficient of variation (COV) of about 18.3%, and accounts for 60.8% of the variance of the dependent variable *Ln_R*.

LVRS model

The location factor *LC* is computed with reference to the value of a typical office unit. By analysing the 1,022 rents, the typical property is designated as a 50 sq. meter unit on mid-floor in a grade B office building built in the early 80's. The lease of this typical unit is on a renewal basis, and the term is two years, commencing at around the valuation date of 1 Oct 1999. From our sample, the average rent of this typical property is about $\$263m^2$.

Applying the derived regression model in Table 4 to estimate the rental value without location variables, the *LC* is worked out for each of the observations and also for the blocks following the steps outlined in equations (3) to (6) above.

The block's *LC* is plotted on the map and is judged of its reasonableness, in terms of continuity and consistency with that of neighbouring office blocks. Caution has to be given not to disregard any anomaly, because some may be genuinely caused by the unique value attributed to its location. Another possibility is that value breaklines are present, leading to the apparent inconsistency in location values. Valuation judgment and expertise, together with a thorough knowledge of the local market, are paramount in the analysis of *LC*.

Five blocks are considered to be outliers in the analysis of *LC*. Three of these blocks are located on Hennessy Road and Lockhart Road. Their *LC*s of 1.11, 1.21 and 1.71 respectively are inconsistent with the pattern shown in the nearby office blocks (around 1.35 – 1.6). Another contributing reason for their exclusion is that there are fewer rents in these office buildings than there are in the neighbouring buildings. For the other two outlier buildings on Hysan Avenue, they have abnormally high *LC'*s (about 1.8) as compared with other office buildings of similar quality on Hysan Avenue and Yun Ping Road (at around 1.3 – 1.45).

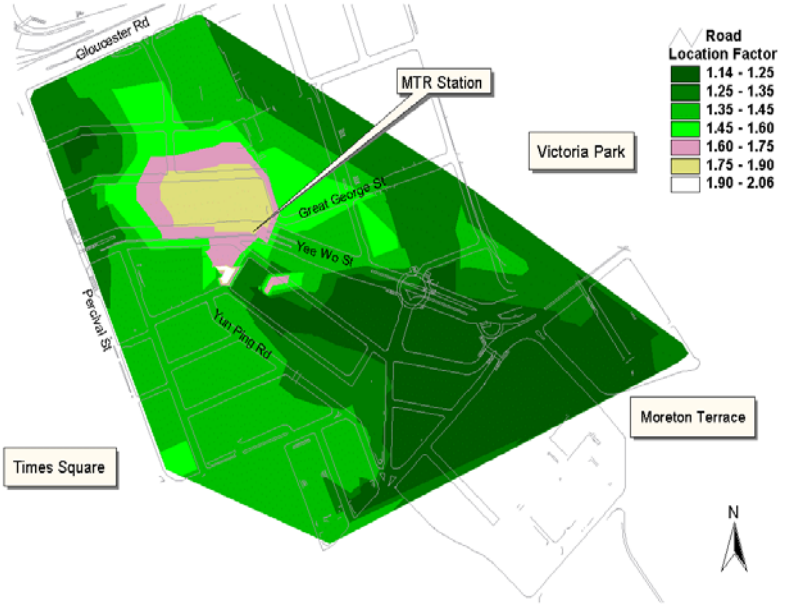
Table 4: Summary of stepwise regression model (without location variables)

Step	Variable Name	Best Fit MRA Model (Step 15)		Regression Statistics at Each Step		
		Est'd Coefficients	t-statistic*	Adjusted R^2	F* (variance ratio)	Standard Error of Estimate
	Intercept	**2.934**	**7.01**	-	-	-
1	***Datedif***	**-0.0241**	**-20.79**	0.268	373.95	0.2766
2	***GradeA***	**0.382**	**16.22**	0.433	390.83	0.2434
3	***StatusF***	**-0.417**	**-11.46**	0.503	345.17	0.2279
4	***Ln_YoC***	**0.671**	**7.23**	0.523	280.33	0.2233
5	***StatusR***	**-0.245**	**-6.65**	0.551	251.60	0.2166
6	***Premat***	**0.188**	**4.19**	0.561	218.87	0.2140
7	***Rate_I***	**-0.180**	**-5.36**	0.571	195.15	0.2117
8	***Anc***	**-0.161**	**-3.74**	0.579	176.39	0.2098
9	***A3Rent_L***	**-0.0876**	**-5.40**	0.583	159.61	0.2087
10	***Ln_Area***	**-0.0364**	**-4.10**	0.588	146.65	0.2075
11	***GradeB***	**0.0758**	**4.77**	0.594	137.01	0.2059
12	***Term00***	**0.120**	**3.44**	0.598	127.78	0.2048
13	***Term06***	**0.107**	**2.52**	0.602	119.68	0.2040
14	***A3Rent_I***	**-0.0816**	**-3.52**	0.604	112.21	0.2034
15	***HdrmO***	**-0.0766**	**-3.33**	0.608	106.51	0.2024
No. of Observations			**1022**			
Predicted Value (mean)			**5.734**			
Adj. R Square			**0.608**			
R Square			**0.614**			
R			**0.783**			
Standard Error of Estimate			**0.2024**			
F* (variance ratio)			**106.51**			
Coefficient of Variation			**18.3%**			
Durbin-Watson			**1.126**			

* F-values and t-statistics: Significance level at 0.05

The rest of the *LC*s are plotted on the map and then interpolated to form the LVRS on the map, representing a logical pattern as expected. For instance, higher values or peaks (factors around 1.8 to 2.0) of the response surface are observed at around Causeway Bay Mass Transit Railway (MTR) station, one of the busiest areas in Hong Kong with the highest rental values for shops. The *LC* then radiates out and diminishes to the surrounding areas of Gloucester Road to the north, Great George Street to the east and Yun Ping Road to the south. Average values (factors around 1.3 to 1.65) are noted in these areas, while even lower values (factors about 1.15 to 1.2) are recorded near the Moreton Terrace area further east, where it is less convenient and is more of a residential neighbourhood. It should also be noted that the *LC* seems to ascend again towards Percival Street in the southwest, as it leads to Times Square, another prestigious office/commercial development, which is often used as an office market pointer. The contour plot of the response surface for offices in Causeway Bay is illustrated in Fig. 1.

Figure 1: Contour plot of location value response surface for offices in Causeway Bay



Multiple regression model (with location variables)

Each of the office blocks has been assigned a location factor from the LVRS. This factor is transformed to *Ln_LC* heuristically and then put back into the stepwise regression model together with *Ln_PRV*[1] and the rest of the independent variables in Table 1. The summary and statistics of the model finally adopted is tabulated in Table 5.

The regression results show that the previous rateable value is the most significant variable. The *Ln_LC* is the fourth variable, explaining another 2.7% of the variance of *Ln_R*. The other regression coefficients generally tally with the previous regression. Overall, this model explains about 78.3% of total variance, while the COV is about 14.0%, well within the limits recommended by International Association of Assessing Officers (IAAO) for heterogeneous properties such as offices[2].

A similar model with *Ln_PRV*, but without the variable *Ln_LC*, is also specified as a control regression. Similar to the previous model, the most significant variables are *Ln_PRV*, *Datedif*, *StatusF* and *Ln_YoC*. The model explains about 75.9% of the variance in *Ln_R*, while the COV is 14.7% and SEE is 0.159. It is clear that the regression with location adjustment is superior, not only because its R^2 is higher, but also it has reduced the variance and standard error during the prediction process.

Limitations of the LVRS model

In the above analysis of the location factor, it is important to satisfactorily establish a spatial relationship representing the variations in location value. To achieve this, there should be reasonably sufficient data in each main area of the jurisdiction. This leads to the question of what should be the minimum number of observations, which is still a subject of contention. It largely depends on the size of the jurisdiction and availability of data. One way to assist the ascertainment of the reasonableness is to display all observations on the map of the jurisdiction. This will help to ensure that visually, a good spread of observations has been obtained.

It must be noted that the explicit location adjustment of the response surface may not denote the "real" value of a certain location, as it only represents the comparative location values for the specific type(s) of property under consideration.

The above LVRS analysis is used in the context of multi-story or strata-titled buildings and the location adjustment is based on the blocks of buildings. However, unlike the LVRS analysis practiced in the U.S. which uses a CAMA

1 Previous study in Hong Kong (Stevenson, 1996) has indicated that the inclusion of Previous Year Rateable Values in the MRA model improves valuation accuracy.

2 The standard applied by IAAO (Eckert, 1990) suggests that the COV for incoming-producing properties, such as offices, in urban jurisdictions should be less than 15%.

model based on the cost approach, our analysis is not appropriate for single dwellings, as it derives the location factor from the same dependent variable.

Table 5: Summary of stepwise regression model (with location variables)

Step	Variable Name	Best Fit MRA Model (Step 15) Est'd Coefficients	t-statistic*	Collinearity VIF	Regression Statistics at Each Step Adjusted R^2	F* (variance ratio)	Standard Error of Estimate
	Intercept	**-1.208**	**-3.24**		-	-	-
1	***Ln_PRV***	**0.699**	**16.49**	3.445	0.432	776.92	0.2436
2	***Datedif***	**-0.0246**	**-28.59**	1.245	0.661	994.88	0.1883
3	***StatusF***	**-0.150**	**-14.98**	1.135	0.707	823.20	0.1749
4	***Ln_LC***	**0.530**	**10.77**	1.650	0.734	704.77	0.1667
5	***Ln_YoC***	**0.601**	**9.27**	1.348	0.746	600.80	0.1629
6	***Rate_I***	**-0.170**	**-6.79**	1.057	0.753	518.74	0.1608
7	***GradeA***	**0.146**	**6.75**	3.808	0.759	459.67	0.1588
8	***Anc***	**-0.130**	**-4.09**	1.054	0.763	412.36	0.1573
9	***A3Rent_I***	**-0.0846**	**-5.14**	1.321	0.767	374.72	0.1560
10	***Term00***	**0.121**	**4.69**	1.048	0.771	345.34	0.1546
11	***A3Rent_L***	**-0.0502**	**-4.26**	1.327	0.776	321.90	0.1531
12	***Premat***	**0.111**	**3.28**	1.079	0.779	300.53	0.1520
13	***Ln_Area***	**-0.0201**	**-2.97**	1.571	0.780	279.90	0.1515
14	***Term06***	**0.0862**	**2.75**	1.100	0.782	262.19	0.1510
15	***Rate_X***	**-0.157**	**-2.74**	1.006	0.783	246.79	0.1505

No. of Observations	**1022**
Predicted Value (mean)	**5.734**
Adj. R Square	**0.783**
R Square	**0.786**
R	**0.887**
Standard Error of Estimate	**0.1505**
F* (variance ratio)	**246.79**
Coefficient of Variation	**14.0%**
Durbin-Watson	**1.789**

* F-values and t-statistics: Significance level at 0.05

While multicollinearity is generally low with maximum VIF at 3.8 in our model, this may not be the case if applied to properties such as flats and houses, where location is highly correlated with variables such as age and building size. Arguably, there is always a certain degree of correlation between location and other variables, and that this multicollinearity effect may not be easily detected. Nevertheless, it clearly demonstrates that the distinct measure of location is a complex process and requires the appraiser's CAMA expertise and local knowledge.

CONCLUSION

The above analysis using the constant quality approach of the standardisation method illustrates how the LVRS model can be adopted in Hong Kong for the valuation of multi-story or strata-title office units for rating purposes. Taking into account the characteristics of the Hong Kong market, the interpolated response surface serves as a sophisticated analytical tool to estimate the location adjustment factors for other properties or blocks of properties. In a computer-assisted rating valuation system using these adjustment factors, the predicted values have been improved.

This study has provided insight of the possible application of the LVRS model in Hong Kong. Given the constraints faced in MRA modeling, more research is needed to refine the interpolation techniques and also test the objectivity of this distinct location measurement by extending the study area. Although it is feasible to define one single MRA model to appraise all properties of the same type by using LVRS, attention must be drawn to the computation difficulties faced by an enormous number of cases. A more sensible approach would be to define a few reasonably sized districts with comparatively clear-cut boundaries and supplement each local model with spatial analysis such as the LVRS.

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