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THE CHANGES AND TRENDS IN URBAN LAND PRICES: AN APPLICATION OF HIERARCHICAL GROWTH MODELLING

Chun-Chang Lee

Department of Real Estate Management, National Pingtung Institute of Commerce, Taiwan. Mingsheng East Road, Pingtung, Taiwan, ROC

Li-Yun Huang

Department of Real Estate Management, National Pingtung Institute of Commerce, Taiwan. Mingsheng East Road, Pingtung, Taiwan, ROC

Shu-Man You

Department of Real Estate and Built Environment, National Taipei University, Taiwan., University Rd., San Shia , New Taipei City, Taiwan, ROC

ABSTRACT

Urban land prices often changes over time; thus, they are a form of longitudinal data or nested structure. This study uses the growth model in hierarchical linear modelling (HLM) to discuss factors affecting the change in urban land prices in Taiwan over time. The empirical results indicate that urban land prices may increase over time, and the growth rate may slow as a result. As the mean intercept, growth rate and acceleration are statistically significant, three parameters are needed to explain the mean growth trajectory. Further population density and internal net migrants would moderate growth rate and acceleration of the urban land prices.

Keywords: Multi-Level growth model, Urban land prices, Random effect, Longitudinal data

JEL Classification: C23, R30

INTRODUCTION

Urban land prices are an index of booms, and reflect the cycle of the real estate market in a region and regional development trend. Many past studies have employed two time points to analyse the changes of data over time, including before and after-measures and future and past-tests. However, the growth trajectory cannot be fully explained (Bryk and Weisberg, 1977; Rogosa *et al.*, 1982; Bryk and Raudenbush, 1987; Gentry and Martineau, 2010).

Past studies have used cross-sectional data for discussion, but the land prices always change. When the urban land prices data are longitudinal, it is important to understand the growth and acceleration of the urban land prices over time. Longitudinal data have several distinctive features. First, there are two sources of heterogeneity: within-subject or intra-subject variations and between-subject or inter-subject variations. Second, the within-subject observations are usually not independent. Third, the between-subject variation may not be constant over time. Finally, longitudinal data are often incomplete or unbalanced, as subjects may drop out of a study at any time for various reasons[1] (Wang *et al.*, 2009). If the data are longitudinal, the estimate using cross-sectional data may cause heteroskedasticity, and the model would have a biased error in estimate. Zoning is a device of land use planning. In the planning period, the urban land prices may change with time, and thus, the land prices are longitudinal data. The growth trajectory of urban land prices can be regarded as multilevel data, and repeatedly observed data in the same individual is nested into the individual and forms two-level data. Thus, this study uses a quadratic growth model in hierarchical linear modelling (HLM) to analyse the growth of the individual data.

HLM have several advantages over the traditional models. First, HLM is capable of dealing with unbalanced and incomplete data under the assumption that observations are "missing at random" (MAR).[2] Second, HLM does not require with-subject observations to be independent of each other, nor to be bounded by restrictive assumptions, such as the compound symmetry. Third, HLM can easily accommodate both time-invariant and time-varying covariates. (Wang *et al.*, 2009). In addition to the advantages of HLM and different changes of land prices over time, time points are nested in the towns. Thus, the application of the growth model can be useful in understanding the initial status, growth rate and acceleration of the urban land prices, and the differences between them; this paper discusses whether the growth rate and acceleration is moderated by cross-level explanatory variables.

LITERATURE REVIEW

Generally, HLM uses cross-sectional data to discuss the dependent and explanatory variables. The growth model also belongs to hierarchical linear modelling. In the model, the dependent variable and the explanatory variable of the same subject at the different time points are collected to

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[1] The incomplete data means respondents fail to answer questions on the survey date; the respondents answer the questions, but interviewers do not record them; or data is missed when interviewers input the data. The incomplete data can represent missing values. Unbalanced data means that the quantity of the two types of data is unbalanced and unequal. The large samples are called majority class, and small samples are minority class. When unbalanced data are used for classification and estimates, the accuracy rate of the large samples is higher than that of small samples.

[2] Missing at random (MAR) means the missing data is not random. Missing data is related to the observed values. The missing values are independent and do not affect each other.

understand the relationship between changes in the two variables over time. This section reviews the literature on hierarchical linear modelling; it then compares HLM with other methods.

Review of the Literature on Hierarchical Linear Modelling

HLM is constructed based on micro data and analyses the macro effect. The micro level (level-1) and macro level (level-2) are used to discuss the impact on the dependent variable. The education-related studies apply HLM to hierarchical data analysis very early. Afterwards, HLM is widely used in psychology, sociology, and enterprise management. HLM is capable of dealing with nested data; the method has started to be gradually used in other fields, and the application range is wide. In recent years, real estate-related studies have paid attention to the use of HLM.

In the studies using housing prices as cross sectional data, Brown and Uyar (2004) employed HLM to discuss the house living area, commute time to the workplace, and the impact of house and neighbourhood characteristics on house prices. The empirical results show that residential house prices are lower when the commute from the residential neighbourhood to the workplace is long; on the other hand, residential house prices may have acceleration per square foot when the commute time is short, and the original house prices would greatly increase. Lee (2009) added two explanatory variables, convenience of life and leisure and sports, in level-2 to discuss the impact of satisfaction with public facilities on house prices. The empirical results indicate in the level-1 housing living area has a significant impact on house prices; in the level-2 satisfaction, convenience of life has different impacts in villages/towns/cities; satisfaction with leisure and sports reach the significance level. Next, Lee (2010) discussed the impact of satisfaction with Taiwan facilities of leisure and sports on house prices. The main purpose is to focus on whether house characteristics and neighbourhood characteristics have an impact on house prices. The houses nested data are used in the neighbourhood concept analysis. In level-1, the independent variables include the house living area, house age, number of rooms and living rooms, house structure, total number of stories and living floor; in level-2, the independent variable includes satisfaction with leisure and sports. The empirical results show that satisfaction with leisure and sports has a significant impact on house prices, and cross level interaction exists. The impact of the house living area on house prices is moderated by leisure and sport facilities.

Lee and Ton (2010) used house age, living area, house structure, house type and residential purpose as explanatory variables of the level-1, and population density, education level and disposable income as explanatory variables of the level-2 to analyse the house prices. The empirical results show house age, living area, structure, type and other variables in the level-1 have an impact on house prices, but the impact has a significant difference across counties; in level-2, only disposable income has a significant impact on the average price. In contrast, this study uses multilevel modelling and traditional regression analysis. The comparison result shows that due to the ignorance of the important explanatory variables, the traditional regression model tends to underestimate the standardised errors of the regression coefficient and increase the probability of type I errors.

From the above literature, HLM considers characteristics of different levels and can prevent biased error in traditional price estimates. It is capable of dealing with residuals in different levels at the same time, measuring the impact of variables in level-1 and level-2 on dependent variables, and calculating the explanatory variances of the cross-level on dependent variables (Hofmann, 1997). When the study data are longitudinal data, the hierarchical growth model can be used for analysis. However, no study has used the growth model to analyse the growth change of the land and house prices. HLM is often used in education research; for example, Muller *et al.* (2001) explored the relationship between the growth trajectory of achievements in science and differences in gender and ethnicity. Seltzer *et al.* (2003) studied the achievements of US students in reading and observed a relationship between their initial status and how rapidly they progress, and compared the growth rates in different ethnic groups (e.g., gender, ethnic, etc.). Gentry and Martineau (2010) discussed leadership development assessment and observed the schools -- which added two independent variables, group performance and active participation -- at five different time points, and discussed the differences in vision change over time. Some research employed the growth model for information studies. Kim *et al.* (2002) analysed fixed telephone household coverage (FTHC) in Europe and other countries from 1994-1999.

Comparison of HLM and Other Research Methods

In the past research, the hedonic price model used ordinary least square (OLS) to evaluate implicit price with individual chrematistics but ignored the data type with hierarchical characteristics, causing estimate-biased error. The OLS is inappropriate for analysing longitudinal data because: (1) it assumes normality, independence and common variance in the measures, which are all unrealistic in longitudinal data; and (2) it assumes an average growth trajectory for all individuals because the model's parameters (intercept and slope) do not vary by individual. (Wang *et al.*, 2009). The data in the study is multi-level data type, and using the OLS would ignore the hierarchical characteristics of the urban land prices and cause a biased error in the estimate.

The HLM can consider the variation of the growth trajectory, whereas the OLS cannot take it into account and is incapable of estimating random effects, the variance of initial status and growth rate. On the other hand, this assumes that the OLS uses slope as the result for measurement, which is centred on the group unit in level 2. As a result, the time variable of level-1 is ignored, or, when time is centralised on the measuring time point, the units of levels 1 and 2 are ignored. This may confuse the effects of level-1 and level-2, and the level-1 result would be incorrect (Gentry and Martineau, 2010). Overall, OLS only analyses one level and ignores the concept of hierarchical nested data. Besides, HLM can estimate random effects and the variances of initial status, growth rate and acceleration.

In addition, univariate repeated measures analysis of variance (URM ANOVA) and multivariate repeated-measures analysis of variance (MRM ANOVA) or structural equation modelling (SEM) are common approaches to study longitudinal data. One of the limitations of URM ANOVA is that it only measures changes between individuals and cannot measure changes within individuals; meanwhile, it does not consider measurement error and cannot be incorporated into a cluster variable analysis. Due to the nested data structure, strong time interdependence would occur if the measured data were nested in the individuals (Hsieh, 2010). There are also other ways to measure change over time, such as MRM ANOVA or SEM. The main obstacle for MRM ANOVA and SEM concerns the level-1 data. Traditional MRM ANOVA and SEM both have a fixed time-series design prerequisite (Raudenbush and Bryk, 2002). The two approaches cannot deal with missing data or change of time point in level 1.

In fact, the longitudinal data research can be divided into dynamic and static research according to the different views. In the dynamic longitudinal data research, event history analysis (EHA) is a typical analysis strategy; in the static longitudinal data research, the two analysis strategies, i.e., SEM and log-linear model (LM), can be used. In the research methods, the long term data of the observed subject can be used to draw an individual growth trajectory. The above suggested research methods can make a response to the growth process of the subject but fail to take level or missing data into account. As compared to other research methods, the HLM growth model is the better method to estimate longitudinal data.

Setting the Empirical Model

In study hierarchy, the level-1 represents time and the level-2 represents villages, townships and cities. The unconditional model and the conditional model are used for estimates and discussion.

Unconditional Growth Model

The unconditional growth model is also called the random coefficient regression model (Raudenbush and Bryk, 2002). This model shows time-related growth in land prices without level-2 (town level) factors used as predictors. This model gives some preliminary evidence and a baseline for subsequent level-2 models with level-2 predictors to be used in subsequent models. The model verifies initial status and the rate of progress of the dependent variables. The unconditional growth model can be divided into two parts: level 1 is the repeated-observations model of villages, townships and cities; level 2 is the comparison model of villages, townships and cities. This study uses quadratic growth model for this setting, and the model is as follows:

Level-1:

$$P_{ti} = \pi_{0i} + \pi_{1i}(Time_{ti} - L) + \pi_{2i}(Time_{ti} - L)^2 + e_{ti}, e_{ti} \sim N(0, \sigma^2) \quad (1)$$

where $i = 1,\ldots,n$ denotes village/township/city; $Time_{ti}$ denotes predicator variable of the village/ township/city i in time point t; L denotes the initial year 2001, and the initial year is used for centring[3]; the intercept, π_{0i}, represents the status of village/township/city i at time L. The linear component, π_{1i} , is the instantaneous growth rate for village/township/city i at time L, and π_{0i} π_{2i} captures the curvature or acceleration in each growth trajectory. It is most common to assume a simple error structure for e_{ti} , namely, that each e_{ti} is independently and normally distributed with a mean of 0 and constant variance, σ^2.

An important feature of Eq. (1) is the assumption that the growth parameters vary across towns. We formulate a level-2 model to represent this variation.

Level-2:

$$\pi_{0i} = \beta_{00} + r_{0i} \quad (2)$$

$$\pi_{1i} = \beta_{10} + r_{1i} \quad (3)$$

$$\pi_{2i} = \beta_{20} + r_{2i} \quad (4)$$

Eqs. (2)~(4) are level-2 between-town equations, representing the initial status (π_{0i}), growth rate (π_{1i}) and the acceleration (π_{2i}); β_{00} is the average of initial urban land prices, β_{10} is growth rate of average urban land prices; β_{20} is acceleration of average of all urban land prices. β_{10} and β_{20} are parameters explaining the relationship between time and land prices in level 1, and can capture the growth trajectory maintained in village/township/city. If the significance level is reached, then time can predict the growth trajectory of urban land prices. In addition, r_{0i} , r_{1i} and r_{2i} are the error terms of the equation, and the error terms meet the normal distribution in which the means are 0 and the variances are τ_{00}, τ_{11} and τ_{22}. We can also examine the random effects components. Using a chi-square test, we can test the null hypothesis that no variation exists in the initial status of towns, the growth rate of towns or the acceleration of towns.

Conditional Growth Model

In different studies, the model is called the intercepts- and slopes-as-outcomes model, the full model and the conditional growth model (Muller *et al.*, 2001; Gentry and Martineau, 2010); the model collects the dependent variable and the explanatory variable of the same land in different time points to know the relationship due to changes in the two variables over time. The growth model can be divided into two parts: the explanatory variable of the level 1 is the time variable in one power and two powers; level 2 has the explanatory variable. There are many factors affecting urban land prices; in particular, population should not be ignored. An agglomeration economy can result in a population concentration, which is one of the important causes affecting urban

[3] Tabachnick, B.G. and L.S. Fidell, 2007. Using multivariate statistics., Boston: Allyn and Bacon. indicated that the explanatory variables are centred to prevent collinearity caused by data interaction in the single-level regression analysis. In addition, in HLM analysis, the explanatory variable uses grand mean centring to prevent collinearity Hofmann, D.A. and M.B. Gavin, 1998. Centring decisions in hierarchical linear models: Implications for research in organizations. Journal of Management, 24(6): 623-641. Available from doi:10.1177/014920639702300602, Mathieu, J. and S. Taylor, 2007. A framework for testing meso-mediational relationships in organizational behaviour. Journal of Organization Behaviour 28(2): 141-172. Available from doi:10.1002/job.436, ibid. Thus, the population density and internal net migrant uses grand mean cantering.

development type. Population migration is one of the important sources in regional population growth. However, the differences in regional social and economic resources can cause spatial displacement of the population. Thus, population density and internal net migrant often imply different regional land price development. This study uses the quadratic growth model, and the setting of the level-1 of the model is the same as in Equ. (1). The level-2 is set as follows:

Level-2:

$$\pi_{0i} = \beta_{00} + r_{0i} \quad (5)$$

$$\pi_{1i} = \beta_{10} + \beta_{11}\left(Density_{1i} - \overline{Density_{1.}}\right) + \beta_{12}\left(Move_{2i} - \overline{Move_{2.}}\right) + r_{1i} \quad (6)$$

$$\pi_{2i} = \beta_{20} + \beta_{21}\left(Density_{1i} - \overline{Density_{1.}}\right) + \beta_{22}\left(Move_{2i} - \overline{Move_{2.}}\right) + r_{2i} \quad (7)$$

where $\left(Density_{1i} - \overline{Density_{1.}}\right)$ means grand mean centring of the population density, i.e., the difference between the population density in the village/township/city at each time point and the grand mean of the population density in the village/township/city; $\left(Move_{2i} - \overline{Move_{2.}}\right)$ means grand mean centring of the internal net migrant, i.e., the difference between the internal net migrant at each time point and the grand mean of the internal net migrant; β_{11}, β_{12}, β_{21} and β_{22} are the effects of variables of level-2 on slope growth parameters; r_{0i}, r_{1i} and r_{2i} satisfy the normal distribution, where the means are 0 and the variances are τ_{00}, $\tau_{11}$and τ_{22}.

On the other hand, the intercept (π_{0i}) of the level-1 is used as an outcome variable of the level-2, in which the population density and internal net migrant are not added to explain π_{0i}, and π_{oi} is set as a random effect to discuss land price differences in villages, townships and cities.

DATA PROCESSING AND DESCRIPTIVE STATISTICS

Data Processing and Resources

The level-1 uses time as the unit, and level-2 uses villages/townships/cities as the unit. In the selection of variables, the dependent variable is the urban land prices index; the main independent variable in the level-1 is the time variable; the level-2 includes two variables, “population density” and “internal net migrant” (see the variable description in Table 1).

This study employs urban price indexes published by the Department of Land Administration, M. O. I., from 2001-2009, and uses year 2008 as the base period to convert the data. The time variable in the level-1 is comprised of the 9 yearly time points from 2001-2009, and the start time is year 2001, also called the initial status. This study uses the initial year in centring[4]. The level-2 uses

[4] Tabachnick, B.G. and L.S. Fidell, 2001. Using multivariate statistics., Needham Heights, MA: Person Education Company. also consider that in general multivariate regression analysis, centring can reduce multi-collinearity between the explanatory variables. HLM has explanatory variables of different levels, including contextual variables or cross-level interactions, so

village/township/city as a unit, and the characteristic variables are population density and internal net migrant. As defined by the Ministry of the Interior, the population density is defined as the population per square kilometre, and it is population of residence booklet divided[5] by land area. Due to increases in the population, the demand for land in the densely populated regions grows, and thus, land prices increase. Accordingly, the land prices of densely populated regions are higher than those of sparsely populated regions. Hence, population is one of the factors affecting land prices. The data are sourced from the Ministry of the Interior. The internal net migrant is defined as the net population migrated, i.e., the difference between the immigrated and emigrated populations. The internal net migrant also includes international migration statistics, i.e., the change of transnational permanent residence defined by the Ministry of the Interior. If the difference is positive, this would indicate that the migrated population is greater than emigrated population, attributing to regional commercial functions or economic development; if the difference is negative, this would indicate that the regions are remote or have commercially undeveloped functions. The variable data are sourced from the Ministry of the Interior.

Table-1. Variable description

Variable	Definition
P_{ti}	Land prices are expressed by urban land prices indexes from 2001-2009.
$(Time_{ti} - L)$	The time is years from 2001 to 2009, totalling to 9 time points. L is 2001, and the initial year is used for centring. Time was coded as 0, 1, 2, …, 8, representing measurement time points with a 1-year time interval from baseline to 9 years.
$(Time_{ti} - L)^2$	In quadratic time, $Time_{ti}$ takes square powers.
$Density_i$	Population density means the average residential population per square kilometre.
$Move_i$	Internal net migrant means the difference between the immigrated and emigrated population in that year.

Sample Statistics Description

Table 2 indicates the 2,808 time points are nested in 312 villages, townships and cities, i.e., each village/township/city has 9 time points. For the urban land prices indexes, the average urban land prices index of the 312 villages/townships/cities is 105.39; for the population density, the average population in the village/township/city per square kilometre is 3,094; the maximum internal net migrant is 5,642, and the minimum internal net migrant is -2,379.

serious collinearity problems may occur. In addition, the intercept of the regression line has meaning in explanation only when all the explanatory variables are equal to zero. Thus, the intercept is equal to the dependent variable. From this, centring is an important link for HLM.

[5] As defined by the Ministry of the Interior, population registered means citisens of the Republic of China who have household register and live or do not live in the region on the standard statistics date.

Table-2. Descriptive statistics

Variables	Quantity	Mean	SD	Minimum	Maximum
P_{ti}	2808	105.39	8.69	54.94	159.55
$Time_{ti}$	2808	4.00	2.58	0.00	8.00
$Density_i$	312	3093.50	6041.51	5.59	40957.23
$Move_i$	312	23.22	769.21	-2379.33	5641.89

Note: time centring has been performed.

RESULTS

This study employs maximum likelihood (ML) to estimate the fixed and random effects of HLM. HLM 6.08 is used for estimates. The growth model in HLM is used to discuss the factors affecting the urban land prices.

Unconditional Growth Model

The model aims to examine whether the initial status (β_{00}), growth rate (β_{10}) and acceleration of the dependent variables are statistically significantly equal to zero. The empirical results are shown in Table 3. The fixed effect shows that the estimate value of β_{00} is 105.391, and this represents the average urban land price index, which is 105.391; the estimate value of β_{10} is 3.146, and this represents that the mean annual growth rate increased by 3.146; the estimate value of β_{20} is -0.562, and this represents the mean acceleration of urban land prices slows down. The estimate value of β_{10} is a positive value, while the estimate value of β_{20} is a negative value. This represents that the land prices increased, with a decreasing rate over time. As the mean intercept, growth rate and acceleration are all statistically significant, three parameters are needed for explaining the mean growth trajectory. As for random effects, the variance τ_{00} of mean urban land prices β_{00}, the variance τ_{11} of the growth rate β_{10} and the variance τ_{22} of the acceleration β_{20} have significant differences across different villages/towns/cities. The estimated values of the variances are 1.922, 4.594 and 0.486; the χ^2 are 516.718, 1140.254 and 926.195, respectively, and their freedom is 311. This shows that the mean urban land prices and growth rate and acceleration of land prices are different in different villages/townships/cities.

Table-3. Analysis results of the unconditional growth model

Fixed effects	Coefficient	se	t-ratio	*p*-value
Mean initial status, β_{00}	105.391***	0.144	731.743	0.000
Mean growth rate, β_{10}	3.146***	0.304	10.345	0.000
Mean acceleration, β_{20}	-0.562***	0.033	-17.050	0.000
Random effects	**Variance component**	**df**	**Chi-square**	***p*-value**
Initial status, r_{0i}	1.922***	311	516.718	0.000
Growth rate, r_{1i}	4.594***	311	1140.254	0.000

Acceleration, r_{2i}	0.486***	311	926.195	0.000
Level-1 error, e_{ti}	5.931			
Deviance(-2LL)	18657.958			
Number of estimate parameters	10			

Note: *** indicates p<0.001

Conditional Growth Model

This model aims to identify the relationship between changes in dependent and independent variables over time. The results are shown in Table 4. For the fixed effects, the grand mean (β_{00}) of urban land prices is 105.39, and reaches a 1% significance level; β_{10} and β_{20} are the growth rate and acceleration of the urban land prices; the estimate values are 3.146 and -0.562 and reach a 1% significance level. The annual growth rate of the urban land prices is 3.15; the urban land prices increase with a decreasing rate over time. As for the moderation effect, the estimate values of β_{11} and β_{12} are negative, and this means that the population density and internal net migrant can moderate the growth rate (β_{10}) of the urban land prices. The growth rate of the urban land prices can slowly increase with the increase in population density or internal net migrant; in addition, the estimate values of β_{21} and β_{22} are positive. The population density and internal net migrant can affect acceleration of the urban land prices. The acceleration of the urban land prices increases with an increase in the population density or internal net migrant.

As for random effects, the estimate value of τ_{00} is 1.910, and it reaches the 1% significance level, indicating mean land prices are different in the villages/townships/cities. The estimate values of τ_{11} and τ_{22} are 4.520 and 0.474, and reach a 1% significance level. This means that the impact of the time variable of the level-1 on the urban land prices has a significant difference after the level-2 controls the population density and the internal net migrant. This means that other explanatory variables of the level-2 are not considered. For the random effects, the estimate value of τ_{00} in Table 4 is 1.910, which is smaller than the estimate value 1.922 of the unconditional growth model τ_{00} in Table 3. The impact of the time variable on the mean urban land prices can be effectively reduced after the level-2 controls the population density and the internal net migrant variables. The mean urban prices still have significant differences after population density and the internal net migrant of the level-2 are controlled for. This represents the explanatory variable of the important level-2 is not considered.

In addition, between-class variance of the conditional growth model (variance of the error term of the level-2) and the between-class variance of the unconditional growth model are compared. As shown in Table 4, the between-class variances τ_{00} , τ_{11} and τ_{22} of the conditional growth model are 1.910, 4.520 and 0.474, respectively. In Table 3, the between-class variances τ_{00} , τ_{11} and τ_{22} of the unconditional growth mode are 1.922, 4.594 and 0.486 respectively. This means that the variance of the error term (unexplained part of the model) can be effectively reduced after population density and internal net migrant are added in the level-2. On the other hand, the difference of the chi-square statistics ($\Delta\chi^2$) can compare the unconditional and conditional growth model fits. The chi-square test shows the variance difference in the two nested models meets the chi-square distribution, and the parameter differences of the two models is the degrees of freedom. Tables 3 and 4 show the variance is 18657.958 and 18643.467, and the difference is 14.491. The degree of freedom of the chi-square statistics is 4 and reaches a 5% significance level, indicating the data fit of HLM conditional growth model is better ($\Delta\chi^2$ =14.491, *df*=4, *p*<0.05).

Table-4.Analysis results of the conditional growth model

Fixed effects	**Coefficient**	**se**	**t-ratio**	***p*-value**
Model for initial status, π_{0i}				
Base, β_{00}	105.391444***	0.155668	677.029	0.000
Model for growth rate, π_{1i}				
Base, β_{10}	3.145961***	0.301371	10.439	0.000
Density, β_{11}	-0.000147**	0.000049	-3.016	0.003
Move, β_{12}	-0.000767**	0.000384	-1.998	0.046
Model for acceleration, π_{2i}				
Base, β_{20}	-0.561992***	0.032985	-17.038	0.000
Density, β_{21}	0.000018**	0.000005	3.269	0.002
Move, β_{22}	0.000083*	0.000043	1.946	0.052
Random effects	**Variance component**	**df**	**Chi-square**	***p*-value**
Initial status, r_{0i}	1.90989	311	516.07552	0.000
Growth rate, r_{1i}	4.52027	309	1112.85309	0.000
Acceleration, r_{2i}	0.47448	309	894.17659	0.000
Level-1 error, e_{ti}	5.93425			
Deviance(-2LL)	18643.467367			
Number of estimate parameters	14			

Note: *** indicates *p*<0.001, ** indicates *p*<0.05, * indicates *p*<0.1

HLM in Table 5 provides an estimated reliability indicator using each growth parameter. The objective of the reliability estimate is proximity of the observed value to the actual value. In the reliability estimates of the initial status (π_{0i}) of the unconditional growth model and the conditional growth model, the value is 0.48, indicating initial status has lower reliability. The observed variance cannot be explained by the variables of the level-1, and the level-2 should add an explanatory variable to explain π_{0i}; the estimated reliability value of the growth rate (π_{1i}) and acceleration (π_{2i}) is between 0.66 and 0.72, with higher estimate reliability. Thus, the parameters of the growth rate and acceleration can serve as functions of the level-2 variables. The level-2 variables can be used for explanation.

Table-5. Reliability of the HLM regression coefficient estimate

	Reliability
Unconditional growth model	
Initial status, π_{0i}	0.487
Growth rate, π_{1i}	0.728
Acceleration, π_{2i}	0.675
Conditional growth model	
Initial status, π_{0i}	0.483
Growth rate, π_{1i}	0.723
Acceleration, π_{2i}	0.666

CONCLUSIONS AND SUGGESTIONS

Urban land prices change dynamically over time. Thus, this study uses HLM for analysis. Though many methods can be selected, HLM is the most appropriate method to evaluate changes in urban land prices over time after the assessment of advantages and disadvantages of the difference methods. The land prices data have a hierarchical relationship or are longitudinal data. HLM is feasible and can substitute the URM ANOVA, MRM ANOVA or SEM in repeated measurement. This study employs the HLM growth model and considers the change in land prices over time. The land prices are regarded as hierarchical data for estimation. Due to the change in the land prices over time, the land prices should be estimated by using a multi-level growth model. However, no study of land prices has employed such a model to date. Therefore, this study can provide reference and improvement suggestions. The results of the unconditional growth model show that the one and two power time variables reached a significant level, and this means that the land prices change over time. The urban land prices increase with a decreasing rate over time in each year; the results of the conditional growth model show that the growth rate (π_{1i}) and acceleration (π_{2i}) of the urban land prices can be moderated by the population density and internal net migrant; second, this study finds that the intercept, growth rate and acceleration of the urban land prices in the level-1 reach significance level, indicating other explanatory variables of the level-2 are not considered, and future studies can discuss this in greater detail. In addition, the random effect τ_{00} of the conditional growth model is smaller than that of the unconditional growth model after comparison of the effects of the unconditional and the conditional growth models. This indicates that the impact of the time variable on the mean land prices can be effectively reduced after the explanatory variables of the level-2 are controlled for. In addition, the empirical results indicate that the important explanatory variables of the level-2 are not considered. Future research can collect the relevant data affecting the land prices (such as business cycles, local government financial policies, and land use planning). If the explanatory variable of the level-1 for change over time can be obtained, it can be introduced in the model in a future study.

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