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PRICE CHANGES OF REPEAT-SALES HOUSES IN KAOHSIUNG CITY: ANALYSES BASED ON HIERARCHICAL LINEAR GROWTH MODELS

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Abstract. This study adopts the hierarchical linear growth modeling approach to analyze the differences in the changes of repeat-sales house prices in Kaohsiung City from 2012 to 2020. The Level 1 time-varying factors include house age and the time of repeat-sales; the Level 2 factors include house attributes such as house area, house type, and house location. Based on the results of the null model, the estimated variance is 0.42816, with a 1% level of significance. This shows that significant differences exist in the mean repeat-sales prices between houses. The interclass correlation coefficient is 91.65%, showing that the interclass variation and intraclass variation of the mean repeat-sales prices are 91.65% and 8.35%, respectively. The estimation results of the non-randomly varying slope model indicate that the sales time and sales time squared significantly affect repeat-sales prices. The annual growth rate and quadratic growth of sales prices do not differ by house type (luxury condominiums and apartment buildings) but are affected by house area and house location. The effect of house age on repeat-sales prices is moderated by house area, house type, and house location.

Keywords: hierarchical linear growth modeling, repeat-sales, house prices, house area, house type, house location.

Introduction

On August 1, 2012, Taiwan began to implement a real estate actual price registration scheme. Before this, the previous sales prices of a new or pre-owned house had remained unavailable to housebuyers. However, the actual price registration scheme is unable to present the repeat-sales prices of the same house at different points in time. Therefore, the actual price registration scheme does not reveal whether changes in the price of a single house over time are in line with market conditions.

The repeat-sales model was first proposed by Bailey et al. (1963) and was later reinterpreted and applied by Case and Shiller (1987). This model centers on analyzing the selling price of a single house at different points in time; it is generally used to formulate a real estate property price index. The interference of external factors can be reduced by observing the same property at different periods, assuming that the structural, material, and external quality of the property remains unchanged. By combining the repeat-sales approach with weighted indices and the hedonic price model, Shiller (1991) examined house price indices in Atlanta, Chicago, Dallas, and San Francisco from 1970 to 1986. Clapp and Giaccotto (1998) wrote that the repeat-sales model increases the precision validity of the standard error in an estimator indicator. Recently, Beltrán et al. (2019) adopted the repeat-sales model to analyze the effects of flooding in England on property prices. The results show that property prices in completely inundated areas fell by 21%, although this reduction was only significant within five years. On the other hand, the effects of flooding on lower-priced houses lasted for 6 to 7 years. Ryu and Song (2020) applied the repeat-sales model to exploring the price of office spaces in Seoul. According to their results, the price of office spaces per 3.3 m^2 per year has risen continuously by 12% from 2000 to 2019.

However, many studies have analyzed the factors affecting house prices using the hedonic price model (Rosen, 1974; Nelson & Schumaker, 2001; Umanailo et al., 2019). Hox (1995) uniquely pointed out that estimating different levels of characteristic variables at the same individual level will lead to fallacies in statistical inference. Giuliano et al. (2010) suggest that hierarchical linear modeling (HLM) can control the variation in research data

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caused by regional differences. Curran et al. (2006) have found that the hierarchical linear growth model (HLGM) approach is extremely suitable for studying stability and individual differences over time, while the relationship between repeat measurements and time can be expressed through functions. Liou et al. (2016) used HLGM to analyze data on the repeat sales of houses, demonstrating that HLM can be used to identify the hierarchical structure of the factors affecting housing sales prices. However, given that a typical HLM housing sales price model cannot be used to predict price changes over time, the authors proposed a two-level hierarchical linear model of individual growth. Furthermore, Lee et al. (2013) asserted that HLGM yields covariates that both change and do not change over time. Therefore, the HLGM can be applied extensively in studies in which the sample changes at different time points, and it can also broaden the sample's degree of variation in an empirical study.

This study applies the repeat-sales model as a basis for analysis through a two-level HLGM. Using this approach, we contend that when a house undergoes multiple transactions, a high correlation should theoretically exist between each transaction. In other words, the outcomes of each transaction for the same house should not be regarded as independent, because the first sales price is very likely to affect subsequent sales prices. In this study, the Level 1 variables are the time of repeat-sales and the house age at the time of sales, which are both measured in units of time. The Level 2 variables are representative of a house's attributes, which do not change over time, and are measured in units of a single house. First, a null model was proposed to search for significant differences between each repeat-sales price and each house. Afterwards, a non-randomly varying slope model was proposed, in which the Level 1 variables are the time of repeat-sales and house age, while the Level 2 outcome variables are designated as the Level 1 intercepts and coefficient. Several house attributes serve as additional variables for explanatory purposes. The objectives of this study are as follows: (1) to examine the effects of changes in repeat-sales time and house age on sales prices; (2) to examine the effects of the Level 2 variables of AREA, TYPE, and LOCATION on the initial sales prices; and (3) to examine the effects of the Level 2 variables on the growth rate and quadratic growth of houses' repeat-sales prices, with the latter representing how rapidly these prices progress.

Previous studies have mostly applied traditional hedonic regression models and single-level repeat sales models (Xu et al., 2018; Hill & Trojanek, 2022) to perform dynamic empirical analyses on repeat-sales housing data. Because single-level repeat sales models do not consider house attributes, the results will become biased when the implicit prices change over time, which is something that cannot be controlled (Anthony, 2018). It is useful to examine the differences within a single entity over time using hierarchical linear models (Curran et al., 2006; Tan et al., 2019). House attributes can be placed on the second level of a two-level hierarchical linear model to examine the effects of house attributes on house price changes. This study applied the HLGM approach to analyze the differences in repeat-sales prices using a two-level model.

1. Theoretical review

1.1. The repeat-sales model and repeat-sales price of houses

Case and Shiller (1987) interpreted the repeat-sales model by stating that the application of this approach is centered on analyzing differences in the sales prices of the same house at different transaction times. This difference is regarded as house price volatility in the market. The advantage of this approach is that the quality of houses can be maintained and the effects of time on house prices can be observed. Wang and Zorn (1997) empirically showed that the repeat-sales model focuses on price changes rather than prices themselves, and that these changes are directly measured by using houses that have been sold at least twice. Compared to the hedonic price model, the repeat-sales model has the advantage of not needing to correctly define the important hedonic attributes of house prices or their functional relations with prices. Guo et al. (2014), on the other hand, developed a new model called the pseudo repeat sale price index, in which locational and community variables are omitted, along with several physical attribute variables that cannot be observed or are difficult to measure. The empirical results reveal that this model can overcome the problem of insufficient repeat-sales data for emerging markets and newly built houses, as well as the problem of omitted variables in the hedonic price model. Additionally, it addresses typical problems, such as small sample sizes and sample selection bias, that occur in the classical repeat-sales model (Melser, 2023).

The repeat-sales model has been applied in a wide body of literature. For example, Harding et al. (2007) applied the repeat-sales model to estimate the depreciation, maintenance costs, and price growth rate of houses. The empirical results demonstrate that older houses have higher depreciation and maintenance costs, thereby lowering the price growth rate. Xu et al. (2018) applied the hedonic price model and the repeats sales model to analyzing the housing market in Beijing between 2005 and 2012; their findings suggest that the added value of older houses stems from the land itself, rather than buildings on the land, and that older houses have higher price growth rates. To investigate the effects of locational attributes on house prices, Genesove and Han (2013) utilized the Case-Shiller repeat-sales price index for empirical analysis, demonstrating that the prices of houses in suburban areas near the city edge increase more slowly than those of houses in suburban areas. This explains why the housing supply elasticity is higher in areas that offer more employment and development opportunities. Bourassa et al. (2009) used the repeat-sales model to investigate differences in house prices in three urban areas in New Zealand. Based on the empirical results, older real estate properties closer to the city center show larger price increases and market scarcity, and thus are more attractive to investors. In addition, the price appreciation of these properties exceeds the average rates on the market. Employing the mixed repeat-sales model, Melser (2017) demonstrated that house price growth rates differ by location, with houses in suburban areas showing a larger price appreciation than houses in the city center. The price growth rate also differs across house types: for example, apartments have a smaller price growth rate than single-family villas. On the other hand, house area (as reflected by the number of bedrooms and bathrooms) has a relatively smaller effect on house prices. Regarding the relationship between housing market conditions and repeat-sales prices, Miles (2017) and Stroebel and Vavra (2019) have verified that house price changes are caused by periodic commercial changes. Bourassa et al. (2009) used the repeat-sales model and found that, at different sales times, business cycles have a considerable effect on house price changes. As far as the effects of transportation on house prices, Kim and Lahr (2014) used the Alonso model to analyze repeat-sales data from houses that had been sold at least twice between 1991 and 2009; they then estimated how the relative accessibility of a metro station, and the anticipation of its commencement date, could affect house price changes. According to their empirical results, the establishment of a light rail system positively affects the sales price growth rate of houses located near commuter stations.

1.2. Hierarchical linear growth modeling

Previous studies on house prices (Xiao, 2016; Halvorsen & Pollakowsk, 1981; Gibbs et al., 2018) are based mostly on the hedonic price model approach and have largely estimated house price indices using the ordinary least squares (OLS) approach. According to Hsiao (1986), when using the OLS approach for setting variables, care must be taken to ensure that important variables correlated with the independent variables are not omitted, so as to avoid biased parameter estimates. Other methods that are commonly used to examine longitudinal data include repeated ANOVA, multivariate repeated measures (MRM), and structural equation modeling (SEM). Although traditional MRM and SEM can be used in analytical methods with a fixed time-series design (Bryk & Raudenbush, 1987), neither approach can address missing data or changes at different points in time. Additionally, because the changes in repeat-sales prices do not occur at fixed time intervals, the transaction times and the changes in sales prices cannot be controlled or observed (Lee et al., 2013).

Lee et al. (2013) used the HLGM approach to examine the factors affecting changes in urban and rural land prices in Taiwan, with their results suggesting that time has a significant effect on urban land prices. This effect is moderated by population density and population migration. Compared to HLGM estimation results, OLS is an approach that can result in overestimations of the error variance and underestimations of the standard error of the regression coefficient. Liou et al. (2016) used HLGM to analyze repeat-sales data of house prices. They note that the HLGM approach differs from typical hierarchical linear models, conventional hedonic house price models, and spatial panel linear regression models as typical hierarchical linear models can distinguish between the structural levels of the factors that affect house prices but cannot be used to predict price changes over long periods of time. Therefore, the authors proposed a two-level hierarchical linear model of individual growth for empirical analysis in which time was set as a Level 1 variable, allowing researchers to observe the changes in the growth of house prices in different transaction years. Moreover, house-attribute variables (i.e., objects of transaction and distance to metro stations) were treated as Level 2 variables, with their long-term effects on the sales prices of houses being determined.

According to Lee et al. (2013), there are various benefits to analyzing longitudinal data through the HLGM approach: (1) this approach can address unbalanced and incomplete data under the assumption that these data are missing at random (MAR); (2) the HLGM does not require observations to be independent of one another and does not have any boundaries for restrictive assumptions, in that the data do not have to be necessarily within the range of study nor do they have to be associated with the study data; and (3) HLGM provides covariates that are both dependent and independent of time. Therefore, the HLGM approach can be used widely on samples that change at different points in time, thereby growing the body of empirical research on a sample's effects on the extent of the changes that occur.

2. Methods

Because repeat-sales prices change over time, the HLGM approach is useful for examining several issues: the differences between the repeat-sales prices of houses; the effects of house attributes on the initial state of repeat-sales prices, price growth rates, and the magnitude of change; and whether house attributes moderate the effects of the timing of repeat-sales on house prices.

2.1. Study framework

In this study, the Level 1 variables are the time of repeat-sales (*Time – T*) and the house age (*Age*) at the time of transaction, both measured in units of time; the Level 2 variables are house area, house type, and house location, which are assessed for a single house. This study investigates the effects of the Level 1 variable of time and the Level 2 variables of house attributes (house area, house type, and house location) on the repeat-sales prices of a house, as well as the extent to which the house attributes moderate the effects of the time of repeat-sales on the repeat-sales prices. That is, we analyze the effects of house area, house type, and house location on the growth rate and quadratic growth of a house's repeat-sales prices (see Figure 1).

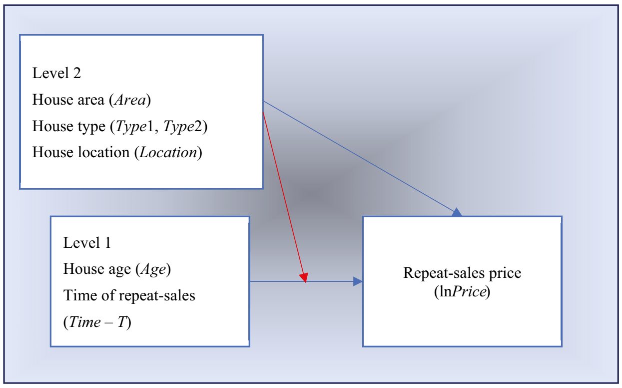

Figure 1. The study framework

2.2. Repeat-sales model

Before finalizing the HLGM, the repeat-sales model must first be introduced to facilitate subsequent discussions. Bailey et al. (1963) first proposed the repeat-sales model as a means of estimating the changes in houses' repeat-sales prices. Hansen (2006) proposed the hedonic price model, which can be used to determine the general pure price changes of a house. However, this approach requires a large volume of information on houses' attributes, resulting in data with lower intensity possibly being included in the regression analysis, leading to analytical bias. In reality, the repeat-sales approach requires less information as only the houses' attributes, the sales prices, and the sales dates are required. Hansen (2006) proposed that this model differs from hedonic price models that have specific restrictions and conditions. The repeat-sales model is expressed in Equation (1):

$$\ln p_{it} - \ln p_{i\tau} = \sum_{t=1}^{T} D1_{it}\alpha_t - \sum_{\tau=1}^{T} D1_{i\tau}\alpha_\tau + \left(X_{it} - X_{i\tau}\right)\beta + \left(\varepsilon_{it} - \varepsilon_{i\tau}\right), \quad (1)$$

where: $\ln p_{it}$ represents the logarithm of the sales price of the i-th house at time t; $\ln p_{i\tau}$ represents the logarithm of the sales price of the i-th house at time τ ($t > \tau$). Assuming that the characteristics of the i-th house at time remain unchanged between two transactions ($X_{it} = X_{i\tau}$), Equation (1) can be transformed into Equation (2):

$$P_{it} - P_{i\tau} = \sum_{t=1}^{T} G_{it}\alpha_t + \eta_{it}, \quad (2)$$

where: G_{it} is a dummy variable of time in which the repeat-sales time is equal to 1 or is set to 0 to indicate no repeat sales; η_{it} is the error term for each repeat-sale as each repeat sales price has an error term, and multiple repeat-sales are treated as independent of each other. More details can be found in Shiller (1991). Bailey et al. (1963) and Case and Shiller (1987) demonstrated that housing attributes can be controlled more accurately using the repeat-sales approach if a house's price variation is analyzed.

In the repeat-sales approach, the quality of a house's attributes is assumed to remain unchanged. If it remains unchanged over time, the maintenance costs will be high, while the quality of a house's structural attributes that are not maintained will diminish over time. Therefore, the requirements of the repeat-sales approach are seemingly difficult to realize. This problem can be solved or quality control can be ensured in the following ways: (1) Using the repeat-sales subsample in which the quality of the housing attributes is relatively constant. However, the estimated price changes may not be representative of the price changes of the entire repeat-sales sample if the subsample is too small; (2) all repeat-sales data are used in a constant repeat-sales regression model (Goetzmann & Spiegel, 1997). However, this method is still limited by quality control and sales time restrictions as a simple repeat-sales model cannot be distinguished by time because of changes in housing attributes or housing prices only. Additionally, the changes in housing attributes determine whether the estimations in the repeat-sales model are randomly distributed.

Furthermore, systematic differences exist between different repeat-sales houses and their turnover rates (two transactions or more). A house with a high turnover rate may generate excessive repeat observations that result in biased estimates, and the range of the data that can be collected in a repeat-sales model is subject to restrictions as the sample is limited to houses that have been sold twice or more. Therefore, systematic differences exist between the price changes in houses that have only been sold once versus multiple times. Thus, the repeat-sales approach may be biased in estimating the overall price changes of a house.

Nevertheless, a broad range of studies has advocated for the use of the repeat-sales model, such as those by Bailey et al. (1963) and Case and Shiller (1987), as well as the intercept modification approach proposed by Goetzmann and Spiegel (1997). Many studies have offered various means for substituting repeat-sales estimations, including arithmetic, geometric, and hedonic-repeated measures (Shiller, 1991, 1993), Bayesian and Stein-like estimators (Goetzmann, 1992), and distance-weighted estimators (Goetzmann & Spiegel, 1997). These studies have examined several estimation models, ultimately demonstrating that useful additional information can be obtained from the empirical results of the repeat-sales approach (Crone & Voith, 1992). Rossini (1997) and Costello (1997) have noted that the repeat-sales approach is more effective than the restricted hedonic approach and that both approaches are better than the median estimation approach. Clapham et al. (2004) asserted that the hedonic price index is relatively more stable than the repeat-sales index. However, there is a dearth of empirical research on this issue.

2.3. Setting the hierarchical linear growth model

In this study, the Level 1 variables are the time of repeat-sales (*Time*) and the house age (*Age*).[1] The latter is corre-

[1] This study assumes that there are no major changes to the attributes of the same house, in that no improvements were made to the quality of living nor the usage of spaces and that the house did not have major damage. The only attribute that varies is house age.

lated with the depreciation of a house over time. Because there are many types of house attributes, we have selected three important attributes–house area, house type, and house location, as literature has shown that these three attributes have remarkable effects on house prices (Lu et al., 2011; Lee & Ton, 2010; Begiazi & Katsiampa, 2019; Rahman et al., 2018). Two sub-models–a null model and a non-randomly varying slope model were developed for analysis.

Null model

The null model is a one-way ANOVA model with random effects (Brown & Uyar, 2004). No independent variables are placed in either of the two levels. The null model is often used as a preliminary model to determine whether HLGM or traditional regression should be used for analysis (Kreft & de Leeuw, 1998). The purpose of the null model in this study is to measure the changes in the repeat-sales prices of a single house across multiple house types. The null model is described by Equations (3) and (4), as follows:

Level 1 Model:

$$\ln Price_{ti} = \pi_{0i} + e_{ti}, e_{ti} \sim N\left(0, \sigma^2\right), \tag{3}$$

where: $\ln Price_{ti}$ is the natural logarithm of the sales price of the i-th house at a time point t; π_{0i} is an intercept term that represents the first sales price of the ith house; e_{ti} is the error term of the Level 1 model, which follows a normal distribution with a mean of 0 and a variance of σ^2; and σ^2 is the intraclass variance of e_{ti}.

Level 2 Model:

$$\pi_{0i} = \beta_{00} + r_{0i}, r_{0i} \sim N\left(0, \tau_{00}\right), \tag{4}$$

where: β_{00} is the grand mean of the first sales price of all housing transaction; r_{0i} is the error term that represents the difference between the mean sales price of a house and the grand mean of the sales prices of all houses at time point 0 (it follows a normal distribution with a mean of 0 and a variance of τ_{00}); and τ_{00} is the interclass variance of r_{0i}. Substituting Equation (4) into Equation (3) yields the following mixed model:

$$\ln Price_{it} = \beta_{00} + r_{0i} + e_{ti}. \tag{5}$$

Next, the intraclass coefficient (ICC) is calculated using the following equation to determine the ratio of the intraclass variance to the total variance: $ICC = \frac{\tau_{00}}{\left(\tau_{00} + \sigma^2\right)}$.

Non-randomly varying slope model

The non-randomly varying slope model sets the Level 1 intercepts and coefficients as Level 2 outcome variables, in which the three house attributes are set as independent variables. The intercept term π_{0i} is modeled as random effects, while the other intercept terms $\pi_{1i} \sim \pi_{4i}$ are modeled as fixed effects. The squares of the Level 1 explanatory variables (the time of repeat-sales and the house age) are also taken alongside their original values and are treated by grand mean centering; the Level 2 house attribute variables are treated by grand mean centering as well. In other words, the three Level 2 variables have direct and cross-level effects on repeat-sales prices. The coefficients of the Level 1 independent variables are set as fixed effects and are explained by the three Level 2 variables. Thus, the effects of the Level 1 independent variables on house prices are moderated by the three Level 2 variables. The model is set as follows:

Level 1 Model:

$$\ln Price_{ti} = \pi_{0i} + \pi_{1i}\left(Time_{ti} - T\right) + \pi_{2i}(Time_{ti} - T)^2 + \pi_{3i}\left(Age_{ti} - \overline{Age..}\right) + \pi_{4i}(Age_{ti} - \overline{Age..})^2 + e_{ti}, e_{ti} \sim N\left(0, \sigma^2\right), \tag{6}$$

where: $Time_{ti}$ represents the year of the transaction of the ith house at time point t; T is the baseline year of 2012, when the actual price registration system was first implemented; $Time_{ti} - T$ represents the conversion of data regarding the transaction of the ith house at time point t, based on the baseline year T (this subtraction would yield 9 time points ranging from 0 to 8 that represent the time of repeat-sales, with 0 as the initial time point [initial state]); $(Time_{ti} - T)^2$ is square of the time of repeat-sales of the i-th house[2]; $Age_{ti} - \overline{Age..}$ is the house age of the ith house at time of sales t and is treated by grand mean centering; $(Age_{ti} - \overline{Age..})^2$ is the square of the house age of the i-th house at time of sales t; π_{0i}, π_{1i}, π_{2i}, π_{3i}, and π_{4i} are coefficients for estimating the growth curve of $\ln Price_{ti}$; and e_{it} is the error term, which follows a normal distribution with a mean of 0 and a variance of σ^2.

Level 2 Model:

$$\pi_{0i} = \beta_{00} + \beta_{01}\left(Area_i - \overline{Area.}\right) + \beta_{02}\left(Type1_i - \overline{Type1.}\right) + \beta_{03}\left(Type2_i - \overline{Type2.}\right) + \beta_{04}\left(Location_i - \overline{Location.}\right) + r_{0i}; \tag{7}$$

$$\pi_{1i} = \beta_{10} + \beta_{11}\left(Area_i - \overline{Area.}\right) + \beta_{12}\left(Type1_i - \overline{Type1.}\right) + \beta_{13}\left(Type2_i - \overline{Type2.}\right) + \beta_{14}\left(Location_i - \overline{Location.}\right); \tag{8}$$

$$\pi_{2i} = \beta_{20} + \beta_{21}\left(Area_i - \overline{Area.}\right) + \beta_{22}\left(Type1_i - \overline{Type1.}\right) + \beta_{23}\left(Type2_i - \overline{Type2.}\right) + \beta_{24}\left(Location_i - \overline{Location.}\right); \tag{9}$$

$$\pi_{3i} = \beta_{30} + \beta_{31}\left(Area_i - \overline{Area.}\right) + \beta_{32}\left(Type1_i - \overline{Type1.}\right) + \beta_{33}\left(Type2_i - \overline{Type2.}\right) + \beta_{34}\left(Location_i - \overline{Location.}\right); \tag{10}$$

$$\pi_{4i} = \beta_{40} + \beta_{41}\left(Area_i - \overline{Area.}\right) + \beta_{42}\left(Type1_i - \overline{Type1.}\right) + \beta_{43}\left(Type2_i - \overline{Type2.}\right) + \beta_{44}\left(Location_i - \overline{Location.}\right). \tag{11}$$

[2] Fitzmaurice et al. (2012) pointed out that time and its square can be used to express the rate of change of growth. The types of growth include slowly declining, increasing, stable, and decreasing.

Substituting Equations (7) to (11) into Equation (6) yields a mixed model.

In which β_{00} is the grand mean of the first sales price of all housing transactions; $Area_i - \overline{Area}.$ refers to the centering of house area using its grand mean; $Type1_i - \overline{Type1}.$ and $Type2_i - \overline{Type2}.$ refers to the centering of house type using its grand mean (house types include apartment buildings, luxury condominiums, and condominiums, with the latter being the baseline house type). For $Type1_i$, luxury condominiums are set as 1, or 0 if otherwise; for $Type2_i$, apartment buildings are set as 1, or 0 if otherwise; $Location_i - \overline{Location}.$ refers to the centering of house location using its grand mean[3] β_{01}, β_{02}, β_{03}, and β_{04} represent the coefficients of the effects of house attributes on the Level 1 intercepts (that is, house attributes directly affect the first sales price π_{0i} of a house); r_{0i} is the error term, which follows a normal distribution with a mean of 0 and a variance of τ_{00}; β_{10} represents the growth rate of the mean house price from 2012 to 2020; β_{20} represents the quadratic growth in the sales prices for different houses; β_{30} represents the effects of house age on the sales price; β_{40} is the coefficient of house age squared; $\beta_{11},\beta_{12},\beta_{13},\beta_{14}$, $\beta_{21},\beta_{22},\beta_{23},\beta_{24}$, $\beta_{31},\beta_{32},\beta_{33},\beta_{34}$ and $\beta_{41},\beta_{42},\beta_{43},\beta_{44}$ represent the effects of each house attribute on the Level 1 slope.

2.4. Description of variables

In this study, the Level 1 variables are measured in units of repeat-sales time. There were 7,076 pieces of sales data from 2012 to 2020. The Level 2 variables are measured in units of houses. There were 3,167 pieces of sales data pertaining to houses sold at least twice. The dependent variable is the natural logarithm of the sales price. As shown in Table 1, the independent variables include the Level 1 variables (the time of repeat-sales and house age), as well as the Level 2 variables concerning house attributes (transferred house area, house type, and house location).

Level 1 variables

(1) Time of repeat-sales

We first convert the data pertaining to the time of repeat-sales based on the baseline year of 2012 (the year the actual price registration scheme was first implemented). The converted Level 1 variable (the time of repeat-sales) consists of 9 time points ranging from 0 to 8; 0 is the initial time point and is denoted as the initial status–that is, the first sales time and its square of each house. Shen et al. (2020) used the difference between the sales month and the baseline month (January 2011), demonstrating the spatial differences in price changes over time.

(2) House age

House age is also a Level 1 variable in this study. The structure and function of a house will generally decrease with time and usage; thus, the age of a house can reflect its remaining lifespan and residual value. In other words, house age has a negative effect on the sales price. Wilhelmsson (2007) points out that an increasing house age will reduce the sales price. Clapp and Giaccotto (1998) suggest that older houses have lower prices because of their high maintenance costs and poorer utility. Lee and Ton (2010) and Frew and Jud (2003) have validated these effects with significant results. The square of house age is included in the model because the rate of depreciation of house age will gradually slow down. According to Lee et al. (2013), quadratic growth (the square of time) indicates that measurements dependent on time variables have different statuses at the individual level at different points in time. In our study, house age is set as a continuous variable treated by grand mean centering. House age is expected to have a negative and gradually diminishing effect on the sales price.

Level 2 variables

(1) House area

The area of a house will affect its sales price. Larger houses offer better and more complete utility in terms of bedrooms, parlors, and bathrooms. Therefore, house area is expected to have a positive effect on sales price. Martins-Filho and Bin (2005), Moralı and Yılmaz (2022), and Reichel and Zimčík (2018) have demonstrated the positive and significant effects of house area on house prices. Therefore, house area is expected to have a positive effect on sales price. In this study, house area is treated by grand mean centering.

(2) House type

The house types in this study are condominiums, luxury condominiums, and apartment buildings. In a study on long-term changes in the age and prices of houses in various British regions, Hudson et al. (2018) showed that sales prices differ across house types. Vangeel et al. (2020) examined the effects of different house types on sales prices in Belgium and demonstrated empirically that the different house types have significant effects on changes in house prices. In our study, condominiums are designated as the reference house type, and two dummy variables are set. For the variable of *Type*1, a value of 1 is assigned to luxury condominiums, or 0 if otherwise; for the variable of *Type*2, a value of 1 is assigned to apartment buildings, or 0 if otherwise. House type is treated by grand mean centering.

(3) House location

According to Lisi (2019), the location of a house is an important attribute in estimations using the hedonic price model. Rahman et al. (2018) studied the relationship between locational factors and sales prices of houses located in each suburb in the Western Melbourne Metropolitan area. Their results show that house location is the

[3] Centering or mean centering refers to the centering of the zero point. The grand mean or group mean is subtracted from the raw data and converted into a deviation score. According to Aiken and West (1991) and Kraemer and Blasey (2004), centering can address the issue of collinearity.

Table 1. Description of variables

Variable type	Variable	Definition	Expected symbol
Dependent variable	Repeat-sales price (ln*Price*)	Repeat-sales data of houses are sourced from the actual price registration system; estimations are performed using the natural logarithm of the grand sales price (in units of NT$10,000)	
Level 1 independent variable	Time of repeat-sales ($Time_{ti} - T$)	The baseline year is assigned as 2012, the year when the actual price registration scheme was first implemented; 2012 years are subtracted from the sales time of a house. ($Time_{ti} - T$) represents the difference between the repeat-sales year and the baseline year. The coefficient of this variable indicates the price growth rate and is expected to have a positive value	+
	$(Time_{ti} - T)^2$	The square of the variable ($Time_{ti} - T$) is taken as an indicator of the quadratic growth of house price and is expected to have a negative value	–
	House age (*Age*)	A continuous variable treated by grand mean centering; its coefficient is expected to have a negative value	–
	House age squared (Age^2)	The coefficient of the square of house age is expected to have a positive value	+
Level 2 independent variable	House area (*Area*)	House area is taken as the transferred area (living area) of a repeat-sales house based on the actual price registration system. House area is treated by grand mean centering; its coefficient is expected to have a positive value. A higher value for this variable indicates a higher grand price	+
	House type (*Type*)	House types include condominiums, luxury condominiums (buildings with 10 floors or less and equipped with elevators), and apartment buildings (those with 11 floors or more and equipped with elevators). Condominiums are the baseline house type, and two dummy variables are set. For the variable of *Type*1, a value of 1 is assigned to luxury condominiums, or 0 if otherwise; for the variable of *Type*2, a value of 1 is assigned to apartment buildings, or 0 if otherwise. Both variables are treated by grand mean centering, and their coefficients are expected to have positive values	+
	House location (*Location*)	The house locations are divided into the CBD and the suburbs based on the administrative districts of Kaohsiung City. The CBD consists of 13 districts–Fongshan, Renwu, Nanzi, Zuoying, Sanmin, Niaosong, Qianzhen, Xinxing, Lingya, Yancheng, Gushan, Qiaotou, and Qianjin. The suburbs consist of 12 districts–Qijin, Linyuan, Daliao, Dashu, Dashe, Gangshan, Yanchao, Alian, Xiaogang, Luzhu, Hunei, and Qieding. The suburbs are the baseline location, and a dummy variable (*Location*) is set. A value of 0 is assigned to the suburbs and 1 to the CBD. Location is treated by grand mean centering; its coefficient is expected to have a positive value	+

primary factor behind higher median house prices in the Western Melbourne Metropolitan area. For our study, 13 administrative districts in Kaohsiung City are designated as the city center (central business district, CBD), while 12 districts are designated as suburbs. Location is set as a dummy variable and treated by grand mean centering. For the variable Location, a value of 1 is assigned to the city center and 0 to the suburbs. The coefficient is expected to have a positive value.

3. Data sources and descriptive statistics of the sample

Kaoshiung City is located in the southwestern part of Taiwan and covers an area of 2952 km^2, making it the largest city by area pn the western coast of Taiwan. With a population of 2.76 million, it is currently the third most populous city in Taiwan. It is also home to the island's second largest international airport and the largest port (Kaohsiung Port). The economy of the city is centered on secondary and tertiary industries, which account for a substantial proportion of the city's gross product. The secondary industries include high tech, heavy industry, and the manufacturing sector. To date, the heavy industry is still a major secondary industry in Kaoshiung City. A map of Kaoshiung City is provided in Figure 2.[4,5]

[4] Figure 2 is adapted and revised from Wikipedia. https://zh.wikipedia.org/wiki/%E9%AB%98%E9%9B%84%E5%B8%82#/media/File:Population_density_map_of_Kaohsiung_(Dec_2009).svg. Last accessed: April 10, 2021.

[5] Contents and data sourced from and revised from Wikipedia. https://zh.wikipedia.org/wiki/%E9%AB%98%E9%9B%84%E5%B8%82. Last accessed: May 10, 2021.

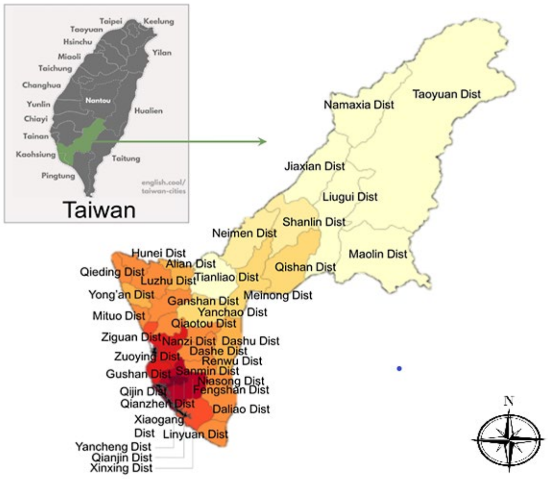

Figure 2. The administrative districts of Kaohsiung City

3.1. Description of data sources

This study analyzes repeat-sales house data, which is difficult to obtain directly because the addresses of repeat-sales houses are not publicly available in Taiwan. To obtain these data, we compared each house attribute to determine whether a house had undergone repeat-sales. We have referenced the method proposed by Yeh (2015), in which data pieces are screened to check if they have the same following attributes: the house address (30 house numbers are taken as the displayed address for a data piece), transferred land area, transferred building area, transferred floor number, initial total number of floors, and the year and month of building completion. To confirm a repeat-sales house, we first checked for data pieces that include the same house address, then compared the building area, land area, floor number, total number of floors, date of building completion, and building type. If the attributes had remained the same for two or more data pieces, with the only differences being the sales prices and sales date, then the data pieces were confirmed to be repeat-sales data.

The data were sourced from the Ministry of the Interior's actual price registration system for real estate properties. The data range spans from January 2012 to September 2020. A total of 302,643 pieces of data were collected. Maintaining the focus on houses, data pertaining to the sales of land, factories, offices, non-arm's length transactions, parking lots, and market stalls were omitted, leaving 206,431 pieces of data for comparison. Next, the repeat-sales data pieces from each administrative district were drawn with respect to their proportions. We used 7,076 Level 1 repeat-sales data pieces.

3.2. Description statistics of the sample

As shown in Table 2, there are 7,076 pieces of repeat-sales data (across 9 (*Time – T*) time points) in Level 1. As shown in Table 3, there are 3,167 pieces of house data in Level 2. In terms of the dependent variables, the 7,076 pieces of repeat-sales data are nested in the 3,167 house units. In terms of sales prices, the mean price of the 7,076 repeat-sales is NT$5,708.360, with a standard deviation (SD) of NT$4,679.260.

Regarding the Level 1 variables, the mean transferred house age is 16.750 years (SD = 12.754 years); the mean number of repeat-sales is 2.234, with a maximum of 9 and a minimum of 2. Regarding the Level 2 variables, the mean

Table 2. Descriptive statistics of the Level 1 variables (n = 7,076)

Variable	Mean	SD	Minimum	Maximum
Sales price (*Price*) (NT$, New Taiwan dollar)	5,708.360	4,679.260	48	5600
House age at the time of sales (*Age*)	16.750	12.754	–0.56[6]	51.02
Number of repeat-sales	2.234	–	2	9

Table 3. Descriptive statistics of the Level 2 data (n = 3,167)

Variable	Mean	Standard deviation	Minimum	Maximum
Transferred house area (*Area*)	125.079	60.879	14.12	610.89
House type (*Type*)	Number of data pieces		Percentage	
Condominiums	637		20.1	
Luxury condominiums	325		10.3	
Apartment buildings	2,205		69.6	
House location (*Location*)				
Suburbs	273		8.6	
CBD (Central Business District)	2,894		91.4	

[6] A negative value indicates the closing date of the pre-sale house.

transferred house area among the 3,167 pieces of data is 125.079 m^2 (SD = 60.879 m^2); houses located in the suburbs accounted for 8.6% (273 pieces) of the sample, while houses located in the CBD accounted for 91.4% (2,894 pieces) of the sample; condominiums, luxury condominiums, and apartment buildings accounted for 20.1% (637 pieces), 10.3% (325 pieces), and 69.6% (2,205), respectively.

In the same data period, there were 136,913 pieces of single sales data, and the mean house area was 134.48 m^2 while the mean house age was 19.95 years. In terms of house type, condominiums, luxury condominiums, and apartment buildings accounted for 19.3%, 9.1%, and 71.6%, respectively. In terms of location, houses in the suburbs accounted for 9.1% while houses in the CBD accounted for 90.9%. The house attribute statistics did not vary greatly between the two samples.

4. Empirical results and analysis

4.1. Null model

A null model was developed for this study to check for significant differences between the mean sales price of each house, as well as to examine the extent to which the variation in house prices is caused by variation between the houses. The estimation results obtained through HLM6.08 software are presented in Table 4.

As shown in Table 4, the estimated coefficient of the grand mean of the first sales price of each house (β_{00}) is 6.132 and attains a 1% level of significance. In terms of random effects, the variance in Level 2 derived from the restricted maximum likelihood approach is 0.428, with a chi-square value of 80,509; it attains a 1% level of significance. This suggests that the mean house prices differ significantly. To understand whether the empirical results can be estimated through the HLGM approach, we first computed the intraclass correlation coefficient (ICC). The ICC was determined to be 0.91648, indicating that the interclass variance and intraclass variance of the repeat-sales prices account for 91.65% and 8.35% of the total variance respectively. In other words, the variance between the sales prices of a single house at different sales times accounts for 8.35% of the total variance. Therefore, it is suitable to use the HLGM approach for subsequent analysis.

4.2. Non-randomly varying slope model

The empirical results of the non-randomly varying slope model are presented in Table 5. In terms of fixed effects, the estimated coefficient of the grand mean of the first sales price of each house (β_{00}) is 6.0497, attaining a 1% level of significance. The estimated coefficient of house area (β_{01}) is 0.0088, attaining a 1% level of significance, which suggests that every 1-m^2 increase in house area increases the sales price by 0.88% (converted using (e^{β} –1) hereafter). The estimated coefficients of the two house types (β_{02} and β_{03}) are 0.2395 and 0.4180, respectively, and both attain a 1% level of significance. This suggests that luxury condominiums and apartment buildings are 27.06% and 51.89% more expensive, respectively, than condominiums. The estimated coefficient of house location is 0.5478, attaining a 1% level of significance. This shows that houses in the CBD are 72.94% more expensive than those in the suburbs. Arribas et al. (2016) have demonstrated that, regardless of the regression model used for estimation, house attributes significantly affect sales prices. Therefore, the results of our study align with those of Arribas et al. (2016).

The estimated coefficient of the time of repeat-sales (β_{10}) is 0.0382, attaining a 1% level of significance. This shows that the price of a house has grown annually by 3.89% from 2012 onwards. The estimated coefficient of the time of repeat-sales squared (β_{20}) is –0.0035, attaining a 5% level of significance. This suggests that the curve of the quadratic growth of house prices in Kaohshiung City opens downward and that the growth rate of house prices gradually falls over time. In other words, an increase in the repeat-sales time increases the sales price of a house, and the margin diminishes with the sales time. In terms of moderating effects, the estimated interaction coefficient between house area and the time of repeat-sales (β_{11}) is –0.0005 and attains a 5% level of significance. The interaction coefficient between house area and the time of repeat-sales squared (β_{21}) is 0.0001, attaining a 1% level of significance. These findings indicate that an increase in house area reduces the growth rate of sales prices and that the quadratic growth gradually reduces over time. The estimated interaction coefficients between the two house types (*Type*1 and *Type*2) and the time of repeat-sales (β_{12}

Table 4. Analysis results of the null model

Fixed effects	Coefficient	Standard error	*t*-ratio	*p*-value
Grand mean of the first sales price of each house β_{00}	6.1317	0.0118	516.458	0.001***
Random effects	Variance	Degree of freedom	Chi-square	*p*-value
Level 2 τ_{00} Interclass variance	0.4282	3,166	80,509.915	0.001***
Level 1 σ^2 Intraclass variance	0.0394			
Deviance	7,354.474			
Number of estimated parameters	2			

Note: *** denotes $p < 0.01$. Standard errors are presented as robust standard errors.

and β_{13}) are 0.0049 and 0.0381, respectively, and do not attain a level of significance; the estimated interaction coefficients between the two house types and the time of repeat-sales squared (β_{22} and β_{23}) are 0.0002 and –0.0025, respectively, and also do not attain a level of significance. These findings indicate that the growth rate and quadratic growth (changes in the growth rate over time) of house prices are not moderated by house type. In other words, the annual growth in house prices do not differ by house types. The estimated interaction coefficient between house location and the time of repeat-sales (β_{14}) is –0.1335, attaining a 1% level of significance; the interaction coefficient between house area and the time of repeat-sales squared (β_{24}) is 0.0182, attaining a 5% level of significance. These findings indicate that the growth rate and quadratic growth (changes in the growth rate over time) of house prices are moderated by house location. Houses in the CBD have a lower growth rate than those in the suburbs. Melser (2017) has demonstrated that houses in suburbs have a higher price appreciation than houses in the city center. Locational differences will diminish the differences in the growth rates of house prices over time.

The estimated coefficient of house age (β_{30}) is –0.0211 and attains a 1% level of significance; the estimated coefficient of house age squared (β_{40}) is 0.0005 and attains a 1% level of significance. This shows that an increase in house age reduces the sales price, and that the decrease becomes more gradual with decreasing house age. Soltani et al. (2021) show that house age has the most substantial effect on sales prices, compared to other house attributes. Shimizu et al. (2010) concur that sales prices change over time and that such changes also vary continuously over time. Lyndsey et al. (2020) report that an increase in house age has diminishing effects on the sales prices of older houses and those suitable for redevelopment. In terms of moderating effects, the estimated interaction coefficient between house area and house age (β_{31}) is 0.0001, attaining a 1% level of significance; the interaction coefficient between house area and house age squared (β_{41}) is 0.000002, attaining a 10% level of significance. These findings indicate that an increase in house area and house age will reduce the decrease in sales prices, and that the depreciation in sales prices accelerates with increasing house age. The estimated interaction coefficients between *Type*1 houses and house age (β_{32}) and house age squared (β_{42}) are 0.0342 and –0.0008, attain levels of significance of 10% and 5%, respectively. This suggests that, compared to condominiums, the decrease in the prices of luxury condominiums is smaller when the house age is higher, while the rate of depreciation falls with an increasing house age. The estimated interaction coefficients between *Type*2 houses and house age (β_{33}) and house age squared (β_{43}) are 0.0278 and –0.0012, attaining levels of significance of 5% and 1%, respectively. This suggests that, compared to condominiums, the decrease in the prices of apartment buildings is smaller when the house age is higher, while the rate of depreciation falls with increasing house age. The estimated interaction coefficient between house location and house age (β_{34}) is 0.0279 and attains a 1% level of significance; the interaction coefficient between house location and house age squared (β_{44}) is –0.0008 and attains a 1% level of significance. These findings indicate that, compared to houses in suburbs, an increase in house age will reduce the decrease in the prices of houses in the CBD, while the depreciation diminishes with increasing house age. Xu et al. (2018) have found that the added value of older houses in Beijing between 2005 and 2012 stems from the land itself rather than buildings on the land, while the price growth rate and quadratic growth are affected by house location. Liou et al. (2016) report that, between 2004 and 2012, the annual quadratic growth of house prices in Taipei City was faster than that of houses in New Taipei City. These findings demonstrate that the quadratic growth of house prices is affected by house location.

In terms of random effects, π_{0i} is a Level 2 variable used to interpret π_{0i} based on the three Level 2 characteristics (i.e., house area, house type, and house location). r_{0i} is the error term with an estimated variance (τ_{00}) of 0.0727 that has a significance of 1%. Therefore, π_{0i} remains random even after controlling for the effects of the three Level 2 variables on house prices. In other words, other house attribute variables affect house prices.

We apply the HLGM approach to analyze repeat-sales data. Our empirical results suggest that the annual growth rate and quadratic growth of sales prices do not differ by house type. The effects of house age and the time of repeat-sales on sales prices are affected by house location and house area. Thus, the annual growth rate and quadratic growth of repeat-sales prices are affected by house location and house area. Controlling for the effects of the Level 2 variables (house area, house type, and house location) and a Level 1 variable (house age) on sales prices will reduce the random component of the initial price (π_{0i}).

Lastly, given that area is a continuous variable and its moderating effects cannot be plotted easily, and house type (*Type*1, *Type*2) did not significantly influence the relationship between the time variables and house price, we did not plot the effects of these variables. We only plotted the effects of house location on sales time and price; house type and location affected the relationship between house age and price (see Figures 3 to 5).

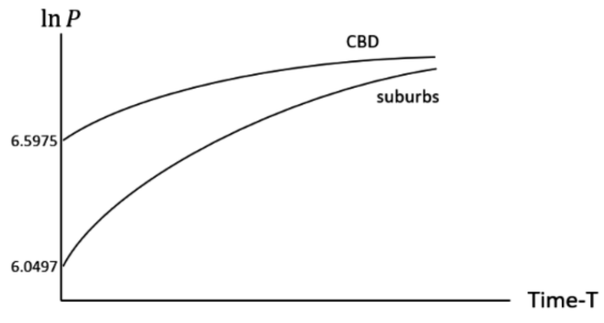

Figure 3. The moderating effects of house location on the relationship between house price and sales time

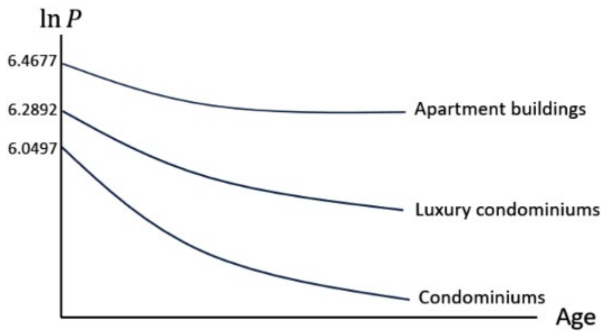

Figure 4. The moderating effects of house type on the relationship between house price and age

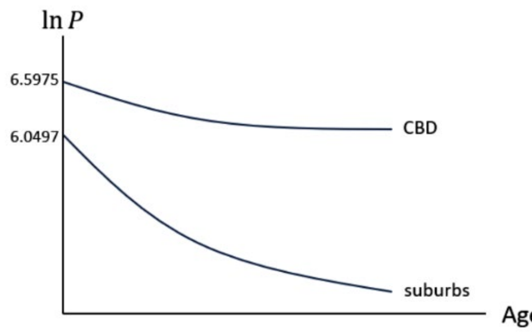

Figure 5. The confounding effects of house location on the relationship between house price and age

Table 5. Analysis results of the non-randomly varying slope model

Fixed effects	Coefficient	Standard error	t-ratio	p-value
Grand mean of the first sales price of each house β_{00}	6.0497	0.0186	325.730	0.001***
Area β_{01}	0.0088	0.0003	31.099	0.001***
*Type*1 β_{02}	0.2395	0.0907	2.641	0.009***
*Type*2 β_{03}	0.4180	0.0698	5.987	0.001***
Location β_{04}	0.5478	0.0571	9.591	0.001***
Time – T β_{10}	0.0382	0.0090	4.260	0.001***
Area β_{11}	–0.0005	0.0002	–2.222	0.026**
*Type*1 β_{12}	0.0049	0.0336	0.146	0.884
*Type*2 β_{13}	0.0381	0.0282	1.350	0.177
Location β_{14}	–0.1335	0.0436	–3.060	0.003***
$(Time - T)^2$ β_{20}	–0.0035	0.0014	–2.542	0.011**
Area β_{21}	0.0001	0.00004	3.358	0.001***
*Type*1 β_{22}	0.0020	0.0050	0.411	0.681
*Type*2 β_{23}	–0.0025	0.0042	–0.578	0.563
Location β_{24}	0.0182	0.0072	2.499	0.013**
Age β_{30}	–0.0211	0.0030	–7.090	0.001***
Area β_{31}	0.0001	0.00003	3.271	0.001***
*Type*1 β_{32}	0.0342	0.0179	1.910	0.056*
*Type*2 β_{33}	0.0278	0.0113	2.459	0.014**
Location β_{34}	0.0279	0.0052	5.286	0.001***
Age^2 β_{40}	0.0005	0.00007	6.925	0.001***
Area β_{41}	0.000002	0.000001	1.858	0.063*
*Type*1 β_{42}	–0.0008	0.0003	–2.450	0.015**
*Type*2 β_{43}	–0.0012	0.0002	–5.912	0.001***
Location β_{44}	–0.0008	0.0001	–5.247	0.001***

	Variance	Degree of freedom	Chi-square	p-value
Level 2 τ_{00} Interclass variance	0.0727	3,162	17,543.4250	0.001***
Level 1 σ^2 Intraclass variance	0.0369			
Deviance	2,305.7188			
Number of estimated parameters	2			

Note: *** denotes $p < 0.01$; ** denotes $p < 0.05$; * denotes $p < 0.1$. Standard errors are presented as robust standard errors.

Conclusions and recommendations

This study focuses on changes in the repeat-sales prices of houses over time in Kaohsiung City. The empirical results suggest that the HLGM approach is a feasible means of exploring house price changes. Notwithstanding the wide availability of other options, examining changes in the sales prices of houses over time through ANOVA can only reveal relative changes in the sales prices between houses; it is unable to directly estimate changes in the sales prices of houses. Moreover, ANOVA does not account for measurement errors–nor does it include variables at the aggregate level (Level 2) for estimation (Lee et al., 2013). Arribas et al. (2016) demonstrate that the variance of each coefficient in HLGM is always smaller than those in OLS. This is because the lower estimation efficiency of OLS will result in a higher variance than that from HLGM. Furthermore, HLGM can also calculate the interclass variance, as well as the ratio of the intraclass variance to the total variance (i.e., the ICC). OLS, on the other hand, can only derive the variance between the horizontal intraclass residuals. Not only is HLGM able to estimate changes in the growth curve of each housing transaction at different points in time, it can also examine the differences between individual-level data, which facilitates investigations into how house attributes affect changes in sales prices (Hsieh, 2015). After analyzing the advantages and drawbacks of each approach, showing that the HLGM approach is the appropriate method to examinine repeated observations in housing transactions over time. It can analyze the curves of the growth rate and quadratic growth of sales prices while elucidating how house attributes affect changes in the growth rate and quadratic growth of sales prices.

According to the empirical results of the null model, the interclass error attained significance, suggesting that major differences exist in the mean house prices in this study, with an ICC of 91.65%. This means that the differences in housing prices caused by different house attributes accounted for 91.65% of the variance in the repeat-sales data. The differences in housing prices of the same house caused by different sales periods accounted for 8.38% of the variance. This result cannot be obtained through a single-level repeat-sales model. The non-randomly varying slope model results indicate that the annual growth rate and quadratic growth of sales prices failed to attain significance in terms of the interaction coefficient between sales time and house type. This suggests that the effects of sales time on sales prices do not differ by house type. House area and house location moderate the effects of sales time on sales prices (i.e., both variables affect the growth rate and quadratic growth). The interaction coefficients between house area, house type, and house location are all significant, which implies that all three variables moderate the effects of house age on sales prices. This finding shows that in repeat-sales data, the growth rate and the changes in the growth rate of the price of the same house are influenced by house area and house location. This result cannot be obtained through a single-level repeat-sales model. The empirical evidence demonstrates that house attributes are an important factor and moderator of the dynamic changes in repeat-sale house prices.

The current repeat-sales approach suffers from conventional drawbacks, such as small sample sizes and sample selection bias (Guo et al., 2014). We recommend that future studies perform HLGM analyses using panel data-based analytical methods. From July 1, 2021, onwards, house numbers must be disclosed on the actual price registration system. This measure would assist future researchers in performing accurate validations and would reduce the need to compare and analyze repeat-sales data. Additionally, house price indices can be developed using the HLGM approach.

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