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THE IMPACTS OF THE QUALITY OF THE ENVIRONMENT AND NEIGHBOURHOOD AFFLUENCE ON HOUSING PRICES: A THREE-LEVEL HIERARCHICAL LINEAR MODEL APPROACH

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ABSTRACT

This paper employs a three-level hierarchical linear model (HLM) to examine the impacts that the quality of the environment and neighbourhood affluence have on housing prices. The empirical results suggest that there are significant variations in the average housing price for different neighbourhoods and administrative districts. The impact of building characteristics on housing prices is subject to the moderating effects of the characteristic variables of different levels. The quality of the environment mitigates the impact of age on the decline of housing prices, and neighbourhood affluence has a positive influence with regard to the impact of age on housing prices across different levels.

Keywords: Three-level hierarchical linear model, Housing prices, Random effects, Moderate effects, Satisfaction with the quality of environment, Neighbourhood affluence.

1. INTRODUCTION

Empirical studies have suggested that housing prices are subject to the influence of various neighborhood characteristics, such as the quality of nearby schools, the quality of the community environment, the development of neighboring lands, and the status of public utilities and infrastructure (Kearns and Parkes, 2003; Kong *et al.*, 2007; Zahirovic-Herbert and Turnbull, 2008; Kleinhans, 2009). Quigley (1985) has argued that the top priorities for consumers in their selections include the neighborhoods environment, public utilities, and services. Consumers first determine the suitability of a community environment and public facilities before they examine specific locations. Because all houses are part of a neighborhood, town and city, Raudenbush and Bryk (2002) state that the hierarchical data organized along those geographic levels has a "nested structure". To understand the influence of different geographic levels on housing prices, Kiel and Zabel (2008) developed the concept of 3Ls (location, location, and location) to estimate housing prices.[1]

Their research indicates that different geographic levels have significant influence on housing prices. The study shows that in addition to local community factors (neighbours, the quality of streets), residents also care about factors relating to the quality of the wider regions (e.g., the quality of schools and crime rates).

It is necessary to take into consideration the impact of different characteristics on housing prices due to the nested nature of housing price data. We argue that the use of a hierarchical linear model can take into account the characteristics of different levels to avoid the bias in estimations of hedonic prices that is seen in conventional approaches. Past studies have applied the hedonic price method and have used ordinary least-squares (OLS) to estimate the implied hedonic prices of houses. However, these approaches tend to ignore the hierarchical nature of housing prices and, hence, produce biased results. This is because housing price data mostly consists of multiple levels.[2]

Brown and Uyar (2004) applied a two-level hierarchical linear model (HLM) to explore the influence of residential building characteristics and neighborhoods characteristics on housing prices. “Areas” of buildings are defined as the analysis variable for the property level, i.e., the first level. “Time to downtown” is the analysis variable for the second level. The research suggests that in addition to having a direct influence on housing prices, neighborhoods characteristics also moderate the impact of building characteristics on housing prices. The shorter the commute time to downtown, the greater the influence of areas on housing prices becomes. On the other hand, the longer the commute time to downtown, the smaller the influence of areas on housing prices becomes. Brown and Uyar (2004) emphasize that that the use of an HLM model is able to classify variables into appropriate analysis units and avoid estimation biases and inference errors. Both the macro level and property level only have single prediction variables. With a focus on the moderate effects of neighbourhood characteristics on building characteristics, the model set-up is also more straightforward.

Lee (2009) applied a two-level HLM to investigate the influence of public facilities on housing prices. The empirical results indicate that the average housing prices among local cities and counties vary significantly. At the macro level, the explanatory power of the variable “convenience of life” with respect to the average housing price of all counties and cities reaches the 5% significance level.The influence of the satisfaction with convenience of life in different counties and cities on housing prices does make a significant difference. Lee *et al.* (2013) used the growth model in hierarchical linear modelling to discuss factors affecting the change in urban land prices in Taiwan over time. The empirical results indicated that urban land prices may increase over time, and the growth rate may slow as a result.

Beron *et al.* (1999) have applied a three-level hierarchical linear model (HLM) to probe the influence of air quality on the marginal willingness to pay (MWTP) for residential houses. Their study suggests that traditional regression models cannot capture the characteristics of geographic clustering. It is not possible to make estimations based on the assumption of independence and homogeneity. (Rather, it is deemed a violation of independent and identical distributions). The use of a hierarchical linear model can efffectively overcome this issue. However, their study did not apply a null model to validate whether the average housing price of different clusters are variant or not. Most importantly, a hierarchical linear model can simultaneously process the residuals of different levels in order to measure the influence of the variables of the individual levels and the variables of macro levels on outcome variables. This approach is able to calculate the explained variances of different levels on individual level outcome variables (Hofmann, 1997).

This paper applies a three-level hierarchical linear model (HLM) to estimate housing prices. Housing prices are subject to the influence of housing conditions (e.g. areas, ages and housing types), as well as to the impact of geographic characteristics of different levels (e.g. quality of villages and neighborhoods, the resources of administrative districts). This paper samples data from different administrative units in Taipei City and categorizes data into the following three levels[3]: property-level, village-level, and administrative-district-level. Given a lack of studies in housing research that apply three-level hierarchical linear models (HLM) to examine housing prices, this paper aims to be a pioneer.[4]

This paper refers to utilization areas, building ages and building types as the property-level characteristic variables (Level 1), satisfaction with the quality of environment (quality of the environment include air pollution, noise, sanitation, garbage removal and water quality) as the village-level characteristic variable (Level 2), and neighborhood affluence indexes as the administrative-district-level characteristic variable (Level 3). This paper examines the purely residential buildings in the 12 administrative districts of Taipei City, and it samples a total of 1,081 data entries for 65 villages. Each administrative-districts-level includes a number of villages. The division of the villages is based on the geographical environment, transportation, urban planning situation, population and other factors. The purpose is to gain an understanding of the influence of characteristic variables of different levels on housing prices and to validate the existence of cross-level moderate effects.

2. RESEARCH METHOD

2.1. Set-up of Empirical Models

We performed an analysis of housing prices with both a fully unconditional model and a conditional model. The set-up of these two models is as follows:

2.2. Fully Unconditional Model

A fully unconditional model is the simplest form of a three-level hierarchical model. In this model, none of the hierarchies is accompanied with predictor variables.

Level 1: Property-level

$$Y_{ijk} = \pi_{0jk} + \varepsilon_{ijk} \quad \varepsilon_{ijk} \sim N(0, \sigma^2) \tag{1}$$

Y_{ijk} = the i-th number of housing price in the j-th village of the k-th administrative district. π_{0jk} = the average housing price in the j-th village of the k-th administrative district.

ε_{ijk} = random property effect, i.e. the difference between the property price ijk and the average housing price.

Level 2: Village-level

$$\pi_{0jk} = \beta_{00k} + r_{ojk} \quad r_{ojk} \sim N(0, \tau_\pi) \tag{2}$$

β_{00k} = the average housing price of administrative district k.

r_{ojk} = random village effect, i.e. the difference between the property price in the village jk and the average housing price in the administrative district.

Level 3: Administrative-districts-level

$$\beta_{00k} = \gamma_{000} + u_{00k}, u_{00k} \sim N(0, \tau_\beta) \tag{3}$$

γ_{000} =Total average housing price

u_{00k} = random administrative-districts effect, i.e. the difference between the average housing price in the administrative district k and the total average housing price.

This straightforward three-level hierarchical model decomposes housing prices Y_{ijk} into three elements. These three elements are $\sigma^2 = Var(\varepsilon_{ijk})$, indicating the variance of average housing price in the same village; $\tau_\pi = Var(r_{ojk})$, indicating the variances of average housing price across different villages; and $\tau_\beta = Var(u_{00k})$, indicating the variances of average housing price across different administrative districts. The purpose is to measure the variances of average housing price in different levels (i.e. properties, villages and administrative districts). The model segments variances into levels in order to highlight the variances at each level. By using this approach, we can also ascertain whether there are variances in the averages of dependent variables in different levels.

When the variances τ_π and τ_β (for r_{ojk} and u_{00k}, respectively) become statistically significant, it implies that there are significant variances in average housing price across villages and administrative districts. The variances of three levels, i.e. σ^2, τ_π and τ_β, are incorporated into the calculation of the variances of the level as a percentage of total variances in order to understand the variances resultant from the property level, village level, and administrative-district level in the total variances of average housing price.

2.3. Conditional Model

The explanatory variables of Level 1 of this model are areas ($AREA$), building ages (AGE) and building types ($TYPE$). A total mean centralization is applied to the first two variables, and their intercepts and slopes are set up for random effects.[5]

Except for the coefficients for the property level (Level 1), the intercept and slope coefficients for both the village level and administrative-district level are added to the characteristic variables. The characteristic variable of the village level (Level 2) is the satisfaction with the quality of environment $\left(ENVI_{jk}\right)$, and that of the administrative-district level (Level 3) is neighbourhood affluence $\left(NEIG_k\right)$. The model set-up is as follows:

Level 1: Property-level

$$Y_{ijk} = \pi_{0jk} + \pi_{1jk} AREA_{ijk} + \pi_{2jk} AGE_{ijk} + \pi_{3jk} TYPE_{ijk} + \varepsilon_{ijk} \quad \varepsilon_{ijk} \sim N(0, \sigma^2) \tag{4}$$

Level 2: Village-level

$$\pi_{ljk} = \beta_{l0k} + \beta_{l1k} ENVI_{jk} + r_{ljk} \quad r_{ljk} \sim N(0, \tau_{\pi ll}), \quad l\text{=0,1,2} \tag{5}$$

$$\pi_{3jk} = \beta_{30k} + r_{3jk} \quad r_{3jk} \sim N(0, \tau_{\pi 33}) \tag{6}$$

Level 3: Administrative-districts-level

$$\beta_{l0k} = \gamma_{l00} + \gamma_{l01} NEIG_k + u_{l0k} \quad u_{l0k} \sim N(0, \tau_{\beta l0}), \quad l\text{=0,1,2} \tag{7}$$

$$\beta_{l1k} = \gamma_{l10} + \gamma_{l11} NEIG_k + u_{l1k} \quad u_{l1k} \sim N(0, \tau_{\beta l1}), \quad l\text{=0,1,2} \tag{8}$$

$$\beta_{30k} = \gamma_{300} + u_{30k} \quad u_{30k} \sim N(0, \tau_{\beta 30}) \tag{9}$$

If γ_{010} is statistically significant, it implies the existence of a significant influence of the administrative-district-level characteristic (i.e. neighbourhood affluence) on the property-level intercept. If γ_{011} is statistically significant, it means that there are moderate effects in the characteristic variables between the administrative-district level and the village level. The higher the satisfaction with the quality of environment, the higher the average housing price becomes. The higher the neighbourhood affluence scores, the higher the satisfaction with the quality of environment and the stronger its influence on the average housing price become. If γ_{010} and γ_{201} reach statistical significance, it means that the administrative-district-level characteristic variable has cross-level moderate effects on property-level explanatory variables. Namely, the higher the neighbourhood affluence, the more it is able to indirectly increase the influence of property-level variables on average housing price. If γ_{111} and γ_{211} reach statistical significance, it means that the administrative-district-level characteristic variable has moderate effects on the influence of village-level characteristics on average housing price that result from the characteristics of the property level.

Moreover, this paper attempts to estimate the random coefficient regression model. This model does not include the characteristic variables of the village and administrative-district levels. Rather, it only takes into account the influence of the explanatory variable of property level (Level 1) on dependent variables. When the variances of random errors become statistically significant, it implies that other characteristic variables are also causing the variances in average housing price. This model allows the freedom of movement of regression lines. Namely, there are no restrictions on intercepts or slopes. The absence of restrictions is a condition for homogeneity. The conditional model explains that the variances in average housing price are caused by variances of difference levels, not only by the characteristics of buildings alone. The characteristic variables of the village level and administrative-district level are also important considerations.

The traditional approach is to use OLS to make estimates in the hedonic price model. The model refers to housing prices as the dependent variables and defines a set of characteristics as the explanatory variables. The traditional model is constructed with three levels, i.e. property level, village level, and administrative-district level, which are as follows:

$$Y_{ijk} = \pi + \pi_1 AREA_{ijk} + \pi_2 AGE_{ijk} + \pi_3 TYPE_{ijk} + \varepsilon_{ijk} \quad \varepsilon_{ijk} \sim N(0, \sigma^2) \tag{10}$$

The symbols π, π_1, π_2 and π_3 indicate unknown parameters. Equation (10) omits the variables of the levels j and k. For each property, the characteristic of the village factor or any common factor simply vanishes from the model. Since the properties in the village level are correlated, equation (10) will produce biased results. Similarly, the administrative-district-level characteristic variable will also be lost, and as a result, there will be correlation errors in the administrative-district level. The addition of the village-level and administrative-district-level variables derives the following:

$$Y_{ijk} = \pi + \pi_1 AREA_{ijk} + \pi_2 AGE_{ijk} + \pi_3 TYPE_{ijk} + \beta ENVI_{ijk} + \gamma NEIG_{ijk} + \varepsilon_{ijk} \quad \varepsilon_{ijk} \sim N(0, \sigma^2) \tag{11}$$

Will this set-up appropriately eliminate the hypothesized correlation so as to avoid any geographic clustering? In fact, there is still correlation in high levels so it is not possible to make estimates on the assumption of independence and homogeneity (i.e., a violation of an independent and identical distribution). The application of a hierarchical linear model can effectively resolve this issue.

2.4. Data Processing and Variable Definitions

This paper sources data for analysis from the Year 2006 Survey of Residential Buildings by the Construction and Planning Agency, Ministry of the Interior, and the Statistical Abstract of Taipei City 2006. The property-level data (Level 1) and village-level data (Level 2) are sourced from the Year 2006 Survey of Residential Buildings by the Construction and Planning Agency, Ministry of the Interior. This paper examines the purely residential buildings in the 12 administrative districts of Taipei City, and it samples a total of 1,081 data entries for 65 villages. The administrative-level data (Level 3) is sourced from both the Year 2006 Survey of Residential Buildings by the Construction and Planning Agency, Ministry of the Interior, and the Statistical Abstract of Taipei City 2006.

The defining characteristic of the village level (Level 2) is satisfaction with the quality of environment. It is the contextual variable aggregated with the satisfaction of individual residents into the satisfaction of village residents. It includes satisfaction with environmental issues, e.g., air pollution, noise, environmental hygiene, garbage removal and drinking water quality. The satisfaction with the quality of environment is measured with the five-point Likert scale. The higher the score, the greater the satisfaction.

Before the HLM analysis, it is necessary to examine the appropriateness of the aggregation of individual variables into a macro variable (i.e. the satisfaction of individual residents into the satisfaction of a village as a whole). The presence of intra-group consistency is an indicator of the appropriateness of intra-group data aggregation. It is necessary to assess the reliability first. This paper refers to r_{wg} (James *et al.*, 1993) to validate the appropriateness of data aggregation. The closer r_{wg} is to 1., the higher the consistency. If r_{wg} is greater than 0.7, the data is suitable for aggregations (James *et al.*, 1993).[6]

The average value of the satisfaction with the quality of environment in this paper stands at 0.86 (between 0.69 and 0.96), indicating that it is appropriate to aggregate individual values into an overall value. Meanwhile, to validate the reliability of the levels of inter-group variances and aggregations, Klein *et al.* (1994) have argued that in the presence of homogeneity in high-level units, inter-group variances should be significantly greater than intra-group variances. This paper follows the suggestion of Bliese (2000) by referring to intra-class correlation coefficients (ICC_S) to illustrate the effectiveness of aggregating individual numbers into a macro variable.[7]

The result shows that ICC_1 for the satisfaction with the quality of environment is 0.11 (F =11.053, p <0.001). This indicates significant inter-group variances. Glick (1985) has suggested that a value of higher than 0.60 for ICC_2 is appropriate. In this paper, ICC_2 for the satisfaction with the quality of environment is 0.90, indicating a good intra-group reliability and validity of aggregations. Below are the definitions of selected variables.

(1) Property-level explanatory variables

The symbol Y_{ijk} is the natural logarithm of actual transaction prices for residential houses and is expressed in the unit of NT$10,000. Areas as a variable ($\mathrm{AREA}_{\mathrm{ijk}}$) is the natural logarithm of indoor living areas and is expressed in the unit of pings (1ping equals 35.58 sq. ft.). Lin and Ma (2007), Brasington and Hite (2008) and Poudyal *et al.* (2009) proved that areas have significant influence on housing prices. The larger the area, the higher the price becomes. This paper expects the variable "areas" has a positive influence on housing prices. The third variable in the property level are the ages of buildings (AGE_{ijk}), defined as the natural logarithm of the year-age from the construction completion to the year of 2006. Lin (2004), Martins-Filho and Bin (2005), Brasington and Hite (2008) and Poudyal *et al.* (2009) have suggested that the variable "building ages" reports significant influence on housing prices. Since buildings depreciate over time, the older the age, the lower the price should be. This paper expects building ages to have a negative impact on building prices. The fourth variable in the property level is building types ($TYPE_{ijk}$). This paper applies dummy variables in the discussion of building types. Congregate housing is defined as 1, others as 0 (e.g. traditional farm houses, detached residential buildings, twin-houses, undetached houses and others). The empirical study by Lin and Ma (2007) indicates that the variable "building types" has significant influence on housing prices. Lin and Lin (1993) have argued that the complexity in building types and purposes in Taiwan makes it impossible for the impact of residential building characteristics to meet the expected results. This paper does not expect any variances between the prices of aggregate housing and other residential buildings.

(2) Village-level characteristic factors: satisfaction with the quality of environment

Both external environmental factors and also the satisfaction of local residents with neighboring environment have an impact on housing prices.[8] Lin and Lin (1993) examined the influence of the satisfaction of individuals with the quality of environment on the levels of housing prices and rents. Rehdanza and Maddisonb (2008) applied the hedonic price method to investigate whether the perceptions of local residents in Germany regarding air and noise pollutions are included in housing prices. The result shows that the satisfaction of residents with the quality of their environment is not formulated into housing prices. In other words, the satisfaction with the quality of environment does not have a direct influence on housing prices. This paper follows the methods developed by both Rehdanza and Maddisonb (2008) and Lin and Lin (1993) to examine whether the levels of satisfaction of individuals with the quality of environment are reflected in housing prices.

This paper refers to the satisfaction of village residents as a whole with the quality of environment as the characteristic variable in the village level. In other words, all the buildings in the same village share the same environmental quality. It is expected that a high level of satisfaction is reflected in the average housing price by an increasing price (Lin and Lin, 1993; Rehdanza and Maddisonb, 2008).

(3) Administrative-districts-level characteristic factors: neighbourhood affluence

Uyar and Brown (2007) have examined the influence of neighbourhood affluence on housing prices. Their construction of an affluence index is based on the concept of a deprivation index.[9] They refer to the methods developed by Suny Downstate Medical Center (2004) and Gener and Raudenbush (1991) to aggregate the standardized Z values of the selected variables. The aggregation is then used as the comprehensive indicator of neighbourhoods. The higher the neighbourhood affluence index, the better off financially the neighbourhood in question. The index consists of the following six economic and social variables: the percentage of home ownership, the percentage of white people in the total population, the percentage of residents above the poverty line, the percentage of residents above 25 years of age having received higher education, the median of downtown family incomes and the median of housing prices. Their paper applies a cross-classified random hierarchical linear model to explore the influence of neighbourhood affluence conditions of different administrative districts and the average student grades in different school districts on housing prices. Their finding suggests that the greater the neighbourhood affluence, the higher the housing price. In other words, neighbourhood affluence has moderate effects on the average housing price of the employment centers concerned. This paper follows the method developed by Uyar and Brown (2007) to construct an index of neighbourhood affluence for the estimation of housing prices.

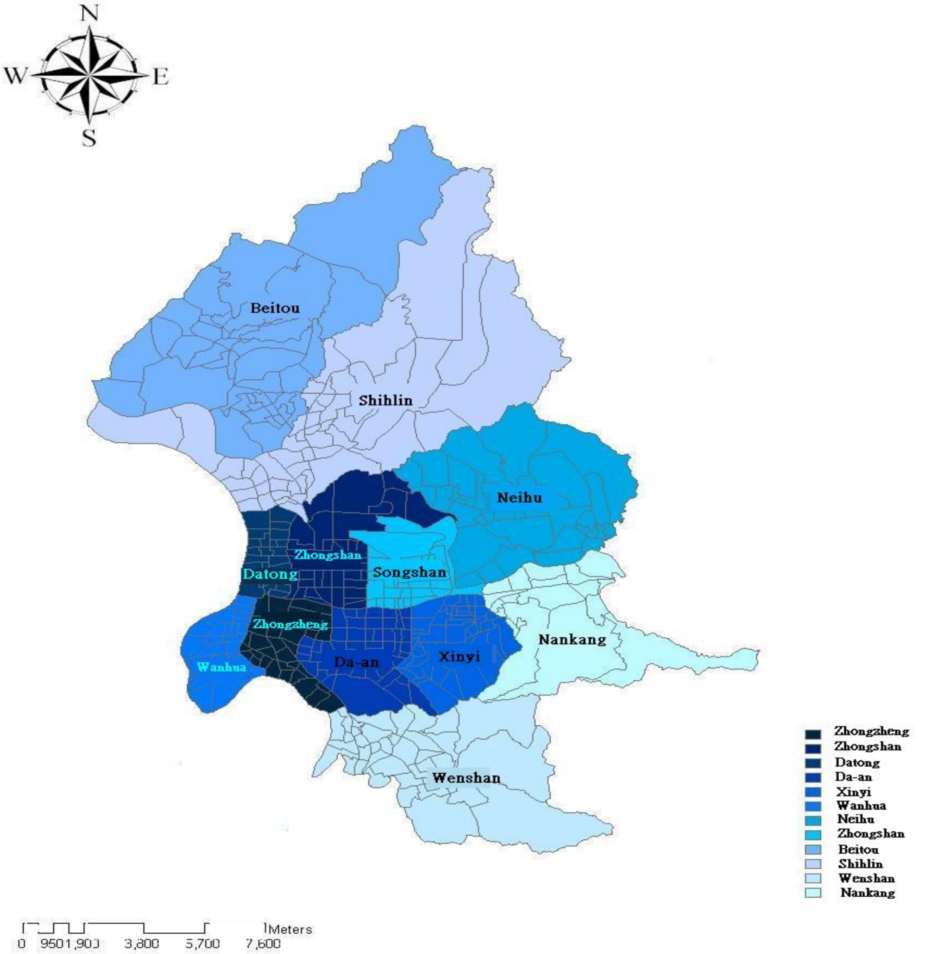
The neighbourhood affluence index, $NEIG_k$, consists of the following four variables: the median of the housing prices of different administrative districts, the average ratio of teachers to students in junior high schools, the percentage of practicing medical professionals in each square kilometer and the percentage of residents having received higher education. The data for these four variables is segmented by administrative districts of Taipei City. The residential buildings in the same administrative district share the same resources and conditions. The median of the housing prices in respective administrative districts is a reflection of the mainstream pricing ranges and the market conditions of the districts concerned. The average ratio of teachers to students in junior high schools is an indicator of the educational resources. The higher the ratio, the more teachers are available to each student in junior high schools. The percentage of practicing medical professionals per square kilometer is an indicator of medical resources. The higher the percentage, the more medical professionals and resources are available to each resident. The percentage of residents having received higher education is indicative of the population mix. The higher the average educational levels, the higher the incomes become. Also, a rich and highly educated population has higher standards with respect to the quality of life. The neighbourhood affluence index, $NEIG_k$, is calculated with standardized Z values and the aggregation of these four variables.[10] The higher the NEIG_k, the better neighbourhood conditions become and the higher average housing prices are expected to be (Uyar and Brown, 2007).

Table1 shows the neighbourhood affluence indexes of respective administrative districts. The most affluent district is Zhongzheng District (a score of 4.60), followed by Zhongshan District (a score of 3.35), and Datong District (a score of 3.00). The worst-off districts are Shihlin District (a score of -2.75), Wenshan District (-2.78), and Nankang District (-3.59). Figure 1 illustrates the distribution of wealth across administrative districts of Taipei. The darker the color, the more affluent it is. Table 2 lists the description of the variables in different levels in the hierarchical linear model.

Table-1. Neighborhood Affluence Indexes in Different Administrative Districts

ID1 Songshan	**ID2 Xinyi**	**ID3 Da-an**	**ID4 Zhongshan**	**ID5Zhongzheng**	**ID6 Datong**
-1.53	0.62	2.53	3.35	4.60	3.00
ID7Wanhua	ID8Wenshan	ID9 Nankang	ID10 Neihu	ID11 Shihlin	ID12 Beitou
0.23	-2.78	-3.59	-1.02	-2.75	-2.67

Figure-1. Neighborhood Affluence Distributions of Administrative Districts in Taipei City



The Lines Indicate Borders between Villages in the Same Administrative Districts.

Table-2. Descriptions of Variables in Respective Levels in the Hierarchical Linear Model

Hierarchical Variables	Variable Names	Variable Descriptions	Expected Outcomes
Independent variables	Y_{ijk}	Natural logarithms for housing prices	
Property-level	$AREA_{ijk}$	Natural logarithms for indoor living areas (including balconies) and expressed in the unit of pings (1 ping=35.58 square feet)	+
	AGE_{ijk}	Natural logarithms of the building ages since construction completion to the year of 2006	-
	$TYPE_{ijk}$	Dummy variables for housing types. Congregate housing is defined as 1, other types of housing as 0 (e.g. traditional farm houses, detached buildings, twin houses and undetached houses)	+/-
Village-level	$ENVI_{jk}$	Average satisfaction with the quality of environment for the village as a whole	+
Administrative- districts-level	$NEIG_k$	Composed of four variables,i.e. the median of the housing prices of different administrative districts, the average ratio of teachers to students in junior high schools, the percentage of practicing medical professionals in each square kilometer, and the percentage of residents having received a higher education	+

3. EMPIRICAL RESULTS AND ANALYSIS

3.1. Description of Sample Statistics

Table 3 shows that the average housing price in Taipei City stands at NT$4,878,500 (at an exchange rate of NTD/USD at 32 in December 2009), with a standard deviation of NT$103,800. The average area per unit is 32.14 pings, with a standard deviation of 1.40 pings. The average building age is 21.54, with a standard deviation of 1.75 years. Housing prices and building ages are negatively correlated. The older the houses, the lower the prices are. Housing prices and areas are positively correlated. The larger the area, the higher the prices are. Housing prices and the satisfaction with the quality of environment are positively correlated. The higher the satisfaction, the higher the average housing prices become. Furthermore, housing prices and neighbourhood affluence indexes are positively correlated. The better-off a neighbourhood is, the higher the housing prices become.

Table-3. Basic Descriptive Statistics and Coefficients of Correlation

	Mean	S.d.	Y_{ijk}	$NEIG_k$	$ENVI_{jk}$	$AREA_{ijk}$	AGE_{ijk}	$TYPE_{ijk}$
Y_{ijk}	487.85	10.38	1					
$NEIG_k$	-0.27	2.53	0.14^{**}	1				
$ENVI_{jk}$	3.74	0.78	0.06^{**}	0.03	1			
$AREA_{ijk}$	32.14	4.06	0.38^{**}	0.02	0.03	1		
AGE_{ijk}	21.54	5.75	-0.17^{**}	-0.02	-0.16^{**}	0.00	1	
$TYPE_{ijk}$	0.69	0.46	-0.26^{**}	0.21^{**}	0.05	-0.15^{**}	-0.03	1

Note: “*“ indicates p<0.1, “**“indicates p<0.05, “***“indicates p<0.01

3.2. Empirical Result Analysis in Hierarchical Linear Model

Fully Unconditional Model (Null Model)

This paper combines all the three levels into a fully unconditional model to examine the variances in the influence of factors in different levels on the average housing price in Taipei City. The fixed effect γ_{000} shown in Table 4 represents the mean of all the average housing price, estimated at NT$4,903,900 ($e^{6.1952}$ =NT$4,903,900). As far as random effects are concerned, the estimated variance for r_{ojk} is0.0859, with χ^2 statistics of 172.232 and a degree of freedom at 53, reaching the 1% significance level. The estimated variance for u_{00k} is0.0424, with χ^2 statistics of 33.490 and a degree of freedom at 11, reaching the 1% significance level. These results indicate that there are significant variances in the average housing price across villages and administrative districts.

This paper examines the degrees of variances in the average housing price of different levels. The variances of the average housing price in villages account for 82.41% (0.6010 / (0.6010 + 0.0859 + 0.0424) = 0.8241), an indication that the average housing prices are most subject to the variances of the property-level characteristics. The variances resultant from the village-level characteristic account for 11.78% (0.0859 / (0.6010 + 0.0859 + 0.0424) = 0.1178) and those resultant from the administrative-district-level characteristic account for 5.81% (0.0424 / (0.6010 + 0.0859 + 0.0424) = 0.0581). Cohen (1988) sets out the criteria for intra-class correlation coefficients (ICCs). If 0.059 > ρ >0.01, it is a low-level correlation. If 0.138 > ρ > 0.059, it is a medium-level correlation. If $\rho \geq$ 0.138, it is a high-level correlation. This paper finds that the variances in housing prices caused by the village-level characteristics are of medium-level correlation. The variances that resulted from the administrative-level characteristics are close to a low-level correlation. Therefore, it is appropriate for this paper to perform the analysis in a three-level hierarchy.

Table-4. Null Model for the Property Level, Village Level and Administrative-District Level

Fixed Effect	**Coefficient**	**se**	**t Ratio**	***p* Value**
Average housing price mean γ_{000}	6.1952***	0.0754	82.153	0.000
Random Effect	Variance Component	*df*	χ^2	*p* Value
Property (level 1) ε_{ijk}	0.6010			
Village (level 2) r_{0jk}	0.0859***	53	172.232	0.000
Administrative District (level 3) u_{00k}	0.0424***	11	33.490	0.001
Deviance	2606.3318			
Number of estimated parameters	4			

Note: "*" indicates p<0.1, "**"indicates p<0.05, "***"indicates p<0.01

3.3. Conditional Model

According to Table 5, the difference between Model 1 and Model 2 is that there are no explanatory variables in Levels 2 and 3 of Model 2. As far as random effects are concerned, Model

2 (a random coefficient model) shows that when the property-level characteristics, i.e. areas, building ages, and building types are controlled, the variance in the errors of Level 1 is reduced from the 0.601 in the null model to 0.495. There are significant variances in the average housing price across villages and administrative districts (γ_{0jk} =0.0891, χ^2 =57.021, df =37; u_{00k} =0.0442, χ^2 =18.867, df =11). The village level (Level 2) and the administrative-district level (Level 3) of Model 1 are added with characteristic variables to explain such variances. Also, in the estimates for the slope variances in the village level, the correlation between building ages, housing types, and average housing price are significant across different villages (r_{2jk} =0.0409, χ^2 =75.471, df =37; r_{3jk} =0.0538, χ^2 =49.737, df =37). This shows that the influence of building ages and building types on housing prices are different due to village-level characteristics. According to the estimated slope variances in the administrative-district level, there are significant variances in the correlation between building ages and average housing price (u_{20k} =0.0210, χ^2 =17.956, df =11). This means that the influence of building ages on the average housing price in different administrative districts is different due to the characteristic variable in the administrative-district level. This paper gains a further understanding of the variances in the average housing price in the village level and building age coefficients across administrative districts. Approx. 33.2% (0.0442/(0.0891+0.0442)) variances in the average housing price in the village level exist across different administrative districts. The estimated variances for r_{1jk} , u_{10k} and u_{30k} in the random coefficient model are not statistically significant. Therefore, there is no random term for the corresponding term in Model 1. After the incorporation of characteristic variables in Level 2 and Level 3 in Model 2, the variance of r_{0jk} increases, while the variance of u_{00k} drops by 77.6%((0.0442-0.0099)/0.0442). These numbers demonstrate the importance of neighbourhood affluence. Another important aspect of model specification and testing is examining how closely the model fits the data. The deviance is a measure of the lack of fit between the data and the model. Although the deviance for any one model cannot be interpreted directly, it can be used to compare multiple models to one another. The difference of the deviances from each model are distributed as a Chi-square statistic with degrees of freedom equal to the difference in the number of parameters estimated in each model.[11]

This paper then compares the goodness-of-fit of Model 2 and the null model. The Chi-square of the deviances of these two model is 193.25, with a degree of freedom at 21 (25-4), reaching the 1% significance level. This shows that the goodness-of-fit of the estimates of Model 2 (as a random coefficient model) is superior to that of the null model. As far as the goodness-of-fit for Model 1 and Model 2, the Chi-square of the deviances of these two models is 15.53, with a degree of freedom at 5 (30-25), reaching the 1% significance level. This shows that the goodness-of-fit of Model 1 is superior to that of Model 2. This paper also compares the OLS and HLM estimates. The OLS estimates find no error terms in either Level 2 or Level 3. The variance of the error term in Level 1 is estimated to be 0.5754, higher than the estimates produced by Model 1 and Model 2. There are slight differences in the estimated coefficients. The levels of significance of the estimated coefficients are similar. As far as the goodness-of-fit for Model 1 and OLS, the Chi-square of the deviances of these two model is 72.8, with a degree of freedom at 16 (30-14), reaching the 1% significance level. This shows that the goodness-of-fit of Model 1 is superior to that of the OLS estimates. Finally, this paper uses Model 1 to perform the empirical analysis.

According to the fixed effects shown in Table 5, areas and building ages have significant influence on the average housing price (γ_{100} =0.8274, t =11.695, the average housing price at NT$4,878,500, the average area at 32.14 pings, 0.8274 equal to approx. NT$125,600; γ_{200} =-0.2300, t =-4.200, the average housing price at NT$4,878,850, the average building age at 21.54 years old,0.2300 equal to approx. NT$52,100). This means an addition of each ping in area can increase the housing price by NT$125,600. The increase of one year in age reduces the housing price by NT$52,100. If the neighbourhood affluence index is included in Level 3, the assessment of the satisfaction with the quality of environment by village residents cannot directly be reflected in the form of changes to the average housing prices. However, the satisfaction with the quality of environment still reports positive moderate effects (γ_{210} =0.1517, t =2.296). This means the satisfaction with the quality of environment can mitigate the decline of housing prices that result from building ages. In other words, it slows down the depreciation of housing prices. An extra year in the building age means a reduction of the housing price by NT$52,100. However, in the village with a better living environment, an extra year in the building age means the reduction is less than NT$52,100. Even if the houses are old, they remain in demand if the surrounding environment is in a good quality. Rehdanza and Maddisonb (2008) used the hedonic price method to examine whether the perceptions of residents regarding air and noise pollutions are capitalized into housing prices. Their study suggested that the satisfaction with the quality of environment is not capitalized into housing prices. In other words, the satisfaction with the quality of environment does not report any direct influence on housing prices. This finding is similar with the conclusion of this paper that the satisfaction with the quality of environment is not directly reflected in the form of changes to average housing price. However, as this paper does not apply the HLM to make estimates, it is not possible to discuss cross-level moderate effects.

As a characteristic in the administrative-district level, the neighbourhood affluence index has a direct impact on housing prices (γ_{001} =0.0483, t =2.672, approximate NT$10,500), as well as cross-level positive moderate effects on the influence of housing prices in the property level on housing prices (γ_{201} =0.0608, t =2.824). In other words, the more affluent a neighbourhood is, the more such affluence is able to mitigate the influence of building ages on housing prices and reduces the rate of depreciation of housing prices. On average, an increase of one year in the building age means a reduction of housing prices by NT$52,100. However, in an affluent neighbourhood, an increase of one year in the building age sees a reduction in housing prices of less than NT$52,100. Namely, in terms of the influence on housing prices, the cross-level positive moderate effects of the neighbourhood affluence index at the administrative-district level on the building ages in the property level are stronger than the moderate effects of the environmental quality at the village level. Neighbourhood affluence not only directly affect the levels of housing prices, it also moderates the negative influence of building ages on housing prices. This indicates a strong emphasis on neighbourhood affluence in the housing market.

The neighbourhood affluence index of the administrative-district-level characteristic has negative moderating effects (γ_{211} =-0.0619, t =-2.492) on the property-level characteristic of building age due to the satisfaction with the village-level characteristic of environmental quality. This shows that the more affluent a neighbourhood is, the higher the satisfaction with the quality of environment and the faster the depreciation speed of average housing price. High satisfaction with the quality of environment reports positive moderating effects. However, the more affluent a neighbourhood is, the weaker these positive moderate effects become. Uyar and Brown (2007) have found that the more affluent a neighbourhood is, the faster buildings depreciate. This implies that the more affluent a neighbourhood is, the more interested developers are and the larger the volume of new units that are constructed. This is why the old houses in an affluent neighbourhood appreciate much faster than their counterparts in other less affluent areas. Figure 2 shows the moderating effects of this model.

As far as random effects are concerned, the variances of the average housing price in the village level (Level 2) reach the 1% significance level (r_{0jk} =0.1046, χ^2 =83.809, df =25), an indication that there are other important characteristics not factored into the consideration. Due to the limitations of sourced data, this paper measures the quality of environment with the subjective evaluations of residents. This may be one reason for the outcomes. The random variances of the building ages and building types in the village level reach the significance levels of 1% and 5%, respectively (r_{2jk} =0.0300, χ^2 =57.585, df =25; r_{3jk} =0.0616, χ^2 =69.852, df =48), an indication of varying influences of building ages and building types on the average housing price, given the variances in the village-level characteristic variables. The variances of the average housing price in the administrative-district level (Level 3) do not reach the 5% significance level (u_{00k} =0.0099, χ^2 =13.108, df =10). This shows that there are no variances in the average housing price across administrative districts after the neighbourhood affluence index has been incorporated into one of the explanatory variables. The random variances of building ages in the administrative-district level do not reach any statistical significance (u_{20k} =0.0027, χ^2 =6.938, df =10). In other words, the building age coefficient becomes non-random in the administrative-district level with the neighbourhood affluence as an explanatory variable.

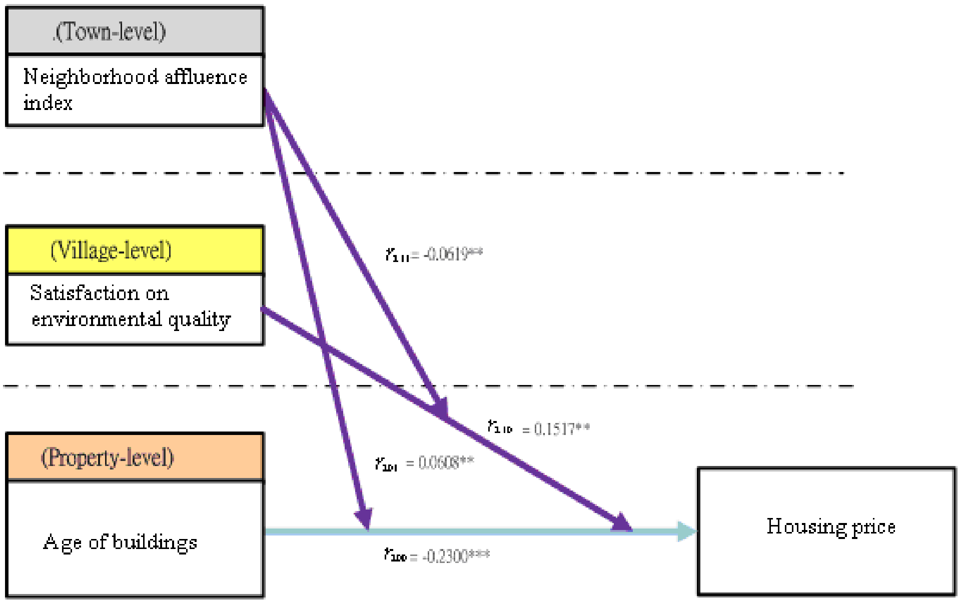
Table-5. Empirical Result Analysis

				Model 1		**Model 2**		**OLS**	
Fixed Effect				**Coe.**	**t Ratio**	**Coe.**	**t Ratio**	**Coe.**	**t Ratio**
Average housing price mean			γ_{000}	6.1242***	86.087	6.0886***	67.530	6.2075***	142.906
		$NEIG_k$	γ_{001}	0.0483**	2.672			0.0380***	3.894
	$ENVI_{jk}$	Intercept	γ_{010}	0.0249	0.467			0.0494	1.541
		$NEIG_k$	γ_{011}	0.0001	0.001			0.0010	0.075
$AREA_{ijk}$		Intercept	γ_{100}	0.8274***	11.695	0.8075***	8.698	0.9142***	12.984
		$NEIG_k$	γ_{101}	0.0203	0.824			0.0029	0.119
	$ENVI_{jk}$	Intercept	γ_{110}	-0.0432	-0.418			0.0260	0.261
		$NEIG_k$	γ_{111}	0.0308	0.883			0.0306	0.919
AGE_{ijk}		Intercept	γ_{200}	-0.2300***	-4.200	-0.2568***	-3.851	-0.241***	-4.969
		$NEIG_k$	γ_{201}	0.0608**	2.824			0.0467**	2.381

$ENVI_{jk}$	Intercept	γ_{210}	0.1517**	2.296			0.1429**	2.369
	$NEIG_k$	γ_{211}	-0.0619**	-2.492			-0.067***	-2.991
$TYPE_{ijk}$	Intercept	γ_{300}	0.0925	1.369	0.1535*	1.901	-0.0183	-0.350
Random Effect			*Variance Component*	χ^2	*Variance Component*	χ^2	*Variance Component*	χ^2
Property (level 1)		ε_{ijk}	0.4943		0.4947		0.5754	
Village (level 2)		r_{0jk}	0.1046***	83.809	0.0891**	57.021		
		r_{1jk}			0.0093	36.680		
		r_{2jk}	0.0300***	57.585	0.0409***	75.471		
		r_{3jk}	0.0616**	69.852	0.0538*	49.737		
Town (level 3)		u_{00k}	0.0099	13.108	0.0442*	18.867		
		u_{01k}	0.0021	8.640				
		u_{10k}			0.0382	17.149		
		u_{11k}						
		u_{20k}	0.0027	6.938	0.0210*	17.956		
		u_{21k}	0.00004	14.217				
		u_{30k}			0.0202	15.049		
Deviance			2397.556		2413.084		2470.339	
Number of estimated parameters			30		25		14	

Note: "*" indicates p<0.1, "**" indicates p<0.05, "***" indicates p<0.01

Figure-2. Moderate Effects of Neighborhood Affluence and Satisfaction with the Quality of Environment



3.4. Conclusions and Suggestions

This paper applies a three-level hierarchical linear model (HLM) to examine whether the satisfaction with the quality of environment can be capitalized into housing prices and to investigate whether there are cross-level moderate effects. The results show that there are indeed significant variances in the average housing price across villages and administrative districts of Taipei City. Furthermore, the influence of the property-level characteristics on the average housing price of different villages and administrative districts are not necessarily the same. In other words, such influence is not homogeneous.

The research findings indicate that the satisfaction with environmental quality does not have a direct impact on average housing price. However, it has indirect and moderate effects on the influence of property-level characteristics on average housing price. As far as neighbourhood affluence is concerned, it has a direct impact on the average housing prices. Neighbourhood affluence has moderate effects on the average housing price. Neighbourhood affluence reports moderate effects on the influence of the satisfaction with the quality of environment as a characteristic at the village level on the average housing price that result from building ages as a property-level characteristic. Moreover, it also has cross-level moderate effects on the influence of building ages as a property-level characteristic on average housing price.

Uyar and Brown (2007) have examined the influence of neighbourhood affluence on housing prices. The index consists of the following six economic and social variables: the percentage of home ownership, the percentage of white people in the total population, the percentage of residents above the poverty line, the percentage of residents above 25 years old having received higher education, the medium of downtown family incomes, and the median of housing prices. The neighbourhood affluence index ($NEIG_k$) in this paper consists of the following four variables: the median housing prices of different administrative districts, the average ratio of teachers to students in junior high schools, the percentage of practicing medical professionals in each square kilometer, and the percentage of residents who have received higher education. We suggest that follow-up studies should make modifications to the social and economic variables selected in this paper. The empirical results of this paper find that some important characteristic variables are not factored in. Follow-up studies are advised to estimate housing prices by referring to different characteristic variables. Finally, Uyar and Brown (2007) have argued that residential buildings are not only nested into villages, but also into school districts. Namely, housing prices are subject to the cross influence of village-level characteristic variables and school-district-level quality factors. However, this paper does not apply a cross-classified random effect model to examine housing prices due to insufficient raw data. We suggest that follow-up studies can source the data of housing prices based on street numbers and the data in the GIS system to segment the raw data into different characteristics to produce better findings. The relation between student grades and class status in Taiwan should be noted.

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[1] Kiel andZabel (2008) used the hedonic price model to estimate the influence of 3Ls on housing prices. Metropolitan statistical areas (MSAs) are defined as a dummy variable. Standard metropolitan statistical areas (SMSAs) are assigned as 1, the others as 0. The town-level variables include the median of the number of bedrooms, poverty rates, unemployment rates, the percentages of commuting time for consensus population less than 20 minutes and between 20 and 40 minutes. Street-level variables are the natural logarithms of the long-term incomes of residents, the natural logarithms of the median ages of residents, the percentage of residents above 25 years old that have received higher education, the number of transactions on the same houses during the past five years, and empty house rates.

[2]The conventional approach of Hedonic pricing ignores the hierarchical characteristics of data by placing characteristic factors of different levels into a single level; hence, they tend to produce aggregation biases, misetimated standard errors and the heterogeneity of regressions (Raudenbush and Bryk, 2002). A hierarchical linear model is able to estimate the characteristic factors of different levels in their respective levels in order to avoid estimate biases.

[3]The measurements used by past studies on neighbourhoods and communities are not necessarily the same. Orford (2000) used postcodes as the measurement units to examine the residential housing markets. However, postcodes cannot fully reflect the cultural backgrounds or characteristics of particular neighbourhoods. Meanwhile, postcodes are nothing but a convenient classification for postal operations. They are not an appropriate measurement unit for neighbourhoods (Wen and Christakis, 2005).

[4]Three-level hierarchical linear models are used in the studies in education and psychology. BrykandRaudenbush (1988) examine whether students' grades are subject to the influence of differences in social and economic statuses of their families and school characteristics. Willson,Shuey, and Elder (2003) explored the ambivalence of married couples who reside with their own parents (families) and parents-in-law (and their families).

[5] TabachbickandFidell (2001) have suggested that centralization can mitigate the problems associated with the multicollinearity of explanatory variables. Kreftand de Leeuw (1998) have indicated that centralization can convert divisions into deviation forms, but it does not affect the strength of regression coefficients. Its impact is only limited to the values of intercepts. There are two centralization methods: group mean centering and grand mean centering. Group mean centering is to centralize with group means. As group means are different, the deducted values (from the number observations) in each group are also different. The use of a group mean as a variable to replace the original variable in the form of a division causes changes to the model. On the other hand, grand mean centering is to centralize with total means. Estimates are made by using original data and total means. Although there are changes to parameter estimates, the relationship between model decompositions and variables remains intact. Hofmann and Gavin (1998) have proven that the model generated with the grand mean centering of explanatory variables of low levels has equal model fit indicators as the model before centralization. However, the covariance is reduced for the high-level intercept parameters and slope intercepts; hence, the impact of collinearity is reduced.

[6] r_{wg} (within-group interrater reliability) aims to validate the perceived intra-group consistency.

[7]James (1982) suggested that ICC_1 serves as an indicator of the existence of significant inter-group variances. The F tests are performed to validate the statistical significance. Bliese (2000) recommended the use of intra-class correlation coefficients($ICCs$), including ICC_1 and ICC_2 , to validate the existence of a shared structure. This can prove the validity of the aggregation of individual-level values into an overall variable. Please refer to Bliese (2000) for the details of calculations.

[8]The assessment of the environmental quality should incorporate the variances in external environmental factors as well as the internal factors, i.e. subjective perceptions of residents. A survey on the evaluation by residents regarding the environmental quality is one of the methods used to study a living environment (Türkoğlu, 1997). Since the quality of environment is an abstract concept, there are different results due to the influence of human factors and natural factors in different spatial scales (Nichol and Wong, 2005). There are two approaches to the assessment of the environmental quality. The first approach is to measure the quality, i.e. the establishment of environmental indicators to reflect the current status. The second approach is based on the perceptions and assessments of local residents. The levels of satisfaction are measured to gauge the evaluations of residents regarding different environmental quality attributes. The result is a comprehensive environmental indicator (Parson, 1997). However, the second approach is discussed less often in the literature concerning housing prices.

[9]Local deprivation is a concept first proposed by Townsend (1987). A lack of local resources prevents a comfortable and convenient living environment. As a result, local residents cannot enjoy social life. The higher the deprivation score, the worst off a neighbourhood is. Local deprivation is mostly discussed in the domains of public health, health, education, and homicides/crimes. The study of deprivation aims to gain an understanding of the influence of neighbourhoodenvironment and social contexts on the behavior, health, educational achievements, and crimes of individuals (MacIntyre, Maciver, and Sooman,1993; Baller,Anselin, andEssner, 2001).

[10]Generally speaking, the use of neighbourhood affluence as a component variable can avoid collinearity variables resultant from multiple similar variables. Meanwhile, the estimates in the HLM require multiple parameters. The use of a component variable can save degrees of freedom.

[11]The deviances of the three-layer model are estimated by the full maximum likelihood method.