Study on the substantiation of location equilibrium in the CUE model

Yamamoto, Hiromichi
Koike, Atsushi
Seya, Hajime

(Citation)
Journal of Urban Management,8(1):89-108

(Issue Date)
2019-04

(Resource Type)
journal article

(Version)
Version of Record

Journal of Urban Management 8 (2019) 89–108

Contents lists available at ScienceDirect

Journal of Urban Management

journal homepage: www.elsevier.com/locate/jum

Research Article

Study on the substantiation of location equilibrium in the CUE model

Hiromichi Yamamoto*, Atsushi Koike, Hajime Seya

Kobe University, Graduate School of Engineering, 1-1 Rokkodai-cho, Nada-ku, Kobe 657-8501, Japan

ARTICLE INFO

Keywords:
CUE Model
LUTI Model
Residential location choice model
Logit model
Transport economics

ABSTRACT

In the Computable Urban Economic (CUE) Model, one land-use transport interaction (LUTI) model, improving the accuracy of the Location Choice Model is important to evaluate the effects of introducing urban transportation policies. However, our previous study revealed that the substantiation of the indirect utility function by a linear expenditure system has not been verified and that location choice behaviors estimated using the logit model depends on the adjustment factor. Therefore, in this study, we first examined the logical meaning of the utility function by a linear expenditure system, and then focused on identifying major constituent factors of the adjustment factor and statistically verified the adjustment factor and urban amenities. As a result, we have identified the following facts: that the conventional indirect utility function may underestimate the effect of introducing urban transportation policies; that if effects are estimated using WLS after adding housing supply factors to the indirect utility function, the estimation accuracy will be improved; and that the major constituent factors of the adjustment factor are those expressing local characteristics of cities and wards.

1. Introduction

In underdeveloped and semi-developed countries in Asia and the ASEAN region, the advent of motorization in association with the rapid economic growth in recent years is causing extreme traffic congestion and deterioration of the urban environment. To solve such urban issues, countries in Asia and ASEAN are aiming to develop sustainable cities by developing cities and traffic networks in an integrated manner. Transit Oriented Development (TOD) is a typical initiative. Therefore, they desire to evaluate land-use plans and transportation plans comprehensively at the planning stage, and they have high expectations for the land-use transport interaction model that will enable them to achieve such comprehensive evaluation.

As for land-use transport interaction models, Lowry's model was first developed in the 1950s, and the entropy model was formulated in the 1970s. Then, in the 1980s, International Study Group on Land Use Transport Interaction (ISGLUTI) developed and applied a large scale practical use model (Ueda, 2010). On the other hand, the Computable Urban Economic Model (CUE model), which is the subject of our study, is a model that incorporates the basics of micro-economics into the land-use transport interaction model, and it has been established (Yamasaki & Muto, 2008; Ueda, 1991; Ueda, 1992; Muto, Akiyama, & Takagi, 2000; Suzuki, Muto, & Ogawa, 2002; Ueda, Tsutsumi, Muto, & Yamasaki, 2013). It is positioned as a practical use urban model for analyzing and evaluating urban economic status and urban policies. As regards the land-use transport interaction models developed as above, Ueda and Tsutsumi (1999) state that one of the commonalities of these models is that the discrete choice model, the logit model in concrete (which started to spread and take root in traffic demand forecasting), is applied to predict location choice behaviors. They also add

* Corresponding author.
E-mail address: hiromichi_yamamoto@mhi.co.jp (H. Yamamoto).

https://doi.org/10.1016/j.jum.2018.09.005
Received 3 June 2018; Received in revised form 25 August 2018; Accepted 27 September 2018
Available online 15 October 2018
2226-5856/

that Anas (1982) contributes greatly to that.

Miyagi and Ogawa have defined the basic formulation for choice as one formulation to calculate traffic distribution for traffic demand forecasting using the logit model. If its basic concept is applied to the forecasting of location choice behaviors, we will reach the following interpretations:

- The utility of choosers is formulated as a linear sum of observable utility and unobservable utility.
- Observable utility is an observable indicator showing the attractiveness of locations and comprising an indirect utility function and indicators unique to local areas, such as dwelling conditions and topographical factors. In substantive analyses, the indicators unique to local areas are positioned as adjustment factors and are determined as exogenous parameters through calibration against actually measured values at the area to be evaluated.
- Unobservable utility is defined as following the Gumbel distribution as the statistical error of changes of choices. A dispersion parameter is also defined as an indicator to determine the distribution shape of the statistical error.

Under the above interpretations, the logit model is applied to the prediction of location choice behaviors in land-use models, and a similar concept is adopted in the CUE model as well. However, previous investigations and research projects (Koike, Tomokuni, & Yamamoto, 2016) has revealed that the conventional CUE model may have the following issues.

A) The indirect utility function, a major constituent of the observable utility, is composed of household income, land price, transport price and distribution parameters to determine the expenditures for each. However, these terms are not defined explicitly for each period of time when decisions are made.
B) According to our previous study (Koike et al., 2016) targeting Kobe City, location choice behaviors are greatly dependent on the adjustment factor rather than the observable indirect utility function, although the adjustment factor has not been verified logically.

The results show that the CUE model, which has been adopted commonly as a practical use model of land-use transport interaction models, can be improved and that the reliability of adopting the logit model for location choice behavior predictions has not been verified sufficiently. We have to solve these issues to ensure a highly reliable land-use transport interaction model that can predict sustainable development of cities where urban transportation policies are to be introduced. Therefore, in this study, we will perform post-implementation evaluations for southern areas of Hyogo Prefecture to examine the two abovementioned issues with the CUE model.

This paper consists of six sections, including the introduction (this section) and the conclusion (Section 6). Section 2 will explain the concept and the formulation of the CUE model, and Section 3 the review results of previous studies and the overview of our preceding study (Koike et al., 2016). In Section 4, we will show the results of our verifications regarding the two issues that we

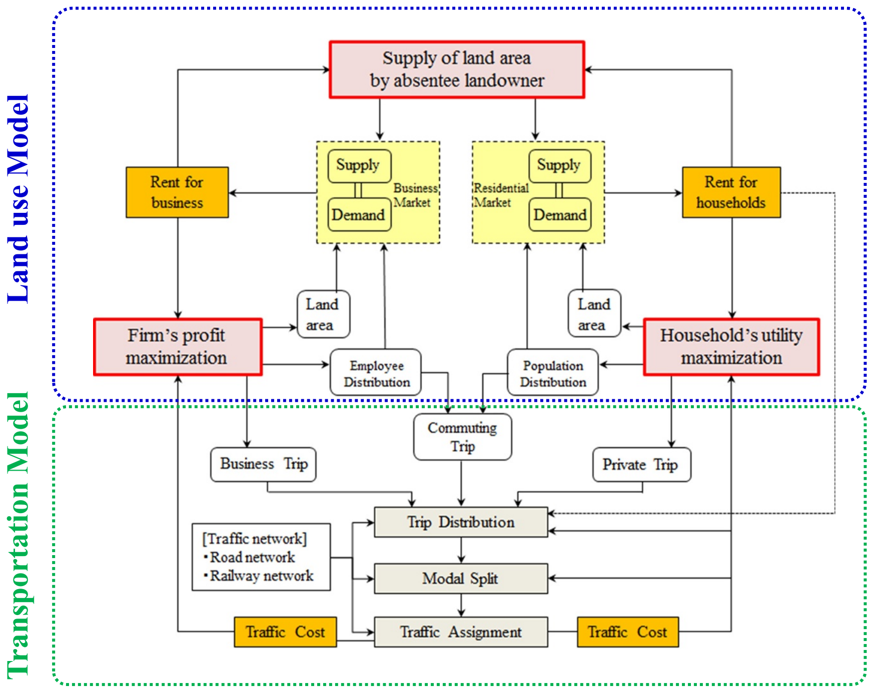


Fig. 1. Overall structure of the CUE Model.

performed for southern areas of Hyogo Prefecture to examine changes during a period of 10 years from 2000 through 2010. In Section 5, we will describe the future course of the development of CUE model based on the understanding we have obtained through the verifications explained in Section 4.

2. Computable Urban Economic (CUE) model

2.1. Overall structure of the CUE model

Fig. 1 shows the overall structure of the CUE model. The acting bodies assumed in the CUE model are households, firms, and landowners. In this model, each body behaves to maximize the utility, and the consumption and input volume of goods (number of trips, land areas) are adjusted according to the prices (land prices, transportation cost) presented from the land and transportation markets. This model can achieve equilibrium both in the land market in the transportation market simultaneously in each zone. This model is based on the following preconditions (Yamasaki & Muto, 2008).

A) Households per capita that have same preference, firms per employee whose job type and industry are alike, and absent landowners are assumed as the economic bodies.
B) The target area is divided into *i* pieces of zones, and the quality of zones in the same application is equal.
C) The developed model is a closed urban model, and the total population and the total number of employees of the urban area (target area) are given exogenously.
D) The land market will expand the balanced land-use probabilistically based on the equal utility principle, while the transportation market will expand the user equilibrium probabilistically based on the equal time principle. This model can achieve equilibrium in both the land and transportation markets simultaneously.
E) Households choose locations while following the utility maximization behaviors, while firms follow revenue maximization behaviors, and any additional costs due to the change of locations will not be taken into account.

2.2. Formulation of the CUE Model

In this paper, we will focus on the evaluation of the household behavior model to simplify the verifications. A household of a representative person will consume private trips (number of trips), land area (housing land consumption), and composite goods, and behave in a way that will maximize the utility under gross income constraints, including time resources. The consumption behavior of households is formulated as Formulas (1) and (2), and the indirect utility function is specified as a logarithmic linear relation using private trips (number of trips), land area (housing land consumption), and composite goods. The number of trips is included in goods consumption because the satisfaction level of a household is estimated to increase as a person goes shopping and on trips more frequently. Although there are various methods to set income, the wage income of consumers, which can be obtained by multiplying the difference between the available time and the commute time by the wage rate (time value), is used in general.

$$V_i = \max_{z_i, x_i, l_i}[\alpha_z \ln z_i + \alpha_x \ln x_i + \alpha_l \ln l_i] \tag{1}$$

$$\text{s. t.} \quad z_i + q_i x_i + r_i l_i = w(\Omega - q_i^{\,w} x_i^{\,w} - q_i^{\,s} x_i^{\,s}) \equiv I_i \tag{2}$$

Here, i is a subscript to show the following: zones V_i: utility level of households in Zone i; z_i: composite goods consumption; x_i: private trip consumption; l_i: housing land consumption; α_z, α_x, α_l: distribution parameters; q_i: private trip generalized price; r_i: land price in Zone i; w: wage rate (time value) of a household [yen/hour]; Ω: total available time (fixed); $q_i^{\,w}$: generalized price for trips to work; $x_i^{\,w}$: consumption in trips to work; $q_i^{\,s}$: generalized price for trips to school; $x_i^{\,s}$: consumption in trips to school; and I: gross income.

Solving the utility maximization question expressed by Formulas (1) and (2) derives the composite goods consumption, private trip consumption, and housing land consumption.

$$z_i = \alpha_z I_i \tag{3}$$

$$x_i = \frac{\alpha_x}{q_i} \bullet I_i \tag{4}$$

$$l_i = \frac{\alpha_l}{r_i} \bullet I_i \tag{5}$$

Here z_i is composite goods consumption, x_i: private trip consumption, and l_i: housing land consumption.

The indirect utility function will be derived from the derived demand functions.

$$V_i = \ln(I_i) - \alpha_x \ln(q_i) - \alpha_l \ln(r_i) + CC = \alpha_z \ln(\alpha_z) + \alpha_x \ln(\alpha_x) + \alpha_l \ln(\alpha_l) \tag{6}$$

Households will choose locations according to their attractiveness. The location choice behaviors to be assumed here are probabilistic behaviors, and households can change their locations to zones where the utility level is higher. Here, the location choice behaviors are formulated as a location choice probability using the logit model. In addition, the attractiveness unique to zones, which is not included in the indirect utility function, is taken into account as the adjustment factor. The population of a zone is obtained by multiplying the total population of the target city by the location choice probability expressed by Formula (7). Here, the role of the dispersion parameter is to determine how greatly the indirect utility function of households will impact their location choice probability. We should keep in mind that the dispersion parameter is fixed uniquely and does not vary depending on the zone.

$$P_i = \frac{exp\{\theta \bullet (V_i + \tau_i)\}}{\sum_i exp\{\theta \bullet (V_i + \tau_i)\}} \tag{7}$$

Here P_i is location choice probability, τ_i: adjustment factor, and θ: dispersion parameter.

3. Investigation of previous studies and overview of the preceding study

3.1. Previous studies about theoretical models of location choice behaviors

The location choice behaviors of households are determined by the location choice probability expressed by Formula (7) and are composed of an indirect utility function and an adjustment factor. As Formula (6) shows, the configuration of the indirect utility function shows that trip cost and land price will be consumed in a fixed manner at the rates of distribution parameters that are fixed exogenously against the gross income of households. However, in previous studies, the prices are not defined explicitly.

For example, Yamasaki and Muto (2008) set the gross income by multiplying the difference between the available time (fixed value) and the commute time by the wage rate that was derived from statistical data disclosed by a public organization. They set the land price based on the official land price and the ten-year government bonds yield, and the trip cost as the minimum expected cost based on the trips occurred. In addition, they derived the distribution parameters from the demand functions (Formulas (4) and (5) in this paper) using the least-squares method, which can be derived by solving the maximization question of the utility function. However, they made no reference to the re-productivity of the location choice behaviors obtained by the indirect utility function using the estimated distribution parameters, and the validity of the method was not explained.

Furthermore, Muto, Ueda, Takagi, and Tomita (2000) set the gross income based on the wage rate and available time (which are given exogenously), the land price according to the statistical data of Gifu City, and the trip cost as a generalized cost based on the trips occurred, but do not make any reference to temporal consistency among the prices either. As regards the estimation of distribution parameters, they only state that calibration using a method that is generally used in applied general equilibrium theory should be applied, but details are not explained. On the other hand, they confirmed the re-productivity of location choice behaviors estimated using the derived distribution parameters, and they said they obtained a high correlation coefficient.

Now we focus our attention on the units of prices consisting of the indirect utility function that have been used in these major previous studies. The unit for income I_i is yen/year, for transportation cost q_i is yen/trip, and for land price r_i derived based on the official land price of the year is yen/year/m^2. That means that the decision-making periods of the units for income, land price, and transportation cost are inconsistent. When we focus on the method to set distribution parameters, some are set based on values at a point in time, some are derived through calibration based on values in a base year, and some are set at the actual expenditure values per month disclosed by local authorities. That means that the conventional indirect utility function uses distribution parameters that are derived by determining price units at points in time for which the decision-making periods are inconsistent. Whether it can accurately estimate the expenditures on each price term is unclear.

From the above, we need to verify the estimation accuracy of location choice behaviors in consideration of the theoretical meaning of the indirect utility function.

3.2. Previous studies on the prediction of location choice behaviors using logit models

Here we will give an overview of the four representative previous studies that use the logit model for the prediction of land choice behaviors by land-use model, and the results of our previous study (Koike et al., 2016) on the types of attractiveness of locations function/indirect utility function and the logit model for the CUE model and the positions of the dispersion parameter and the adjustment factor.

In the four representative previous studies, Hayashi and Tomita (1988) expressed the attractiveness of the locations function/ indirect utility function V of households using a household attribute variable and a residential house attribute variable that can be observed. Tomita and Terashima (2003), assuming that households will take utility maximization behaviors under income constraints, defined an indirect utility function while taking into account the external diseconomies due to the transportation environment load in addition to the direct utility function comprising composite goods consumption and the floor area demand (area of a house). Sugiki and Miyamoto (2003) used composite goods consumption, explanatory variable vectors, and parameters to define, as the change of residence generation model, the utility of households. Omori, Takagi, and Akiyama (2004) determined the attractiveness of the locations function based on membership values depending on environmental factors and lateral distance from the origin point to the barycenter.

On the other hand, when we focus on the dispersion parameters in the logit model, Omori et al. (2004) specified the dispersion parameter as θ = 1, while Hayashi and Tomita (1988), and Sugiki and Miyamoto (2003) made no clear reference to it. Tomita and Terashima (2003) used α, which appears to be a dispersion parameter, but made no detailed reference to how they determined it. Therefore, no previous study has statistically verified the dispersion parameter in the logit model, and the time stability and validity have not been studied either.

Table 1
Attractiveness function of location and logit models.

Previous studies	Attractiveness function of location Indirect utility function	Logit model	Dispersion parameter	Adjustment factor
Hayashi and Tomita (1988)	V	$P = \frac{exp(V)}{\sum exp(V)}$	θ = 1 (practically)	Nothing
Tomita and Terashima (2003)	$V = \max[U(Z, l, X, S)]+\mu\bullet\gamma(f)$ s. t. $pZ + rA+(e + q)X + wS = w\left(\Omega - \frac{\sum NT}{T}\right) + y$	$P = \frac{exp(\alpha V)}{\sum exp(\alpha V)}$	The setting method is not clearly indicated	Nothing
Sugiki and Miyamoto (2003)	$U = \xi z + \varsigma Y$	$P = \frac{exp(U)}{\sum exp(U)}$	θ = 1 (practically)	Nothing
Omori et al. (2004)	$u = \frac{\int z \bullet \mu(z)dz}{\int \mu(z)dz}$	$P = \frac{exp(\theta \bullet \mu)}{\sum exp(\theta \bullet \mu)}$	θ = 1	Nothing
CUE model	$V_i = \ln(I_i) - \alpha_x\ln(q_i) - \alpha_l\ln(r_i)+C$ s.t. $C = \alpha_z\ln(\alpha_z) + \alpha_x\ln(\alpha_x) + \alpha_l\ln(\alpha_l)$	$P = \frac{exp[\theta(V_i+\tau_i)]}{\sum exp[\theta(V_i+\tau_i)]}$	θ = 1	Constant term correction in base year

However, the indirect utility function of households in the CUE model is formulated as a utility maximization question that consumes private trips, land areas and composite goods as described above under the constraint of gross income, including time resources, and the dispersion parameter is set as $\theta = 1$ in many cases. The attractiveness unique to the zone is set as adjustment factor τ, and the constant term is corrected so that the estimated value by the model will be in good agreement with the observed value in a base year. However, currently, the logistical meaning of the derived adjustment factor has not been verified.

In the formula of Tomita and Terashima (2003) in Table 1, each term demonstrates the following: Z: composite goods consumption; A: floor area demand (area of a house); X: number of trips; S: leisure time; $\gamma(f)$: direct utility into which external diseconomies due to transportation environment load are incorporated; p: price of goods; r: land price, e: service goods consumption per free trip; q: average transportation cost per free trip; w: wage rate; Ω: available time; N: population; T: time required for commuting; and y: assets income. In the formula of Sugiki and Miyamoto (2003), U: direct utility function; Y: explanatory variable vector; ξ and ς: parameters; and z: composite goods consumption. In the formula of Omori et al. (2004), u: utility level; $\mu(z)$: membership values depending on environmental factors; and z: lateral distance from the origin point to the barycenter. In the CUE model, z_i: composite goods consumption; V: (indirect) utility function; I: gross income; x_i: private trip consumption; l_i: housing land consumption; P_i: location choice probability; τ_i: adjustment factor; and θ: dispersion parameter.

4. Verifying the substantiation of location choice behaviors predicted by the CUE model targeting the southern area of Hyogo Prefecture

4.1. Verification policy

In this chapter, we will verify, in accordance with the procedure shown in Fig. 2, the two issues of the current CUE model regarding the location choice behaviors mentioned in Chapter 1. The administrative divisions as of 2016 are adopted to set target areas for which the substantiation of location choice behaviors will be verified, and Table 2 shows the 22 wards and cities located in the southern area of Hyogo Prefecture that are subject to verification. As shown in Fig. 3, we set a total of six verification cases targeting the population distribution from 2000 to 2010 while focusing on evaluation of single points in time and evaluation of terms of time. The basic data to be used in the substantiation verification is set as shown in Table 3.

4.2. STEP 1: Verifying the method to estimate the distribution parameters of the indirect utility function

4.2.1. Purpose of verification

The location choice behaviors of the CUE model can be explained logistically by the indirect utility function (6). However, the distribution parameters that will determine the expenditures have not been defined explicitly, which is one of the issues of CUE model. In this section, we will suggest new two methods to estimate the distribution parameters comprising the indirect utility function and verify their validity by comparing the setting methods with those of conventional methods.

4.2.2. Method to estimate distribution parameters

Considering that the CUE model is based on aggregated data, we will estimate the distribution parameters by means of the

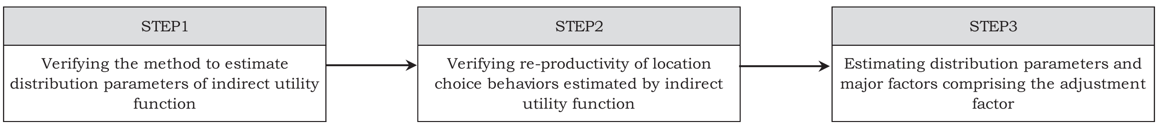
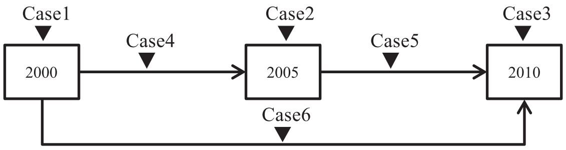


Fig. 2. Flowchart showing examination steps.

Table 2
Target area subject to verification (Southern area of Hyogo Prefecture).

Wards of Kobe City [9 wards]	Surrounding cities of Kobe City [13 cities]
Higashi-Nada, Nada, Chuo, Hyogo, Kita, Nagata, Suma, Tarumi, Nishi	Amagasaki, Itami, Kawanishi, Takarazuka, Nishinomiya, Ashiya, Akashi, Sanda, Miki, Ono, Kakogawa, Takasago, Himeji



Segment	Case	year covered
evaluation of single point in time	Case1	Population distribution in 2000
	Case2	Population distribution in 2005
	Case3	Population distribution in 2010
evaluation of term of time	Case4	Population change from 2000 to 2005
	Case5	Population change from 2005 to 2010
	Case6	Population change from 2000 to 2010

Fig. 3. Verification cases.

Table 3
Basic data to be used in analysis.

Constituent factor of indirect utility function	Contents
Population	Set using the information of the census of the Ministry of Internal Affairs and Communications statistics [2000/2005/2010]
Income	Set using public information of cities of Hyogo Prefecture [2000/2005/2010]
Representative trip cost	Using the information of the Kinki region person trip survey (2000/2010), set the representative traffic price for each region weighted by the number of trips about trains and cars for commuters. '05's data is set proportionally from that of '00 and '10.
Land price	Set using public information of each city of Hyogo Prefecture [2000/2005/2010]

following.

I. Maximum likelihood estimation method
II. Weighted Least Squares Regression (WLS).

In the maximum likelihood estimations, the parameters are estimates as follows using Anas (1981)
[Evaluation of single points in time: Cases 1–3]

$$V_i^t = \ln(I_i^t) - \alpha_x \ln(q_i^t) - \alpha_l \ln(r_i^t) \tag{8}$$

$$P_i^t = \frac{exp(\theta \bullet V_i^t)}{\sum_i exp(\theta \bullet V_i^t)} \tag{9}$$

$$L^* = \frac{\hat{N}^t!}{\sum_i \hat{N}_i^t} \bullet \sum_i (\hat{N}_i^t \bullet \ln P_i^t) \tag{10}$$

Here V_i^t is the indirect utility function in area i in the year of t; I_i^t: income in area i in the year of t; q_i^t: representative trip cost in area i in the year of t; r_i^t: land price in area i in the year of t; P_i^t: location choice probability in area i in the year of t; θ: dispersion parameter (θ = 1); $\hat{N}_i^t$: number of residents in area i in the year of t [observed value]; $\hat{N}^t$!: the factorial of the number of residents in all areas in the year of t [observed value]; and L^*: likelihood function.

[Change in term of time: Cases 4–6]

$$V_i^{t1} = \ln(I_i^{t1}) - \alpha_x \ln(q_i^{t1}) - \alpha_l \ln(r_i^{t1}) \tag{11}$$

$$V_i^{t2} = \ln(I_i^{t2}) - \alpha_x \ln(q_i^{t2}) - \alpha_l \ln(r_i^{t2}) \tag{12}$$

$$P_i^{t2,t1} = \frac{exp\{\theta(V_i^{t2} - V_i^{t1})\}}{\sum_i exp\{\theta(V_i^{t2} - V_i^{t1})\}} \tag{13}$$

$$L^* = \frac{\Delta\hat{N}^t!}{\sum_i \Delta\hat{N}_i} \bullet \sum_i \{\Delta\hat{N}_i' \bullet \ln(P_i^{t2,t1})\} \tag{14}$$

$$\Delta\hat{N}_i' = \hat{N}_i^{t2} - \hat{N}_i^{t1} = \hat{N}_i^{t1} \bullet \rho + \Delta\hat{N}_i \tag{15}$$

Here V_i^{t1} is indirect utility function in area i in base year ($t1$); V_i^{t2}: indirect utility function in area i in prediction year ($t2$); I_i^{t1}: income in area i in base year ($t1$); I_i^{t2}: income in area i in prediction year ($t2$); q_i^{t1}: representative trip cost in area i in base year ($t1$); q_i^{t2}: representative trip cost in area i in prediction year ($t2$); r_i^{t1}: land price in area i in base year ($t1$); r_i^{t2}: land price in area i in prediction year ($t2$); $P_i^{t2,t1}$: location choice probability in area i in base year ($t1$) and prediction year ($t2$) [estimated value]; θ: dispersion parameter (θ = 1); $\hat{N}_i^{t2} - \hat{N}_i^{t1}$: the amount of population migration in area i in base year ($t1$) and prediction year ($t2$) [observed value]; $\Delta\hat{N}_i$: the number of population migration in the society in base year ($t1$) and prediction year ($t2$) [observed value]; ρ: threshold value, $\Delta\hat{N}^t$: the factorial of the number of migration of residents in all areas in base year ($t1$) and prediction year ($t2$) [observed value]; and L^*: likelihood function.

When using WLS, which is known as the Berkson-Theil method, the parameters are estimated as follows.

[Evaluation of single points in time: Cases 1–3]

The explained variables of this estimation method are composed of the location choice probability and income of the indirect utility function, and the representative trip cost and land price of the indirect utility function are used as explanatory variables. By doing so, this method eliminates the effect of dispersion parameter θ in the logit model, and makes it possible to assume that the dispersion parameter θ is 1. Each term is composed of the difference between the value of the factor in area i and the average in all areas, and the distribution parameters α_x, α_l are estimated with the WLS method with the variance of explained value as the weight value: σ.

$$V_i^t = \ln(I_i^t) - \alpha_x \ln(q_i^t) - \alpha_l \ln(r_i^t) \tag{16}$$

$$P_i^t = \frac{exp(\theta \bullet V_i^t)}{\sum_i exp(\theta \bullet V_i^t)} \tag{17}$$

$$\frac{\{\ln(\hat{P_i^t}) - \ln(\hat{P_{avr}^t})\} - \{\ln(I_i^t) - \ln(I_{avr}^t)\}}{\sigma} = A_x \bullet \frac{\{\ln(q_i^t) - \ln(q_{avr}^t)\}}{\sigma} + A_l \bullet \frac{\{\ln(r_i^t) - \ln(r_{avr}^t)\}}{\sigma} + C \tag{18}$$

$$\alpha_x = -A_x \quad , \quad \alpha_l = -A_l \tag{19}$$

Here, V_i^t is the indirect utility function in area i in the year of t; I_i^t: income in area i in the year of t; q_i^t: representative trip cost in area i in the year of t; r_i^t: land price in area i in the year of t; P_i^t: location choice probability in area i in the year of t; θ: dispersion parameter (θ = 1); $\hat{P_i^t}$: location choice probability in area i in the year of t [observed value]; $\hat{P_{avr}^t}$: average location choice probability in all areas in the year of t; I_{avr}^t: average income in all areas in the year of t; q_{avr}^t: average representative trip cost in all areas in the year of t; r_i^t: average land price in all areas in the year of t; and σ: weight value by variance σ^2 of explained variable.

[Change in term of time: Cases 4–6]

$$V_i^{t1} = \ln(I_i^{t1}) - \alpha_x \ln(q_i^{t1}) - \alpha_l \ln(r_i^{t1}) \tag{20}$$

$$V_i^{t2} = \ln(I_i^{t2}) - \alpha_x \ln(q_i^{t2}) - \alpha_l \ln(r_i^{t2}) \tag{21}$$

$$P_i^{t2,t1} = \frac{exp\{\theta(V_i^{t2} - V_i^{t1})\}}{\sum_i exp(V_i^{t2} - V_i^{t1})} \tag{22}$$

Also, in the cases evaluating changes during a term of time, the dispersion parameters are estimated in the same way as in the evaluation of a single point. However, in evaluating changes during a term of time, the amount of change in each factor during the term is calculated beforehand using Formulas (24)–(26), and then, the dispersion parameters are estimated by Formula (23).

$$\frac{\{\ln(\Delta\hat{P}_i) - \ln(\Delta\hat{P}_{avr})\} - (\Delta I_i - \Delta I_{avr})}{\sigma} = A_x \bullet \frac{(\Delta q_i - \Delta q_{avr})}{\sigma} + A_l \bullet \frac{(\Delta r_i - \Delta r_{avr})}{\sigma} + C \tag{23}$$

$$\Delta I_i = \{\ln(I_i^{t2}) - \ln(I_i^{t1})\} \tag{24}$$

$$\Delta q_i = \{\ln(q_i^{t2}) - \ln(q_i^{t1})\} \tag{25}$$

$$\Delta r_i = \{\ln(r_i^{t2}) - \ln(r_i^{t1})\} \tag{26}$$

$$\alpha_x = -A_x \quad , \quad \alpha_l = -A_l \tag{27}$$

Table 4
Results of estimated distribution parameters.

			Conventional set value			Estimated by maximum likelihood estimation			Estimated by WLS		
			Trip cost	Land price	Constant term	Trip cost	Land price	Constant term	Trip cost	Land price	Constant term
Evaluation of single points in time	Case1	Estimated parameter	0.04	0.06	–	0.52	-0.14	–	-0.61	-0.33	0.00
		t value	–	–	–	221.50	-120.20	–	0.90	1.10	0.00
		Modified likelihood ratio	–			0.003			0.09		
		Coefficient of determination									
	Case2	Estimated parameter	0.03	0.07	–	0.79	-0.09	–	-0.55	-0.24	-0.01
		t value	–	–	–	314.20	-103.00	–	0.80	0.90	0.00
		Modified likelihood ratio	–			0.005			0.06		
		Coefficient of determination									
	Case3	Estimated parameter	0.03	0.05	–	1.30	-0.03	–	-0.25	-0.15	-0.08
		t value	–	–	–	497.20	-45.50	–	0.30	0.70	-0.20
		Modified likelihood ratio	–			0.009			0.03		
		Coefficient of determination									
Evaluation of term of time	Case4	Estimated parameter	0.03	0.07	–	7.17	-3.40	–	5.66	-3.34	-0.34
		t value	–	–	–	118.10	-198.60	–	-1.10	2.10	-1.60
		Modified likelihood ratio	–			0.025			0.19		
		Coefficient of determination									
	Case5	Estimated parameter	0.03	0.05	–	8.22	-2.88	–	6.40	-3.12	-0.30
		t value	–	–	–	109.10	-140.90	–	-1.10	2.10	-1.60
		Modified likelihood ratio	–			0.016			0.29		
		Coefficient of determination									
	Case6	Estimated parameter	0.03	0.05	–	4.89	-2.77	–	2.90	-3.47	-0.38
		t value	–	–	–	141.70	-286.60	–	-0.90	3.30	-2.10
		Modified likelihood ratio	–			0.049			0.38		
		Coefficient of determination									

Here V_i^{t1} is the indirect utility function in area i in base year ($t1$); V_i^{t2}: indirect utility function in area i in prediction year ($t2$); I_i^{t1}: income in area i in base year ($t1$); I_i^{t2}: income in area i in prediction year ($t2$); q_i^{t1}: representative trip cost in area i in base year ($t1$); q_i^{t2}: representative trip cost in area i in prediction year ($t2$); r_i^{t1}: land price in area i in base year ($t1$); r_i^{t2}: land price in area i in prediction year ($t2$); $P_i^{t2,t1}$: location choice probability in area i in base year ($t1$) and prediction year ($t2$) [estimated value]; θ: dispersion parameter (θ = 1); $\Delta\hat{P}_i$: difference in location choice probability between base year ($t1$) and prediction year ($t2$) (observed value); $\Delta\hat{P}_{avr}$: average of $\Delta\hat{P}_i$ in all areas; ΔI_i: difference in income between base year ($t1$) and prediction year ($t2$); ΔI_{avr}: average of ΔI_i in all areas; Δq_i: difference in representative trip cost between base year ($t1$) and prediction year ($t2$); Δq_{avr}: average of Δq_i in all areas; Δr_i: difference in land price between base year ($t1$) and prediction year ($t2$); Δr_{avr}: average of Δr_i in all areas; and σ: weight value by variance σ^2 of explained variable.

4.2.3. Results of comparison of estimated distribution parameters

Table 4 shows the results of distribution parameters estimated by the two different methods. In addition, as the distribution parameters that have been used in the conventional CUE model, we included values set based on monthly consumer spending (Kobe City) recorded in the Hyogo Statistical Report [Commodity Prices/Households] and made comparisons and verifications with the estimated values. The comparison identified the following characteristics.

1) The representative trip cost α_x: The values estimated by the maximum likelihood estimation method and the values estimated by WLS show remarkably greater values compared to conventional set values, either with plus or negative signs according to the evaluation case. That means that changes in the representative trip cost associated with the introduction of urban transportation policies have a great influence on the location choice behaviors and that evaluations using conventional set values may underestimate or overestimate the effect of the introduction of transportation policies.
2) Land price α_l: Both the values estimated by the maximum likelihood estimation method and the values estimated by WLS were negative values compared to conventional set values. The positive land price values of α_l show that a rise in land price in an area, which is common in areas where urban transportation policies are introduced, pushed down the utility of households, negatively influencing the location choice behaviors in the area. On the other hand, negative land price values of α_l show that a rise in land price in an area associated with the introduction of urban transportation policies raised the utility of households in the area. This means that the attractiveness of the area will rise as the land price in the area rises, exercising an attracting effect in relation to the location choice behaviors.
3) When values estimated in evaluations of single points in time are compared with those estimated in evaluations of terms of time, the conventional set values are close in any cases. On the other hand, in both evaluation by the maximum likelihood estimation method and estimation by WLS, values are different by case. That perhaps shows the difference in the consumption of each factor comprising the utility function for each point/term of time when decisions are made.

From the above, as regards the first issue of this study, we believe that the conventional set values might not be able to accurately express the expenditure scale of factors and may be inadequate as a method to set distribution parameters comprising the indirect utility function. Furthermore, considering that the maximum likelihood estimation method is a method with high reliability when the sample size is relatively large, it is not suitable for estimation in this analysis since they use a small number of samples based on aggregated data. Of course, if residential zones and workplace zones are divided like in the study by Anas, (Omori et al., 2004) and a sample size of the second power of the number of areas is secured, the maximum likelihood estimation method would be a good option. However, in the CUE model, which is used practically, residential zones and workplace zones are not divided in many cases to facilitate the interconnection with the traffic volume distribution model. Therefore, we consider WLS to be a suitable method. According to the above, we will use WLS to estimate the distribution parameters in the studies hereafter.

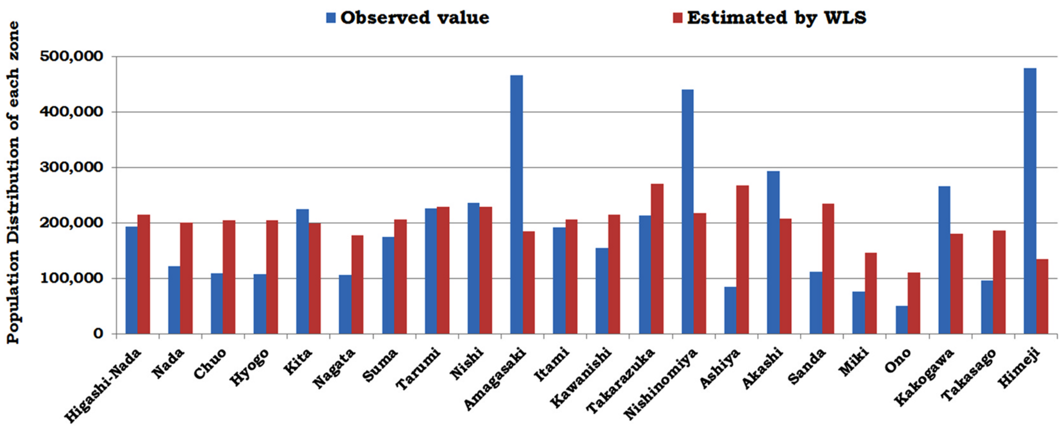


Fig. 4. Results of location choice behaviors estimation.

4.3. STEP 2: Verifying the re-productivity of location choice behaviors estimated by the indirect utility function

4.3.1. Purpose of verification

Location choice behaviors in the CUE model can be expressed statistically by the indirect utility function of Formula (6). However, as the second issue of the CUE model, the location choice behaviors cannot be explained sufficiently by the indirect utility function alone, and therefore depend largely on the adjustment factor of the logit model. Therefore, we will estimate the location choice behaviors only by the indirect utility function while using the distribution parameters estimated in the previous section and compare them with the actual number of location choices. After identifying the major factors that cause errors in the estimation of location choice behaviors, we will consider the future course of improvement of the indirect utility function.

4.3.2. Verifying the estimated results of location choice behaviors

Fig. 4 shows the actual numbers of location choices (observed values) in Case 1 (2000) and results of location choice behavior estimation by Formula (6) in which the distribution parameters estimated in Table 3 are applied.

The results of the comparison show that, although there are slight differences depending on the method to set distribution parameters, it is difficult to estimate the actual number of location choices only by the indirect utility function. Specifically, in areas with many locations–such as Amagasaki City, Nishinomiya City, Akashi City, and Himeji City–results are overestimated, while in areas with few locations–such as Ashiya City, Miki City, and Ono City–they are underestimated. As the reason of such results, we can cite the fact that although housing supply factors are taken into account when people actually conduct location choice behavior, they are not included in the indirect utility function explaining location choice behaviors statistically. In the estimation of location choice behaviors according to the conventional CUE model, these factors are incorporated as factors comprising the adjustment factor of the logit model and are not identified in the process of the estimation. Conventionally, the adjustment factor has been determined uniquely through calibration based on values in a base year as shown in Table 1 and handled as a fixed value in predicting the future. Therefore, this method does not take into account changes at points of time in the future after the base year, which causes errors in the estimation of location choice behaviors. From the above, it is important to incorporate the housing supply factors in the indirect utility function to improve the accuracy of location choice behavior estimation by the CUE model.

Although there are some candidate indicators to show the housing supply factors, we have decided to use inhabitable land area as an alternative indicator to the housing supply factors and to incorporate it into the indirect utility function since a wide variety of information is organized regarding inhabitable land area and it is available easily.

4.4. STEP 3: Estimating distribution parameters and major factors comprising the adjustment factor

4.4.1. Purpose of verification

In the verifications we conducted in previous sections, we showed the future direction in which we will apply the WLS method in estimating distribution parameters and in which we will incorporate the inhabitable land area into the indirect utility function. In this section, in the light of this direction, we will re-estimate the distribution parameters and analyze the correlation with urban amenities to identify the cause of errors in location choice behaviors that we cannot explain only with the factors mentioned above. Through this analysis, we will identify the factors comprising the adjustment factor of the conventional CUE model.

4.4.2. Verification method

In this section, we will derive the distribution parameters and analyze the cause of errors in location choice behaviors using the following two approaches.

[Approach 1: Comprehensive estimation]

- Overview: Inhabitable land area and urban amenities will be incorporated into the indirect utility function of Formula (6), and the distribution parameters and urban amenity parameters will be estimated comprehensively by WLS.
- Estimation formulas: estimated by Formulas (28)–(36).

(Evaluation of single point in time: Cases 1–3)

$$\frac{\{\ln(\hat{P}_i^t) - \ln(\hat{P}_{avr}^t)\} - \{\ln(I_i^t) - \ln(I_{avr}^t)\}}{\sigma} = A_x \bullet \frac{\{\ln(q_i^t) - \ln(q_{avr}^t)\}}{\sigma} + A_l \bullet \frac{\{\ln(r_i^t) - \ln(r_{avr}^t)\}}{\sigma} + \beta_{23} \bullet \frac{(X_{23i}^t - X_{23avr}^t)}{\sigma} + \beta_N \bullet \frac{(X_{Ni}^t - X_{Navr}^t)}{\sigma} + C \tag{28}$$

$$\alpha_x = -A_x \quad , \quad \alpha_l = -A_l \tag{29}$$

Here β_{23} is the inhabitable land area parameter; β_N: parameter to show urban amenity N; X_{23i}^t: inhabitable land area in area *i* in the year of *t*; X_{23avr}^t: average inhabitable land area in all areas in the year of *t*, X_{Ni}^t: urban amenity N in area *i* in the year of *t*, N_{Navr}^t: average urban amenity N in all areas in the year of *t*; and σ: weight value by variance σ^2 of explained variable.

(Evaluation of term of time: Cases 4–6)

$$\frac{\{\ln(\Delta\hat{P}_i)-\ln(\Delta\hat{P}_{avr})\}-(\Delta I_i-\Delta I_{avr})}{\sigma}=A_x\bullet\frac{(\Delta q_i-\Delta q_{avr})}{\sigma}+A_l\bullet\frac{(\Delta r_i-\Delta r_{avr})}{\sigma}+\beta_{23}\bullet\frac{(\Delta X_{23i}-\Delta X_{23avr})}{\sigma}+\beta_N\bullet\frac{(\Delta X_{Ni}-\Delta X_{Navr})}{\sigma}+C \tag{30}$$

$$\Delta I_i=\{\ln(I_i^{t2})-\ln(I_i^{t1})\} \tag{31}$$

$$\Delta q_i=\{\ln(q_i^{t2})-\ln(q_i^{t1})\} \tag{32}$$

$$\Delta r_i=\{\ln(r_i^{t2})-\ln(r_i^{t1})\} \tag{33}$$

$$\Delta X_{23i}=\{\ln(X_{23i}^{t2})-\ln(X_{23i}^{t1})\} \tag{34}$$

$$\Delta X_{Ni}=\{\ln(X_{Ni}^{t2})-\ln(X_{Ni}^{t1})\} \tag{35}$$

$$\alpha_x=-A_x \quad , \quad \alpha_l=-A_l \tag{36}$$

Here ΔX_{23i} is the difference in the inhabitable land area between base year ($t1$) and prediction year ($t2$); ΔX_{23avr}: average of ΔX_{23i} in all areas; ΔX_{Ni}: difference in urban amenity N between base year ($t1$) and prediction year ($t2$); ΔX_{Navr}: average of ΔX_{Ni} in all areas; and σ: weight value by variance σ^2 of the explained variable.

[Approach 2: Stepwise estimation]

- Overview: The following two steps will be taken to conduct an estimation.

1) Incorporate only the inhabitable land area in the indirect utility function of Formula (6) and estimate the distribution parameters by the WLS method.
2) Set the residual error obtained by the calculation in (1) as the explained variable, and the urban amenities as the explanatory variable, and estimate the parameters by the WLS method.

- Estimation formulas: estimated by Formulas (37)–(44).

(Evaluation of single point in time: Cases 1–3)
(Scope of 1))

$$\frac{\{\ln(\hat{P}_i^t)-\ln(\hat{P}_{avr}^t)\}-\{\ln(I_i^t)-\ln(I_{avr}^t)\}}{\sigma}=A_x\bullet\frac{\{\ln(q_i^t)-\ln(q_{avr}^t)\}}{\sigma}+A_l\bullet\frac{\{\ln(r_i^t)-\ln(r_{avr}^t)\}}{\sigma}+\beta_{23}\bullet\frac{(X_{23i}^t-X_{23avr}^t)}{\sigma}+C \tag{37}$$

$$\alpha_x=-A_x \quad , \quad \alpha_l=-A_l \tag{38}$$

$$\Delta P_i^t=\hat{PI}_i^t-PI_i^t \tag{39}$$

(Scope of 2))

$$\Delta P_i^t=\beta_N(X_{Ni}^t-X_{Navr}^t)+C \tag{40}$$

Here $\hat{PI}_i^t$ is explained as the variable of Formula (37), P_i^t: values estimated with parameters obtained by Formula (37); ΔP_i^t: residual error of Formula (37); and σ: weight value by variance σ^2 of explained variable.

(Evaluation of term of time: Cases 4–6)
(Scope of 1))

$$\frac{\{\ln(\Delta\hat{P}_i)-\ln(\Delta\hat{P}_{avr})\}-(\Delta I_i-\Delta I_{avr})}{\sigma}=A_x\bullet\frac{(\Delta q_i-\Delta q_{avr})}{\sigma}+A_l\bullet\frac{(\Delta r_i-\Delta r_{avr})}{\sigma}+\beta_{23}\bullet\frac{(\Delta X_{23i}-\Delta X_{23avr})}{\sigma}+C \tag{41}$$

$$\alpha_x=-A_x \quad , \quad \alpha_l=-A_l \tag{42}$$

$$\Delta P_i^{t2,t1}=\hat{PI}_i^{t2,t1}-PI_i^{t2,t1} \tag{43}$$

(Scope of 2))

$$\Delta P_i^{t2,t1}=\beta_N(\Delta X_{Ni}-\Delta X_{Navr})+C \tag{44}$$

Here $\hat{PI}_i^{t2,t1}$ is explained as the variable of Formula (41); $P_i^{t2,t1}$: values estimated with parameters obtained by Formula (41); $\Delta P_i^{t2,t1}$: residual error of Formula (41); and σ: weight value by variance σ^2 of explained variable.

4.4.3. Setting urban amenities

To identify the factors that influence location choice behaviors, we set 23 urban amenities in total, including inhabitable land area. When setting the urban amenities, we selected factors that will lead to population migration rather than factors that will follow population migration, and used the Hyogo Statistical Report as the main source of data. When the data was insufficient, we supplemented it with statistical information issued by cities, wards, and government offices. Consequently, we prepared cross-section

Table 5
List of urban amenities.

Classification		Amenity		Classification		Amenity	
population	1	Ratio of 15 years old or younger	%	facility	13	School density	per thousand
	2	Ratio of 65 years old or younger	%		14	Retail sales area density	per thousand
	3	Population ratio below junior high school	%	regional environment	15	Passenger car ownership ratio	per thousand
	4	Population ratio below university	%		16	Penal Code offense recognition ratio	per thousand
	5	Single household ratio	%		17	The number of train stations	station
	6	Nuclear family households ratio	%		18	The number of prefectural designated cultural properties	facility
residential house	7	The number of tatami in the living room per person	per population		19	Urban park density	per thousand
	8	Density of new construction starts in buildings and residential house	per thousand	industrial	20	All industry employee density	%
	9	Rate of residential house for over 35 years	%		21	Secondary industry ratio	%
	10	house ownership ratio	%		22	Tertiary industry ratio	%
	11	detached housing ratio	%	land	23	Inhabitable land area	Km^2
	12	vacant house ratio	%				

data for the evaluation of single points in time (Cases 1 - 3), while pooling data for the evaluation of terms of time (Cases 4–6) (Table 5).

4.4.4. Estimation by WLS

As described above, location choice behaviors were estimated using the WLS method. In this analysis, however, we took the following steps.

- Carry out a VIF-test for explained and explanatory variables before the estimation by WLS, and eliminate explanatory variables whose VIF is higher than 10.
- Eliminate explanatory variables whose correlation with explained variables is 0.1 or less in Approaches 1 and 2.

4.4.5. Estimation results: Approach 1 / comprehensive estimation

Table 6 shows the results of the estimation. In the evaluations of single points in time (Cases 1–3), the inhabitable land area (X23) showed high significance in all cases as a positive factor, while the significance of distribution parameters was low except in Case 2, and both plus and minus signs were given depending on the point of time, and the results were unstable. When we focused on correlations with urban amenities, we identified population: proportion of nuclear families (X6); local environment: number of railroad stations (X17); and industry: density of employees in all industries (X20) as common positive factors, and facilities: density of schools (X13) and local environment: density of city parks (X19) as common negative factors. We interpret the results as meaning that the number of nuclear families has increased in association with the progress of urbanization and they are requiring attractive urban areas with high accessibility by rail and with industrial clusters. In addition, we can see that facilities and local environment, such as the density of schools and city parks, do not have a high effect on location choice behaviors.

In evaluations of terms of time (Cases 4–6), the estimated values showing distribution parameters tend to differ greatly depending on the term of time, and we were not able to obtain stable results. Furthermore, regarding the identification of urban amenities, although we extracted facilities: density of sales areas as a common positive factor, we were unable to find other communalities. A possible factor behind the results is that change in local environment was different depending on the term selected. As a result, with the results of this analysis, we were unable to identify communalities/directions of the estimation of location choice behaviors during terms of time.

4.4.6. Estimation results: Approach 2 / stepwise estimation

Table 7 shows the results of the estimation. In the evaluations of single points in time (Cases 1–3), distribution parameters and inhabitable land areas of the indirect utility function were estimated by the WLS method, and we obtained stable estimation results of both of the parameters as factors of enough significance. In addition, the WLS performed using the residual errors obtained based on this estimation results and explained variables and urban amenities identified that housing-related factors showed correlation. Number of houses: share of houses of 35 years old or older (X9) and the rate of owned houses were identified as positive factors, while the area (in tatami) of dwelling rooms per person (X7) was a negative factor.

Next, we will evaluate the estimation results of each area in detail. The results of Case 3 (2010) are shown in Figs. 5 and 6 as a representative case. Fig. 5 shows the estimated results of distribution parameters and inhabitable land area of the indirect utility function, while Fig. 6 shows the residual errors obtained from the estimations in Fig. 5 and the estimated results of urban amenities. The results of Cases 1 and 2 are not listed (evaluation of single points in time: Cases 1–3) because they show a tendency similar to that of Case 3. Based on Fig. 5, we will classify the tendencies of residual errors into four cases: 1) positive residual errors common to

Table 6
Estimation results: Approach 1 / comprehensive estimation.

			Case 1 [year:2000]			Case 2 [year:2005]			Case 3 [year:2010]			Case 4 [year:2000 ⇒ year:2005]			Case 5 [year:2005 ⇒ year:2010]			Case 6 [year:2000 ⇒ year:2010]		
			Estimated Parameter	t value	P value	Estimated Parameter	t value	P value	Estimated Parameter	t value	P value	Estimated Parameter	t value	P value	Estimated Parameter	t value	P value	Estimated Parameter	t value	P value
dispersion parameter		θ	1.00	–	–	1.00	–	–	1.00	–	–	1.00	–	–	1.00	–	–	1.00	–	–
distribution parameter		αx	-1.19	3.72	***	-1.08	5.00	***	-0.16	0.42		8.83	-2.34	**	4.43	-1.50		-4.38	1.11	
		αl	-0.21	0.99		0.47	-3.19	**	0.27	-0.97		-0.13	0.07		0.46	-0.43		9.99	-2.57	***
constant term		C	-0.07	-0.41		-0.74	-4.61	***	-0.63	-1.70		-0.34	-2.63	**	-0.30	-3.08	**	-0.38	-2.92	**
urban ammenity	land	X23	0.01	3.15	**	0.01	4.17	***	0.01	3.65	***	1.38	2.36	**				-1.94	-2.71	**
	population	X1	-13.48	-4.36	***	–	–		-19.20	-1.49		–	–		–	–		106.30	2.13	*
		X2	–	–		–	–		–	–		56.74	2.62	**	-39.87	-3.18	**	-92.43	-3.03	**
		X5	–	–		–	–		–	–		–	–		–	–		-128.83	-3.43	**
		X6	4.69	3.89	***	3.95	4.53	***	8.73	3.24	**	–	–		8.54	1.77		-145.94	-3.34	**
	residential house	X7	-0.10	-1.39		0.23	4.03	***	–	–		–	–		0.77	3.44	***	2.63	4.09	***
		X9	–	–		1.29	3.44	**	–	–		–	–		-6.29	-2.07	*	15.48	2.01	*
		X10	–	–		2.90	4.69	***	3.06	1.70		7.17	1.20		-11.61	-2.07	*	13.30	1.47	
		X11	-0.67	-1.19		–	–		–	–		–	–		22.18	5.42	***	–	–	
		X12	–	–		–	–		3.24	1.16		-13.23	-3.60	***	–	–		–	–	
	facility	X13	-0.30	-3.51	***	-0.28	-5.72	***	-0.46	-2.67	***	-5.31	-3.70	***	–	–		5.28	1.98	*
		X14	-0.00	-3.45	***	-0.00	-3.73	***				0.00	1.99	*	0.00	2.91	**	-0.01	-2.74	***
	regional environ-ment	X15	–	–		-0.01	-7.68	***	-0.01	-3.47	***	–	–		–	–		0.01	2.33	*
		X17	0.03	3.82	***	0.01	2.35	*	0.02	2.06	*	–	–		0.44	3.42	***	–	–	
		X18	–	–		-0.01	-2.48	**	-0.01	-1.14		0.43	4.58	***	–	–		–	–	
		X19	-0.83	-3.05	**	-1.49	-7.99	***	-1.56	-3.62	***	–	–		-8.89	-2.68	**	–	–	
	industrial	X20	8.75	3.02	**	19.87	8.69	***	8.75	2.46	**	–	–		–	–		–	–	
		X22	–	–		–	–		–	–		–	–		20.62	2.63	**	20.35	1.82	
Double Correlation		R	0.988			0.997			0.979			0.893			0.958			0.939		
Decision Factor		R^2	0.976			0.994			0.958			0.797			0.918			0.882		

* : Significant at less than 10%,
** : Significant at less than 5%,
*** : Significant at less than 1%

Table 7
Estimation results: Approach 2 / stepwise estimation.

				Case1 [year:2000]			Case2 [year:2005]			Case3 [year:2010]			Case4 [year:2000 ⇒ year:2005]			Case5 [year:2005 ⇒ year:2010]			Case6 [year:2000 ⇒ year:2010]		
				Estimated Parameter	t value	P value	Estimated Parameter	t value	P value	Estimated Parameter	t value	P value	Estimated Parameter	t value	P value	Estimated Parameter	t value	P value	Estimated Parameter	t value	P value
Estimated Parameter	dispersion parameter		θ	1.00	-	-	1.00	-	-	1.00	-	-	1.00	-	-	1.00	-	-	1.00	-	-
	distribution parameter		αx	-0.85	1.86	*	-1.09	2.07	*	-0.98	1.77	*	5.09	-0.88		6.22	-1.48		3.07	-0.87	
			αl	-1.03	3.95	***	-0.80	3.67	***	-0.65	3.62	***	-2.97	1.44		-2.99	2.52	**	-3.57	2.85	**
	inhabitable land area		X23	0.01	4.60	***	0.01	4.44	***	0.01	4.70	***	0.13	0.29		0.52	0.57		-0.06	-0.17	
	constant term		C	0.55	2.15	**	0.60	2.13	**	0.58	2.05	*	-0.34	-1.61		-0.30	-1.50		-0.38	-2.03	*
	Double Correlation			0.762			0.743			0.751			0.437			0.549			0.613		
	Decision Factor			0.580			0.552			0.564			0.191			0.301			0.376		
Estimated Urban Amnity	urban ammenity	population	X1	-	-		-	-		-	-		30.48	2.08	*	-	-		-	-	
			X5	-	-		-	-		-	-		-	-		-	-		-20.71	-2.17	**
		residential house	X7	-0.25	-5.22	***	-0.24	-2.65	**	-0.16	-1.34		-	-		0.29	1.40		-	-	
			X8	-	-		0.04	1.28		-	-		-	-		-	-		-	-	
			X9	2.34	4.24	***	3.90	4.20	***	2.02	1.93	*	-	-		-	-		-	-	
			X10	-	-		2.71	2.09	*	2.73	2.22	**	-	-		-	-		-	-	
			X11	-	-		-	-		-	-		-	-		14.12	4.09	***	18.36	3.20	***
			X12	-	-		-3.43	-1.28		-	-		-10.60	-2.95	***	-	-		-9.43	-2.01	*
		facility	X13	-0.23	-2.50	**	-0.18	-1.63		-	-		-	-		-	-		-	-	
			X14	-0.00	-1.20		-0.00	-1.18		-	-		-	-		0.00	1.75	*	-	-	
		regional environ-ment	X15	-	-		-0.00	-1.74		-0.00	-2.18	**	-	-		-	-		-	-	
			X17	0.01	1.46		-	-		0.03	2.69	**	-	-		0.27	2.12	***	0.30	2.36	**
			X18	-	-		-	-		-	-		0.32	2.98	***	-	-		-	-	
			X19	-	-		-	-		-	-		-	-		-	-		6.62	2.31	**
		industrial	X20	-	-		8.18	3.14	***	-	-		49.30	1.14		-	-		-	-	
			X22	-	-		-	-		-4.25	-1.79	*	-	-		-	-		-	-	
		constant term	C	-0.00	-0.00		-0.00	-0.00		-0.00	-0.00		0.00	0.00		0.00	0.00		-0.00	-0.00	
	Double Correlation		R	0.875			0.890			0.777			0.681			0.788			0.685		
	Decision Factor		R^2	0.766			0.792			0.603			0.464			0.621			0.469		

* : Significant at less than 10%,
** : Significant at less than 5%,
*** : Significant at less than 1%

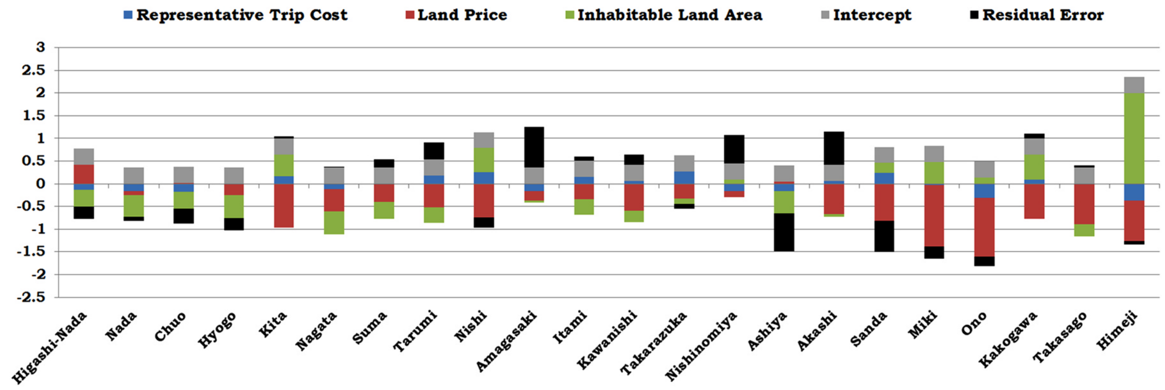


Fig. 5. Approach 2 / stepwise estimation WLS-1. Estimation results of distribution parameters and residential rand area.

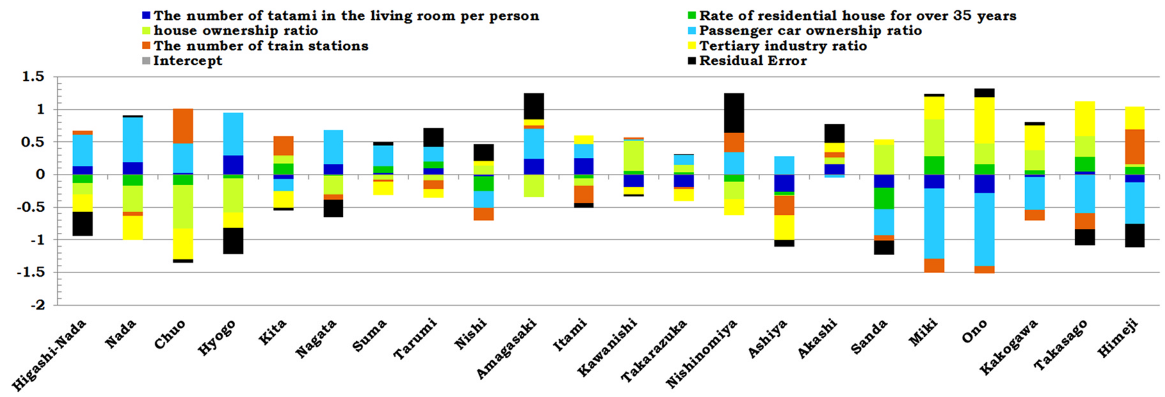


Fig. 6. Approach 2 / stepwise estimation WLS-2. Estimation results of residual errors and urban amenities.

Amagasaki City, Nishinomiya City, and Akashi City; 2) negative residual errors common to Amagasaki City and Miki City; 3) negative residual errors of Sanda City; and 4) negative factors common to Higashinada Ward, Nada Ward and Chuo Ward. Then we will explain the factors of the residual errors with Fig. 6.

In the case of 1), the area (in tatami) of dwelling rooms per person (X7) and vehicle ownership rate (X15) (which are negative factors) are expressed as positive values, and the number of railroad stations (X17) (which is a positive factor) is expressed as a negative value. These results show that these areas are good locations with well-developed transportation systems and good access to downtown. Therefore, we can judge that the cause of the residual errors is that the attractiveness of Osaka, a big city, is not explained adequately. In the case of 2), the local features of Ashiya City and Miki City are extracted as the causes of residual errors. In both cities, the area (in tatami) of dwelling rooms per person (X7) is expressed as a positive value. However, their interpretation is different between the two cities. In the case of Ashiya City, the value seems to express a characteristic of a quiet residential area where high-income earners possess houses with wide lot areas. For Miki City, on the other hand, the value seems to express the characteristic that residents possess wide lot areas since the city is a suburban area. Actually, the vehicle ownership rate (X15) (which is a negative factor) is expressed as a high negative value, and we can extract as a cause the fact that public transportation services in the area are not well developed. In the case of 3) Sanda City, the fact that the city is a new residential area was extracted as the cause of the residual error. Specifically, the fact that the number of old houses is low is pointed out (number of houses: share of houses of 35 years old or older (X9) [which is a positive factor] is expressed as negative), and as is in the case of Miki City, the vehicle ownership rate (X15) is expressed as a negative value. That shows the public transportation services in the city have not been developed as it is a new residential area. In the case of 4), the fact that these areas are urban-type areas was extracted as a cause of the residual errors. The following characteristics were pointed out concretely: the number of old houses is low (number of houses: share of houses of 35 years old or older (X9) [which is a positive factor] is negative); and the rate of owned houses is also low (rate of owned houses (X10) [which is a positive factor] is expressed as negative). We think these factors are showing that the areas are adjacent to Sannomiya.

As described above, we extracted factors causing residual errors as shown in 1) to 4). However, Fig. 6 shows residual errors that cannot be explained even with these factors. These can be roughly divided into two groups: positive residual errors as observed in the cases of Amagasaki City, Nishinomiya City, and Akashi City, and negative ones as observed in Higashinada Ward, Hyogo Ward, and Himeji City. The areas in the former case fall within the scope of 1), and we estimate that the attractiveness of Osaka City is not expressed adequately and that this fact caused the errors. Therefore, we will add a railroad express dummy as a factor to further explain the accessibility to Osaka City. As regards the latter cities, we will add a business space dummy since they are cities or peripheral cities where there are many commercial facilities.

Next, we will show the result of the evaluations of terms of time (Cases 4–6). Although the direction of the signs of distribution parameters and the inhabitable land area of the indirect utility function is stable, it was difficult to secure adequate significance. Furthermore, we were unable to obtain significant results of the distribution parameter for representative trip cost in any cases. That is perhaps because there was little change in the transportation environment during the target periods and it was difficult to obtain significant estimation results. That means that in areas where the transportation environment is already well developed, like Japan, it is difficult to evaluate its changes in the during a short period of time, such as 10 years. Therefore, in Japan and other developed countries, it seems to be necessary to conduct analysis for long periods of time, such as around 30 years. On the other hand, in areas where the transportation environment is changing in a short period of time, such as in newly emerging countries, we can perhaps obtain significant results that could contribute to the judgement of urban transportation policies. From the above, when conducting evaluations of terms of time, we have to set appropriate verification periods depending on the environment of the target area. In this study, as urban amenity factors which cause residual errors, housing: ratio of detached houses (owned + rented houses) (X11) and local environment: number of railroad stations (X17) were identified as positive factors. That means that the results show that changes (increases) in the two factors will greatly affect the increase in population during the target periods.

According to the results of the study in this section, we obtained stable results in evaluations of singe points in time (Cases 1–3) and decided to add the two dummies as factors causing residual errors. On the other hand, in the evaluations of terms of time (Cases 4–6), it was difficult to obtain stable results with the terms of time set in this study. In the next section, we will focus only on the evaluations of single points in time to analyze the causes of residual errors, including the dummy factors.

4.4.7. Approach 2 / stepwise estimation: Identifying factors causing residual errors by adding dummy variables to the evaluations of single points in time

In consideration of the evaluation results in the previous section, we will focus only on the evaluations at single points in time of Approach 2 / stepwise estimation (Cases 1–3) in this section, and evaluate the 25 explanatory variables shown in Table 8, including the dummy variables.

Table 9 shows the results of estimations before the dummy variables were added (the same results as in Table 7) and those after the adding of dummy variables. It shows that coefficients of determination of 0.850 or more are secured after the dummy variables are taken into account, and the reliability has increased. The business space dummy (X25) and the rate of employees engaging in tertiary industries (X22) are commonly expressed as negative values. This means that urban cities and peripheral cities where many business facilities are located will serve as negative factors in behaviors to choose residential locations. Next, the railroad express dummy (X24) and the number of railroad stations (X17) are commonly expressed as positive values. However, the number of railroad stations (X17) shows high significance in all cases. This means that, when behaviors to choose residential location are evaluated by city and ward, convenient accessibility and variety of transportation systems (development of two or more railroads) will cause increases in population. In addition, the share of houses of 35 years old or more (X9) and the area (in tatami) of dwelling rooms per person (X7) show significance in all cases, and the rate of residents of 65 years old or less (X2) and the density of sales area (X14) show significance in some cases.

Next, we will show detailed tendencies in each city and ward in Fig. 7. We have obtained results that can explain more explicitly the tendencies described in 1) to 4) in the previous section.

Concretely, as a factor of residual errors in Nishinomiya City in 1), for Akashi City and Amagasaki City, factors related to the

Table 8
List of urban amenities.

Classification		Amenity		Classification		Amenity	
population	1	Ratio of 15 years old or younger	%	facility	13	School density	per thousand
	2	Ratio of 65 years old or younger	%		14	Retail sales area density	per thousand
	3	Population ratio below junior high school	%	regional environment	15	Passenger car ownership ratio	per thousand
	4	Population ratio below university	%		16	Penal Code offense recognition ratio	per thousand
	5	Single household ratio	%		17	The number of train stations	station
	6	Nuclear family households ratio	%		18	The number of prefectural designated cultural properties	facility
residential house	7	The number of tatami in the living room per person	per population		19	Urban park density	per thousand
	8	Density of new construction starts in buildings and residential house	per thousand	industrial	20	All industry employee density	%
	9	Rate of residential house for over 35 years	%		21	Secondary industry ratio	%
	10	house ownership ratio	%		22	Tertiary industry ratio	%
	11	detached housing ratio	%	land	23	Inhabitable land area	Km^2
	12	vacant house ratio	%	dummy factor	24	Railway: Limited Express Dummy	0 or 1
					25	Commercial area surrounding dummy	0 or 1

Table 9
Estimation results: Approach 2 / stepwise estimation. Comparing before and after the dummy variables are taken into account.

				Before dummy factor addition (Same as the results in Table 6)									After dummy factor addition								
				Case1 [year:2000]			Case2 [year:2005]			Case3 [year:2010]			Case1 [year:2000]			Case2 [year:2005]			Case3 [year:2010]		
				Estimated Parameter	t value	P value	Estimated Parameter	t value	P value	Estimated Parameter	t value	P value	Estimated Parameter	t value	P value	Estimated Parameter	t value	P value	Estimated Parameter	t value	P value
Estimated Parameter	dispersion parameter		θ	1.00	-	-	1.00	-	-	1.00	-	-	1.00	-	-	1.00	-	-	1.00	-	-
	distribution parameter		αx	-0.85	1.86	*	-1.09	2.07	*	-0.98	1.77	*	-0.85	1.86	*	-1.09	2.07	*	-0.98	1.77	*
			αl	-1.03	3.95	***	-0.80	3.67	***	-0.65	3.62	***	-1.03	3.95	***	-0.80	3.67	***	-0.65	3.62	***
	inhabitable land area		X23	0.01	4.60	***	0.01	4.44	***	0.01	4.70	***	0.01	4.60	***	0.01	4.44	***	0.01	4.70	***
	constant term		C	0.55	2.15	***	0.60	2.13	**	0.58	2.05	*	0.55	2.15	**	0.60	2.13	**	0.58	2.05	*
	Double Correlation			0.762			0.743			0.751			0.762			0.743			0.751		
	Decision Factor			0.580			0.552			0.564			0.580			0.552			0.564		
Estimated Urban Amnity	urban amme-nity	population	X2	-	-		-	-		-	-		5.94	2.43	**	-	-		-	-	
			X6	-	-		-	-		-	-		-	-		-1.62	-1.46		-	-	
		residential house	X7	-0.25	-5.22	***	-0.24	-2.65	**	-0.16	-1.34		-0.26	-7.04	***	-0.13	-1.45		-0.16	-2.16	**
			X8	-	-		0.04	1.28		-	-		-	-		-	-		-	-	
			X9	2.34	4.24	***	3.90	4.20	***	2.02	1.93	*	1.09	1.88	*	1.82	2.97	**	1.76	2.51	**
			X10	-	-		2.71	2.09	*	2.73	2.22	**	-	-		-	-		1.24	1.45	
			X12	-	-		-3.43	-1.28		-	-		-	-		-	-		-	-	
		facility	X13	-0.23	-2.50	**	-0.18	-1.63		-	-		-0.16	-1.66		-	-		-	-	
			X14	-0.00	-1.20		-0.00	-1.18		-	-		-0.00	-2.16	*	-0.00	-2.19	**	-	-	
		regional environ-ment	X15	-	-		-0.00	-1.74		-0.00	-2.18	**	-	-		-0.00	-1.42		-0.00	-2.87	**
			X17	0.01	1.46		-	-		0.03	2.69	**	0.02	2.36	**	0.03	3.14	***	0.03	3.31	***
		industrial	X20	-	-		8.18	3.14	***	-	-		-	-		-	-		-	-	
			X22	-	-		-	-		-4.25	-1.79	*	-0.87	-1.13		-2.98	-1.68		-3.98	-2.47	**
		dumdum factor	X24	-	-		-	-		-	-		0.20	1.84	*	0.18	1.39		0.13	0.98	
			X25	-	-		-	-		-	-		-0.56	-4.38	***	-0.66	-4.16	***	-0.59	-4.46	***
		constant term	C	-0.00	-0.00		-0.00	-0.00		-0.00	-0.00		0.23	1.55		0.30	1.68		0.12	1.65	
	Double Correlation		R	0.875			0.890			0.777			0.958			0.948			0.926		
	Decision Factor		R^2	0.766			0.792			0.603			0.917			0.898			0.858		

* : Significant at less than 10%,
** : Significant at less than 5%,
*** : Significant at less than 1%

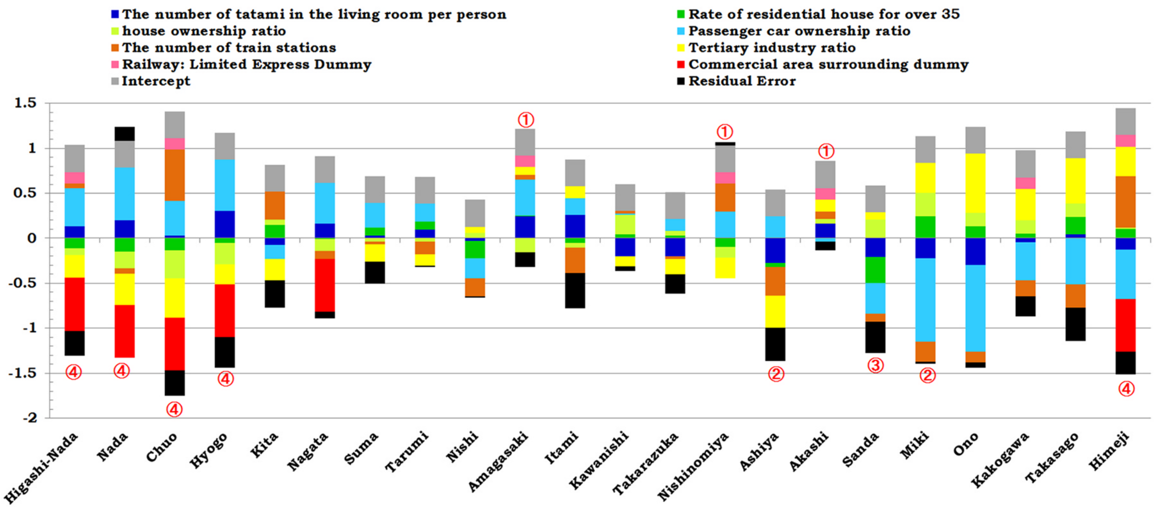


Fig. 7. Approach 2 / stepwise estimation WLS-2. Residual errors and estimation results of urban amenities.

attractiveness of Osaka City are identified. That means that this figure shows that good accessibility to Osaka (number of railroad stations (X17) and railroad express dummy (X24)) and the development of transportation means within the area (low vehicle ownership rate (X15)) triggered the increase in population, and land prices increased as a result (small area (in tatami) of dwelling rooms per person (X7)). Out of cities mentioned in 2), as factors of residual errors in Ashiya City, factors related to quiet residential sections where high-income earners are living are identified: large area (in tatami) of dwelling rooms per person (X7), high ratio of tertiary industries (X22) and low vehicle ownership rate (X15) with well-developed transportation system in the area. On the other hand, as factors of residual errors in Sanda City, factors related to a suburban area located away from the midtown are identified: large area (in tatami) of dwelling rooms per person (X7), large share of houses of 35 years old or older (X9), high vehicle ownership rate (X15) due to insufficient public transportation service in the area, and low rate of tertiary industries (X22). As regards factors related to residual errors in Sanda City in 3), factors showing a new residential area are identified: low share of houses of 35 years old or older (X9), small area (in tatami) of dwelling rooms per person (X7) and high vehicle ownership rate (X15) due to insufficient public transportation service in the area. For each ward of Kobe City and Himeji City in 4), factors related to urban areas and peripheral cities are identified: high business space dummy (X25), high rate of tertiary industries (X22), and low rate of owned houses (X10).

The result mentioned above shows that it might be possible to enhance the accuracy of estimation of location choice behaviors if factors showing local characteristics are taken into account in addition to the indirect utility function, including the transportation environment. In interpreting the results of this analysis, attention should be paid to the following matters.

- In Approach 2 / stepwise estimations mentioned in this paper, which obtained good results, estimations were performed based on the premise that there is no correlation between the development of transportation systems and other urban amenities. On the other hand, when the effect of the development of transportation system is estimated by this method actually, if there is a positive correlation or causality between the development of transportation systems and an urban amenity, the effect might be underestimated, and if there is a negative correlation, it might be overestimated. Therefore, when actually taking into account an urban amenity, it is necessary to check the correlation and causality with the transportation system to be developed in order to select adequate factors.
- Although we suggested that urban amenities should be considered in addition to the indirect utility function when estimating location choice behaviors, the ripple speed of the effect of the development of transportation system is considered to be different. For example, when a transportation system is developed, the time and cost-saving effect will improve the transportation convenience directly, which will influence the location choice behaviors in a short period of time. On the other hand, the effect of improvements and changes in urban amenities is considered to ripple little by little after the development of the transportation system and influence the location choice behaviors later. Let us consider an example in the past. In the case of the large-scale redevelopment of areas around Nishinomiya Kitaguchi Station of Nishinomiya City, Hyogo Prefecture, a large shopping mall was completed and the axis for redevelopment was established in 2008. However, it took more than five years until the station reached first place in the Sumitaimachi Ranking (ranking of cities where people want to live) (Recruit Co. Ltd.), an indicator showing the attractiveness of peripheral cities, and gained attention from families with small children. Therefore, when estimating location choice behaviors, we should handle the indirect utility function and urban amenities while taking into account the ripple speed of the effect of the development of transportation systems and urban cities.
- As regards the local characteristics identified in this study, the level of reaction to them might differ depending on the attributes of the party that will make location choices. For example, the working group will react to the accessibility to urban areas, the high-income earning group to quiet residential areas, and families with small children to new residential areas. It is desirable for the

CUE model to be able to take into account the differences in location choice behaviors depending on the attributes of parties to make choices in the future.

4.5. Study conclusions

We carried out stepwise evaluations at several points in time and terms of time while targeting southern areas of Hyogo Prefecture to solve the issues the conventional CUE model is facing: the issue of how to define distribution parameters of indirect utility function and the issue of location choice behaviors being dependent on the adjustment factor. As a result, we found the following.

A) The conventional method to define distribution parameters of the indirect utility function might underestimate or overestimate location choice behaviors that will vary with changes in representative trip cost and land prices as a result of development of transportation systems. Furthermore, it is difficult to estimate location choice behaviors accurately with the indirect utility function alone. As a measure to solve these issues, if the inhabitable land area is incorporated into the indirect utility function as an alternative to housing supply factors and if distribution parameters are estimated using WLS while the population distribution in the base year is set as an explained variable, we might be able to estimate location choice behaviors more accurately.
B) This study revealed that the factors comprising the adjustment factor on which location choice behaviors estimated by the conventional method are dependent are local characteristics of each city and ward (urban amenities). Therefore, we might be able to improve the estimation accuracy of location choice behaviors by taking into account factors indicating the local characteristics in addition to the indirect utility function incorporating the transportation environment. When adopting an urban amenity in estimating location choice behaviors, it is necessary to consider the following before incorporating it into the CUE model: correlation/causality between the development of transportation systems and urban amenities, the ripple speed of the effect on the location choice behaviors of the urban amenity to be improved after the development/introduction of a transportation system, and the difference in response level to an urban amenity depending on social attribute.
C) In this study, we performed evaluations of single points in time and evaluations of terms of time and obtained good results in the former evaluations. However, it is necessary to choose an appropriate evaluation method from the two according to the target to be evaluated.

For urban cities where basic transportation systems have been completed, like in Japan, the significant method to evaluate the effect of urban transportation policies is to use distribution parameters and urban amenities extracted based on data at a point in time. This will ensure estimation accuracy for location choice behavior.

On the other hand, in areas which are developing rapidly, such as newly emerging countries, evaluations using distribution parameters and urban amenities extracted based on data at a point of time may underestimate or overestimate the effect of an urban transportation policy since they are experiencing great changes.

In cities with well-established city environments and transportation environments, such as in Japan, the environment of the city will not change greatly in a short evaluation period of about 10 years, and we cannot obtain significant results. Therefore, our important mission is to analyze changes during long periods of time, such as 30 or 50 years, to identify the factors leading to the development of the city and to apply the results to the development of newly emerging foreign countries.

On the other hand, in areas where the city and transportation environment are changing rapidly, such as in newly emerging countries, distribution parameters and urban amenities should be set while focusing on changes during a short period of time, such as 5 or 10 years, when estimating location choice behaviors. By doing so, we can more accurately estimate the effects of the development of transportation systems and urban development. In addition, in newly emerging countries, disparity in population rate by age group and economic disparity have a great influence on location choice behaviors, so we have to take them into consideration in the future.

One of the future challenges identified by this study is further study of the interpretation of the results of distribution parameters estimated by WLS. In verification this time, the land price α_l, a distribution parameter, was estimated as a negative value, and we interpreted the results as follows: "The results show that a rise in land price in an area associated with the introduction of urban transportation policies raised the utility of households in the area. This means that the attractiveness of the area will rise as the land price in the area rises, exercising an attracting effect in relation to the location choice behaviors." However, seeing the results from the theoretical background of microeconomics, such negative land price distribution parameter α_l, shows that the demand function is upward-sloping, which deviates from the normal theory. As a factor behind the estimation results this time, we can point out that the land price data used in this study is balanced land prices and that identified problems are not examined in this study. Therefore, we should validate the results of this study from various viewpoints and take additional measures, such as consideration of the identified problems, in order to further improve the results obtained this time.

5. Future direction of the development of the CUE model

Based on the verification results of the validity of the CUE model obtained in the previous chapter, we will describe the future direction of CUE model development.

1) A CUE model that can estimate location choice behaviors more accurately
The CUE model, a practical model to evaluate the effects of transportation development, requires more improvement as described

below to improve its performance in estimating location choice behaviors and to obtain more accurate results than it currently does.

When estimating the effect of the development of transportation systems in Japan in a short period of five years, it is desirable to add a factor to express the housing supply volume in addition to the conventional indirect utility function comprising income, transportation cost, and land consumption. As a factor to serve as an alternative to the housing supply volume, inhabitable land area is considered to be adequate since the data is easy to collect. In addition, the distribution parameters should be set using Formulas (37)–(39) by means of WLS based on the number of location choices in the base year.

However, when estimating the mid-to-long term effect, for five years or more, urban amenities expressing the local characteristics of the target area should be taken into account in addition to the indirect utility function and the inhabitable land area, which serves as an alternative to housing supply volume. The urban amenities should be extracted using Formulas (37)–(40) based on the number of location choices and the city environment in the base year, and incorporated into the indirect utility function.

2) Applying the CUE model to the development of cities in newly emerging countries

When developing city plans and transportation plans in areas in Asia or ASEAN countries, the CUE model is considered to be an adequate method. However, at present, there are few cases in which the CUE model was applied (Chen, Tsutsumi, Yamasaki, & Iwakami, 2013; Yamamoto et al., 2017).

As contrasted with urban areas such as in Japan, these areas are experiencing rapid changes, and we may not be able to obtain significant results with the conventional analysis method when estimating future location choice behaviors using parameters estimated based on the environment in a base year. Therefore, in newly emerging countries, it is necessary to perform the evaluations of terms of time that did not yield significant results in this study to verify the effect of the analysis method.

In addition, in diversified societies, the location choice behaviors are estimated to vary depending on differences in age, income, and social and economic attributes. Particularly when applying the CUE model in estimating Asian and ASEAN countries in the future, it is important to develop a CUE model that can take into account the social and economic attributes.

However, if the social and economic attributes are divided into excessively detailed groups, the CUE model will become too complicated and lose value as an estimation model for general purpose applications. Therefore, it is required to determine appropriate segmentation for the social and economic attributes through questionnaire investigation for residents living in the southern areas of Hyogo Prefecture and analyses of microdata before incorporating them into the CUE model.

6. Conclusions

In this paper, we verified the substantiation of location choice behaviors estimated by the conventional CUE model and clarified the issue of the expenditure scale of the indirect utility function, the linear expenditure system, and the components of the adjustment factor whose position has been ambiguous so far.

As a result, we have obtained new information and knowledge about the future direction of the establishment of a CUE model that can more accurately estimate the location choice behaviors and can take diversified societies into account. Our task ahead is to verify the future direction suggested here to further improve the reliability of the CUE model.

References

Anas, A. (1981). The estimation of multinomal logit model of joint location and travel mode choice from aggregated data. *Journal of Regional Science, 21*(2), 223–242.

Anas, A. (1982). *Residential location markets and urban transportation.* Academic Presshttps://trid.trb.org/view/198673.

Chen, H., Tsutsumi, M., Yamasaki, K., & Iwakami, K. (2013). An impact analysis of the Taiwan Taoyuan international airport access MRT system – Considering the interaction between land use and transportation behavior. *Journal of the Eastern Asia Society for Transportation Studies,* pp315–pp334.

Hayashi, R., & Tomita, Y. (1988). A model for zonal forecast of life cycle progress, residential location and population attributes using random utility models and a micro-simulation technique. *Infrastructure Planning Review,* (395), 85–94 (in Japanese).

Koike, A., Tomokuni, M., & Yamamoto, H. (2016). Ex-post evaluation and expansion of the location choice functions in CUE model. *Infrastructure Planning Review, 72*(5), 695–705 (in Japanese).

Muto, S., Akiyama, T., & Takagi, A. (2000). Econometric evaluation of an urban road network project considering the spatial structure change. *Traffic Engineering, 44*, 205–214 (in Japanese).

Muto, S., Ueda, T., Takagi, A., & Tomita, T. (2000). The benefit evaluation considering the relocating sectors with computable urban economic model. *Infrastructure Planning Review,* (17), 257–266 (in Japanese).

Omori, T., Takagi, A., & Akiyama, T. (2004). A location equilibrium model with fuzzy reasoning for evaluating urban policy. *Infrastructure Planning Review, 21*, 255–264 (in Japanese).

Sugiki, N., & Miyamoto, K. (2003). Sensitivity analysis on spatial and entity aggregation in land-use micro simulation model. *Infrastructure Planning Review*(28) (in Japanese).

Suzuki, T., Muto, S., & Ogawa, K. (2002). Evaluation of land development control to prevent urban suburbanization and promote reurbanization in Central District. *Infrastructure Planning Review, 19*(2), 195–202 (in Japanese).

Tomita, Y., & Terashima, D. (2003). Packaging of land-use, housing and transport policies for optimal urban structure. *Infrastructure Planning Review*(28) (in Japanese).

Ueda, T. (1991). A model analysis on the impact of transport improvement on household locations through increase in opportunities for life activities. *Infrastructure Planning Review, 9*, 237–244 (in Japanese).

Ueda, T. (1992). A general equilibrium model with re-defined location surplus. *Infrastructure Planning Review, 10*, 183–190 (in Japanese).

Ueda, T. (2010). *Regional and urban economics analysis learned with Excel.* Corona Company. (in Japanese) https://ci.nii.ac.jp/ncid/BB00573176.

Ueda, T., & Tsutsumi, M. (1999). A unified framework of land use models recently developed in Japan. *Infrastructure Planning Review,* (625), 65–78 (in Japanese).

Ueda, T., Tsutsumi, M., Muto, S., & Yamasaki, K. (2013). Unified computable urban economic model. *The Annals of Regional Science, 50*(1), 341–362.

Yamamoto, H., Sano, J., Yamasaki, K., Yanagisawa, K., Koike, A., & Tsutsumi, M. (2017). Socioeconomic evaluation of transit oriented development using a Detailed Spatial Scale CUE Model in Taiwan. *The Journal of Asian Transportation Studies, 4*(4), pp565–pp584.

Yamasaki, K., & Muto, S. (2008). Analysis of the effects by road construction with endogenous induced/developed traffic. *Study of Transportation Policy, 11*(2), 14–25 (in Japanese).