HOW DOES THE VALUE OF TRAVEL TIME SAVING VARY OVER THE INDIVIDUAL'S INCOME?

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Abstract: This paper analyzes how the value of travel time savings (VTTSs) varies over individual’s income. First, we formulate a time allocation model and examine the variation of VTTS over income with the comparative static analysis. The results show that the variation of VTTS over income depends on whether the marginal utility is increasing or decreasing with respect to the work time. As a shape of utility function cannot be fixed a priori, we cannot know clearly the variation of VTTS over income. Then, we analyze the VTTS over income empirically with the travel data of urban rail in Tokyo. We estimate the multinomial logit model and the mixed logit model for six different income groups. The empirical analysis shows that the VTTS increases as the income increases.

Key Words: Value of travel time savings, Income, Discrete choice model

1. INTRODUCTION

In order to measure the benefit stemming from a transport project, the starting point is generally the traveler’s willingness to pay: the amount of money each individual would be willing to pay for the change in his or her circumstances (Small, 1999). Typically the dominant benefit component of a transport investment is the travel time saving. There have been many empirical and theoretical studies of the Value of Travel Time Saving (VTTS) after the economic theory of the time allocation was introduced in the 1960s. It was Becker (1965) who first suggested that a consumer gains only utility from the consumption of time, not from the goods consumed directly. After the Becker’s work, several researchers such as DeSerpa (1971), Evans (1972) and Small (1982) have developed the time allocation model in which consumer’s utility is maximized with respect to time and goods consumption under the constraints of the available time and money budgets. Simultaneously, several different definitions of the VTTS have been proposed (Jara-Diaz, 2000). Especially DeSerpa’s definition of VTTS is important as it includes two types of distinct value of time: a value of time as a resource and a value of time as a commodity.

As far as the empirical analysis of the VTTS is concerned, the disaggregate discrete choice model has been the most popular approach taken. Train and McFadden (1978) using the choice of mode for the home to workplace trip, show that the conditional indirect utility function formulated in discrete choice theory will give the value of travel time savings as the marginal substitution rate between travel time and travel cost. In similar manner, Truong and Hensher (1985) and later discussions (Bates, 1987; Truong and Hensher, 1987) show how Becker’s model and DeSerpa’s model can be incorporated into the VTTS estimation within
the discrete choice model framework.

Nowadays, the VTTS is often estimated with the discrete choice model like the Multinominal Logit model in practical transport planning. However, when an additive separable utility function with respect to the income is used, a parameter of the individual income cannot be estimated explicitly because they do not influence the individual choice of travel service. On the other hand, it is well known that the VTTS is closely related to the wage rate. Jiang and Morikawa (2004) present theoretically that it increases as the wage rate increases under specific conditions. However, they do not examine the impact of “income” but the impact of “wage rate” on the VTTS. Few researchers have validated the variation of VTTS over income with the empirical data, mainly because it is quite difficult to obtain the data of individual income. Axhausen et al. (2004) is one of the exceptions. They empirically analyze the VTTS over the annual income with the stated preference data and conclude that the VTTS increases as the income increases. In this paper, we examine the variation of VTTS over income not only empirically but also theoretically. The empirical analysis of this paper uses not the stated preference data but the revealed preference data of Tokyo rail users.

The rest of this paper is organized as follows. Section 2 formulates a time allocation model to derive the VTTS and discuss the variation of VTTS over income theoretically. Section 3 presents the empirical analysis on the VTTS with the data of urban rail route choice in Tokyo. Finally, Section 4 summarizes the paper.

2. THEORETICAL ANALYSIS

2.1 Formulation of the Time Allocation Model
We will formulate a time allocation model based on Becker (1965) and DeSerpa (1971). First, we assume that an individual allocates the amounts of time and consumption of goods in order to maximize her/his utility under the constraints of available time and budget. The individual gains the utility from the leisure time, the work time, the travel time and the consumption of a composite good. Let the utility of the individual be $u$. Then, the time allocation model can be formulated as

$$
\max_{z,T,T_w,t} u = u(z,T,T_w,t) \\
\text{s.t.} \quad z + c = \omega \cdot T_w, \quad t + T_w + t = T^o, \quad t \geq \tilde{t}
$$

Where $z$ is the amount of the composite good with the price as 1, $T$ is leisure time, $T_w$ is work time, $t$ is travel time, $c$ is travel cost, $\omega$ is wage rate, $T^o$ is available time and $\tilde{t}$ is minimum travel time. The final constraint of equation (4) is so-called the time consumption constraint, which means the travel time should be equal to or larger than the fixed minimum travel time.

The Lagrange function corresponding to the above time allocation model is shown as

$$
L = u(z,T,T_w,t) + \lambda (\omega \cdot T_w - z - c) + \mu (T^o - T - T_w - t) + \kappa (t - \tilde{t})
$$

Where $\lambda$, $\mu$ and $\kappa$ are the Lagrange multipliers. The first-order conditions of optimality are derived as
\[
\frac{\partial u}{\partial z} = \lambda, \quad \frac{\partial u}{\partial T} = \mu, \quad \frac{\partial u}{\partial T_w} = \mu - w\lambda, \quad \frac{\partial u}{\partial t} = \mu - \kappa
\]  

(6)

and equations (2) to (4). Next, let the indirect utility function of the individual as \( v(c, T^c, t) \). Then, by applying the envelope theorem (Varian, 1992) to the above utility maximization problem, we can obtain

\[
\frac{\partial v}{\partial c} = \frac{\partial u}{\partial c} + \lambda \frac{\partial}{\partial c} (\bar{c} - \bar{z}) = -\lambda
\]  

(7)

\[
\frac{\partial v}{\partial t} = \frac{\partial u}{\partial t} + \kappa \frac{\partial t}{\partial t} = -\kappa
\]  

(8).

As the VTTS can be defined as the willingness to pay for travel time savings, the VTTS can be derived from equations (7) and (8) as

\[
VTTS = \frac{\partial v/\partial t}{\partial v/\partial c} = \frac{\kappa}{\lambda}
\]  

(9).

On the other hand, from the first-order optimality conditions, we can obtain the VTTS as

\[
VTTS = \frac{k}{\lambda} = \omega + \frac{\partial u/\partial T_w}{\lambda} - \frac{\partial u/\partial t}{\lambda}
\]  

(10).

As Oort (1969) presents, the VTTS consists of three parts: the wage rate, the value of work time gained, and the value of travel time as a commodity.

2.2 Comparative Statistic Analysis on VTTS over income

In general, the income is determined as the sum of the wage income and the non-wage income. In our model, we exclude the latter type of income for the analytical simplification. The wage income can be expressed as the product of the wage rate and the work time. Thus, in order to see the variation of VTTS to income, we must see the impacts of both the wage rate and the work time on three components of VTTS shown in equation (10), which satisfy the first-order optimality conditions of equations (2), (3), (4) and (6). Therefore, we analyze them with a method of comparative static analysis that is originally presented by Kono and Morisugi (2000).

We first derive the total differential of equations (2) to (4). Then we can obtain

\[
\begin{bmatrix}
\frac{\partial^2 u}{\partial z^2} & \frac{\partial^2 u}{\partial z \partial T} & \frac{\partial^2 u}{\partial z \partial T_w} & \frac{\partial^2 u}{\partial T \partial T_w} & \frac{\partial^2 u}{\partial T \partial t} & \frac{\partial^2 u}{\partial T_w \partial t} & \frac{\partial^2 u}{\partial t^2} \\
\frac{\partial^2 z}{\partial z \partial T} & \frac{\partial^2 z}{\partial z \partial T_w} & \frac{\partial^2 z}{\partial z \partial t} & \frac{\partial^2 z}{\partial T \partial T_w} & \frac{\partial^2 z}{\partial T \partial t} & \frac{\partial^2 z}{\partial T_w \partial t} & \frac{\partial^2 z}{\partial t^2} \\
\frac{\partial^2 u}{\partial t^2} & \frac{\partial^2 u}{\partial t^2} & \frac{\partial^2 u}{\partial t^2} & \frac{\partial^2 u}{\partial T^2} & \frac{\partial^2 u}{\partial T \partial t} & \frac{\partial^2 u}{\partial T_w \partial t} & \frac{\partial^2 u}{\partial t^2} \\
\frac{\partial T}{\partial T} & \frac{\partial T}{\partial T_w} & \frac{\partial T}{\partial t} & \frac{\partial T}{\partial T_w} & \frac{\partial T}{\partial t} & \frac{\partial T}{\partial T_w} & \frac{\partial T}{\partial t} \\
\frac{\partial T_w}{\partial t} & \frac{\partial T_w}{\partial T} & \frac{\partial T_w}{\partial T_w} & \frac{\partial T_w}{\partial T_w} & \frac{\partial T_w}{\partial t} & \frac{\partial T_w}{\partial T_w} & \frac{\partial T_w}{\partial t} \\
\frac{\partial t}{\partial z} & \frac{\partial t}{\partial T} & \frac{\partial t}{\partial T_w} & \frac{\partial t}{\partial t} & \frac{\partial t}{\partial T} & \frac{\partial t}{\partial T_w} & \frac{\partial t}{\partial t} \\
\frac{\partial t}{\partial z} & \frac{\partial t}{\partial T} & \frac{\partial t}{\partial T_w} & \frac{\partial t}{\partial t} & \frac{\partial t}{\partial T} & \frac{\partial t}{\partial T_w} & \frac{\partial t}{\partial t}
\end{bmatrix}
\begin{bmatrix}
\frac{\partial u}{\partial z} \\
\frac{\partial u}{\partial T} \\
\frac{\partial u}{\partial T_w} \\
\frac{\partial u}{\partial t} \\
\frac{\partial T}{\partial T} \\
\frac{\partial T}{\partial T_w} \\
\frac{\partial T}{\partial t}
\end{bmatrix}
= \begin{bmatrix}
1 & 0 & 0 \\
0 & 1 & 0 \\
-\omega & 1 & 0 \\
0 & 1 & -1
\end{bmatrix}
\]  

(11).

For the analytical simplification, we assume the utility function is additive separable with respect to \( z, T, T_w, t \). This means
We also assume the marginal utilities both with respect to the consumption of the composite good \( z \) and with respect to the leisure time \( T \) are positive and are decreasing according to neoclassical microeconomics theory. Therefore, there are

\[
\frac{\partial^2 u}{\partial z \partial T} > 0, \quad \frac{\partial^2 u}{\partial z^2} < 0, \quad \frac{\partial u}{\partial T} > 0, \quad \frac{\partial^2 u}{\partial T^2} < 0
\]  

Then, equation (11) and (13) lead to:

\[
\frac{\partial z}{\partial \lambda} < 0, \quad \frac{\partial T}{\partial \mu} < 0
\]  

From these assumptions and results, we can rewrite the equations (2), (3) and (4) into

\[
z(\lambda) + c = \omega \cdot T_w(\lambda, \mu) \quad (15)
\]

\[
T(\mu) + T_w(\lambda, \mu) + T(\mu, \kappa) = T^0 \quad (16)
\]

\[
t(\mu, \kappa) = T \quad (17)
\]

The impact of the change of work time can be examined by the total differential of equation (15). If the change of work time is independent both from travel cost and from wage rate, we can obtain

\[
\frac{\partial z}{\partial \lambda} \frac{\partial \lambda}{\partial T_w} = \omega
\]  

From the equation (18) and \( \frac{\partial z}{\partial \lambda} < 0 \) of equation (14), we can obtain

\[
\frac{\partial \lambda}{\partial T_w} < 0
\]  

Then, let us start to examine the VTTS of equation (10) over work time. First, as we assume the wage rate is independent from the change of work time, the first term of equation (10) is neutral to the variation of work time. Second, as the utility function is assumed to be additive separable with respect to travel time and work time, the third term of equation (10) is also neutral to the variation of work time. Finally, as for the second term, \( \lambda \) decreases as the work time increases, while the change of \( \frac{\partial u}{\partial T_w} \) depends on the signs of \( \frac{\partial^2 u}{\partial T_w^2} \). If the marginal utility with respect to work time is increasing, that is \( \frac{\partial^2 u}{\partial T_w^2} > 0 \), then the VTTS will increase as work time increases. However, else if the utility function holds \( \frac{\partial^2 u}{\partial T_w^2} < 0 \), we cannot obtain the simple results on the change of VTTS.

In the same manner, we can also examine the variation of VTTS to the change of the wage rate. First, the first derivative of the first term of equation (10) is positive constant. Second, the second term of equation (10) is neutral to the change of wage rate, because the utility function is assumed as independent from the wage rate. Finally, the third term is also neutral to the change of wage rate. Therefore, we can obtain simply that the VTTS increases with a constant rate as the wage rate increases.
The results of the above theoretical analysis show that the variation of VTTS over income depends on whether the marginal utility is increasing or decreasing with respect to work time. As we cannot expect a shape of utility function a priori, we cannot know clearly the variation of VTTS over income. Thus, we can examine it only through the empirical analysis.

3. EMPIRICAL ANALYSIS

3.1 Derivation of VTTS from the Discrete Choice Model
We will use a discrete choice model to analyze the VTTS empirically. We first derive the VTTS from the discrete choice model with the time allocation model. As McFadden (1974) and Ben-Akiva and Lerman (1985) present, the discrete-choice-based travel demand model assumes a condition that an individual chooses exclusively a unique discrete travel good/service in her/his choice set. Then, we formulate the individual conditional utility maximization as

$$\max_{z,T_c,\tilde{t}_i} u_i = u(z,T,T_w,t_i)$$ \hspace{1cm} (20)

subject to

$$z + c_i = \omega \cdot T_w, \ T + T_w + t_i = T^c, \ t_i \geq \tilde{t}_i$$ \hspace{1cm} (21, 22, 23).

The subscript $i$ of each variable means the variable with a condition that the $i$-th travel service is exclusively chosen. As the conditional choice model is the same as the original time allocation model except this condition, we can derive the VTTS from the envelope theorem and the first-order optimality conditions as

$$VTTS_i = \frac{\partial v_i}{\partial \tilde{t}_i} \bigg/ \frac{\partial v_i}{\partial c_i}$$ \hspace{1cm} (24)

Where $v_i$ means the conditional indirect utility function, which is usually called as the utility function in the discrete choice theory. We can apply a popular discrete choice model like the multinomial logit model to the estimation of VTTS.

3.2 Sample Data Construction
We use the data of the Tokyo Metropolitan Travel Census 2000 (Institution for Transport Policy Studies, 2000) for the empirical analysis. This survey was conducted by a joint research team of the Ministry of Land, Infrastructure and Transport, Japan and the Institute of Transport Policy Studies, Japan. The survey consists of three surveys: the first is the paper-based interview survey on the home-to-work and the home-to-school travels of passengers with seasonal tickets; the second is the paper-based questionnaire survey on the travels of passengers without seasonal tickets; and the third is the paper-based interview survey on the service of rail operators. The passenger travel surveys were conducted in October, 2000. The passenger travel data include the records of rail-use travels with travel purpose, travel route, times of start and termination with socio-demographic data. They cover the Kanto Region including eight prefectures: Tokyo, Kanagawa, Saitama, Chiba, Ibaraki, Gunma, Tochigi and Yamanashi.

As far as the income data is concerned, since the travel survey data does not include the information of individual income, we will use the macro income data of zones where the
individual resides. This approximation may be acceptable, if the distribution of rail-use traveler’s income is common across the zones. The zonal average annual income data comes from the Individual Income Index 2000, which includes the official individual annual income used for a taxation by local governments. We processed the local-government-based income data into the zone-based income data. Then, we categorize the zones by their average annual income. For this categorization, we apply the Sturges’ rule to the income data of 261 zones and finally obtain six categories shown in Figure 1.

![Graph of average annual income of zones](image)

Figure 1 Zone categorization in the Tokyo Metropolitan Area by average annual income

The sample travel dataset was constructed with the following steps. First, we selected the home-to-work travel data of passengers with seasonal tickets. This is because about more than 80% of rail-use workers in Tokyo own the seasonal tickets. Second, we chose the travelers with one or more than one alternative routes. This leads to the elimination of the travelers with too short travel time. This elimination is done because we intend to analyze the rail route choice of travelers and we need the data of travelers with alternative routes. Third, we assigned the travel data to the above six income groups by the zone of their domiciles. Fourth, we selected randomly 1,000 travel data for each income group. As the category 1 (with annual income of 3,000 to 3,500 thousands yen/year) and the category 6 (with annual income of 5,500 to 7,500 thousands yen/year) contain less than 1,000 travel data, we simply use all individual data. Finally, we obtained 154 samples for the category 1, 1,000 samples each for the category 2, 3, 4 and 5, and 893 samples for the category 6, respectively.

### 3.3 Parameter Estimation

We use the discrete choice model to analyze the rail route choice of travelers. First, we assume an error component in the conditional indirect utility function as

$$
\bar{v}_i = v_i + \varepsilon_i
$$

(25)

Where $\varepsilon_i$ is the error term corresponding to $i$-th travel service. If the error term follows the independent and identical distribution of Gumbel, we can derive the multinomial logit model (MNL). In the MNL, an individual’s probability of choosing a route from her/his choice set is expressed as

$$
P_i = \frac{\exp(\lambda v_i)}{\sum_{j \in J_i} \exp(\lambda v_j)}
$$

(26)
Where $P_i$ is the probability of choosing an $i-th$ route; $J$ is the individual’s choice set and $\lambda$ is a scale parameter.

We also use the mixed logit model (MXL) in order to consider the commonality of routes. This is because we often observe that the routes in the individual’s choice set overlap in some parts due to the high density of rail network in Tokyo. There have been some researches which incorporate the commonality into the discrete choice model (for example, Yai et al., 1990; Russo, F. and Vitetta, 2003). We structure the covariance of the error terms based on the overlapping lengths of all pairs of routes with a method proposed by Shimizu and Yai (1999).

First, we divide the error component into two terms: one is a white noise term $\varepsilon_i$ following the independent and identical distribution of Gumbel, and the other is a structured error term $\eta_i$, shown as
\[ \tilde{v}_i = v_i + \eta_i + \varepsilon_i. \] (27)

If $\eta_i$ be given, a probability of choosing an $i-th$ route would be expresses as
\[ L_i = \frac{\exp\{z(v_i + \eta_i)\}}{\sum_{j \in J} \exp\{z(v_j + \eta_j)\}} \] (28).

However, as $\eta_i$ distributes as the probabilistic variable, the expected probability of choosing the $i-th$ route is presented as
\[ P_i = \int_{-\infty}^{\infty} f(\eta_i | \Omega) \cdot L_i \cdot d\eta_i \] (29).

Where $f(\eta_i | \Omega)$ presents a probability density function of $\eta_i$. As the integral of equation (29) is not the closed form, we should use a simulation technique to obtain the probability. Then, in order to consider the commonality of pairs of routes, we first specify $\eta_i$ as a product of two components: one is a vector $\mu$ whose elements are the probabilistic variables following some specific probability distribution; and the other is a vector $Z_i$ whose elements are the network variables. Thus, $\eta_i$ can be expressed as
\[ \eta_i = \mu \cdot Z_i. \] (30).

The vector $Z_i$ is defined as follows: the $k-th$ element of $Z_i$ is 1 if the $k-th$ unit section is included in the $i-th$ route and is 0 if not. The unit section is defined as a finite line with an arbitrary length, by which the transport network can be divided into the natural number. Next, we assume that any unit section generates an error following the same normal distribution with a mean of zero and a variance of $\zeta^2$. Let us consider the length of the unit section is 1 km. And suppose $L_i$ is the length (km) of the $i-th$ route and $L_{ij}$ is the total overlapping length (km) of the $i-th$ route and the $j-th$ route. Then, the variance and the covariance of the error term in the conditional indirect utility function are derived as
\[ \text{Var}(\mu \cdot Z_i + \varepsilon_i) = L_i \cdot \zeta^2 + \frac{\pi^2}{6} \] (31)
\[ \text{Cov}(\mu \cdot Z_i + \varepsilon_i) = L_{ij} \cdot \zeta^2. \] (32)

These mean the variance of the error term in the conditional indirect utility function of a route is in proportion to the length of the route, whereas the covariance of the error terms between different two routes is in proportion to the overlapping length between them. In other words,
the commonality of routes is incorporated with a hypothesis that the more the two routes are overlapping, the higher the correlation of their error terms is. As the unknown parameter with respect to variance-covariance matrix is only $\zeta^2$, we can estimate it by the simulation method shown by Train (1993).

### 3.4 Estimation Results

The results of model estimations for six income groups with the MNL and the MXL are shown in Table 1 and Table 2, respectively.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Unit</th>
<th>Category 1 (3,000 - 3,500)</th>
<th>Category 2 (3,500 - 4,000)</th>
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<tr>
<td></td>
<td>coefficient</td>
<td>t statistics</td>
<td>coefficient</td>
</tr>
<tr>
<td>In-vehicle travel time</td>
<td>minute</td>
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<td>Travel cost</td>
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<tr>
<td>Number of transfer at stations</td>
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<td>-4.91</td>
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<tr>
<td>Congestion Index</td>
<td>minute</td>
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<td>minute</td>
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<td>-4.11</td>
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<td>Estimated VITS</td>
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<td>5.91</td>
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<th>Category 6 (5,500 - 7,000)</th>
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<td>In-vehicle travel time</td>
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<td>-13.9</td>
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<tr>
<td>Initial log likelihood</td>
<td></td>
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<td>-681.1</td>
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<tr>
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<td>-681.3</td>
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<td>Estimated VITS</td>
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</tbody>
</table>
The congestion index is defined as the disutility stemming from the in-vehicle congestion, which is converted into the in-vehicle time. The congestion disutility of a link is derived from a product of the travel time and the congestion factor where the congestion factor is a quadratic function of in-vehicle congestion ratio which can be derived from dividing the link flow capacity by the link flow. The reason why the congestion index is used in the models is because the in-vehicle congestion is widely regarded as the critical factors influencing the route choice in the Tokyo Metropolitan Area (Yai, et al., 1997; Kato, et al., 2003). These tables show that all models have the high fitness from a statistical viewpoint. As far as the variables are concerned, the most variables are statistically significant. The exceptions are the "congestion index" in the category 3 and 4 of the MNL model, the "congestion index" in the category 2 and 3 of the MXL model and the "access and egress travel time to and from stations".

### Table 2 Parameter estimation results for six income groups with the MXL model

<table>
<thead>
<tr>
<th>Variables</th>
<th>Unit</th>
<th>Category 1 (3,000 - 3,500)</th>
<th>Category 2 (3,500 - 4,000)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Coefficient</td>
<td>t-statistics</td>
</tr>
<tr>
<td>In-vehicle travel time</td>
<td>minute</td>
<td>-0.192</td>
<td>-2.74</td>
</tr>
<tr>
<td>Travel cost</td>
<td>yen</td>
<td>-0.0067</td>
<td>-2.33</td>
</tr>
<tr>
<td>Number of transfer at stations</td>
<td>times</td>
<td>-1.69</td>
<td>-6.2</td>
</tr>
<tr>
<td>Congestion Index</td>
<td>minute</td>
<td>-0.0328</td>
<td>-1.75</td>
</tr>
<tr>
<td>Access and egress travel time</td>
<td>minute</td>
<td>-0.133</td>
<td>-2.87</td>
</tr>
<tr>
<td>Parameter w.r.t variance of error</td>
<td></td>
<td>0.0092</td>
<td>2.07</td>
</tr>
<tr>
<td>Initial log-likelihood</td>
<td></td>
<td>-1.69</td>
<td>-10.36</td>
</tr>
<tr>
<td>Optimal log-likelihood</td>
<td></td>
<td>-1.115</td>
<td>-8.59</td>
</tr>
<tr>
<td>Likelihood ratio</td>
<td></td>
<td>0.228</td>
<td>0.228</td>
</tr>
<tr>
<td>X² statistics</td>
<td></td>
<td>115.5</td>
<td>478.6</td>
</tr>
<tr>
<td>Estimated VTTS</td>
<td></td>
<td>22.2</td>
<td>10.8</td>
</tr>
</tbody>
</table>

### Table 2 Parameter estimation results for six income groups with the MXL model (continued)

<table>
<thead>
<tr>
<th>Variables</th>
<th>Unit</th>
<th>Category 3 (4,000 - 4,500)</th>
<th>Category 4 (4,500 - 5,000)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Coefficient</td>
<td>t-statistics</td>
</tr>
<tr>
<td>In-vehicle travel time</td>
<td>minute</td>
<td>-0.192</td>
<td>-2.74</td>
</tr>
<tr>
<td>Travel cost</td>
<td>yen</td>
<td>-0.0067</td>
<td>-2.33</td>
</tr>
<tr>
<td>Number of transfer at stations</td>
<td>times</td>
<td>-1.69</td>
<td>-6.2</td>
</tr>
<tr>
<td>Congestion Index</td>
<td>minute</td>
<td>-0.0328</td>
<td>-1.75</td>
</tr>
<tr>
<td>Access and egress travel time</td>
<td>minute</td>
<td>-0.133</td>
<td>-2.87</td>
</tr>
<tr>
<td>Parameter w.r.t variance of error</td>
<td></td>
<td>0.0092</td>
<td>2.07</td>
</tr>
<tr>
<td>Initial log-likelihood</td>
<td></td>
<td>-1.69</td>
<td>-10.36</td>
</tr>
<tr>
<td>Optimal log-likelihood</td>
<td></td>
<td>-1.115</td>
<td>-8.59</td>
</tr>
<tr>
<td>Likelihood ratio</td>
<td></td>
<td>0.228</td>
<td>0.228</td>
</tr>
<tr>
<td>X² statistics</td>
<td></td>
<td>115.5</td>
<td>478.6</td>
</tr>
<tr>
<td>Estimated VTTS</td>
<td></td>
<td>22.2</td>
<td>10.8</td>
</tr>
</tbody>
</table>

### Table 2 Parameter estimation results for six income groups with the MXL model (continued)

<table>
<thead>
<tr>
<th>Variables</th>
<th>Unit</th>
<th>Category 5 (5,000 - 5,500)</th>
<th>Category 6 (5,500 - 7,000)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Coefficient</td>
<td>t-statistics</td>
</tr>
<tr>
<td>In-vehicle travel time</td>
<td>minute</td>
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<td>-4.09</td>
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<tr>
<td>Travel cost</td>
<td>yen</td>
<td>-0.0153</td>
<td>-5.47</td>
</tr>
<tr>
<td>Number of transfer at stations</td>
<td>times</td>
<td>-1.32</td>
<td>-5.44</td>
</tr>
<tr>
<td>Congestion Index</td>
<td>minute</td>
<td>0.0546</td>
<td>1.84</td>
</tr>
<tr>
<td>Access and egress travel time</td>
<td>minute</td>
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<td>-8.16</td>
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<tr>
<td>Parameter w.r.t variance of error</td>
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<tr>
<td>Initial log-likelihood</td>
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<td>-9.81</td>
</tr>
<tr>
<td>Optimal log-likelihood</td>
<td></td>
<td>-0.504</td>
<td>-6.59</td>
</tr>
<tr>
<td>Likelihood ratio</td>
<td></td>
<td>0.331</td>
<td>0.36</td>
</tr>
<tr>
<td>X² statistics</td>
<td></td>
<td>65.8</td>
<td>644.1</td>
</tr>
<tr>
<td>Estimated VTTS</td>
<td></td>
<td>24.6</td>
<td>34.8</td>
</tr>
</tbody>
</table>
stations” in the category of the MXL model. In the MXL model, the “parameter with regard to the variance of error term” is statistically significant in all categories. This means that the commonality of rail routes influences the traveler’s route choice significantly.

The comparison of estimated VTTSs over income between the MNL model and the MXL model is shown in Figure 2. First, the estimated VTTS is about 10-70% of the wage rate as the average wage rate in Tokyo is 51.7 yen/minute (as of the year 1999). Second, the estimated VTTSs with the MXL model are higher than the estimated VTTSs with the MNL model. This reflects the results that the ratio of estimated coefficients of travel time in the MXL model to that in the MNL model is higher than the ratio of estimated parameters of other variables. This is probably because the commonality of routes stems mainly from the travel time along the overlapped routes, and the MXL model can estimate the real marginal utility with respect to travel time by eliminating the commonality in travel time due to the overlapped routes. Third, the comparison of the estimation results among various income categories shows that the tendency of the one model is similar to that of the other model. The higher the income is, the higher the VTTS is. The exceptions are the category 1 and 4. The category 1 has higher VTTS than the category 2, while the category 4 has lower VTTS than the category 3. The reason for that the VTTS of the category 4 is lower than the VTTS of category 3 is not clear. On the other hand, the reason for that the VTTS of the category 1 is larger than that of the category 2 may be because of the influence of the travel time on VTTS. The individuals with lower income tend to travel longer in Tokyo (Yoshida and Endo, 1999). Therefore, if the VTTS increases as the travel time increases, this makes the VTTS of the low income group higher. However, as far as the empirical analysis of the VTTS over travel time is concerned, some researches (e.g. Wardman, 1998; 2001; 2004; Jiang and Morikawa, 2004) show that the VTTS increases as the travel time increases, whereas other researches (e.g. Hensher, 1997; Hultkrantz and Mortazavi, 2001; Kato, 2006) show that the VTTS decreases as the travel time increase. Moreover, in order to examine the variation of VTTS over travel time, we may need to consider the individual’s choice of location to live in addition to the travel choice. Although Kato (2007) examines it with a joint-choice model of location to live and travel, this should be examined in the further study.

![Figure 2 Estimated VTTS over average annual income with two models](image)

The comparison of estimated VTTSs over income between the MNL model and the MXL model is shown in Figure 2. First, the estimated VTTS is about 10-70% of the wage rate as the average wage rate in Tokyo is 51.7 yen/minute (as of the year 1999). Second, the estimated VTTSs with the MXL model are higher than the estimated VTTSs with the MNL model. This reflects the results that the ratio of estimated coefficients of travel time in the MXL model to that in the MNL model is higher than the ratio of estimated parameters of other variables. This is probably because the commonality of routes stems mainly from the travel time along the overlapped routes, and the MXL model can estimate the real marginal utility with respect to travel time by eliminating the commonality in travel time due to the overlapped routes. Third, the comparison of the estimation results among various income categories shows that the tendency of the one model is similar to that of the other model. The higher the income is, the higher the VTTS is. The exceptions are the category 1 and 4. The category 1 has higher VTTS than the category 2, while the category 4 has lower VTTS than the category 3. The reason for that the VTTS of the category 4 is lower than the VTTS of category 3 is not clear. On the other hand, the reason for that the VTTS of the category 1 is larger than that of the category 2 may be because of the influence of the travel time on VTTS. The individuals with lower income tend to travel longer in Tokyo (Yoshida and Endo, 1999). Therefore, if the VTTS increases as the travel time increases, this makes the VTTS of the low income group higher. However, as far as the empirical analysis of the VTTS over travel time is concerned, some researches (e.g. Wardman, 1998; 2001; 2004; Jiang and Morikawa, 2004) show that the VTTS increases as the travel time increases, whereas other researches (e.g. Hensher, 1997; Hultkrantz and Mortazavi, 2001; Kato, 2006) show that the VTTS decreases as the travel time increase. Moreover, in order to examine the variation of VTTS over travel time, we may need to consider the individual’s choice of location to live in addition to the travel choice. Although Kato (2007) examines it with a joint-choice model of location to live and travel, this should be examined in the further study.
4. CONCLUSIONS

We analyzed the variation of VTTS over income both theoretically and empirically. We examine it with the comparative static analysis. The results of theoretical analysis show that the variation of VTTS over income depends on whether the marginal utility is increasing or decreasing with respect to work time. As we cannot expect a shape of utility function a priori, we cannot know clearly the variation of VTTS over income. Next, we examine the variation of VTTS over income with the rail route choice data in the Tokyo Metropolitan Area. The results of empirical analysis show that the VTTS seems larger as the income is higher. This is the same results as Axhausen et al. (2004) with the stated preference data.

The empirical analysis in this paper shows that the commuters in the category with the highest VTTS have almost three times larger VTTS than the commuters in the category with the lowest VTTS. The variation of VTTS over income may require the transport planners to reconsider the analytical framework in the cost-benefit analysis. Although the benefit is often evaluated with a single VTTS in the practical transport planning, we may need to classify the travelers into several categories according to their income and to evaluate the benefit with the corresponding VTTSs. Especially, in the regions or countries where there is the serious inequality in the individual’s income, a transport investment may have the very different impacts on the high-income travelers from the low-income travelers. Thus, it may be essential to consider explicitly the variation of VTTS over income in order to consider the equality in the impact of the transport investment.

Finally, we point out further research topics. First, in our theoretical analysis, we assumed that the wage rate is independent from the work time. However, the rise of wage rate may change the work hour as well. We should elaborate the further theoretical analysis on the variation of VTTS over income with a consideration of substitution between the wage rate and the work time. Second, as this paper focused on the relationship between the VTTS and the income, it did not consider the other factors that influence the VTTS. However, as shown earlier, the commuting time has the strong relationship with the individual income. It is necessary to analyze the variation of VTTS over income with a consideration of other related factors. Third, in the empirical analysis, we used the data of urban rail commuters in the Tokyo Metropolitan Area in the empirical analysis. We need to extend the empirical analysis with the other datasets including not only the revealed preference data but also the stated preference data.

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