Macro Modeling of Intercity Travel Demand with Heterogeneous Elasticity

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ABSTRACT

Comparing to air service, which is able to alter the fleet assignments corresponding to the demand change, railway company cannot easily change the train service configuration, because it is closely related to the invested infrastructure in the past. Therefore, railway company must try to keep the number of passengers through demand stimulus countermeasures such as fare discount or speed improvement, in case of downward shift of demand function due to population decrease, business depression, and so on. In order to efficiently concentrate their resource for countermeasures, railway company should pick up markets where service level elasticity are comparatively large. Historically, simple gravity models of one elasticity value have been frequently used to analyze the intercity travel demand. However, for the above purpose, we should permit heterogeneity of elasticity over the different OD pairs: they might differ according to the trip purpose shares, adaption to newly improved transport modes, etc. This paper proposes gravity models with heterogeneous elasticity, which is considered to be related to other measureable factors of each OD pair. We apply several models to the intercity trip data obtained by the most recent National Net Passenger Trip Survey in Japan. The finding of this study teach us where service improvement is promising for stimulating travel demand and securing the number of passengers for service continuation of railway.

1. INTRODUCTION

In Japan it is expected that intercity traffic flow will decrease because of decreasing population or development of information and communication technology. Now, intercity traffic flow is already decreasing. In the situation of intercity traffic flow increasing, it was important to forecast the increase of intercity traffic demand in order to invest in infrastructures. Actually, LOS (Level of Service) of intercity transportation was improved by speed increase of railway and construction of airports. But in the situation of intercity traffic flow decreasing, it becomes difficult to improve LOS by large-scale investment. Furthermore, negative changes occur and are enlarged through positive feed-back loop. The number of passenger decreases in number by the LOS reduction (*e.g.* frequency reduction or abolition of route) and decreasing the number of passengers reduce LOS, and so on.

In order to prevent the continual shrinkages through the positive feedback loop, the number of passengers should be secured by providing alternative service and stimulating travel demand. For example, "Low Cost Carrier" is the business model to succeed in stimulating travel demand by paying attention to "low fare". Against LCC, existing "Full Service Carrier" produces other service (i.e. strengthening of airline alliance or frequent-flyer program), paying attention to some needs other than cheap fare and tries to maintain their network. In the situation of intercity traffic flow decreasing, transportation companies should try to improve LOS not by construction of infrastructure but rather

the others, and stimulate travel demand. For doing so they should understand of needs of intercity passengers.

However it is expected that needs of intercity passengers are different for each origin-destination (OD) pairs. For example, it is clear that what service business passengers desire are differ from what service leisure passengers desire. Business model of LCC is hard to apply to OD pairs with low fare elasticity. Therefore information of LOS elasticity is important for considering how to stimulate travel demand, and this research pay attention to heterogeneous LOS elasticity.

In existing research about intercity travel demand, heterogeneous LOS elasticity was discussed. In almost of existing research like Yao and Morikawa (2005), Nijeogovan (2006) and Wardman (2006), they divided the OD traffic flow into groups of homogeneous elasticity. This classification is effective for forecasting large change of OD traffic flow (*e.g.* construction of new railway line) in the situation where heterogeneity of elasticity cannot be disregarded. Wardman (2006) explains the rapid increase of traffic flow in Britain at the 1990s by GDP growth, and report that GDP elasticity differs according to distance or relation with London. But this way has problems: firstly estimation results of models of groups differ greatly by dependent on the groupings. Secondly, the heterogeneity of LOS elasticity is totally dependent on the pre-knowledge of the analyst, then we can't find a new target of stimulating travel demand.

In this paper, we try explain the LOS elasticity by the explanatory variables instead of using group model. At first we assume that traffic flow are followed the gravity model with heterogeneous LOS elasticity. Next, we explain difference of LOS elasticity by explanation variables. Parameters of this model are estimated using the data of 2005 National Inter-city Travel Survey in Japan. The estimation results show that ODs with shorter distance or higher air share have larger elasticity on speed. ODs with shorter distance, lower air share or higher business rate have larger fare elasticity.

This paper is organized as follows. Descriptions of gravity model with heterogeneous elasticity are presented in Section 2. Data for OD matrices and the explanatory variables are explained in Section 3. The estimation results are discussed in Section 4. Finally, conclusions are provided in Section 5.

2. Model

2.1 OD traffic model

As OD matrix estimation methods, multiple regression analyses of logarithm of traffic were often used. Y_{ij} is the observed OD traffic flow between cities $i, j \in C$. Logarithm of Y_{ij} follows the Gaussian distribution. Means of the Gaussian distribution are μ_{ij}, and the variance are fixed as σ^2:

$$\ln\left(Y_{ij}\right) \sim Gaussian\left(\mu_{ij}, \sigma^2\right), \quad \forall (i, j) \in C ? C \tag{1}$$

$$Y_{ij} > 0, \quad \forall (i, j) \in C ? C$$

OD pairs of "zero trip" (*i.e.* $Y_{ij} = 0$) are neglected in this estimation process. However in intercity travel, "zero trips" are often observed, because frequencies of long-distance local trips are low. Traffic flows of "zero trips" observed ODs are estimated by the model obtained by the ODs of positive observed trips. Consequently it may cause over-estimation. In this paper, the Poisson regression which can use the information of "zero trips" is used instead. Therefore,

$$Y_{ij} \sim Poisson\left(\lambda_{ij}\right), \quad \forall (i, j) \in C ? C \tag{2}$$

$$Y_{ij} \geq 0, \quad \forall (i, j) \in C ? C$$

λ_{ij} denote expected OD traffic flows per day. Logarithm of them are explained by logarithm of explanatory variables $X_{ij}{}^n$ ($n \in N$) and random effect δ_{ij}:

$$\ln\left(\lambda_{ij}\right) = \sum_{n \in N} \alpha_n \ln\left(X_{ij}{}^n\right) + \beta + \delta_{ij}, \quad \forall (i,j) \in C? C \tag{3}$$

$$\delta_{ij} \sim Gaussian\left(0, s^2\right), \quad \forall (i,j) \in C? C \tag{4}$$

where α_n, β and s are parameters to be estimated. Random effect δ_{ij} represents the individual characteristics which cannot be explained by the explanatory variables. As Equation (4), random effect δ_{ij} is assumed to follow the Gaussian distribution where means are 0 and the variance is s^2. When we use S_i, S_j, the city scales of origin city i and destination city j, and GC_{ij} the generalized costs between cities i, j as explanatory variables, Equation (3) can be rewritten in the form of Gravity model including random effect:

$$\lambda_{ij} = \exp(\beta) \frac{S_i{}^{\alpha_1} S_j{}^{\alpha_2}}{GC_{ij}{}^{-\alpha_3}} \exp(\delta_{ij}). \tag{5}$$

Generalized Linear Mixed Model (GLMM) written by Equations (2) ~ (4) were used in some existing researches of OD traffic. Perrakis (2012) presented a statistical Bayesian approach on OD matrix estimation, in which parameter α_n follow the Gaussian distribution and random effect follow the Gamma distribution. He reported that the model suggests a good overall fit to the data in Belgian region of Flanders.

2.2 Elasticity model

In this paper, heterogeneity of LOS elasticity is permitted. We assume that LOS elasticity (parameter α_n) is explained by the linear function of explanatory variables $Z_{ij}{}^m$ ($m \in M$) with parameter $\gamma_m{}^n$, β'^n:

$$\alpha_{ij}{}^n = \sum_{m \in M} \gamma_m{}^n Z_{ij}{}^m + \beta'^n. \tag{6}$$

Substituting Equation (6) into Equation (3), OD traffic model with heterogeneous elasticity is written by linear model:

$$\ln\left(\lambda_{tij}\right) = \sum_{n \in N} \left\{ \sum_{m \in M} \gamma_m{}^n \left(Z_{ij}{}^m \ln\left(X_{tij}{}^n\right)\right) + \beta'^n \ln\left(X_{tij}{}^n\right) \right\} + \beta + \delta_{ij}. \tag{7}$$

Parameters of this linear model with one random effect can be estimated by maximum integrated likelihood method. In estimation of this model glmmML() "R" package is used.

3. Data

In this section, the data used in this analysis (Table.1) are presented.

Table.1. Data used in analysis

Explained variable		
	[1] OD Traffic (50 Zones)	National Inter-city Travel Survey(2005)
Explanatory variables for OD traffic model		
Zone scale variable		
	[2] Population of Zone	National Population Census (2005)
OD characteristics		
	[3] Average Route distance	weighted mean of route distance
LOS index		
	[4] Fare per Distance	Fare / Average Route Distance
	[5] High-Speed Index	$\exp(2.44535) \times (\text{average route distance})^{0.458} / \text{time}$
Explanatory variable for elasticity model		
	[a] Average Route distance	=[3]
	[b] Business Rate	National Inter-city Travel Survey(2005)
	[c] Air Share	National Inter-city Travel Survey(2005)

3.1 Explained variables in OD traffic model

The OD matrix data derived from 2005 National Inter-city Travel Survey in Japan are used as the explained variables. This OD matrix includes the OD traffic flows per a day in fall between 50 zones (*i.e.* almost prefectures). This survey is very large scale survey exceeding 1.5 million samples chosen from people using 5 modes (*i.e.* airline, railway, ship, bus, car). And we can derive the data of travel behavior including transfer and trip purpose, because samples are questioned about real origin, real destination and travel route.

In this paper, OD flows where average route distance (under-mentioned) exceeds 300 km are used for the analysis. ODs under 300 km distance car occupies the maximum share (Figure. 1), are not suitable for the analysis of relation between LOS of public transportation and OD traffic flows.
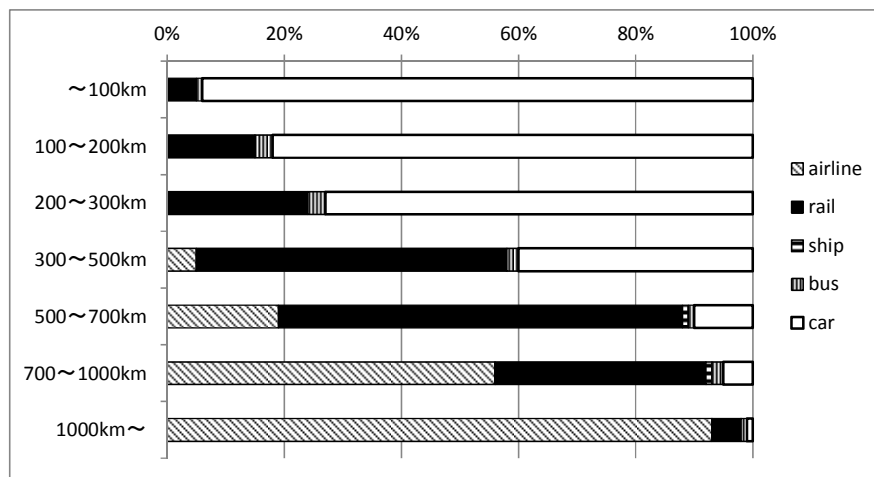

Figure.1. Mode shares of distance groups

3.2 Explanatory variables in OD traffic model

3.2.1 Zone scale variables

In this paper, the data of zone population derived from 2005 National Population Census in Japan is used as one of explanatory variables $X_{ij}{}^{n}$ in OD traffic model (*i.e.* Equation (3)). In the estimation, the product of population of origin zone and one of destination zone are used as the explanatory variable. It is considered that population of origin zone and one of destination zone have same effect, because the going trips and the returning home trips are not distinguished in the OD matrix. It is expected that the parameter of zone scale variable is positive because the larger the zone scale variable is, the larger OD traffic flow becomes.

3.2.2 OD characteristics

In this paper, the information of airline and railway service is used as the OD characteristics, because in the subjects of this analysis (*i.e.* over 300 km) airline or railway occupies the maximum share (Figure.1). As OD characteristics, three variables (*i.e.* [3] ~ [5] in Table.1) are used. At first, used routes $k \in K$ are listed using the data of National Inter-city Travel Survey, and route distance $d_{ij}^{\ k}$, route fare $f_{ij}^{\ k}$ and route time $t_{ij}^{\ k}$ are set by the JTB timetable book. These variables are characteristics between representative railway stations of zone and include the characteristics of access or egress to airport. Average route distance D_{ij}, average route fare F_{ij} and average route time T_{ij} are calculated as the weighting by route traffic flow per a day $n_{ij}^{\ k}$ derived from the National Inter-city Travel Survey:

$$D_{ij} = \frac{\sum_k d_{ij}^{\ k} n_{ij}^{\ k}}{\sum_k n_{ij}^{\ k}}. \tag{8}$$

$$F_{ij} = \frac{\sum_k f_{ij}^{\ k} n_{ij}^{\ k}}{\sum_k n_{ij}^{\ k}}. \tag{9}$$

$$T_{ij} = \frac{\sum_k t_{ij}^{\ k} n_{ij}^{\ k}}{\sum_k n_{ij}^{\ k}}. \tag{10}$$

When the average route distance D_{ij}, average route fare F_{ij} and average route time T_{ij} are directly used for the estimation simultaneously, it may cause multicollinearity because these three variables have high correlation coefficients each other. Therefore, the route fare and time scaled by route distance are used. Fare per distance is calculated by:

$$FR_{ij} = \frac{T_{ij}}{D_{ij}}. \tag{11}$$

The relation between logarithmic average route distance D_{ij} and average route time T_{ij} can be seen in Figure.2. From Figure.2 we can find out that the longer average route distance is, the higher average route speed D_{ij}/T_{ij} is. Therefore, logarithm of expect route time, $\ln\left(ET_{ij}\right)$ are calculated by:

$$\ln\left(ET_{ij}\right) = 0.4558 \ln\left(D_{ij}\right) + 2.44535. \tag{12}$$

For explanatory variable in OD traffic model, High-Speed index HS_{ij} are calculated by:

$$\ln\left(HS_{ij}\right) = 0.4558 \ln\left(D_{ij}\right) + 2.44535 - \ln\left(T_{ij}\right). \tag{12}$$

High-Speed index represents how short the average route time is, compared with expected route time (Figure.2).
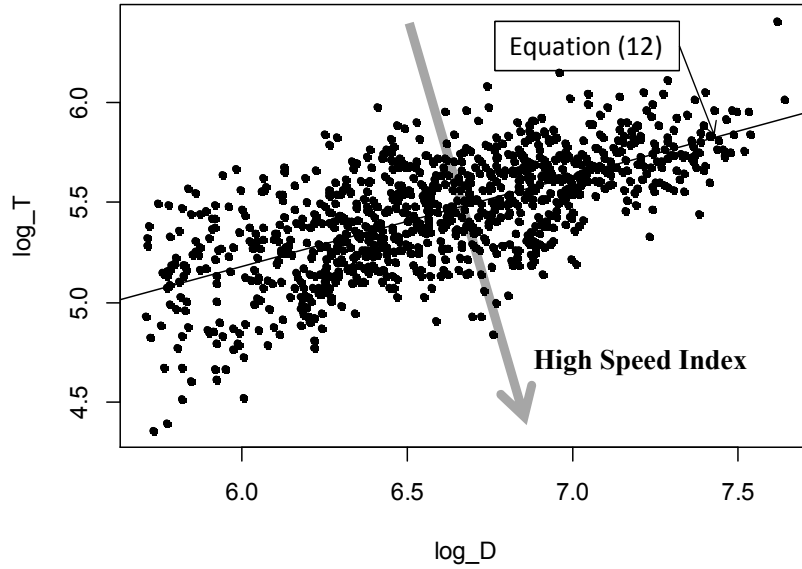
Figure.2. Scattergram of logarithmic distance and logarithmic time

Correlations of the OD characteristics obtained here (i.e. average route distance, fare per distance and High-Speed index) are presented in Figure.3. From Figure.3 we can confirm that these three variables have low correlation coefficients each other. It is expected that the parameter of average route distance and fare per distance is negative, and the parameter of High-Speed index is positive.
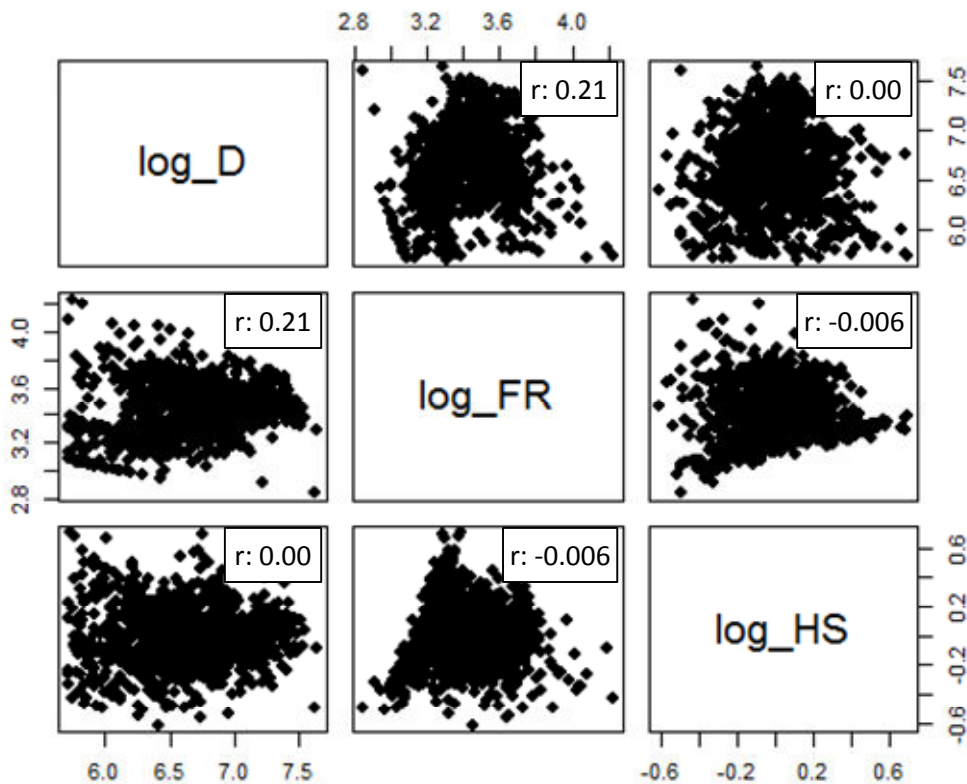

Figure.3. Relationships between explanatory variables in OD traffic model

3.3 Explanatory variables in elasticity model

In this paper, fare per distance FR_{ij} and High-Speed index HS_{ij}, are considered as LOS which can be changed by policy. The heterogeneous elasticity of them is explained by the other factors. As

explanatory variables in elasticity model, three variables, [a] ~ [c] in Table.1 are used. Consulting existing research that Yao and Morikawa (2005) was built two models for business purpose and the other purpose, and Wardman (2006) reported the heterogeneity of GDP elasticity over distances, Business trip rate BR_{ij} derived from the National Inter-city Travel Survey, and average route distance D_{ij} are used as explanatory variables in elasticity model. It is expected that sensitivity of cost and time for airline passengers are different from one for railway passengers, because transfer in airport requires more time for security check and boarding check-in than one in railway station, and fare systems of airline are differ from ones of railway. Therefore, air share AR_{ij} derived from the National Inter-city Travel Survey are also used as explanatory variable in elasticity model.

In this analysis, parameters of two models are estimated. One of two models is Heterogeneous Elasticity Model in which LOS elasticity are explained by three variables [a], [b], [c] in Table.1 and the other is Homogeneous Elasticity Model in which all elasticity are constant.

4. Results

Results of estimations are presented in Table.2 and Table.3. From Residual Deviance and AIC in Table.2, we can recognize that the Heterogeneous Elasticity Model fits better to the data than the Homogeneous Elasticity Model. Parameters except for business rate in the elasticity model of High-Speed index are statistically significant. In the Homogeneous Elasticity Model, according to the assumptions, parameters of population and High-Speed index are positive and parameters of average route distance and fare per distance are negative.

Let's see the estimation result of the elasticity model in Table.3, there are three findings:

(1) ODs with shorter distance have larger elasticity of High-Speed index and larger elasticity of fare.
(2) ODs with higher air share have larger elasticity of High-Speed index and smaller one elasticity fare.
(3) ODs with higher business rate have larger elasticity of fare.

It was generally considered that business trips which apt to be decided regardless of the traveler's decision have small elasticity of fare. But estimation result (3) shows the opposite effect. This means that business passengers who are mostly repeater of same OD adjust the frequency according to fares, and the others apt to decide the trip according to attraction of destinations or ceremonial occasions regardless of fares.

Table.2. The comparison between two models

	Homogeneous Elasticity Model	Heterogeneous Elasticity Model
Residual Deviance	9190	8895
AIC	9202	8917
Degrees of Freedom	1874	1869
Number of Samples	1880	1880

Table.3. The estimation results of models (z-value = coef / se(coef))

	Homogeneous Elasticity Model	Heterogeneous Elasticity Model
(Intercept)	-16.5155*** (-18.470)	-7.3020*** (-4.962)
[1]Population ($population_{origin} \times population_{destination}$)	1.0706*** (44.615)	1.1302*** (48.970)
[2]Average Route Distance	-1.1908*** (-27.273)	-2.6550*** (-15.709)
[3]Cost per Distance		
(Intercept)	-0.5868*** (-6.726)	-1.2589*** (-6.698)
[a]Average Route Distance	---	0.0004072*** (6.963)
[b]Business Rate	---	-0.002966*** (-13.518)
[c]Air Share	---	0.001429*** (4.173)
[4]High-speed index		
(Intercept)	0.5781*** (5.175)	0.7253*** (3.399)
[a]Average Route Distance	---	-0.0009411*** (-2.846)
[b]Business Rate	---	---
[c]Air Share	---	-0.007861*** (-2.907)
Random coefficients	0.7211	0.6603

Figure.4 presents estimated LOS elasticity of several ODs based on the Heterogeneous Elasticity Model. From Figure.4 we can find that ODs, with shorter distance and harder to use a railway due to geographical features (*e.g.* Kochi - Miyazaki and Kochi - Wakayama), have higher elasticity of speed. Elasticity of speed of these ODs is more than twice the elasticity of speed of the Homogeneous Elasticity Model. In these ODs which have no direct air flight, it expected that we can stimulate travel demand effectively by time reducing policy (*e.g.* improvement of connection). Similarly, we can find that ODs with shorter distance and lower air share (*i.e.* high railway share), have higher fare elasticity. Fare elasticity of these ODs is more than twice the fare elasticity of the Homogeneous Elasticity Model. In these ODs, we can stimulate travel demand effectively by fare-reduction policy.
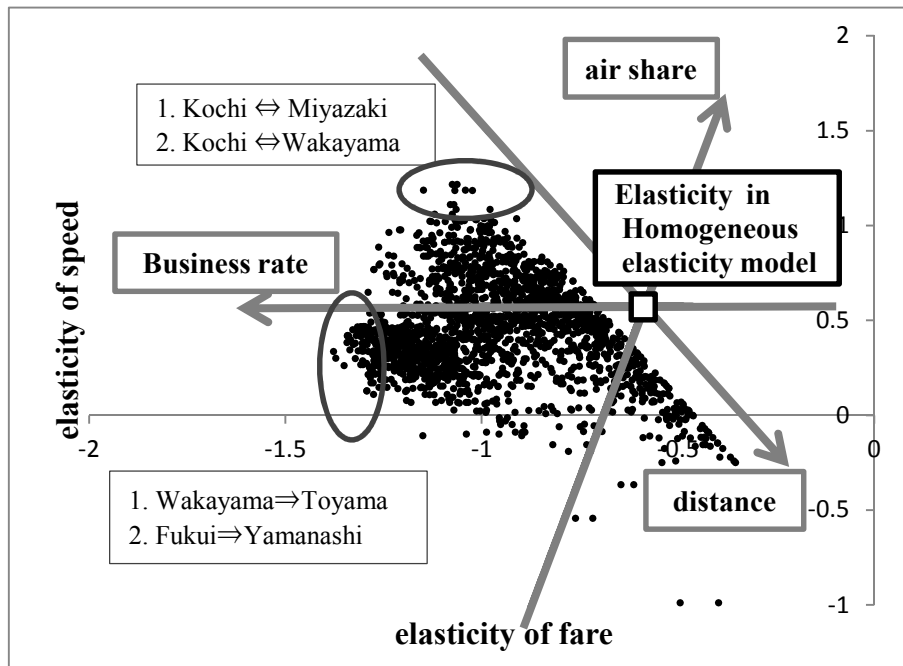
Figure.4. Estimated LOS elasticity of several ODs

5. Conclusion

In this paper, it is explained that railway companies must try to keep the number of passengers by stimulating travel demand in order to maintain the inter-city transportation network under demand shrinkage. The inter-city demand model with heterogeneous LOS elasticity is proposed. This model is valuable for considering the efficient way to stimulate travel demand (*e.g.* alternative fare reduction for passengers with high fare elasticity).

Parameters of the model are estimated using the data of the National Population Census in Japan. The estimation results show that ODs with shorter distance or higher air share have larger elasticity of speed, and ODs with shorter distance, lower air share or higher business rate have larger fare elasticity. These results will help to stimulator travel demand.

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