

# Development and Empirical Analysis of a Model for Matching Land Transaction Considering the Influence of Excursion Travel Behavior

Risa Kobayashi\*<sup>1</sup> and Eiji Hato<sup>2</sup>

<sup>1</sup>Research Associate, Department of Civil Engineering, the University of Tokyo, JAPAN

<sup>2</sup>Professor, Department of Civil Engineering, the University of Tokyo, JAPAN

## SHORT SUMMARY

This study aims to develop a new formulation of land transaction equilibrium on a neighborhood scale from real data, including travel behavior data, by introducing a matching algorithm, and to clarify the effect of excursion-inducing urban renewal projects on transactions. We formulated a choice for land transaction behavior based on the MNL model for estimation using actual land transaction data. A dynamic discrete choice model formulated sequential visiting location choice behavior. The estimated parameters of the transaction model were used to calculate the choice probability, and each owner's preferences were defined and matched using the Deferred Acceptance algorithm. The results revealed that installing urban renewal projects that change visiting behavior can achieve land transaction matching that does not create blocking pairs and can increase total utility in the entire neighborhood.

**Keywords:** Discrete choice model for land, DA algorithm, Recursive logit model, Tourism, Urban development

## 1 INTRODUCTION

The land-transportation interaction model framework has helped to measure the impact of urban development and transportation policy interventions on both markets. These frameworks have primarily aimed at evaluating policies for metropolitan areas, and many have assumed aggregate units such as zones or households, and frameworks based on economic theory have assumed equilibrium in the land market in terms of price or quantity. However, that resolution makes it difficult to describe changes in land transactions associated with dramatic visiting patterns caused by high-density, partial urban renewal development, as in city centers nowadays. In addition, improvements in observation technology and expanding the scope of land and building data utilization. This background calls for and enables the extension of land-transportation interaction models with relaxed equilibrium conditions and their validation using individual-level travel and land transaction behaviors.

Land transaction behavior in economics has been approached from multiple perspectives, including search theory and matching problems, and their application in urban planning and civil engineering. Search theory, initially framed by Stigler (1961, 1962), explores the market behaviors of buyers and sellers, providing an understanding of housing market dynamics in Wheaton (1990). This theory has been integrated into macroeconomic models considering the two-sided search between sellers and buyers. In parallel, the concept of matching in land transactions is rooted in the Deferred Acceptance (DA) algorithm (Gale & Shapley, 1962), which offers a robust framework for understanding stable matching problems. This approach conceptualizes transactions based on owners' preferences, leading to stable matching where each participant finds the most suitable counterpart without any preferable alternative. Furthermore, land market issues in land-transportation models incorporate demand and supply aspects for lands or houses influenced by travel behavior. Models like MUSSA (Martinez, 1996) use the Multinomial Logit (MNL) model to simulate bidding behavior, considering the random utility maximization theory by McFadden (1978) and Rosen's hedonic theory (Rosen, 1974). Hurtubia et al. (2019) further extend this by proposing a method to estimate maximum bids in auctions, addressing the unrealistic perfect match assumption in a previous model by Martínez & Henríquez (2007) and offering a more detailed view of market price calculation without simplifying the attributes of participants. However, market clearing by price equilibrium is assumed, and market clearing by matching two economic agents is not dealt with.

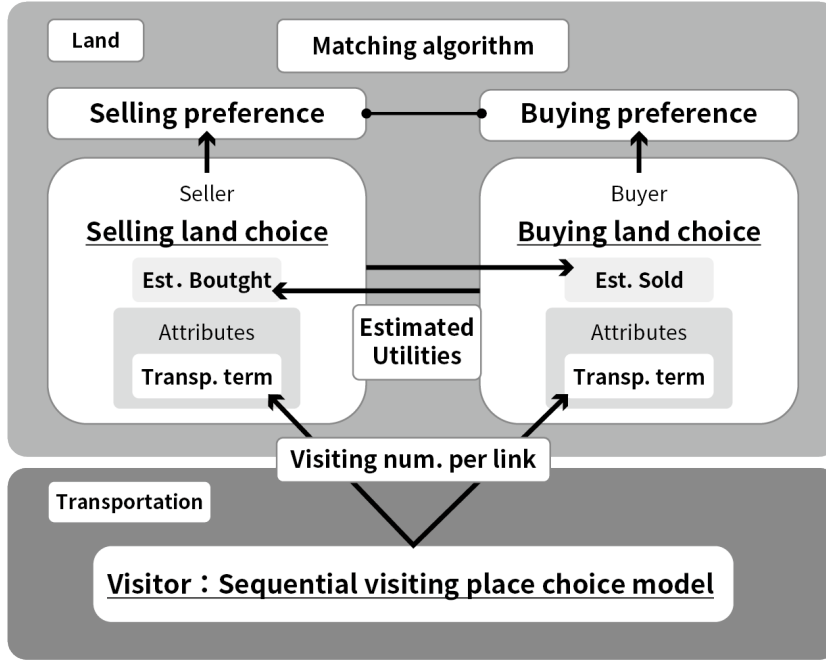


Figure 1: The Model overview in this study

Although the land transaction problem is treated mainly as a matching or search-theoretic problem in the housing market, the impact of travel demand on land transactions has not been considered or included in the model. At the same time, many location choice models in land-transportation models based on economic theory that consider transportation effects assume only price or total volume equilibrium but not behavioral equilibrium, although they assume the random behavior of two economic agents. At the same time, the methodology of market clearing between supply and demand is still in the process of improvement. In addition, due to the difficulty of obtaining land transaction data, empirical studies have been limited, and the impact of transportation has not been empirically clarified.

This study aims to formulate land transaction behavior as a matching problem by introducing a DA algorithm and to clarify how land use that leads to changes in travel behavior contributes to changes in the matching state of land transactions. The land transaction behavior assumes two economic agents, the selling landowner (seller) and the buying landowner (buyer), and a behavioral model is constructed assuming that visitors are the agents of travel behavior. The main features of this study are (1) the disaggregated multiple economic agents –sellers buyers, and travel agents; (2) the formulation of market equilibrium as a matching problem, which is different from price equilibrium in previous studies, and (3) the demonstration using real data for the proposed model. By achieving the objectives, we can obtain suggestions on how policy should intervene in changes in the three states of travel behavior, land use, and land transactions.

## 2 METHODOLOGY

Figure 1 shows the model overview proposed in this study.

### *Selling or buying lands choice model*

We use an MNL model to describe discrete choice behavior toward lands with the landowner as the agent to estimate the probability of each land selling and buying behavior. We formulate the choice probabilities of selling behavior  $P^S$  (Eq. 1) and buying behavior  $P^B$  (Eq. 2) and specify the deterministic term as Eq. (3) and Eq. (4) of the model, respectively.

$$P_{\{\{i\},\{i\}^-\}}^S = \frac{e^{V_{\{\{i\},\{i\}^-\}}}}{\sum_{\{\{i\},\{i\}^-\}' \in I^s} e^{V_{\{\{i\},\{i\}^-\}'}}} \quad (1)$$

$$P_j^B = \frac{e^{V_j^B}}{\sum_{j' \in J} e^{V_{j'}^B}} \quad (2)$$

$$V_{\{\{i\}, \{i\}^-\}}^S = \boldsymbol{\theta}^T \mathbf{X}_{\{i\}^-} + \alpha \sum_{l, i_l \in I^s} NQ_l + \gamma \sum_{l, i_l \in I} \delta_l^{buy} (\hat{\boldsymbol{\theta}}_{buy}) \quad (3)$$

$$V_j^B = \boldsymbol{\theta}^T \mathbf{X}_j + \alpha \sum_{l, j \in J} NQ_l + \gamma \sum_{l, i_l \in I} \delta_l^{sell} (\hat{\boldsymbol{\theta}}_{sell}) \quad (4)$$

We assume that the landowner chooses a combination  $i = \{\{i\}, \{i\}^-\}$  of land to sell  $\{i\}$  and land to keep  $\{i\}^-$  from the set of land he owns  $I^s$  (Eq. 1, 3) and that the landowner chooses a land  $j$  to buy from a sold lands set  $J$  (Eq. 2, 4).

The deterministic terms of utility (Eq.3, 4) for each model consist of three terms.  $\mathbf{X}$  is the vector of explanatory variables for land attributes.  $N$  is the pedestrian travel demand volume, and  $Q_l$  defines the choice probability of link  $l$ . The third term represents the estimated bought or sold land numbers on link  $l$  to which land  $\{i\}$  or  $j$  belongs. The parameters to be estimated are  $\boldsymbol{\theta}_{sell, buy} = [\boldsymbol{\theta}, \alpha, \gamma]$  respectively.

### Sequential visiting location choice model

This model is based on the discounted recursive logit (DRL) model (Oyama & Hato, 2017). For agent  $n$ , we assume a Markov process that sequentially chooses a location as a place to visit and reaches the final destination. In this case, if we define the vector of places to visit based on sequential choice as a tour  $\sigma$ , the probability of choosing a tour is as follows:

$$P_n(\sigma_n = [s_1, s_2, \dots, s_T]) = \prod_{\tau=1}^{T-1} P^d(s_{\tau+1} | s_\tau) \quad (5)$$

$d$  is the final destination, and  $P^d(s_{\tau+1} | s_\tau)$  is the conditional choice probability. Let us consider a directed graph  $\mathcal{G} = (\mathcal{E}, \mathcal{S})$ .  $\mathcal{E}$  and  $\mathcal{S}$  are the set of edges and visit place locations, respectively. The agent chooses from the set of possible transitional locations the alternative that maximizes the sum of instantaneous utility and the maximum expected utility discounted by a discount factor  $\beta$ . The expected utility can replace the value function of the Bellman equation.

$$V^d(s_\tau) = \mathbb{E} \left[ \max_{s_{\tau+1} \in \mathcal{S}(s_\tau)} \{v(s_{\tau+1} | s_\tau) + \beta V^d(s_{\tau+1}) + \mu_{s_\tau} \varepsilon(s_{\tau+1})\} \right] \quad (6)$$

$v(\cdot)$  is the deterministic utility component characterized by the unknown parameter. The random component  $\varepsilon(s_{\tau+1})$  is assumed to be an i.i.d generalized extreme value distribution with non-negative scale parameter  $\mu$ . The transaction probability from  $s_\tau$  to  $s_{\tau+1}$  is Equation 7.

$$P^d(s_{\tau+1} | s_\tau) = \frac{e^{\frac{1}{\mu} \{v(s_{\tau+1}|s_\tau) + \beta V^d(s_{\tau+1})\}}}{\sum_{s'_{\tau+1} \in \mathcal{S}(s_\tau)} e^{\frac{1}{\mu} \{v(s'_{\tau+1}|s_\tau) + \beta V^d(s'_{\tau+1})\}}} \quad (7)$$

The calculation of the value function, including the time discount rate, is performed using the same procedure as Oyama & Hato (2017). Since we were assuming a generalized extreme value distribution, Equation 7 can be expressed in log-sum form, and by taking exponents on both sides, we obtain Equations 8 and 9.

$$V^d(s_\tau) = \begin{cases} \mu \ln \sum_{s_{\tau+1} \in \mathcal{S}(s_\tau)} \delta \cdot e^{\frac{1}{\mu} \{v(s_{\tau+1}|s_\tau) + \beta V^d(s_{\tau+1})\}}, & s_\tau \neq d \\ 0, & s_\tau = d \end{cases} \quad (8)$$

$$e^{\frac{1}{\mu} V^d(s_\tau)} = \begin{cases} \sum_{s_{\tau+1} \in \mathcal{S}(s_\tau)} \delta \cdot e^{\frac{1}{\mu} \{v(s_{\tau+1}|s_\tau) + \beta V^d(s_{\tau+1})\}}, & s_\tau \neq d \\ 1, & s_\tau = d. \end{cases} \quad (9)$$

To calculate the choice probability in Equation 7, it needs to solve the Bellman equation, which describes the algorithm for solving the equation according to the recursive logit (RL) model (Fosgerau et al., 2013).

$|S| \times |S|$  matrix  $\mathbf{M}^d$  and  $|S| \times 1$  vector  $\mathbf{z}^d$  is defined as follows:

$$z_{s_\tau} = \begin{cases} \sum_{s_{\tau+1} \in \mathcal{S}(s_\tau)} M_{s_\tau, s_{\tau+1}} (z_{s_{\tau+1}})^\beta, & s_\tau \neq d \\ 1, & s_\tau = d, \end{cases} \quad (10)$$

$$M_{s_\tau, s_{\tau+1}} = \delta(s_{\tau+1} | s_\tau) e^{v(s_{\tau+1} | s_\tau)} \quad (11)$$

Using  $\mathbf{M}$  and  $\mathbf{z}$ , the value function expressed in Equation 14 can be obtained as a solution to a linear equation. Following Oyama & Hato (2017), Equation 12 is solved by iteration until the fixed point converges.

$$\begin{aligned} \mathbf{z} &= \mathbf{M} \odot \mathbf{X}(\mathbf{z}) + \mathbf{b} \\ \mathbf{X}(\mathbf{z}) &= \mathbf{z}^\beta \end{aligned} \quad (12)$$

### *Land transaction matching algorithm based on estimated utilities*

We use the estimation results to solve a matching problem for land transactions. In the matching problem, based on the two sets of economic agents and the order of their preferences, the DA algorithm is applied to achieve stable matching, which is a perfect matching in which no unstable pairs exist for the two sets of economic agents. Here, we assume a set of two economic agents, the seller, and the buyer, and their order of preference is defined by the choice probability obtained by the parameter estimation in the selling and buying land choice model. Both sellers and buyers are assumed to be either in a state where no matching is established ("free") or in a state where matching is tentatively established ("tentative matching").

The matching algorithm is as follows according to the DA algorithm. First, the "free" buyer makes an offer for the land with the highest choice probability among his alternatives. Next, if the seller who owns the land is free, he accepts the offer, and a "tentative matching" is established. If the seller who owns the land is already "tentative matching", the choice probabilities of the tentatively matched buyer and the newly offered buyer are compared, and the seller will be "tentative matching" with the buyer with a higher choice probability. If the "tentative matching" with the seller is resolved, the buyer removes the resolved seller's land from his preference list and becomes free. The above procedure is repeated until there are no more buyers who have not been tentatively matched.

## 3 RESULTS AND DISCUSSION

### *Description of case studies and data for estimation and simulation*

We selected Dogo, a tourist and neighborhood scale in Japan, as the focus of this study for two main reasons. Firstly, detailed survey data on land and travel behavior were available for this area since there were enough land transaction records and tourist/pedestrian behavior surveys conducted at two different periods. Secondly, the city underwent urban renewal projects to enhance the attractiveness, convenience, and safety of tourist visits. These projects were executed in two phases: the first phase, from 2007 to March 2009, involved developing pedestrian zones and squares, and the latter phase, from 2013 to September 2017, saw the addition of new tourist facilities. Alongside these infrastructural developments, a six-month initiative from September 2017 sought to install art installations inside and around the area, aiming to improve the area's appeal to visitors.

Tourist/pedestrian behavior was surveyed in December 2009 and from November 2017 to January 2018. In both surveys, questionnaires were distributed and collected on-site. In addition to the socioeconomic attributes of individual respondents, they were asked to indicate the location and transportation mode for their entire itinerary. Of the responses, individuals who visited at least three places within walking distance of the hot spring facility, the main building, and the geographical center in Dogo were considered the target of the estimation.

The land transaction record data is based on documents of Certificate Copy of Real Property (all matters). Since the Certificate Copy of Real Property changes in ownership and the reasons for such changes, it is possible to identify the location and date of a transaction or acquisition.

### *Estimation results of choice models*

The estimation result of the sequential visiting location choice model (Table 1) reveals two main tourist preferences for land transactions and urban renewal projects. For land transactions, both

Table 1: Estimation Results of Sequential Visiting Location Choice Model

	2009		2017	
	Est.	t-value	Est.	t-value
Spa Dummy	1.59	4.38**	1.91	1.24
Hotel Dummy	-0.54	-1.36	2.80	2.07**
Shop Dummy	1.39	4.79**	3.87	2.80**
Heritage site Dummy	1.66	5.72**	3.05	2.55**
Transaction num. (2004-2009)	0.04	0.90	0.07	0.60
Transaction num. (2013-2017)	-	-	-0.25	-1.03
Project for the square of the main bldg. Dum	0.85	2.89**	0.55	0.90
Project for square of station Dum	1.26	5.73**	-0.94	-0.84
Distance	0.00	-0.00	0.18	1.82*
Art installation Dum	-	-	1.59	2.16**
Project for new bath bldg. Dum	-	-	3.15	1.28
Time discount rate $\beta$		0.10		0.10
Initial Log-likelihood		-398.74		-124.61
Final Log-likelihood		-315.36		-89.36
Adj. Likelihood ratio $\rho^2$		0.19		0.20
Samples		88		118

\*\* :5% significant, \*:10% significant

non-significance transaction number parameters indicate that tourism behavior was not affected by the frequency of land transactions during the urban renewal project period. Regarding urban renewal projects, it is suggested that in 2009, whether or not the area was around the square of Dogo station was relatively more likely to be chosen as a location to visit than whether or not it was around the square in front of the main building. In 2017, the influence of the presence or absence of art installations was stronger than that of other urban projects. These results suggest that not land transactions themselves but urban renewal projects that result from those transactions, as well as projects that do not improve the infrastructure, such as art installations, positively influence the visiting location choice behavior.

The estimation result of the selling or buying land choice model (Table 2), estimated simultaneously, shows the impact of variables related to attributes, the estimated number of people visiting, and each other's behavior on the decision. In the selling land choice behavior, the estimated visiting number parameter was significantly positive, indicating lands facing high-visiting links were kept. Conversely, estimation results of the buying land choice model showed related parameters were insignificant period-wise, suggesting visiting may not influence buying decisions. Finally, in the selling model, the parameters related to estimating the other's behavior were negatively significant in all periods. This suggests that sold lands are located in links with fewer buyers, which is expected to transact by the seller's proposal unsuccessful. Therefore, we decided to employ the matching algorithm by the buyer's proposal to validate land transaction behavior.

Table 2: Estimation Results of Selling or Buying Land Choice Model

	2004-2009		2009-2013		2013-2017		2017-2021	
	Sell	Buy	Sell	Buy	Sell	Buy	Sell	Buy
Cluster size	Est. -2.459	-1.219	-3.29	-2.97**	-3.16	-1.66	-1.11	-30.65
	t-value -7.13**	-6.10**	-6.00**	-3.22**	-5.47**	-4.36**	-1.53	-0.21
Opening width (/10m)	Est. 0.86	0.13	1.42	0.36	1.52	-0.16	1.86	0.10
	t-value 10.00**	0.54	8.99**	0.69	9.79**	-0.39	10.16**	0.35
Estimated visiting num.	Est. 4.13	0.04	2.41	3.04	0.73	-24.75	0.90	-20.41
	t-value 3.61**	0.08	2.50**	1.09	1.75*	-0.785	1.85*	-0.81
Estimated bought land num.	Est. -0.14	-	-0.84	-	-0.47	-	-0.34	-
	t-value -10.09**	-	-12.10**	-	-10.91**	-	-6.21**	-
Estimated sold land num.	Est. -	-0.10	-	-0.16	-	-0.02	-	-0.087
	t-value -	-2.86**	-	-1.75*	-	-0.28	-	-0.89
Initial Log-likelihood	-1692.09	-234.99	-1272.88	-136.68	-975.99	-122.29	-712.72	-100.71
Final Log-likelihood	-1205.43	-109.16	-563.47	-37.06	-496.89	-48.22	-407.98	-25.60
Adj. Likelihood ratio $\rho^2$	0.29	0.53	0.55	0.72	0.49	0.60	0.422	0.736
Sample	2093	98	1607	57	1230	51	884	42

\*\*.: 5% significant, \*: 10% significant

### Matching results of land transaction

Figure 2 (a) shows the matching results using the DA algorithm with the estimated results for each of the four time periods. The algorithm converged, indicating that it can produce land transactions that reach a stable solution. Figure 2 (b) shows the actual number of transactions per link (y-axis) and the number of matching transactions per link (x-axis). Although there are some gaps, points in the figure are generally distributed on the diagonal, suggesting the effectiveness of the matching algorithm for forecasting. The link that showed a gap between the actual number of transactions and the matching number of transactions is noteworthy in that they had been rapidly converted to vacant land and parking lots between 2013 and 2021 (named as HLU link). The HLU link shows a higher actual number of transactions than the matching, suggesting the lands were traded at a lower price. This result is consistent with the current situation where lands have not been used effectively even if it is transacted.

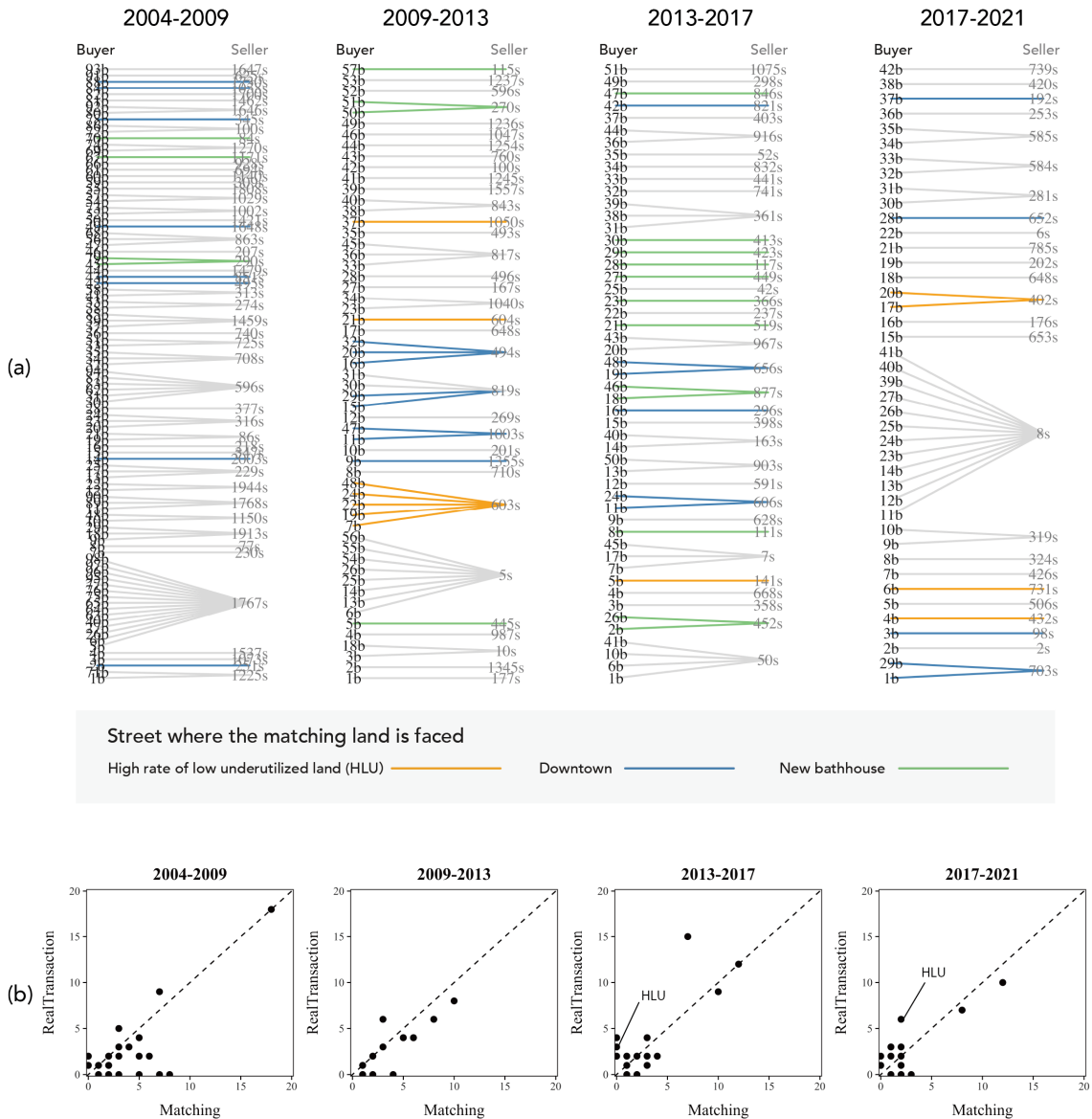


Figure 2: (a) Matching results and trends from 2004 to 2021, (b) Actual transaction number and matching number from 2004 to 2021

### Simulation results for matching influenced by pedestrian changes

We simulated using the estimated parameters to identify changes in visiting and land transaction behavior due to the urban renewal projects. Since the matching results revealed a gap in the HUL

link, we assumed that new hot spring facilities were installed in the HUL link in 2008. Specifically, this policy simulation was conducted in the following steps: 1) Re-estimate the visiting location choice model with the addition of the HUL link as an option and a dummy variable, 2) Recalculate the number of allocated visiting people based on the estimation results, 3) Re-estimate the land transaction model based on the recalculated number of allocated visiting, and 4) Re-match the model.

The re-matching results are shown in Figure 3, the relationship between new sellers and matched buyers compared to the matching results shown in Figure 2, and the renewal rate of matching. It is found that between 30% and 50% of the buyers were matched with new sellers in all periods. This suggests that installing places to visit and stay may affect the matching of land transactions that satisfy preferences and that public projects are effective in land management in the specific area, suggesting a new urban development policy.

To clarify the spatial distribution of matching changes, Figure 4 shows the increase or decrease in the number of matching transactions per link and the change in total utility due to matching transactions in the Dogo neighborhood area. Matching, concentrated on specific links, was dispersed throughout the area, and the total utility increased in all periods. This indicates that building new facilities on the underutilized street can lead to satisfactory transactions throughout the area. These results suggest that measures that induce the visiting of underutilized lands will promote decentralized land transactions and higher utility for matching in the area. In other words, the results suggest that the project may affect the utility of landowners who own land not only in the project link but also in other links.

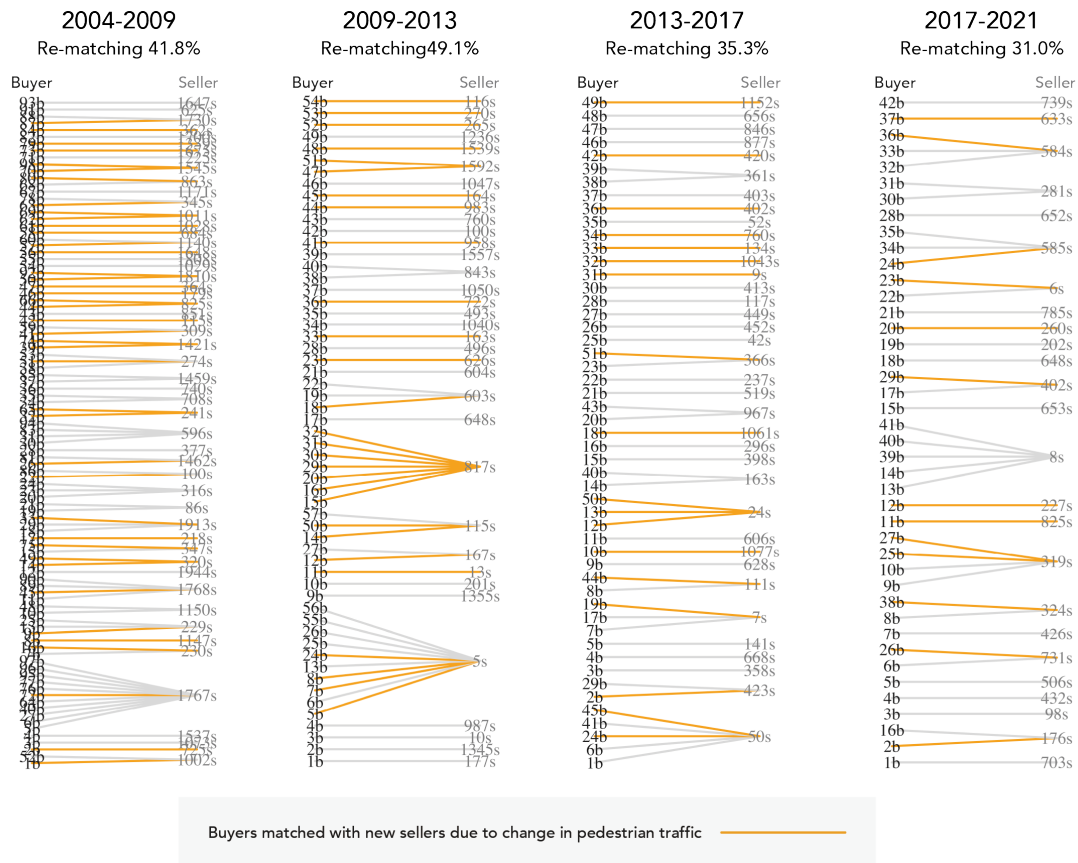


Figure 3: New land transaction matching results generated by urban project implementation from 2004 to 2021

#### 4 CONCLUSIONS

In this study, we formulated land transaction behaviors as a matching problem using the DA algorithm, attempting to estimate the equilibrium state of land transactions from data and the estimated results of a travel behavior model. Prior studies have hypothesized the existence of two economic agents, land sellers and buyers, but have not considered the impact of travel behavior



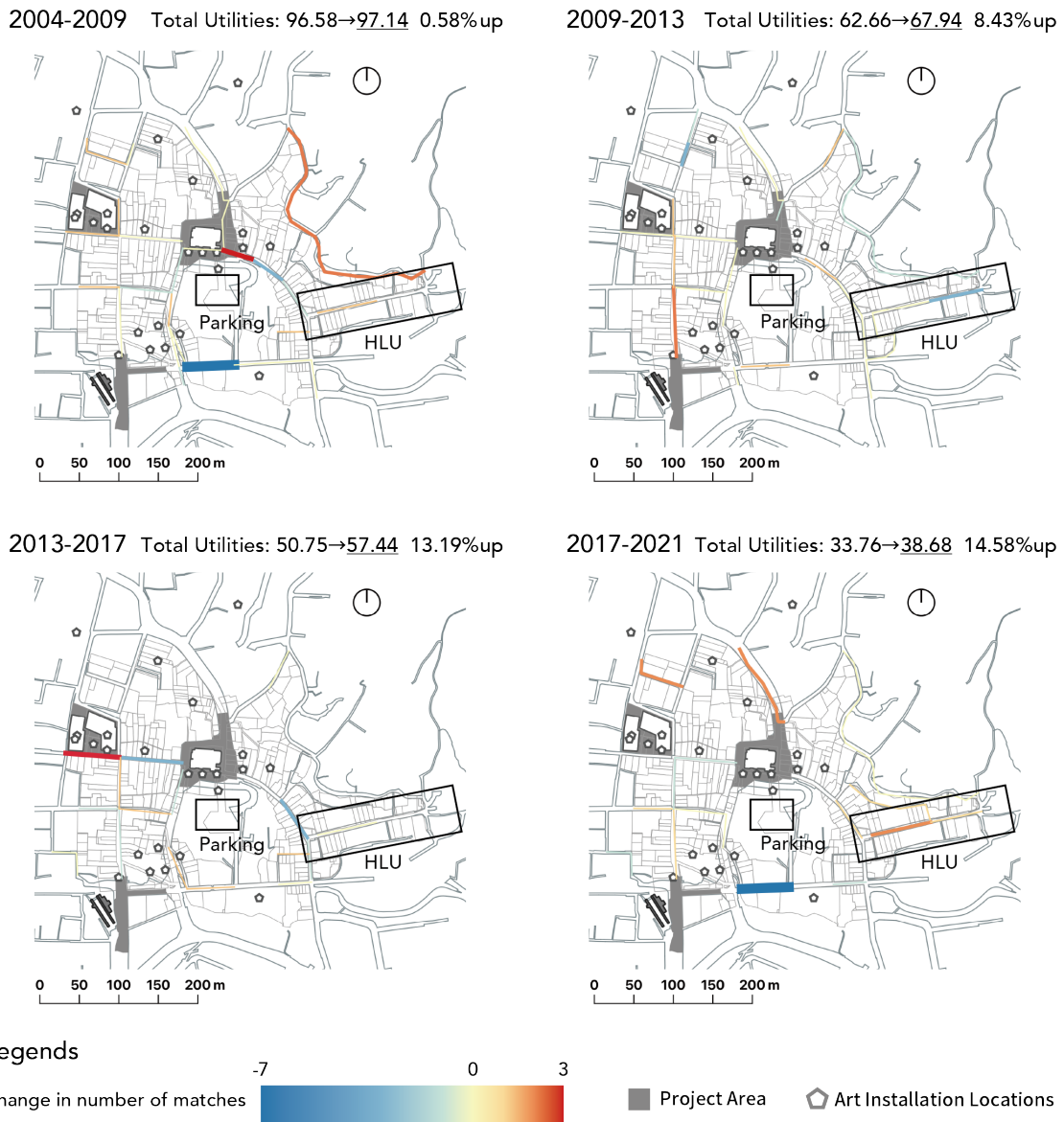


Figure 4: Change in matching results by link and total utility from 2004 to 2021 from estimated and simulated

on land transactions. Moreover, most land-transportation interaction models have assumed aggregated units and focused only on price or total quantity equilibrium, leaving issues replicating equilibrium states. Against this, our study hypothesized an ideal state where sellers and buyers matched based on their preference order. We formalized their behavior using the MNL model based on utility maximization theory and also visiting behavior as a travel behavior that affects land transactions. By utilizing model estimation parameters, we clarified the preference order of both agents and executed the DA algorithm. This approach enabled estimating a stable matching state for land transactions, previously treated as an aggregate in past research. Firstly, the study comprehensively acquired land transaction data using documents of Certificate Copy of Real Property. Concurrently, by formulating and estimating a sequential visiting model for visitors using travel behavior surveys in areas where land transactions occurred, we presented a micro-interactive model framework that reveals the impact of travel behavior on land transactions at a neighborhood scale smaller than 1km mesh.

Our findings are as follows: from the estimation results, we clarified that the location of the urban project was more likely to be chosen as a visiting place, and the estimated number of visitors positively influences keeping land behaviors. The matching results from the buyer-proposing algorithm suggested the presence of equilibrium and disequilibrium in stable matching, which is not apparent from land transaction data alone. It also indicated that the links with imbalanced matching correspond to underutilized land usage. Finally, the simulation assumes that urban renewal

projects that induce visiting specific underutilized street indicated an increase in the total utility of matching in the area.

## ACKNOWLEDGEMENTS

This study was supported by JST's ACT-X Project (Grant No.: JPMJAX22A6).

## REFERENCES

- Fosgerau, M., Frejinger, E., & Karlstrom, A. (2013). A link based network route choice model with unrestricted choice set. *Transportation Research Part B: Methodological*, 56, 70–80.
- Gale, D., & Shapley, L. S. (1962). College admissions and the stability of marriage. *The American Mathematical Monthly*, 69(1), 9–15.
- Hurtubia, R., Martinez, F. J., & Bierlaire, M. (2019). A quasi-equilibrium approach for market clearing in land use microsimulations. *Environment and Planning B: Urban Analytics and City Science*, 46(3), 445–468.
- Martinez, F. (1996). Mussa: land use model for santiago city. *Transportation Research Record*, 1552(1), 126–134.
- Martínez, F. J., & Henríquez, R. (2007). A random bidding and supply land use equilibrium model. *Transportation Research Part B: Methodological*, 41(6), 632–651.
- McFadden, D. (1978). *Modeling the choice of residential location, chapter 3 spatial interaction theory and planning models, a. karlqvist, l. lundqvist, f. snickars, and j. weibull, eds.* Amsterdam: North Holland.
- Oyama, Y., & Hato, E. (2017). A discounted recursive logit model for dynamic gridlock network analysis. *Transportation Research Part C: Emerging Technologies*, 85, 509–527.
- Rosen, S. (1974). Hedonic prices and implicit markets: product differentiation in pure competition. *Journal of political economy*, 82(1), 34–55.
- Stigler, G. J. (1961). The economics of information. *Journal of political economy*, 69(3), 213–225.
- Stigler, G. J. (1962). Information in the labor market. *Journal of political economy*, 70(5, Part 2), 94–105.
- Wheaton, W. C. (1990). Vacancy, search, and prices in a housing market matching model. *Journal of political Economy*, 98(6), 1270–1292.