The impact of availability of bike sharing systems on rental housing price in Japanese regional cities

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SHORT SUMMARY

Bike sharing systems (BSS) have gained attention as a convenient and sustainable transportation mode. In this study we conducted a generalized propensity score analysis to estimate the impact of availability of BSS on house rental price based on a hedonic approach. We evaluated the convenience of each BSS station based on the average number of available bikes and calculated a BSS availability indicator (BAI) as a treatment variable. As the output of several steps of the generalized propensity score analysis, the function of potential outcome at each BAI level was estimated. Results show that the increase in BAI leads to an increase of house rental prices compared with housing units without available BSS up to a certain BAI value.

Keywords: Bike sharing system, Availability, Generalized propensity score, Hedonic analysis, Housing value

1. INTRODUCTION

In recent years, bike sharing systems (BSS) have gained attention as a transportation mode complementary to transit. In Japan, the government has highlighted the convenience of BSS and formulated guidelines for its introduction and operation to support local governments in promoting its implementation[1]. Against this background, BSS is expected to expand in Japan.

BSS is not only a convenient transportation mode but has been shown to be able to bring various external effects such as environmental impact and health benefit (Olabi et al., 2023). The impact on property values is also an expected external effect and previous studies analyzed it quantitatively using hedonic analysis (Qiao et al., 2021; Lee, 2022; Zhou et al., 2022; Shr et al., 2023).

Although some studies focused on the docked BSS and revealed the impact on property values (Lee, 2022; Shr et al., 2023), they have not fully evaluated the convenience of BSS. These studies calculated the distance between targeted housing units and BSS stations and utilized this measurement as a treatment variable, but disregarded bike availability at the BSS station, an important factor that can considerably affect the convenience of BSS and should be considered in the analysis. This study aims to fill this research gap and quantify the causal impact of BSS on property values, explicitly considering bike-availability.

[1] https://www.mlit.go.jp/road/bicycleuse/share-cycle/guideline.pdf

2. METHODOLOGY

Study area

We selected target cities for analysis based on the following criteria: (1) availability of BSS data (as explained below), (2) absence of shared mobility services such as other operator's BSS, e-scooter sharing, in order to analyze the effect of only targeting BSS (3) a sufficient number of BSS stations to ensure an adequate sample size of the treatment group.

Consequently, we selected Shizuoka city as a study area. Shizuoka city is located far from large metropolitan areas such as Tokyo, Osaka and Nagoya and exhibits a lower modal share of public transportation and higher modal share of private car than the cities located in such large metropolitan areas. The modal share of Shizuoka city as per the Nationwide Person Trip Survey in 2021 is summarized in Table 1.

The distribution of BSS stations in Shizuoka city is illustrated in Figure 1. Docked BSS in Shizuoka city is operated by OpenStreet Inc.[2] and there are 215 BSS stations in Shizuoka city as of January 22, 2024.

Table 1: Modal share of Shizuoka city in 2021

	Modal share of representative transportation (weekday) [%]					
City	Railway	Bus	Private car	Motorbike	Bicycle	Walk/Other
Shizuoka	6.4	2.6	52.5	3.6	14.2	20.7

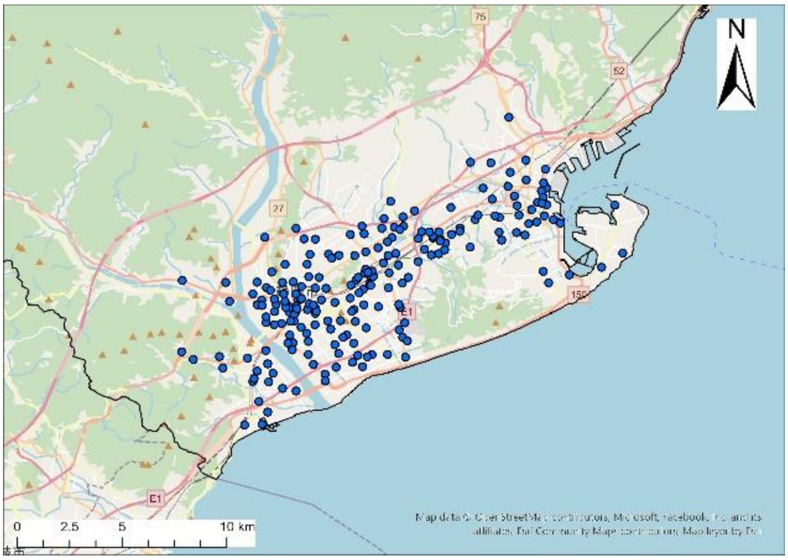

Figure 1: Distribution of BSS stations

BSS data (treatment variable)

As we mentioned in the Introduction section, the availability of BSS is considered as the treatment variable in this study. The data is processed by the following steps.

First, data of the number of available bikes is downloaded from the Public Transportation Open Data Center (ODPT)[3], a site providing open data on the Japanese public transportation system. We collected General Bikeshare Feed Specification (GBFS) data for Shizuoka city from

[2] https://www.openstreet.co.jp
[3] https://www.odpt.org/en/

January 9 to January 22, 2024, with 5 minutes intervals and calculated the average number of available bikes for each station during this period.

Next, to evaluate the availability of BSS for each housing unit, this study introduces we adapted a BSS availability indicator (BAI) Qiao et al. (2021) to station-based systems. BAI for a housing unit i is the weighted average number of available bikes at BSS station j located within a buffer zone of D[m] from the housing unit i:

$$BAI_i = \sum_{j \in S_i} m_j \frac{D - d_{ij}}{D} \tag{1}$$

Where m_j, S_i, d_{ij} indicates the average available number of bikes during a period at BSS station j, buffer zone centered on housing unit i, and Euclidian distance from housing unit i to BSS station j [m], respectively (Figure 2). Here the radius of buffer D is set as 1000 [m] and BAI for each housing unit is calculated. The distribution of BAI is indicated in Figure 3.

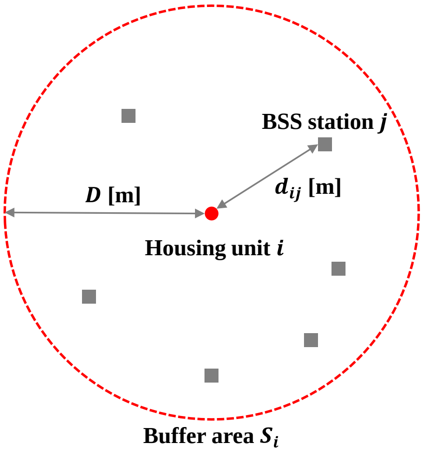

Figure 2: Calculation of BAI

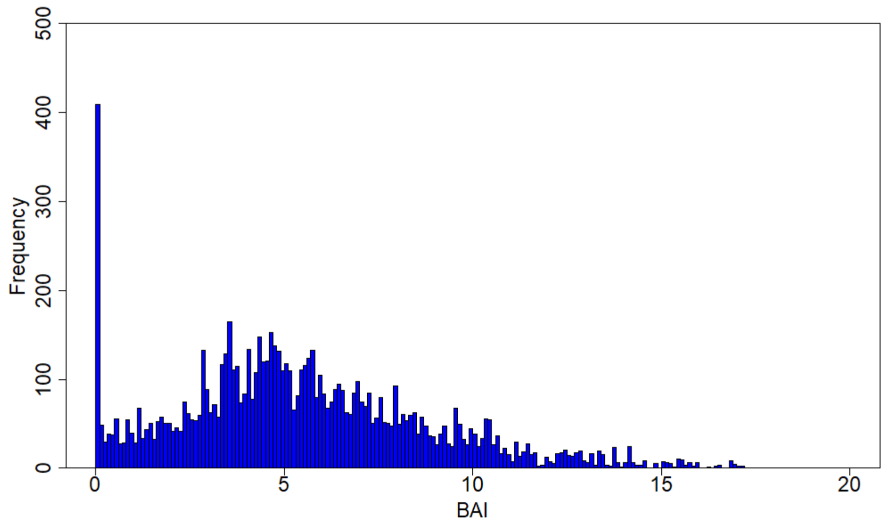

Figure 3: Distribution of BAI

Rental housing data (outcome)

Following Qiao et al. (2021), we select house rental price per month as the outcome to measure the value of property. We utilize the records of rental houses posted on LIFULL HOME'S[4], one of the largest housing rental information platforms in Japan, for the period from February 1 to March 15, 2024. This database includes price, location and other information such as area, structure, build year for each housing unit. Totally, 8,432 houses were used for the analysis in Shizuoka city.

Generalized propensity score analysis

The propensity score analysis was proposed by Rosenbaum and Rubin (1983) and is a widely used approach to estimate causal impact quantitatively by controlling for covariates. As we explained above, the treatment variable in this study is a continuous variable, so we adopt generalized propensity score analysis, an extended method of propensity score to continuous treatments (Hirano and Imbens, 2004).

Generalized propensity score is defined as the conditional density of treatment T given the covariates $\boldsymbol{X}$. In this study, we consider the variables related to housing unit and built environment characteristics as covariates $\boldsymbol{X}$. The generalized propensity score R_i is estimated with a normal distribution with parameters $\sigma, \beta_0, \boldsymbol{\beta_1}$ using a regression model:

$$R_i = r(T_i, \boldsymbol{X_i}) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{1}{2\sigma^2}(\ln(T_i) - \beta_0 - \boldsymbol{\beta_1} \cdot \boldsymbol{X_i})^2\right) \tag{2}$$

As described in Table 2, there are missing values for some covariates. In the estimation, these missing values are imputed by MissForest (Stekhoven and Bühlmann, 2012). In addition, the treatment variable is log-transformed, but when the value equals zero, we use $\ln(0.001)$.

Based on the estimated generalized propensity score $\widehat{R_i}$, the conditional expectation of outcome Y_i given treatment T_i and generalized propensity score R_i is modeled via OLS with parameters $\alpha_0, \alpha_1, \alpha_2, \alpha_3, \alpha_4, \alpha_5$. The average potential outcome $E[Y]$ at treatment level t is then estimated:

$$E[\ln(Y_i)|T_i, R_i] = \alpha_0 + \alpha_1 \ln(T_i) + \alpha_2 \ln(T_i)^2 + \alpha_3 R_i + \alpha_4 {R_i}^2 + \alpha_5 \ln(T_i) R_i \tag{3}$$

$$E\left[\widehat{\ln(Y(t))}\right] = \frac{1}{N}\sum_{i=1}^{N}\left(\widehat{\alpha_0} + \widehat{\alpha_1}\ln(t) + \widehat{\alpha_2}\ln(t)^2 + \widehat{\alpha_3}\hat{r}(t, \boldsymbol{X_i}) + \widehat{\alpha_4}\hat{r}(t, \boldsymbol{X_i})^2 + \widehat{\alpha_5}\ln(t)\hat{r}(t, \boldsymbol{X_i})\right) \tag{4}$$

Through this process, we can obtain the function of potential outcome at each continuous treatment level excluding the influence of covariates.

3. RESULTS AND DISCUSSION

As we mentioned in the previous chapter, generalized propensity score analysis has several steps to estimate causal impact. Table 2 indicates the result of estimation of generalized propensity score based on formula (2) and Table 3 indicates the results of conditional expectation of outcome estimation based on formula (3). Using these models, functions of potential outcome at each BAI

[4] https://www.homes.co.jp/

level shown in Figure 4 is estimated following formula (4). This curve indicates potential values of house rental price excluding the effect of covariates at each BAI level, so that, for example, the margin between potential outcome at BAI = 0 and BAI = 5 can be interpreted as the average treatment effect of increasing BAI from 0 to 5 on house rental price. The median of the average available number of bikes in the term m_j is 1.95 in Shizuoka city, so an increase of 1 in BAI corresponds to the installation of representative station at the distance of 487 [m] from the housing unit.

In addition, to clearly understand the impact of increase of BAI, the average treatment effect at each BAI level based on BAI = 0 ($ATE_0(BAI)$[%]) is calculated by the following formula:

$$ATE_0(BAI) = \left(\exp\left(E\left[\ln\left(\widehat{Y(BAI)}\right)\right] - E\left[\ln\left(\widehat{Y(0)}\right)\right]\right) - 1\right) \times 100 \tag{5}$$

The calculated ATE_0 at each BAI level is described in Table 4. Results show a 11.6%, 16.9%, and 18.0% increase in house rental prices given a BAI increase from 0 to 1,3, and 5, respectively. The value of BAI = 5 is close to median of BAI in Shizuoka city. However, in the case of BAI valuers larger than 5, ATE_0 does not increase and remails close to $ATE_0(BAI = 5)$. These results suggest that in this context, even if a BSS station with an excessively large number of available bikes is introduced, the impact on the value of property is almost equal to that of the installation of a BSS station with moderate availability.

Table 2: Result of generalized propensity score estimation

Variables	Estimate	Std. Error	P-value	
Constant	-1.552	0.195	0.000	***
Age of housing unit [year]	-0.138	0.021	0.000	***
Dummy for wooden structure	-0.387	0.043	0.000	***
Area of housing unit [m^2]	-0.042	0.032	0.189	
Dummy for 1F	0.020	0.035	0.560	
Number of rooms	0.022	0.031	0.482	
Dummy for all electrification	-0.147	0.099	0.137	
Dummy for self-locking door	-0.168	0.059	0.005	***
Dummy for delivery box	-0.164	0.048	0.001	***
Dummy for bike parking	0.006	0.044	0.899	
Dummy for earthquake reinforcement	-0.020	0.063	0.754	
Dummy for separate bathroom	-0.143	0.045	0.002	***
Dummy for independent washing stand	0.066	0.044	0.132	
Dummy for free internet	0.045	0.041	0.275	
Dummy for female only	-0.148	0.214	0.490	
Dummy for student only	0.813	0.224	0.000	***
Dummy for no pets allowed	-0.205	0.049	0.000	***
Distance to station [m]	-0.589	0.019	0.000	***
Distance to bus stop [m]	0.001	0.017	0.944	
Distance to elementary school [m]	-0.212	0.017	0.000	***
Distance to university [m]	-0.717	0.017	0.000	***
Distance to convenience store [m]	-0.146	0.018	0.000	***
Distance to supermarket [m]	-0.005	0.018	0.765	
Distance to general hospital [m]	-0.202	0.018	0.000	***
Dummy for residential land use	3.066	0.188	0.000	***
Dummy for commercial land use	2.612	0.197	0.000	***
Dummy for industrial land use	2.939	0.192	0.000	***
Observations	8432			
Adj. R^2	0.411			

*: p<0.1, **: p<0.05, ***: p<0.01

Table 3: Result of conditional expectation of outcome estimation

Variables	Estimate	Std. Error	P-value
Constant	10.756	0.035	0.000 ***
BAI	-0.013	0.008	0.095 *
BAI^2	-0.004	0.001	0.000 ***
GPS	-0.199	0.405	0.623
GPS^2	1.729	1.097	0.115
BAI*GPS	0.169	0.034	0.000 ***
Observations	8432		
Adj. R^2	0.029		

*: $p<0.1$, **: $p<0.05$, ***: $p<0.01$

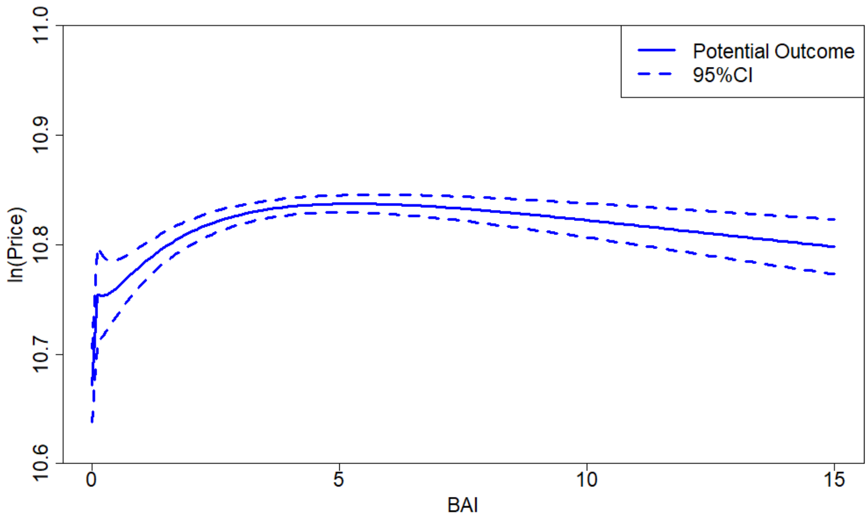

Figure 4: Function of potential outcome at each BAI level

Table 4: ATE_0 at each BAI level

BAI	ATE_0 [%]	t-value
0	0.0	0.000
1	11.6	5.687
2	15.0	7.713
3	16.9	8.784
4	17.7	9.275
5	18.0	9.409
6	18.0	9.317
7	17.7	9.081
8	17.3	8.755
9	16.8	8.374
10	16.3	7.963
11	15.7	7.540
12	15.1	7.116
13	14.6	6.701
14	14.0	6.299
15	13.5	5.914

4. CONCLUSIONS

In this study, we conducted a generalized propensity analysis to reveal the impact of availability of BSS on house rental prices. We first calculated BAI score for each housing unit as an indicator of BSS availability by using the data of the number of available bikes at each station with 5 minutes intervals for 2 weeks. We then conducted a generalized propensity score analysis with the BAI score as a treatment variable, house rental price as an outcome, variables regarding housing unit and built environment characteristics as covariates and estimated function of potential outcome at each continuous treatment level excluding the influence of covariates. The estimated function shows an 11.6%, 16.9%, and 18.0% increase in house rental price given a BAI increase from 0 to 1,3, and 5 respectively. On the other hand, even if BAI increase to about 6 or more, the treatment effect does not increase from the effect observed when BAI is around 5.

There are some limitations to our study. First, we did not consider spatial correlation of each BSS station or house unit. By incorporating spatial correlation into the estimation of potential outcome, we could gain more robust results. Second, we considered only one definition of BAI. By adding other measures to assess the convenience of BSS such as the potential demand of BSS, it could provide deeper policy implications of BSS.

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