Defining the Spatial Impacts of Changing the YouBike Fees: A Case Study of Taipei's Elimination of the "first 30 minutes is free" Policy

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ABSTRACT

In the 1960s, the first shared bike pilot program, "White Bike," was launched in Europe. Since then, numerous studies related to bike sharing have been published. While most researchers have focused on the current operation of bike sharing systems, relatively few have studied how policy shifts might affect user behavior. Paradoxically, policy shifts are quite common for most bike sharing systems. For example, in April 2014, Taipei City government officials canceled YouBike's "first half hour is free" policy and now charge their users NT$5 instead.

In this study, we explored how this fee shift affected the O-D trip distribution and behavior of the YouBike participants, especially in terms of demand and trip length. We analyzed Smart card datasets one year before and after the policy change went into effect to define any differences in demand generated by the change in fee. The datasets included time stamps, check-out stations and return stations. We utilized several spatial models to estimate the changes in demand before and after the policy shift. Compared to the traditional regression model, our spatial model had better fit because it included spatial varying parameters that can capture spatial heterogeneity. The study results not only helped us to quantify the relationship between the change in fee policy and travel demands it also allowed us to develop a procedure for defining the spatial impact of the policy shift. Both contributions will be useful for future policymakers and system operators.

1. INTRODUCTION

1.1 Literature Review

Over 60 years ago, the first bike sharing system, "White Bike," was established in Amsterdam, the capital of the Netherlands. Ride sharing systems have been of interest to scholars ever since. In the early studies, researchers treated bike sharing as a traditional mode of travel, and according to their results, transportation stations, population density, employment rate, and land use were all impacted by the popularity of bike sharing. Later, several scholars began to explore if the presence of bike friendly aspects, such as sidewalks, bicycle paths and fewer intersections would increase the popularity of such programs (Buck et al., 2013; Cocoran et al., 2014; Fishman, 2016; Lewis, 2011).

Subsequent researchers found that compared to other traditional modes of travel, cyclists are more affected by the outside environment. Therefore, their safety, interaction with neighbors, local security and resident density significantly influences bike-sharing usage. If government officials were to improve automobile drivers' awareness of cyclists, these measures may increase the popularity of such programs (Fraser & Lock, 2011). It must be noted that the fact that the bike sharing station is close to stores and public transportation sites (MRT or subway) has been found to significantly increase the usage of bike sharing programs, particularly in nice weather. El-Assi et al. (2017) systemically reviewed factors related to bike sharing demand. Combined with the local operations data in Toronto, Canada, they found that population density, employment rate, temperature, humidity, rainfall/snowfall, number of intersections, presence of bike paths, traffic volume, other bike-sharing stations, distance to a college or transportation station and travel distance are all associated with bike demand. Utilizing these factors, they established a liner travel model to predict the origin and destination of the cyclists who utilize these systems.

Overall, based on existing studies, aspects such as high population density and employment rate, sufficient number of bike-friendly infrastructures, roads with less traffic, fewer intersections, good socio-economic conditions, fair weather and urban design features can increase the demand for bike sharing (O'Brien et al, 2014; Caulfield et al, 2017). However, these studies have only focused on big cities, CBD's (Central Business Districts) and commuting trips in America and Europe, where traffic characteristics are very different from those in Taiwan. For example, people use public transportation and motorcycles much more frequently in Taipei than in the West (37.4% compared to 25.9%). Also, the usage rate of bike sharing in Taiwan is higher (5.1%) than in the United States and Europe. Finally, very few scholars have focused on the impacts of fee policies, rather they choose to predict travel demand and analyze operations management.

Therefore, the goal of this study was to build a demand model for YouBike and determine the difference in popularity after the fee policy changed. We also built a local spatial regression model to control for all other related environmental factors, such as population density, points of interest (POI), income level, employment rate, etc.

1.2 Price Rate

In order to encourage people to use this new bike sharing system, fees for short distance trips were waived, particularly in large cities, such as YouBike in Taipei and other northern cities, T-Bike in Tainan, CityBike in Kaohsiung, and P-Bike in Pingtung. To be specific, YouBike in New Taipei, Taoyuan and Miaoli, CityBike and P-bike were free for the first 30 minutes, while other systems charged the minimal fee of five to ten dollars for the same length of time. However, due to a limited budget and shortage of bikes, government officials in Taipei City cancelled this free policy and began to charge five dollars for the first five minutes after April 1, 2015. Although the fee policy was changed fairly recently, we chose to highlight the change in 2015 in our study because of limited data.

1.3 The YouBike Program in Taipei, Taiwan

According to our data, the O-D locations of most bike sharing stations in the Central Business Districts (CBDs) in Taipei are located very close to public transportation, such as the MRT train and bus stations. The YouBike system began in November, 2012. In its first eight months of operation, there were 400 YouBike stations and 13,072 bikes, which resulted in 120,282,785 trips.

As previously stated, in April 2015, YouBike canceled its "first 30 minutes are free policy" and began to charge five dollars for the first half hour of use. The details of the fee policy for two types of users: single-use renters and members. Members pay NT$5 for the first 30 minutes, NT$10 per 30 minutes within four hours, NT$20 for 30 minutes for four to eight hours, and NT$40 per 30 minutes after eight hours. Single-use renters have no discount for the first 30 minutes but are charged the same long-term rate as the members. In Taiwan, these fees are usually paid by registered iPASS Card or Easy Card.

1.4 YouBike Data

The YouBike datasets included five variables: borrowing time, return time, ride time, origin station, and destination station. In order to estimate a possible change in demand for YouBike, we chose the time period from April 2014 to March 2016, a year before the policy changed and a year after the rate increased.

Since April 1st 2015, government officials in Taipei City cancelled the free policy than began to charge five dollars within the first 30 minutes instead. Table 2 shows a summary of monthly demand for YouBike in Taipei City. As shown in Table 2, after the price rate increased, the demand also decreased significantly. Before the policy change, there were approximately 2,036,330 trips per month; however, after the change was instituted, the numbers fell to only 1,389,360 trips. Figure 1 shows a significant drop in the total demand after April 2015. This situation was likely caused by the cancellation of the free policy, meaning that users would rather walk than pay the fee for short distance trips.

Table 1 The change in the number of YouBike rentals during the study period

You-bike demand (April 2014 ~ March 2016)			
Before the change of fee policy		After the change of fee policy	
Sum	24,435,957	Sum	16,672,323
Average (per month)	2,036,329.75	Average	1,389,360.25
Maximum	2,495,757	Maximum	1,605,922
Minimum	1,661,167	Minimum	991,737

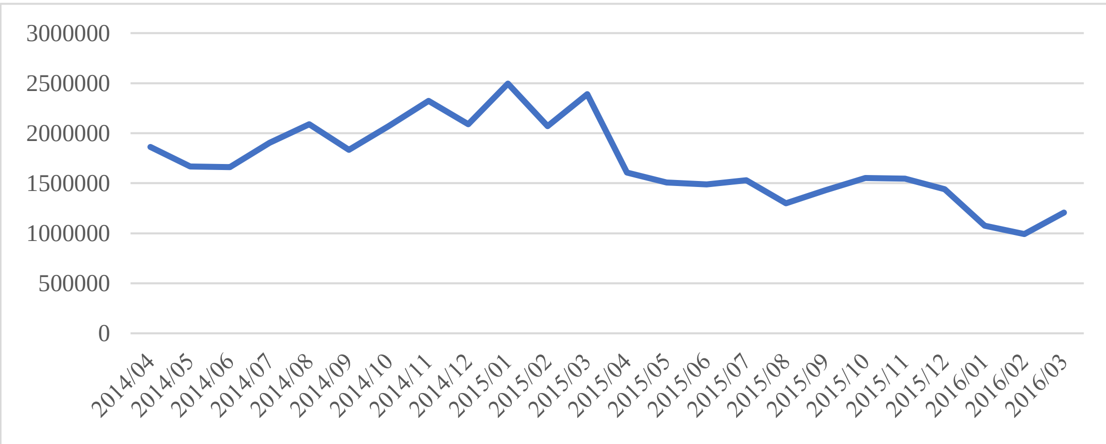


Figure 1 The number of YouBike rentals during the study period

2. METHODOLOGY

2.1 Local Moran's I

The main methods utilized were hotspot analysis and spatial prediction models. For the former, we used Local Moran's I and Local General G index. Specifically, we employed Local Moran's I to compare the differences between the target feature value (the number of bike trips taken from station i) to the adjacent feature value and the mean value, respectively. The correlation between the target feature and the adjacent one can be divided into four types: high-high, high-low, low-high, and low-low. If there were H-H or L-L, this indicates a similar spatial pattern in the areas nearby. Also, Local Moran's I could be used to determine whether or not a spatial clustering is present between YouBike's stations.

$$I_i = \frac{(x_i - \bar{x})}{{s_i}^2} \times \sum W_{ij}\left(x_j - \bar{x}\right) \tag{1}$$

$${s_i}^2 = \frac{\sum_{j,j\neq i}(x_j - \bar{x})^2}{n-1} - \bar{x}^2$$

x_j : demand for YouBike in nearby areas, W_{ij} : Spatial weight matrix, $\bar{x}$: average demand for YouBike
${s_i}^2$: variance of demand for You-bike demand

2.2 Local General G

In addition to Local Moran's I, we utilized Local General G analysis, which could accurately distinguish hot spots and cold spots. To put it simply, this technique could be used to determine the distribution of these cold and hot spots of the YouBike stations throughout Taipei City.

$$G_i^* = \frac{\sum_i W_{ij}\, x_j - \bar{x}\sum_j W_{ij}}{\sqrt{\frac{n\sum_j {W_{ij}}^2 - (\sum_j W_{ij})^2}{n-1}} \times S} \tag{2}$$

$$S = \sqrt{\frac{\sum_j {x_j}^2}{n} - \bar{x}^2}$$

x_j : demand for YouBike in nearby areas, W_{ij} : Spatial weight matrix, $\bar{x}$: average demand for YouBike,
n : sample size

2.3 The Linear Regression Model

In addition to the fee change, this study also focused on the impacts of different variables, such as temperature, humidity, rainfall, population density, number and location of mass transit stations and distance to schools. Similar to previous studies, our hypothesis was that lower temperatures, higher humidity and rainfall levels, may cause a decrease in bike sharing; however, the proximity of bike sharing stations to schools would cause an increase in the use of bike sharing programs. Traffic conditions would also affect the usage, such as the presence and location of trains, MRT, buses and high-speed rail stations.

The simplest model for predicting demand for YouBike is the linear regression model, because its purpose is to find a regression line that fits all possible data. The most common format is ordinary least squares, which is show below.

$$Y = \beta_i X_i + \varepsilon \tag{3}$$

Y : the number of YouBike trips taken, X_i : explained variables, i.e. temperature.

2.4 The Spatial Panel Model

This is an advanced regression model which considers spatial and temporal effects. We used this spatial autoregressive model to calculate spatial error and spatial lag patterns rather than employing other spatial lag and spatial error models. According to the spatial error model, the spatial pattern was in the error term; for spatial lag model, the spatial pattern was in the dependent variable which was related to bike sharing demand nearby. The formula for the SAR model is shown below.

$$y_{it} = \delta \sum_{j=1}^{N} W_{ij}\, y_{jt} + X_{it}\beta + \mu_i + \varepsilon_{it} \tag{4}$$

i	: spatial units i, i=1, N
t	: day t, t=1,T
Yit	: the number of bike sharing trips at stops i and day t.
δ	: the spatial autoregressive coefficient
Wij	: a spatial weight matrix
Xit	: a N x K matrix of observations regarding the independent variables
β	: regression parameter
μi	: a specific spatial effect
εit	: an independently and identically distributed error term for station i and day t with a mean of zero and a variance of σ2.

3. RESULTS

3.1 Moran’s I

In Figures 2, the Local Morans’ I maps show that most of the high-high points were concentrated in the down town area of Taipei City and in large univeristy campuses (such as National Taiwan University) we found that YouBike was very popular with both commuters and students. Also, there were many low-high points distributed around the high-high points mostly located at the suburb area. In addition, the low-low points were mainly located in areas with very few MRT stations, meaning that the stations with fewer MRT routes passed by, the lower the population density and traffic volume in this area.

According to Figure 3, the cancellation of the first 30 minutes free policy did not cause significant changes in the demand for bikes in the high-high stations of the downtown area. However, the low-high points nearby actually increased in demand. In Taipei's wealthiest area, even if the government raised the fees, the residents would not be likely to change the way they commute. More specifically, after this policy was put in place, there were two high-low points near sightseeing attractions (Figure 5). The upper point was at a MRT Beitou station, where there were many historical relics and famous hot springs. The lower spot was near the reknowned Nangang Exhibition Hall, where many displays and concerts are held, which frequently draw huge crowds. Compared to other locations in residential areas, the usage will be higher.

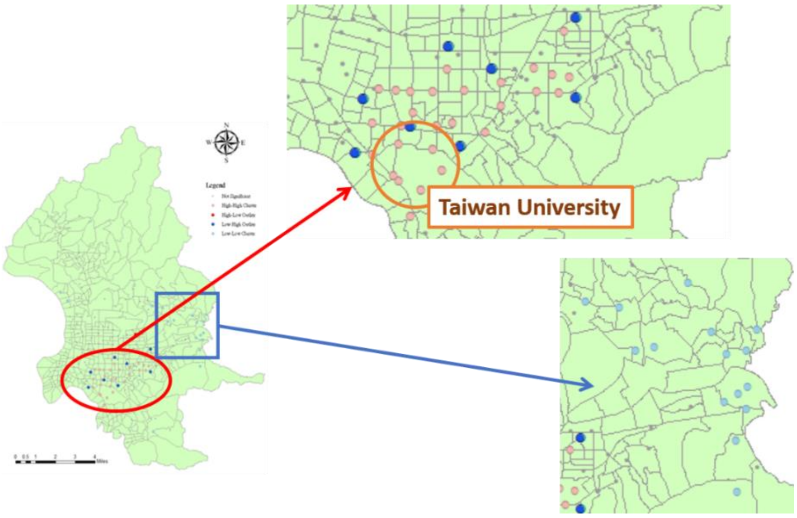
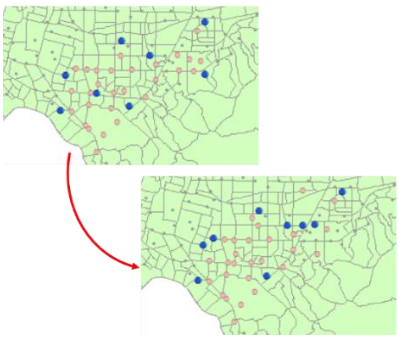


Figure 2 Details of Moran's I results



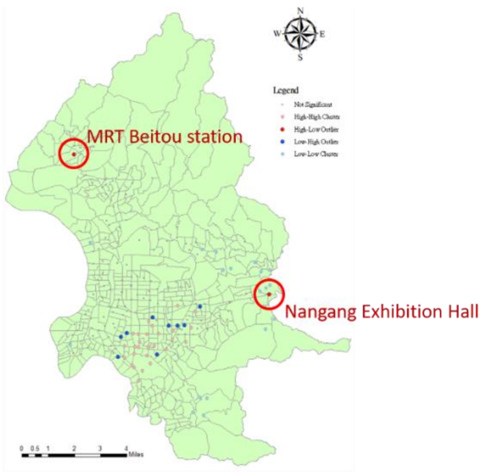


Figure 3 H-H cluster in LISA, Taipei

3.2 General G:

As shown in Figures 4, there were no significant changes of usage after the adjustment of fees nor major alterations in hot spots or cold spots. As mentioned above, the slight fee adjustment did not affect the usage rates; however, some hotspots decreased mainly around the campus area. This indicates that particularly college students would choose another mode of travel for short trips. For a short trip, students may have chosen YouBike when it was free in order to save a few minutes. However, after the fee was raised, they were not willing to spend extra money and would be more likely to walk. However, the return stations were not affected, because their numbers were significantly reduced so vehicles would be returned at several fixed stations.

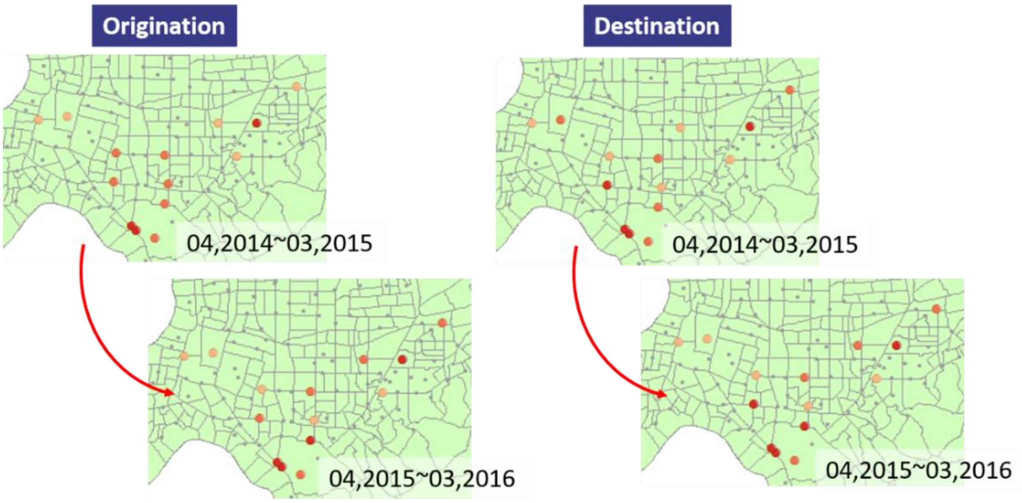


Figure 4 Details regarding Local General G

3.3 Explanation of the Variables

In order to analyze the impact of the changed policy on the demand for bicycles, we built regression models based on the O-D data (origination and destination) before and after the price change.

- **School:** This variable includes all the schools from junior high to University within one km of each YouBike station. We did not include the elementary and kindergarten students, because they would be unlikely to use YouBike because of the height limitation.

- **Population:** This study estimated the corresponding population from the village nearest to the YouBike station.

- **Transportation Stations:** This variable is the sum of the transportation nodes, including train stations, MRT, bus, and high speed rail way stations within one km of each YouBike station.

- **Intersections:** This includes all types of intersections within one km of each YouBike station. It should be noted that we collected this data using the ArcGIS automatic building function.

- **Humidity, Temperature and Rainfall:** This data was collected from the Taipei weather stations, Then, we used kriging to estimate the value for each bike station.

- **Policy:** The price policy variable was set after April 1st, 2015, while 0 represents the original policy.

3.4 The Correlation of all Variables (VIF)

In the regression models, VIF was used as an index to check the variable correlations to prevent collinearity which would bias our model's performance as well as the estimated results. According to Heli (2015), if the VIF number is lower than five, the correlation of the variables is acceptable. Table 3 shows that the VIF values of all the predictive variables were under the threshold value.

Table 2 VIF variables

Weekday		**Weekend**	
Temperature	**2.39**	Temperature	**3.35**
Humidity	**1.23**	Humidity	**1.36**
Rainfall	**1.21**	Rainfall	**1.20**
Population	**1.10**	Population	**1.10**
Transportation Stations	**2.10**	Transportation Stations	**2.10**
School	**1.69**	School	**1.69**
Intersection	**2.69**	Intersection	**2.68**
Policy	**2.34**	Policy	**3.76**

3.5 Spatial Regression Models

Table 4 shows the results of the models during the weekend and weekdays. According to the OLS model, on weekdays, population density, rainfall, humidity, and the fee policy had a negative influence; however, nearness to a school, temperature, transportation stations, intersections had a positive impact on demand for bike sharing. During the weekend, population density, rainfall, humidity, nearness to transportation stations and change in fee policy had a negative effect while nearness to schools, temperature, and fewer intersections had a positive impact on the demand for bike sharing. In sum, we used the OLS model in this study to check the residuals of the model via the j-b test. The results showed that it was significant which means the residuals did not follow the normal distribution. Thus, in this study, we continuously used the spatial regression models.

In order to compare model performances, AIC was used as our index. For both weekend and weekday predictive models, the AIC of the SARARRE model (SARAR model with random effect) was lower than the other models. Thus, this model performed best. During weekdays, the significant predictive variables of population density, humidity, rainfall and change of fee policy had negative influences, while nearness of transportation stations, fewer intersections, temperature, and proximity to school had positive effects. It must be noted that some variables showed inconsistent effects according to existing studies, such as population density. The possible reason may be that in this study we set the village population as equal to the YouBike stations' population, which may have caused some nearby YouBike stations to share the same population values. Overall, the areas with low population density, higher temperatures, less humidity and rainfall, and more schools and fewer intersections had higher percentages of bike sharing. Most of our findings are consistent with existing studies (O'Brien et al, 2014; Caulfield et al, 2017). Moreover, after the fee police change, the average weekday demand reduced by 85 trips per station per day. For the weekend model, most variables were similar to the weekday one. The only different was that the school variable was not significant at that time and the fee policy reduced trip demand even more. In other words, on the weekends, people may have more time to walk to a destination instead of using the bike sharing program. Also, as previously stated, the school variable was only significant during weekdays, which means people often rode bikes to school on weekdays even through the price had been raised. Also, the lambda parameter in the weekend and weekday models showed a positive effect on bike sharing demand, which means the usage of nearby stations had a positive relationship.

Table 3 Model results

weekday	**ols**	**lagre**	**errre**	**sarre**
Intercept	2.91E+02 ***	1.38E+02	3.26E+02 ***	3.26E+02 ***
Temperature	2.18E+00 ***	1.31E+00 ***	2.52E+00 ***	2.47E+00 ***
Humidity	-1.32E+00 ***	-0.86E+00 ***	-1.47E+00 ***	-1.47E+00 ***
Rainfall	-3.49E+00 ***	-1.76E+00 ***	-3.53E+00 ***	-3.55E+00 ***
Population	-1.33E-02 ***	-1.65E-02 *	-1.44E-02 ***	-1.47E-02 ***
Transportation stations	1.43E-01 *	-2.46E-01	-1.45E-02	-3.08E-03
School	5.38E+00 ***	7.21E+00	2.12E+00 ***	2.78E+00 ***
Intersection	1.94E-01 ***	1.95E-01	2.23E-01 ***	2.16E-01 ***
Policy	-7.97E+01 ***	-4.18E+01 ***	-8.64E+01 ***	-8.56E+01 ***
lambda	-	2.94E-02 ***	-	8.21E-04
rho	-	-	4.329e-02	3.256e-02
AIC	330173.0585	330614.822	330224.335	329892.7818
weekend	**ols**	**lagre**	**errre**	**sarre**
Intercept	3.55E+02 ***	2.16E+02 ***	3.56E+02 ***	3.58E+02 ***
Temperature	4.87E+00 ***	3.60E+00 ***	4.92E+00 ***	5.08E+00 ***
Humidity	-1.79E+00 ***	-1.00E+00 ***	-1.78E+00 ***	-1.81E+00 ***
Rainfall	-9.21E-01 ***	-1.03E+00 ***	-1.08E+00 ***	-1.10E+00 ***
Population	-1.69E-02 ***	-1.93E-02 ***	-1.84E-02 ***	-1.84E-02 ***
Transportation stations	-3.86E-01 ***	-6.48E-01 ***	-3.34E-01 ***	-3.51E-01 ***
School	1.50E+00 .	2.78E+00	6.42E-01	4.68E-01
Intersection	2.36E-01 ***	2.42E-01 ***	2.50E-01 ***	2.49E-01 ***
Policy	-1.47E+02 ***	-9.52E+01 ***	-1.49E+02 ***	-1.49E+02 ***
lambda	-	2.10E-02 ***	-	3.23E-04

rho	-	-	3.19E-02	2.81E-02
AIC	133139.6822	133272.0653	133146.7769	133112.2593

4. CONCLUSIONS

For this study, we built a bike sharing demand model and used it to estimate the impacts caused by the change in fee policy. The Moran's I and General G results showed that the spatial patterns of cold spots and hotspots changed slightly, especially in the CBD, university area and near points of attraction. In addition, the spatial prediction regression model showed that the increase in price reduced the bike sharing demand significantly, especially on weekends. The main contribution of this study was to quantity the spatial temporal relationship between fee changes and bike sharing demand, because most previous studies mainly focused on the impact of environmental and socio-economic factors on demand. Our results showed that even a slight fee increase (5 NTD dollars) caused a significant decrease in bike sharing usage.

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