# On-road Parking in Taipei City: Spatial Analysis of Policy Impact

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**ABSTRACT:**

Car parking has become a major challenge in densely populated urban areas and advanced to one of the major topics in urban planning and policy-making. In previous research, parking behavior has been described by factors such as cruising time, time to destination, parking fee and the purpose of parking. Among these factors, the parking fee is the most dominant factor affecting individual parking behavior, as it became apparent after the new policy to generally charge on-road parking in Taipei had been implemented in 2015. It appears, however, that parking prices are not always reasonably set and were based on actual parking behavior. Based on annual governmental survey data combined with infrastructure data, we have been able to investigate relationships and separate spatial clusters of higher and potentially less reasonable parking fees in order to provide a basis for developing efficient strategies. In order to capture the spatial heterogeneity that exists in explanatory variables over different traffic zone (TRZ), first we employ spatial autocorrelation techniques to seek the similarity of spatial patterns, and then find out about clustered area in Taipei city. After knowing the relationship between these patterns, regression coefficients will then be calculated between each set of input variables (e.g., the distance between on-road and off-road parking lots, distance to the nearest mass transit station, the location of a business or commercial districts), a statistical model is set up and developed for the currently implemented parking system. In this research, a GIS-based procedure taking into account dominating variables, conditions and characteristics is implemented in order to eventually estimate an improved price for each TRZ to improve the parking situation in Taipei City.

## 1. Introduction

Parking is one of the crucial issues of transportation, and on-street parking is a common form of parking (Biswas et al., 2017). Based on the theories proposed in previous research, factors such as cruising time for parking spaces, time to destination, parking fee and the purpose of parking can be variables to describe potential parking behavior (Yun et al., 2009, Ma et al., 2013, Brooke, 2016). Among these factors, parking fee is the most influential factor to affect parking behavior. In addition, Shoup brought up the concept that free parking may lead to traffic congestion and even worse parking system, and proposed that general charging for parking would be a solution to this problem (Shoup, 1997). The Taipei City Government employed an identical concept and introduced user payment for on-road parking in order to reduce the long holdover on specified parking lots in residential areas. To accomplish this, a new parking policy was implemented in 2015, which generally charged on-road parking including alleys with a width of less than 8 meters. However, there is only limited research that can show the impact of this policy before and after having been employed, and it cannot show the practical change of the policy.

Various strands of literature have been focusing on parking-related issues by employing different methods to analyze the influencing factors. Disaggregate data on travelers' responses to changes of parking attributes are collected to build models to analyze the parking type choice (Axhausen and Polak, 1991). The Discrete Choice Model is generally considered to be taken to reveal the driver's practical parking behaviors, where Multinomial Logit Model (MNL), and Mixed Multinomial Logit Model (MMNL) are also taken to analyze driver behaviors. Not only parking price but also other potential characteristics are adopted in these models. An MNL model was also developed in Beijing Lama Temple (Ma et al., 2013), which investigated the correlation between each influential factors by a stated-preference survey. Subjective values of time and types of users in dissimilar scenarios are involved in the MMNL model, whilst various parking choices are also examined to simulate the behavior of drivers (Ibeas et al., 2014).

In theory, previous work discussed relevant condition with respect to the parking issues, yet they still fall shore of a shortage of mentioning different driver's preference in terms of parking price. But according to the case study in Seattle, the original hypothesis was confirmed in the empirical analysis, while the price also affected the parking duration, and with no elastic to the parking occupancy price but highly related to time and the neighborhoods (Ottosson et al., 2013). In addition, the effect of driver characteristics on their parking behaviors has also not been discussed in much detail. Hence a new promoted research discussed both deficiencies to put parking price cut-off into consideration and meanwhile described different types of parking analysis models (Inci and Lindsey, 2015). After this, to better capture spatial heterogeneity in the global model, a Geographical Weighted Model (GWR) was used to evaluate the price sensitivity, which included the spatial characteristics of the former research (Pu et al., April 2017).

Based on the previous research, drivers parking behaviors are divided into several categories, and they affect each other in parking issues (Brooke, 2016). Drivers can be classified into long-term and short-term, who are commuters and drivers who go on business trips. Or in other words, long-term parkers use to park under multiple purpose and occupy parking spaces for a longer time, while short-term spend less occupying time under a simple purpose (Inci and Lindsey, 2015). In this research, all the discussions are based on annual data and yearly change, thence only long-term parkers are analyzed in the overall analysis. For these long-term parkers, as garage parking can be an alternative to curb parking. While the variables "distance" or "price" of either garage parking or curb parking increase, drivers will tend to choose the other type, causing market competition and economic equilibrium in the parking issues.

Based on reviews, we know that driver's behavior might change due to the environment, while policy could be a controller to change the whole parking situation. Therefore, it is important to discuss the policy effectiveness after implementation. In this paper, an overview of the current parking circumstances and the background in Taipei City will be introduced first. By exploring the on-road parking situation, we further highlight the parking policy impact and spatial heterogeneity.

## 2. Backgrounds

A new parking fee policy of charging on-street parking has been implemented in Taipei in 2015, which broke the original equilibrium of parking behavior. Before the policy was implemented, people used to park on the street under long holdover, thus this increases the inefficiency of the parking system, especially in residential districts. New visitors spent a long time cruising on-road to seek for a parking lot. In order to solve this problem, the government tended to generally charge for on-street parking, including alleys. From 2006 to 2017, Parking Supply and Demand Surveys were annually conducted annually by the Taipei City Parking Management and Development Office. Six administrative districts were investigated twice a year, which provided detailed information about demand, supply, and illegal-parking of both on-street and off-street parking on traffic zone (TRZ) levels. There are 684 TRZs in 12 administrative districts, supplying over 18,000 curb parking places, and half of them are now charged since the parking policy has come into being in 2015. (see

Figure 1 for the spatial distribution of traffic zone) Table 1 shows the numbers of charged road segments in each administrative district before and after, and also shows the total area size of the TRZs in each district.

The original statistics of parking demand and supply were disseminated by the city government in a spreadsheet format. TRZ data was provided in a shapefile format, and it only contained traffic zone numbers, and showed the spatial distributions. Curb-parking space data was also shown in a shapefile format with road names and administrative districts included. Parking Fee data was published in road segments level, involving charging time, parking fee, and charging road name. Due to the dispersion of data, initial data processing was prerequisite to better compile data for further analysis. We first filtered light vehicle out of the curb-parking spaces data. Then TRZ data were joined to the spreadsheet based on the zone numbers, we overlaid the land use map which was released by the National Land Surveying and Mapping Center to add attribute data of land use type into each TRZ. Third, each curb-parking space could expand TRZ attributes data by intersecting, and could also be joined to the parking fee data through the key of road names. Finally, data were filtered by temporal attributes: the year curb parking spaces started to be charged, to indicated the newly parking supplies after the policy. Figure 2 shows the workflow of initial data processing.

Here we divided the curb-parking spaces to each TRZ, producing a parking availability map in order to discuss efficiency of curb-parking space, see Figure 3. After data processing, we extracted all the charged curb-parking spaces in Taipei city, see Figure 4. Figure 5. shows all curb parking spaces in Taipei on a map with the fee information involved. Figure 6 and Figure 7 show the ratio of parking demand to supply in each TRZ, describing the heterogeneous parking situation in current Taipei which include a heterogeneous pattern.

Table 1. Numbers of charged road segments before and after the parking policy change.

| Administrative District | Charged Road Segments before 2015 | New Charged Road Segments after 2015 | Increase (%) | Total Area size of TRZ in the district (km$^2$) | Numbers of Traffic Zones |
|---|---|---|---|---|---|
| Shih-Lin | 169 | 270 | 59.76% | 9.0523 | 81 |
| Da-Tong | 100 | 168 | 68.00% | 4.7878 | 39 |
| Da-An | 257 | 428 | 66.54% | 9.7670 | 92 |
| Chung-Shan | 224 | 292 | 30.36% | 10.3911 | 95 |
| Chung-Cheng | 165 | 230 | 39.39% | 7.4922 | 49 |
| Nei-Hu | 303 | 493 | 62.71% | 16.0071 | 59 |
| Wen-Shan | 207 | 387 | 86.96% | 6.8870 | 56 |
| Bei-Tou | 145 | 252 | 73.79% | 8.4858 | 58 |
| Song-Shan | 203 | 356 | 75.37% | 6.9364 | 40 |
| Xin-Yi | 117 | 213 | 82.05% | 6.0063 | 57 |
| Nan-Gang | 116 | 201 | 73.28% | 6.1872 | 27 |
| Wan-Hua | 111 | 172 | 54.95% | 7.4664 | 56 |


Figure 1. Spatial distribution of traffic zones

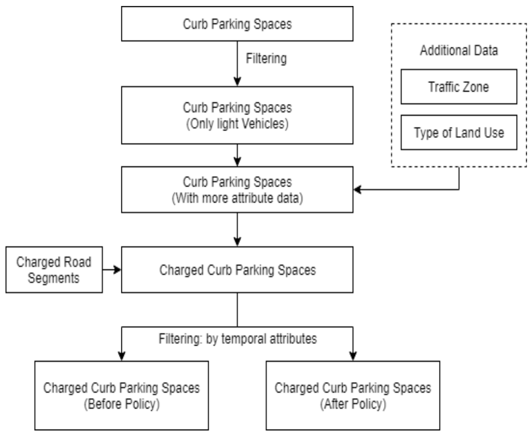
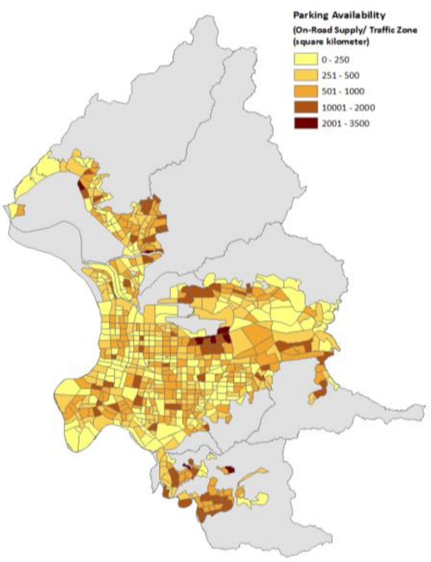



Figure 2. The workflow of initial data processing



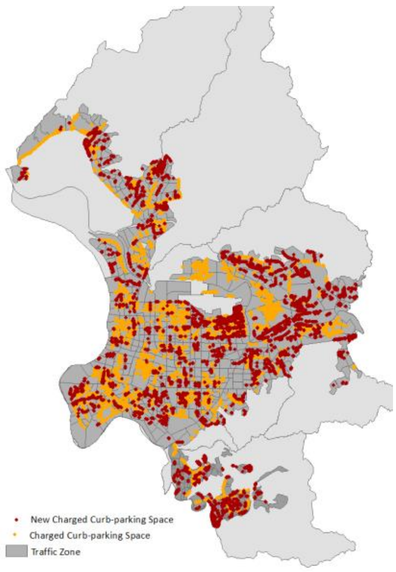



Figure 3. All 684 traffic zones and the curb parking availability in each zone in km$^2$.

Figure 4. Investigated charged curb-parking spaces in different TRZ of 12 administrative districts. This figure indicates that the newly charged curb-parking space, are distributed in a heterogeneous pattern.

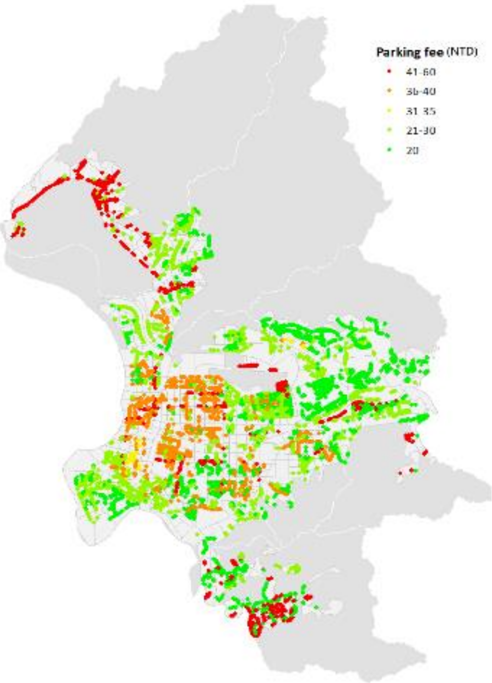



Figure 5. All parking fees of curb parking spaces in Taipei city

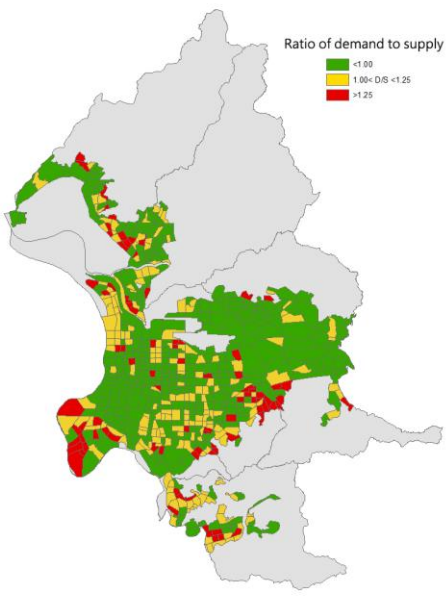



Figure 6. Ratio of demand to supply before the new policy.

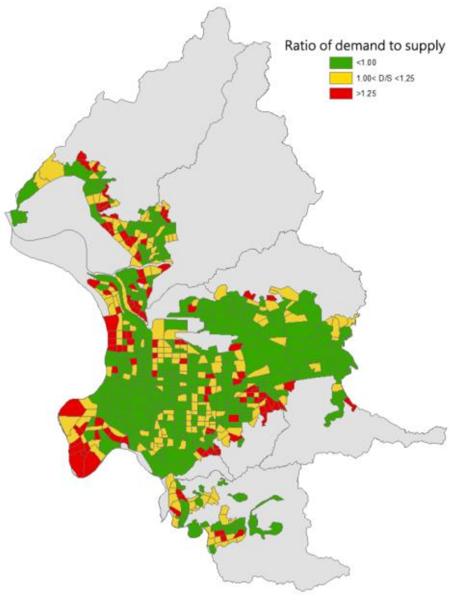



Figure 7. Ratio of demand to supply after the new policy.

In accordance with principles, the city government used to assess the effectiveness of a newly implemented policy to decide if to take actions for another step. In regards to the parking issue, abundant research has been done to discuss factors and changes in parking behavior. Although citizens are well concerned about the policy impact, most governance results are shown in the perspective of the government, which shows not transparently. Data and reports could only show the reduction of parking demand in specified districts and were given out in an incomprehensible way without pointing out the spatial distribution of the parking lots. Moreover, pricing for parking, either on-road or off-road, was developed according to the "Taipei City Public Parking Lot Rate Autonomy Act", which indicated that the management agency of the parking lot shall set the differential rate according to the region, traffic flow and time period. Considering that the price is an influential factor of the parking behavior, it is important to set the parking fee in a reasonable way.

## 3. Methodology

### 3.1. Related Research

Based on the characteristics of our data, and the implementation of this parking policy, we can see that parking fees are spatially related. Also, according to the "Taipei City Public Parking Lot Rate Autonomy Act", parking fee are set differently due to the properties in each region. But after observing Figure 5, we assumed that there are there are outliers showing the policy might be not designed well to meet the city government's expectations. Feature properties should be similar if the parking lots are along the same road, or in the same TRZ, performing more similarity between closer features than ones in longer distances, and these parking fee should be charged in the same rate. However, they appear in different colors showing in Figure 5. Parking fee data seems to cluster in most districts but different color representing the differential rates appear on the map too. Therefore, we have reasonable doubts to assume there are outliers, either high or low in current situation. To solve this question, it is important to scrutinize an area via a spatial analysis, as it well illustrates all the importance in a spatial perspective while processing data with different dimensions (Bailey and Gatrell, 1995).

Many research was done to analyze the spatial patterns between different areas, while similar patterns would be grouped together and revealed after using a spatial autocorrelation. It is a statistical approach for quantifying the spatial relations among a set of univariate data observations. By employing these following methods, we gain more perceptions of the present, which may help us to learn the objects change in the future (Harris and Batty, 1993, Long and Robertson, 2018). Regarding the spatial autocorrelation, Moran's I (Moran, 1950) is considered the most widely used, which measures the attribute similarity and location proximity into one single index, standardizing data to adjust for the variance of the observations, and normalized for the total sum of the spatial weights (Wartenberg, 1985, Overmars et al., 2003). However, the former methods only discuss the spatial relationship in a global concept, features with similarity can only be detected whether showing clustered or dispersed, but we cannot know where the clustered phenomena are. In order to point out locations of clustered areas, Local Indicators of Spatial Autocorrelation (LISA) are need. For example, hot spot analysis based on $Gi^*$(Getis and Ord, 1992), and cluster and outlier analysis based on Anselin local Moran's I (Anselin, 1995), are adopted to better identify the spatial patterns, fundamentally exploring the clustered situations in certain areas. These methods are carried out within the ArcGIS software environment, to further discuss the relationships and geographic patterns (Mitchell et al., 1999, Mitchel A., 2005).

The equation for hot spots analysis can be defined as following, where $G_i^*$ index reports a z-score and p-value for each single feature in the equation, representing the index of standardizing feature and distance to a z-score. Z-score is the standard deviation of the whole statistics, showing the intensity of the clustering, while p-value is the probability to reject null hypothesis, and both of them are associated with the standard normal distribution. When a high z-score and small p-value appear in the result, then it indicates a clustered area of high values. And if a low z-score and small p-value appear, then it indicates a clustered area of low values. Here we take 95% as our required significance level. Where z-scores are greater than 1.96, they indicate a significant "hot spot" in a 95% confidence level, and if z-scores are lower than −1.96 indicate a significant "cold spot" ($p < 0.05$). To avoid type I error in the statistic, we then raise the confidence level to 99%, showing the most significant results of hot spot and cold spot areas.

All curb-parking spaces are transferred into points before analysis, representing features j in the formula. Weights between each features are determined by the inverse Euclidean distance between two features. Therefore, feature attributes like parking fee in each parking space was examined. Based on the statistic, we can know the similarity of features and if the clustered areas show significant.

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j} x_j - \bar{X} \sum_{j=1}^{n} w_{i,j}}{S \sqrt{\frac{\left[ n \sum_{j=1}^{n} w_{i,j}^2 - \left( \sum_{j=1}^{n} w_{i,j} \right)^2 \right]}{n-1}}}$$

(Equation 1)

And S can be defined as the following formula, where $x_j$ represents the attributes (parking fee) for feature j , $\bar{X}$ is the mean of all features, and $w_{i,j}$ shows the spatial weight determined by the inverse Euclidean distance between two features, and n is the number of total feature:

$$\bar{X} = \frac{\sum_{j=1}^{n} x_j}{n}$$

(Equation 2)

$$S = \sqrt{\frac{\sum_{j=1}^{n} {x_j}^2}{n} - (\bar{X})^2}$$

(Equation 3)

And the same parameters are plugged into the cluster and outlier analysis. An I value, a z-score, a pseudo p-value, are calculated. A positive value for I indicates that a feature has neighboring features with similarly high or low attribute values. But if there's a negative value, it indicates neighboring features with dissimilar values, which should be considered as an outlier. Apart from hot spot analysis, the p-value is more important to know if outliers exist in clustered areas, as then p-value should be small to indicate the low probability and the clusters would be considered statistically significant.

$$I_i = \frac{x_i - \bar{X}}{S_i^2} \sum_{j=1, j \neq 1}^{n} w_{i,j}\left(x_j - \bar{X}\right)$$

(Equation 4)

where $x_j$ represents the attributes for feature i , $\bar{X}$ is the mean of all the corresponding attribute values, and $w_{i,j}$ shows the same spatial weight as the hot spot analysis, which are determined by the inverse Euclidean distance between two features, and n is the number of total feature:

$$S_i^2 = \frac{\sum_{j=1, j \neq i}^{n} \left(x_j - \bar{X}\right)^2}{n - 1}$$

(Equation 5)

When comparing the two analyses to identify spatial patterns, the hot spot analysis is used to group value similar area. If a high attribute value or is surrounded by other high value, which means the neighboring features have the similarity, then a hot spot area appears. On the contrary, the cluster and outlier analysis identifies the grouping areas according to proximity, based on these local Moran's I values and associated p-values, features can then be classified by cluster/outlier type (COType) and divided into five categories. And p-value are more sensitive to the low values in clustered areas. This can better to distinguish low values which should be considered as an outlier in the hot spot areas (Sánchez Martín et al., 2019).

### 3.2 Empirical Analysis and Results

To find out the relationship based on the geographical characteristics, spatial analysis, and spatial autocorrelation are often used to identify clustered features. The hypothesis with respect to the current situation is that the conspicuous distributions of parking ratio highly relates to the parking fee, where some areas are favored over other factors, such as amounts of other parking space provided in different types, or the shorter distances to the desired spots. Hence the parking situation also differs from the landscape and land use, as this can lead to non-uniform distribution. Referencing to the previous research, we applied these methods to seek the similarity of spatial patterns in Taipei.

Confidence levels of 95% and 99% are set in the statistics, while a 95% confident hot spot areas are the z-scores of features over 1.96, corresponding p-value is under 0.05, colored in pink on the map. And 99% confident hot spot areas are the z-scores of features over 2.58, corresponding p-value is under 0.01 colored in red. If z-score perform negative in the results, then features are considered to be cold spots with low value clustered. Therefore, points colored in light blue and blue show the 95% and 99% significant cold spots on the map, representing parking lots with lower parking fee. Then if the z-scores are between 1.96 and -1.96, they are considered as not significant spots, colored in gray on the map.

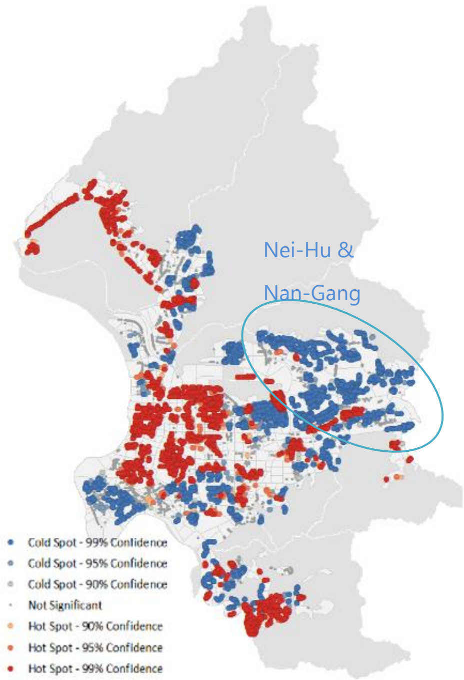



Figure 8. Hot Spot Analysis on Parking Fee

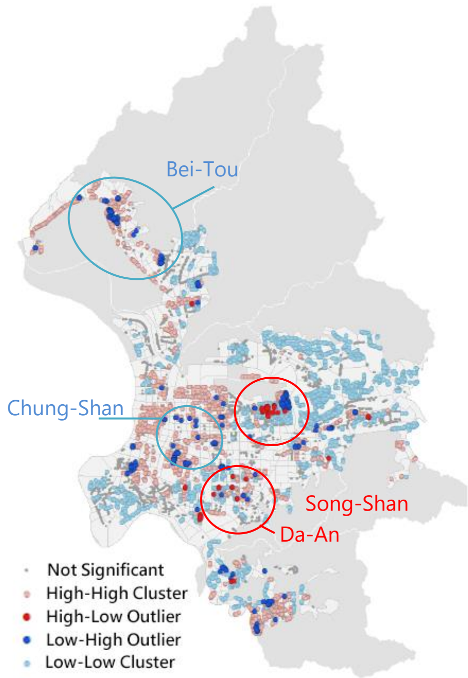



Figure 9. Cluster and Outlier Analysis on Parking Fee

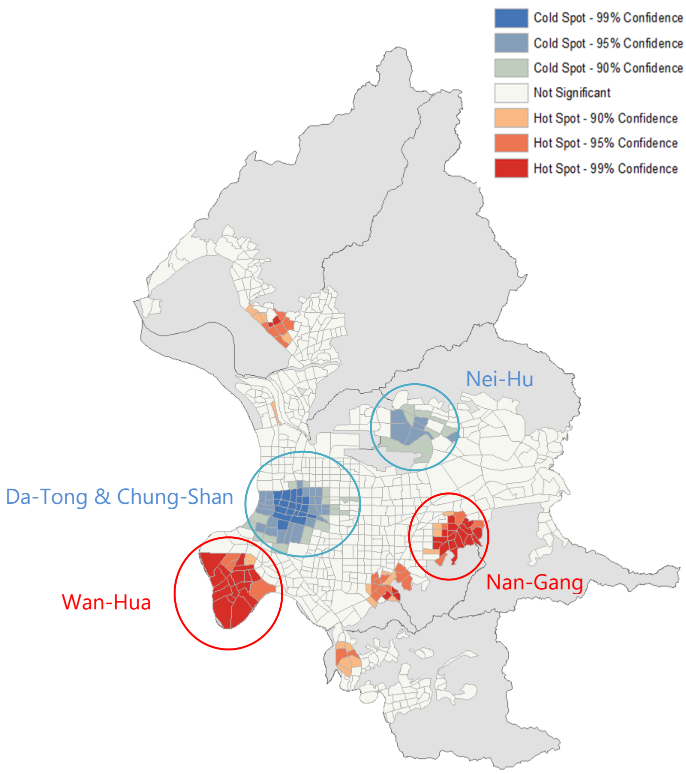



Figure 10. Hot Spot Analysis on Parking Ratio

The spatial distribution of the parking fee generally displays a clustered pattern, while there are still outliers in the city. In Figure 8, the central area in Taipei city is the significant hot spots area, and as the distances increase, the parking fee decreases and forms significant cold spots areas as Nei-Hu and Nan-Gang District. After applying the cluster and outlier analysis, we further find out locations of low parking fee in hot spots areas, and vice versa, (see Figure 9). Parking fees are considered to be charged too low in Bei-Tou and Chung-Shan district, while Da-An and Song-Sang district are considered to be charged too high. When identifying the TRZ which the outliers are in, we found that outliers mainly appear in the mixed-use and industrial areas.

Based on Figure 8, parking fee cluster in the central area, however, the hot spot areas are not directly related to the ratio of demand to supply. We apply the same methods to find out the hot spot areas of the parking ratio, see Figure 10. According to the regulation of setting the parking fee, high price to be correlated to high parking demand areas, thus the current situations shows opposite in Wan-Hua, Da-Tong, Chung-Shan and Nan-Gang districts. In the figure, we can see a 99% confident result that a high ratio clustered in Wan-Hua and Nan-Gang districts, coloring red to show the z-score over 2.58 and a low ratio clustered in Nei-Hu, Da-Tong and Chung-Shan districts coloring blue to show the z-score under -2.58. In addition, a representative area like Wen-Shan district also contributes significantly to the high ratio. However, referring to the parking availability map, these two districts are under different influences: while Nei-Hu provides more curb-parking space but drivers in Chung-Shan district have less demand for curb-parking space.

## 4. Conclusions and research prospects

This paper introduced the parking situation and discussed the parking policy impact in a spatial perspective. Since Taipei city government implemented the new parking policy which generally charge for on-road parking, people’s parking behaviors have changed. In some specific areas, like Nei-Hu and Wen-Shan districts, it seems, however, that parking prices are not always reasonably set and based on actual parking behavior. To know the direct or indirect factors to affect driver’s behaviors, numerical research was reviewed in the article, including MNL, MMNL, and GWR methods. Also, initial data processing is required to better compile all dispersed data together for the further analysis. Therefore, visualized maps are constructed to observe the current situation. Spatial distribution of all TRZs are mapped to join statistic data and spatial data together in a more comprehensive way. The result of the ratio of parking demand to supply in each TRZ describes the parking situation in current Taipei which exhibits a heterogeneous pattern with respect to show the sufficiency of parking lot in each TRZ.

The Taipei City Government set parking fee in each TRZ based on the "Taipei City Public Parking Lot Rate Autonomy Act", according to the region, traffic flow and time period. A map of parking fee in each parking lot displayed the current situation, with respect to show if the price was set reasonable and spatial related. Additionally, spatial autocorrelation was employed in the research, so as to capture the similarity spatial patterns in the heterogeneous situation. Hot spot analysis and cluster and outlier analysis displayed the clustered areas at a high or low parking fees. In comparisons of these two method, hot spot analysis can be used to group neighboring features with the similarity, showing the hot spot area representing high resemblance. The cluster and outlier analysis groups features according to the proximity, and p-values in this statistic are more sensitive to different value that appear in hot spot areas. It can better distinguish where the outliers are in whole Taipei city. Above, these methods can help to know if the parking policy was implemented efficiently, for the areas which considered significant to show the policy effectiveness, parking fee would show clustered on the map, and positively corresponded to the parking ratio. Hence we found some outlier in the hot or cold spot areas, showing the policy can be improved in these specific spots. Moreover, the parking ratio in Wan-Hua district performed a high parking demand but charged at a lower parking fee. After these the data visualization and processing, we get a better understanding of locations and the circumstances. Future research can focus on the areas representing outliers and find out if the policy is efficient. And further target these spots to reiterate the parking fee in order to province feedback on the situation of the parking system.

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