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## Bicycle Parking in Station Areas in the Netherlands

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### Abstract

Cities in the Netherlands have encouraged cycling in order to create a more healthy, liveable and sustainable environment. Accordingly, cycling has become an important travel mode in cities for both unimodal and multimodal travel. Consequently, the increase of bicycle use results in an increase in the demand for bicycle parking, thus encouraging illegal bicycle in station areas where supply is unable to meet demand. As space becomes scarce in these areas, managing the existing parking supply becomes crucial in the urban environment. This research attempts to explain bicycle parking behavior by finding determinants for parking near a station with a metro service, train service or both services at the same location. The results not only show that the determinants for parking in these station areas differ, but also that each station areas attracts different groups of people.

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**Keywords:** bicycle parking; neighborhood characteristics; socio-economic characteristics; trip characteristics; discrete choice; multinomial logit

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### 1. Introduction

Extensive planning in the past half century has stimulated cycling resulting in an increase in bicycle use in the Netherlands, Germany and Denmark [10]. The key for success in these countries is a mixture of mutually reinforcing policies including cycling facilities, traffic calming, traffic education, promotional events and integration of public transport. Additionally, car use in these countries is more expensive compared to countries like the USA due to taxes and restrictions on car parking, ownership and use.

In other countries where cities have a limited share of biking, bicycle sharing systems are introduced to provide an alternative to car or transit [12]. These bicycle sharing systems were introduced so people can pick up or leave a bicycle at a service station close to their origin or destination. In the Netherlands a different type of bike sharing exists where people can use a publicly available bike at train stations but have to return the bike to the same storage location.

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This form of bike sharing has proved especially useful for people who use the bicycle mode as an egress trip from the train station [8].

Many researchers have pointed out the importance of bicycle as an access mode for train travel. However, cyclists can have multiple reasons to park near a station, since these areas usually also provide access to activities like work, recreation and sports. As a result, sufficient parking supply is offered in most station areas to accommodate the demand for parking. In order to manage the supply for parking, it becomes crucial to understand the actual use of these parking facilities combined with the motivation for parking in the area. This will provide insights in future planning for parking facilities in station areas.

In this research we focus on the motivations for bicycle parking in station areas. We are particularly interested in the influence of neighborhood characteristics on the choice for parking near a station, and the differences in choice between a metro, train or metro & train shared location area. Our paper is structured in the following way. First we will discuss some interesting literature related to bicycle parking. Then we will discuss the methodologies used including the data used, and the models used to study the motivations for parking. Next we will analyze the model results followed by a brief discussion of these results. Finally we will come with a conclusion summarizing the results of this study and give some future recommendations.

## 2. Literature

Heinen and Buehler [6] review the literature on bicycle parking aiming to understand the impact of the presence, amount and quality of bicycle parking on bicycle ownership, behavior, and preferences. Additionally, they also identify empirical and methodological gaps in the literature. Overall, they found that bicycle parking supply is correlated with more bicycle parking, that cyclists prefer higher quality parking facilities over lower quality parking facilities and that parking supply appears to be a determinant of cycling. Moreover, empirically they found few quantitative studies on bicycle parking in cities in general, and limited evidence on the effect of good quality parking. Finally, methodologically they found that the most common research design is cross-sectional while the least common research design are intervention studies. Out of the 94 papers reviewed they found that 16 focused exclusively on bicycle parking while the rest mentions bicycle parking as a factor among others. Additionally, Heinen and Buehler mention that how bicycle parking was measured is often not well defined and that bicycle parking behavior has received a lot of attention in urban centres but not in other locations.

Molin and Maat [9] studied the effect of a new parking pricing policy, where at railway stations paid high-quality parking is provided while at stations further away free lower-quality parking is provided. They performed a stated choice experiment on train travellers who park their bicycle close to the train station. In the experiment, individuals were given free and paid parking alternatives with varying costs, walking time and surveillance. Based on these choices, a Latent Class model was estimated to provide insight in bicycle parking and train traveller preferences. Their results show that under a new pricing policy most cyclists would continue to cycle to a station. Additionally, The people that did stop cycling to the station chose either walking or public transit as an alternative. This indicates that charging for parking near a station can help in distributing bicycle parkers further away from the station.

Chen et al. [4] focus their research on the determinants for bicycle access and egress mode in Nanjing. They used survey data which was collected over the year 2011 in April and May which yields information on trip characteristics, transfer characteristics, socio-economics, attitudes and preferences. For their analysis, they select a metro station situated in a dwelling district and a metro station situated in a shopping district. They estimate two transfer choice models: one considering walk as access mode and the other one considering bus as access mode to the station. They found that more than half of the metro-users prefer to use bicycle transfer services, and that the surrounding land-use determines how they are used. Additionally, they found that bike rental services can potentially stimulate bicycle transfer and that travellers generally prefer walking unless the parking facility is close to the metro station and the travel distance is far.

Halldorsdotir et al. [5] study the differences in the preferences of train travellers in both the home-end as well as the activity-end part of the trip in Copenhagen. They use data from a travel survey which collects travel diaries and socio-economic information of the Danish population. They estimate two mixed logit models jointly to capture the different preferences structure at both home-end and activity-end. Their result show that adding parking places at the

activity-end of the trip results in a positive effect for cycling choices while at the home-end of the trip the results were negative. Additionally, they also found that a flexible fare structure may encourage the use of the bus service.

Lee and Ko [7] study the relationships between neighboring environment and residents bicycle mode choice with Seoul as their geographical scope for analysis. They used neighbourhood environment, and socio-demographic factors as explanatory variables in a random intercept logit model. Their analysis shows that bicycle lane density affects the bicycle mode choice in denser cities like Seoul, implying that the accessibility of bicycle lanes is an important factor for planners in order to encourage bicycle use. Additionally, socio-economic characteristics like gender, income, occupation, vehicle ownership, shorter travel distances and housing type all showed statistical significant correlation with bicycle use. Moreover, the study showed that neighborhoods with high levels of mixed land-use result in more bicycle travel. On the other hand, residential density did not show any statistically significant correlation.

This research is an extension to our previous work in [13] where we researched the behavior of cyclists travelling to the train station in the western region of the Netherlands. The data that was used is from a national travel survey which was aggregated over the years 2015-2017. A multinomial logit model was used to estimate where an individual has the choice to travel to the closest station or a station further away. The choice set was determined by looking at a 10 kilometer radius around the place where the person lived. The results showed that people are willing to travel as far as the fourth closest station, prefer to travel to the closest station if that station is skipped by the intercity train, and that municipalities not part of a city are prepared to travel to the 3rd closest station.

### 3. Methodology

#### 3.1. Data

For our research, records from a GPS tracking app are used to analyze an individual's travel behavior. This data was collected between June and October 2018, and between June and July 2019 in order to study the effects of the new metro line in Amsterdam which opened on 21st of July 2018. These tracking records have been mapmatched and been through modality deduction in order to infer individual trip details. As a result, we work with processed data which contains information about an individual's trip schedule on a specific date. For our research we make a selection of these records which involve parking near a station. The selection that we are working with is based on people who park their bicycle close to a station. Therefore, we define a catchment area by taking a 200 meter radius around a metro or train station and select all bicycle trips with a destination trip inside the catchment area. As a result, 4751 records were obtained which will be further used when generating the choice alternatives for an individual.

Furthermore, our dataset was further enhanced with neighborhood characteristics. First of all, we used the catchment area of 200 meter around each station to gather information about jobs, building densities and catering buildings in the area. This data contains information on building characteristics in the Metropolitan region of Amsterdam provided to us by the municipality. Secondly, open data was available on the address density and population density of several neighborhoods and districts in the Netherlands.[3]

#### 3.2. Choice set generation

To generate our choice set we took a slightly different approach of what [14] are using. Their alternative choice set is created by considering the ten closest stations by road distance from the origin of the bicycle trip. Since we did not have any road distances to the station, we used the haversine distance for each bicycle trip to every station in our data was taken. Consequently, we selected the 10 closest stations as the travel alternatives. However, if this selection did not include a metro or a train station as an alternative a metro or train station was added manually as the 10th option. As a result, 80.6% of the generated choices were actually also in observed choice set. Therefore, generated alternatives which did not include the observed choice set had to be removed from the dataset, resulting in a final dataset containing 3858 records.

#### 3.3. Modelling Framework

In our research we will be using discrete choice models which are based on random utility theory. This model assumes that each individual has a utility for each choice and selects the station to park based on their maximum utility.

For the full mathematical details readers are referred to Ben-Akiva [1]. Equation 1 shows how utility is calculated for alternative  $i$  and individual  $n$ .

$$U_{in} = V_{in} + \epsilon_{in} \quad (1)$$

The systematic utility  $V_{in}$  accounts for observed heterogeneity, typically in the form of a linear-in-parameters function of explanatory variables. A random variable  $\epsilon_{in}$  in the utility function accounts for the unobserved heterogeneity. We will be using a multinomial logit model which assumes that the random variable of the utility follows an extreme value distribution. Given a choice set  $C_n$  for each individual, the probability that alternative  $i$  was chosen is given by:

$$P(i|C_n) = \frac{\exp V_{in}}{\sum_j \exp V_{jn}} \quad (2)$$

An important limitation of the MNL model is that it does not allow correlation between alternatives or correlation between individuals. In our data it is very likely that individuals perform the same trip every day as part of their daily schedule. Therefore, in this research we will estimate a panel logit model in order to allow correlation between these individual trips. This correlation is captured in an additional normal error term which allows us to account for repeated choices by the same individual. As a result the utility function changes as shown in equation 3 where  $t$  represents choice at time  $t$ . In this equation our  $\sigma_{in}$  is the same for each individual while the other error term is still varying over trips. Readers who are interested in the full mathematical details are referred to [11].

$$U_{int} = V_{int} + \varepsilon_{int} + \sigma_{in} \quad (3)$$

Consider a sequence of alternatives, one for each time period,  $i = i_1, \dots, i_T$ . Conditional on  $\beta$  the probability that an individual makes this sequence of choices is a product of multiple logit formulations as shown in equation 4.

$$L_{in} = \prod_{t=1}^T \frac{\exp V_{int}(\beta)}{\sum_j \exp V_{jnt}(\beta)} \quad (4)$$

Since we are dealing with normal error terms, the unconditional probability is an integral over all possible values of  $\beta$  as shown in equation 5. Simulation is required to generate the normal error terms to solve the integral in equation 5.

$$P_{in} = \int L_{in}(\beta) f(\beta) d\beta \quad (5)$$

We will start estimating the coefficients of different attributes corresponding to every alternative by means of an MNL model. Since the panel logit model does not have a unique optimal solution, we will use the coefficients of the MNL model as a starting point for simulated estimation of our panel logit model.

The coefficients for each attribute of an alternative are estimated using Biogeme, which is a software package developed by [2]. It uses the maximum likelihood estimation technique to estimate the coefficients of the alternatives.

The discrete choice model allows us to create alternative specific coefficients for each alternative. However, since we are dealing with 10 alternatives each representing a bundle of explanatory variables, we work with generic coefficients crossed with a station type dummy variable. As a result, each attribute now has their impact split over 3 coefficients; one coefficient for train stations only, one coefficient for metro stations only, and one coefficient for the combination of metro and train at the same station location.

#### 4. Model results

Table 1 shows the results of the final multinomial logit model. Each column shows the value of the coefficient followed by the t-test in parenthesis. The column headers indicates whether the coefficients belong to a metro station, train station or metro & train station. The final model shows an adjusted Rho-square of 0.384. In the remainder of this work we assume results are significant when the t-test is higher than 1.96 or lower than -1.96.

Table 1. Multinomial logit results

	Explanatory	metro	train	metro & train
trip characteristics	haversine distance	-1.12 (-23.73)	-1.01 (-19.97)	-0.685 (-15.79)
	activity_time_per day	-0.95 (-5.76)	-1.16 (-4.82)	0.124 (0.69)
	dummy_activity_at_station	0.479 (5.05)	0.381 (2.83)	-0.587 (-5.72)
	rail service used	0.358 (1.85)	-0.159 (-0.97)	0.33 (2.55)
	dummy_weekend	-0.206 (-1.55)	-0.287 (-1.43)	-0.31 (-2.19)
neighborhood characteristics	building_density	0.314 (2.78)	-0.165 (-1.18)	0.725 (4.41)
	population_density	0.00713 (1.73)	-0.175 (-12.25)	-0.0632 (-4.86)
	adress density per km2	-0.167 (-1.69)	1.25 (8.28)	0.413 (4.4)
	count_fulltime_jobs	0.0729 (2.66)	0.856 (8.07)	
	count_catering	0.00097 (0.09)	0.31 (3.98)	0.558 (13.73)
socio-economic characteristics	income>2500	0.303 (2.28)	-0.941 (-4.36)	0.487 (3.5)
	education	-0.283 (-2.73)	0.715 (4.77)	-0.501 (-4.5)
	Senior age	-0.328 (-2.96)	-0.232 (-1.19)	-0.442 (-3.59)
	Young adult age	0.232 (1.3)	-0.568 (-1.93)	-0.198 (-1)

Table 2. Panel logit results

	Explanatory	metro	train	metro & train
trip characteristics	haversine distance	-1.12 (-21.52)	-0.895 (-17.94)	-0.856 (-14.55)
	activity_time_per day	-0.654 (-3.53)	-1.09 (-4.25)	0.107 (0.44)
	dummy_activity_at_station	0.573 (5.22)	0.0371 (0.25)	-0.302 (-2.2)
	rail service used	-0.428 (-1.98)	-0.161 (-0.94)	0.336 (1.87)
	dummy_weekend	-0.381 (-2.53)	-0.0444 (-0.21)	-0.269 (-1.44)
neighborhood characteristics	building_density	0.555 (4.48)	-0.211 (-1.47)	1.1 (4.81)
	population_density	0.00782 (1.83)	-0.192 (-12.17)	-0.0229 (-1.36)
	adress density per km2	0.168 (1.36)	1.16 (7.46)	0.231 (1.88)
	count_fulltime_jobs	0.109 (3.94)	0.841 (7.88)	
	count_catering	-0.00132 (-0.12)	0.236 (2.82)	0.658 (11.29)
socio-economic characteristics	income>2500	-0.0867 (-0.53)	-0.635 (-2.63)	1.07 (3.63)
	education	-0.00573 (-0.04)	0.205 (1.17)	-1.01 (-4.96)
	Senior age	-0.452 (-3.29)	-0.415 (-1.7)	-0.694 (-2.8)
	Young adult age	-0.02 (-0.08)	-0.27 (-0.91)	-0.656 (-1.98)
	sigma_train		1.97 (10.04)	
	sigma_metro_train			2.54 (12.24)

#### 4.1. Trip characteristics

The results for the haversine travel distance shows that as distance increases parking near the station becomes less likely. The impact of distance however is a lot less at metro & train stops. This means that people are willing to cycle further to a station with a metro & train service. The activity time per day shows that as activity time increases it is less likely the person parks near a metro or train station. However, when the location offers both a train & metro service the model found no importance. The dummy activity at station variable shows that if a person has an activity in the station area, he is more likely to park near a metro station or a train station but not near a metro& train service. This might indicate that cyclists are likely to also use these modalities to travel onward. This result is further confirmed when we look at the rail service used variable. People who park near a station with metro & train services are more likely to travel onward using the rail service. Finally, the dummy weekend variable shows that in weekends overall there is less parking in the station areas compared to working days. This is mostly true for the metro & train stations, and can probably be explained by the fact that there is more parking pressure on a working day compared to the weekends.

#### 4.2. Neighborhood characteristics

The results for the building density shows that as building density increases more people will park near a metro station or a metro and train station combined. For train stations, a negative sign was found but the low t-test result means that the result was insignificant. The population density shows a heavy negative impact in train station areas indicating that as population density near a train station increases, it becomes less likely the station is chosen. This result was also found for stations with both metro and train services, while population density at for metro station areas shows to have a positive result although the results are not significant. The address density per km<sup>2</sup> variable shows that as the address density increases, the likelihood of parking near a train station or metro and train station area increases. For metro stations we see the exact opposite effect but these result are not significant. Due to high correlations of full time jobs with other explanatory variables the coefficient for metro and train combined were removed. The other coefficients show that as the amount of full-time jobs in the area increases, the amount of bicycle parking in the area also increases. This makes sense especially in a city like Amsterdam where people prefer to use the bicycle to travel to their work. Finally, as the amount of catering in the station area increases, the choice for a station area or metro & train station area also increases. Especially the impact in metro & train station areas is shown to be a lot higher compared to the train station areas. On the other hand, metro stations have no significance in the model possibly because there are not a lot of catering services in the metro station areas.

#### 4.3. Socio-economic characteristics

The income variable shows that people with a higher net income are more likely to travel to metro and metro & train stations and less likely to travel to train stations. Moreover, the impact of income in station areas is much higher compared to the metro and metro & train areas. On the other hand, people with a bachelor or master degree are more likely to travel to a train station area and less likely to travel to a metro station or metro & train station area. For the age variable we focused on two groups of people: seniors (60+) and young adults (18-29). The results for senior people show that these people are not likely to park at a metro, train or metro & train station at all. Furthermore, the results for young adults did not show any significance indicating that the model was not able to find anything important regarding the bicycle parking behavior of this group.

#### 4.4. Panel logit results

In this section we will compare the results of the panel logit with the multinomial logit. The results for the panel logit are shown in table 2. First of all, The rho-square shows an increase from 0.384 to 0.442 which was expected since we are dealing with panel data. Secondly, both  $\sigma_{train}$  and  $\sigma_{metro\_train}$  are shown to be significant in our model. This shows that there is a lot of variation among individuals choosing to park at a train station or a metro\_train station. Moreover, this variation seems to have a higher impact in metro\_train station areas compared to train station areas. Thirdly, we can see that some variables which were significant before are now insignificant, and the impact of most of our explanatory variables has also changed. However, for our metro station explanatory variables  $dummy\_weekend$ ,  $building\_density$  and  $count\_fulltime\_jobs$  seem to gain in terms of significance. Additionally, both metro and train station areas lose significance in their socio-economic characteristics except for metro\_train stations which seems to even slightly gain significance.

### 5. Discussion

The results for the panel model shows some interesting results compared to the multinomial logit model. First of all, the increase in rho-square from 0.384 to 0.442 shows that the model performance improved by adding correlation between individuals. Secondly, the increase in the impact and significance for  $dummy\_weekend$ ,  $building\_density$  and  $count\_fulltime\_jobs$  indicate that the model potentially underestimated the impact of these variables in the multinomial model. Additionally, the decrease in impact and significance of  $dummy\_activity\_at\_station$  for train stations and population density and address density for metro & train stations gives the impression that the multinomial overestimated the impact of these variables. Finally, it is surprising to see that the socio-economic characteristics have similar significance but increased impact for metro & train stations compared to the multinomial model.

The final model shows that the model is able to find explanatory power in all variables, and that the impact and significance can vary depending on the station area we are looking at. For metro stations the trip characteristics seems to be the most important since these variables were found to be the most significant. However, overall the impact of the variables for metro stations appear to be lower compared to the other station areas. Moreover, for train stations a lot of explanatory power was found in the neighborhood characteristics, especially for the variables address density per km<sup>2</sup>, full-time jobs, income and education. Furthermore, the impact of train station variables is substantially higher compared to the other station areas. Finally, for metro & train stations both trip and neighborhood characteristics seem to be the most important. The building density and the amount of catering in the area appear to have the most impact in these station areas. Socio-economics also proved to be important variables but the trip and neighborhood characteristics seem to work better for metro and train stations. However, in the panel model we found that the socio-economic characteristics lost their significance except for areas where metro & train were located. This indicates that socio-economics can play an important role in measuring bicycle parking near metro & train stations.

The final results also shows that the sign of the explanatory variables can differ in some station areas. This was especially true in the case of the dummy variable activity at the station and the income variable. The dummy variable shows that people generally park near a metro or train station for an activity but not near a metro & train station. This is probably because people use the metro & train station as a multimodal hub to travel onward to work or an activity at a different location. The income variable shows that people with a higher income prefer to park near a metro & train station while people with a lower income prefer to park near a train station.

One of the reasons why this research was conducted was to investigate the potential of neighborhood characteristics in station choice modelling. The results show that neighborhood characteristics are especially important for train stations and metro & train stations. Moreover, the explanatory variables for the neighborhood characteristics seem to favor a particular kind of station area based on the value of the t-test. Population density, address density and full-time jobs appear to be of high importance for train station areas and a lot less important for the other areas. The amount of catering services in the area also seem to be of high importance in metro & train station areas but less important in train station areas.

This research is an extension and improvement to our previous work. First of all, we expand the study area by considering station areas instead of train or metro trips with bicycle as access mode. This resulted in more data which caused us to gain a better understanding of why people travel to a station area. Secondly, by adopting a different modelling approach we were better able to highlight the similarities and differences in the effect of bicycle parking near a metro or train station. This approach would not have been possible in our previous research since there was a lower amount of data. Thirdly, in our previous research we used an open source library to generate trip alternatives, while in this research we generated trips based on the distance that a person has to travel to the station. Finally, we added neighborhood characteristics by considering different data sources that were available to us.

## 6. Conclusion

The final results show that there are differences and similarities in bicycle parking near a metro, train or metro & train station. The most important difference is that most people with an activity park near a station with a metro or train service but not near a station that offers both. Additionally, train station areas seem to attract cyclists with a lower income and higher education level while metro station areas and station areas with combined metro & train service seem to attract cyclists with a higher income and lower education level.

Although we did our best to investigate the similarities and differences between stations, some improvements could potentially be made. First of all, the choice-set generation could be improved to generate alternatives that are more likely for the trip that is being performed. Currently, the choice set is created using the haversine distance while distance by road might be more realistic. Furthermore, the results for the neighborhood characteristics are limited to the variables of which we have information. There might be other variables related to mixed land-use which could potentially help for our prediction. Finally, in the current work, we report on only multinomial logit model results. In future research we intend to test more complex models such as mixed logit or panel logit models with our data.

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