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The Impact of a New Public Transport Line on Parking behavior

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Abstract

To reduce congestion problems in urban environments, policy makers around the world recognize the importance of public transport quality improvement, P&R facilities near peripheral public transport stops, and parking price incentives. This paper proposes a logit model to study the short-term and long-term impact of a new subway line in Amsterdam on the parking behavior. Three groups of travelers are defined in this research: (a) travelers inside Amsterdam, (b) travelers from Amsterdam to outside Amsterdam, and (c) travelers from outside to inside Amsterdam. From the model it is found that in the short term the subway line resulted in an increase in parking near the city center of Amsterdam, especially caused by commuters traveling from outside Amsterdam. However, one year later, the parking demand has dropped significantly which is possibly an effect from increased parking tariffs. Further, before the opening of the public transport line, higher parking tariffs lead to more parking near destination. Experiments with parking tariff cross-variable models reveal that parking tariffs consist of two underlying bi-modal distributions, which are the location of origin and destination with respect to Amsterdam, and whether the time period is during summer or autumn. Parking tariffs affect the parking behavior from and to Amsterdam. Another finding is that during the autumn parking tariffs significantly affect the parking behavior in the short-term. This model can be extended further with more specific location variables, continuing the parking tariffs research, and the addition of more trip, spatial and personal attributes.

Keywords: effect analysis; parking demand; logistic regression model; logit model; parking behavior

1. Introduction

Population increase, income growth, urbanization and limited road network constructions have led to rapid growth of private car use during the last decade [1] [2]. Subsequently, almost all urban areas around the globe suffer from serious traffic congestion problems [2] on environmental [3][4], social [5] [6] and economic level [1] [7]. Sustainable parking policy incentives play an important role in reducing the car-mode share in cities, and consequently reduce

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or eliminate these congestion problems [8]. To discourage car use and encourage other modes of transport, such as public transit in cities [9] [10] major cities improve the public transport quality [11], build Park and Ride (P&R) parking locations [12] and set parking pricing [13] [14]. This paper studies the impact of these incentives on parking in Amsterdam, the Netherlands. Public transport in central Amsterdam is encouraged with a new subway line, the North-South line. This subway line, put into service on July 22, 2018, connects the North to the South of Amsterdam via the city center. Figure 1 visualizes the route of the North-South line in red, and the locations of the P&R infrastructure in Amsterdam.

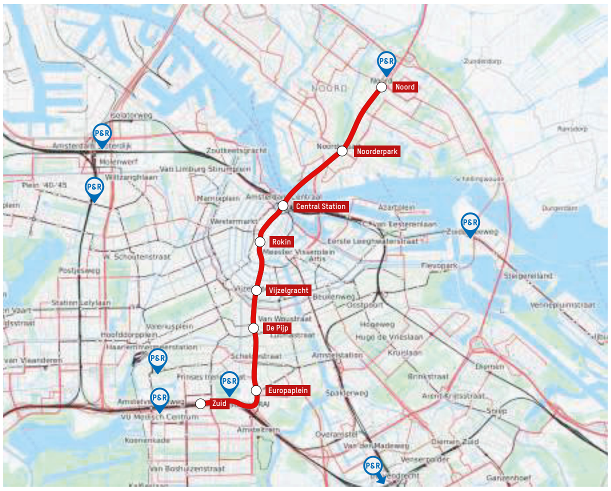


Fig. 1: Route of the North-South subway line with the park and ride locations.

The aim of this case study is to find the long-term and short-term impact of the North South line on the parking behavior in Amsterdam, the Netherlands. More specifically, we investigate how the North-South line changes the preferred main transport mode of the car to transit traveler (i.e. whether it is mainly car, or a public transport mode). Independent variables included are the origin and destination location of the trip, and the parking tariffs. For this study a logit model is applied. The following measurement times are distinguished: Pre-North-South line (1 June, 2018 until 21 July, 2018), post-North-South line 2018 (22 July, 2018 until 31 October 2018) and post-North-South line 2019 (1 June, 2019 until 31 July, 2019).

The paper is organized in the following sections. Section 2 describes relevant literature. Section 3 presents the data set and describes the development with an empirical study. Section 4 discusses the logit model results. Finally, in Section 5 our findings are concluded and implementations for future studies are discussed.

2. Related Literature

With the growing awareness of the negative effects of car use, studies on parking behavior and Park and Ride (P&R) facilities are becoming increasingly prominent in transportation research.

For example, Mahmoud et al. [15] investigated the choices of cross-regional drivers in a P&R station in the Greater Toronto and Hamilton area. They revealed that the most important factors for the transit station choice are the access distance and the direction of the station with respect to the workplace. They also found that cross-regional travelers were more sensitive to changes in station access distance than local transit P&R users.

Likewise, Zhao et al. [16] investigated P&R decision behavior with a multinomial logit model. They carried out an online and field survey on the use of P&R facilities. This survey contains both personal attributes (e.g. age, and income) and travel characteristics (e.g. time from origin to parking lot, parking duration, and transfer times). They concluded that the most important reasons *not* to use P&R are the shortage of parking space, inconvenient transfer, and high fees for parking. The top reasons to use P&R include saving time and saving fuel consumption.

Pang and Khani [17] implemented mixed logit models on transit on-board survey data to investigate the P&R location choice behavior of heterogeneous commuters in the Austin Metropolitan Statistical Area. Their main conclusion is that travelers who are more likely to be motivated by short car travel time are also more likely to be motivated by few transfers and short walking time. Further, they found that travelers with higher income are less motivated by high transit service frequency, and that non-Caucasians drive a higher fraction on freeways compared to other roads.

Sharma et al. [18] also investigated the P&R lot choice behaviors with two multinomial logit models. In the first model the assumption is made that travelers choose alternatives that have maximum utility. The second model assumes that travelers make decisions in order to minimize the regret in comparison to other alternatives. Variables included in their model were the travel time for the car network and the transit network. They found that travelers prefer P&R lots where they can minimize their transit travel time, and where their car and transit travel costs are reduced.

Macioszek and Kurek [12] examined the features associated with a P&R system in the city of Cracow (Poland) with a logit model. They have found that the most important factors that increase the likelihood of P&R use are age, number of years having a driving license, monthly income (gross), and an average number of trips made during a day.

An alternative approach to simulate the parking choice behavior is with fuzzy set theory. This takes the uncertainty and subjectivity of the parking choice behavior of the human decision maker into account in the framework of Possibility Theory. Examples of applications of fuzzy sets in the context of parking are by Dell'orco et al. [19], and Ottomanelli et al. [20].

Khaliq et al. [21] implemented a multinomial logit model in an agent based simulation model. The parking spot choice is based on the expected number of free parking spaces, distance to destination and length of parking space. The results indicate that the streets attributes significantly affect the parking choice behavior of agents. One year later, Khaliq et al. [14] implemented another multinomial logit model from survey data where the respondents were asked if they would park in hypothetical street segments with different parking attributes. They found that the most important attributes for choosing a parking location are "walking distance to destination" and "parking cost". Contrary to their previous study, less effective characteristics are the street level attributes.

To summarize, a common and effective method to investigate parking behavior is a variant of the logit model. In the present paper a logit model is applied to study parking behavior. To the best of our knowledge, limited research has been done into the effects of a public transport line on parking behavior, which distinguishes this paper from the above-mentioned studies.

3. Empirical study

The data used in this study is provided by ICT service provider Mobidot [22]. The data set consists of measurements and analysis of travel behavior of trips, collected from sensor information with the smartphone app Sesamo. The observations are collected in two measurement periods, namely around the period of the opening of the North-South line in 2018 and one year later in 2019. The target group is the car to transit traveler, limiting the research sample to 1410 trips, measured from 397 users. These users are similar in being all frequent car to transit travelers, giving the opportunity to compare the effects between the different periods. This section presents the independent variables type of trip, parking tariffs, and weather variables, and the dependent variable parking near to origin versus parking near to destination.

3.1. Type of trips, inside Amsterdam versus outside Amsterdam

Four types of trips are compared: trips inside Amsterdam (in-in), trips from inside Amsterdam to outside Amsterdam (in-out), and trips from outside Amsterdam to inside Amsterdam (out-in), versus trips outside Amsterdam (out-out). For this categorization, Amsterdam is defined as the municipality of Amsterdam.

3.2. Parking tariffs

In between the measurements in 2018 and 2019 the parking tariffs in Amsterdam have increased strongly up until 100% [27]. To study the impact of this tariff change on the parking behavior, parking tariffs are added to the model. For this addition some preparatory steps have been taken. First, the recent parking tariff information is obtained from the open dataset of the municipality of Amsterdam. This consists of parking zone polygons with the corresponding tariffs and tariff times. Second, the parking tariff information before the tariff change is retrieved. Due to the lack of open historical tariff data, the old tariffs are added manually to the tariff zones, by comparing a parking tariff map before and after the tariff change. Next, each parking location from the sample is matched with the corresponding tariff zone with the use of the Ray casting algorithm [28]. Finally, for each parking time, and parking location the related tariffs are added to the trips.

3.3. Weather

In a previous work it is found that weather can significantly affect the parking location choice [29]. For this reason, weather variables, retrieved from the Royal Netherlands Meteorological Institute (KNMI) are added to the model. The selected weather variables are the sum of precipitation, sunshine duration, horizontal view, and average temperature of the last hour. The variance inflation factors between the variable combinations are around 1, meaning these variables do not correlate with each other.

3.4. Dependent variable: Transit location near origin and near destination

For the car to transit trips we address the mode share of car versus the mode share of public transport. For this variable, the distance between the coordinates of the location of origin, and the parking location for transit (e.g. the location between the "car" and the "public transport" segment of the trip) is calculated. Similarly, the distance between the parking location for transit and the destination is calculated. These distances are calculated with the cosine haversine function [30] in 1.

$$d = 2r \cdot \arcsin\left(\sqrt{sin^2\left(\frac{\Phi_2 - \Phi_1}{2}\right) + cos(\Phi_1)(\Phi_2) \cdot sin^2\left(\frac{\lambda_2 - \lambda_1}{2}\right)}\right) \tag{1}$$

where Φ_1 and Φ_2 are the latitudes (in radians) of point 1 (the transit location) and point 2 (the origin location, or the destination location) respectively, and λ_1 and λ_2 are the longitudes (in radians) of point 1 and point 2 respectively.

Based on these distances, it can be determined whether the transit location is closer to origin or destination. This provides an approximation whether the largest distance is either traveled by public transport ("closer to origin") or by car ("closer to destination"). Figure 2 visualizes the car to transit parking locations in Amsterdam, where parking near to origin, and near to destination are distinguished. Panel 2a presents the parking locations before the opening of the new subway line. It can be observed that most of the car to transit parking locations in Amsterdam are closer to origin than to destination. Further, the parking locations are reasonably spread around the center.

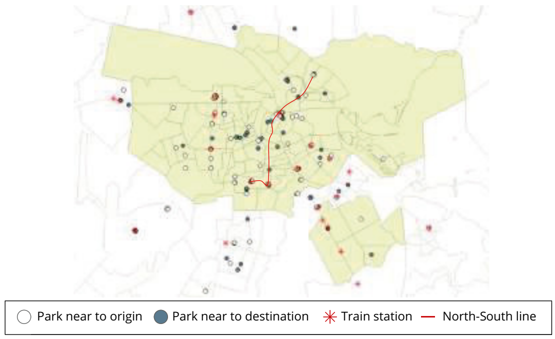
Shortly after the opening of the subway in 2018 (Panel 2b) the number of parked cars near the subway stations of the North-South line has increased substantially. It can also be noted that more commuters park near to their destination, which can indicate that the North-South line attracted more travelers from outside Amsterdam. Remark that drivers from the research sample especially park close to the north station (the northernmost point of the North-South line). In this location P&R infrastructure is located (Figure 1). The P&R locations on the left side of the south station are mainly occupied by commuters who park near to origin.

One year after the opening of the North-South line, in Panel 2c, a completely different pattern of parking locations can be noticed. Apart from the location nearby Amsterdam Central Station (the cluster in the middle of the North South line) the amount of parked cars close to the new subway line has decreased. However, there is no fundamental change in the park near origin in 2019. Instead, the patterns of the parking locations one year after the North-South line are more similar to Panel 2a. The decrease of the parked cars in Panel 2c can be caused by a change in the parking tariff on July 14, 2019.

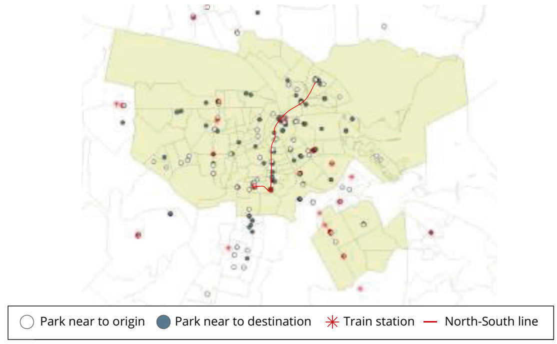
4. Logit models

This section discusses the results from the logistic regression (logit) model on the short-term and long-term parking behavior. Logistic regression can be compared with multiple linear regression, but takes into account the fact that the dependent variable is categorical. This model is applicable for this study, as the response takes one of only two possible values representing the presence or absence of an attribute of interest [31], which whether chooses the car or public transport as main transport mode. Because the dataset is well balanced, the independent model variables type of trip, parking tariffs, and weather can be included to the model, even though the sample size is small. To avoid collinearity problems the correlation of each coefficient is compared and none of the coefficients correlate [32].

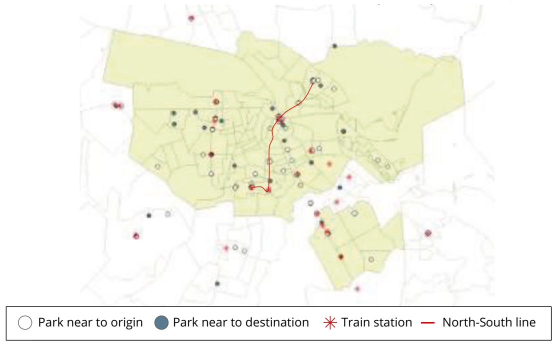
Table 1 presents the logit model results, and the significance according to an independent samples t-test. Note that the weather variables are not included in the model. This is because the only significant weather variable was the hour sum of precipitation, having a negative impact on parking near to origin before the opening of the North-South line. In other words, before the opening of the North-South line a general commuter prefers to park near destination when



(a) Parking locations pre-North-South line.



(b) Parking locations post-North-South line, 2018.



(c) Parking locations post-North-South line, 2019.

Fig. 2: Car to transit locations for near origin versus near destination, for the three measurement periods.

raining, and thus chooses the car as main transport mode. However, the rest of the weather variables and measurement periods are effectively random. We will discuss the final model results row by row.

4.1. Logit results type of trips, inside Amsterdam versus outside Amsterdam

The first coefficient, near to origin, gives insight into the likelihood of parking near to origin. Each time period contains a small positive value, indicating that a commuter is modestly more expected to park near the location of origin. For the second coefficient, the trips inside Amsterdam, none of the coefficients is significant when a confidence level of 95% is considered. This means that travelers inside Amsterdam do not have a clear preference to park near to origin or destination. For the third coefficient, the car to transit trips from Amsterdam to outside Amsterdam, an increase from before the opening metro line (0.766) to one year later (1.31) can be noted, meaning that in general more commuters from Amsterdam to outside Amsterdam park near to origin. For the fourth coefficient, the trips to Amsterdam, we see that travelers tend to park on an effectively random location, because the t-test value is negligibly low (−0.004). But after the opening of the North-South line in 2018 travelers tend to park inside and close to Amsterdam (near to destination) with clear significance (t-test value of −4.41). This indicates that travelers from outside Amsterdam tend to park inside Amsterdam after the opening of the North-South line. However, one year later (post-North-South line 2019) travelers from outside Amsterdam to inside seem to park closer to the location of origin instead. This can be a result of the parking tariff change in April 2019.

4.2. Logit results parking tariffs

The fifth coefficient shows the effects from the parking tariffs on the parking choice behavior. Before the opening of the North-South line commuters tend to park near to destination when the tariffs are higher, but apart from that, no significant parking impact is found.

In order to find whether the effects are caused by the parking tariff change, experiments with several logit models are conducted. The results from these experiments are given in Table 2. Both models contain cross-variables between the type of trip and the measurement period. The left part of the table presents the results with cross-variables between

Table 1: Results from the logit model of transfer location for the complete dataset and the three measurement periods.

	Complete data set			**Pre-North-South line**			**Post-North-South line (2018)**			**Post- North-South line (2019)**		
Coefficient	Value	t-test	sig. **	Value	t-test	sig.	Value	t-test	sig.	Value	t-test	sig.
Near origin	0.522	4.98	Yes	0.605	2.58	Yes	0.630	4.23	Yes	0.328	1.67	Yes
Near origin, in-in*	-0.211	-1.26	No	0.112	0.329	No	-0.456	-1.78	No	-0.130	-0.426	No
Near origin, in-out*	0.786	4.25	Yes	0.766	2.13	Yes	0.497	1.77	No	1.31	3.67	Yes
Near origin, out-in*	-0.322	-2.37	Yes	-0.001	-0.004	No	-0.865	-4.41	Yes	0.434	1.57	No
Near origin, tariff	-0.001	-0.032	No	-0.272	-3.85	Yes	0.087	1.56	No	0.057	1.07	No

* This value is compared to the dummy variable, transit near to destination, out-out.

** For significance level $\alpha = 0.05$ the following hypotheses are considered: $H_0 : \mu_i = \mu_0$ versus $H_1 : \mu_i \neq \mu_0$ for coefficient i [34], where μ_0 is the mean. Given $\alpha = 0.05$, H_0 is rejected (i.e. "sig." is "Yes") if the absolute t-value is greater than 1.962, 1.966, 1.965, and 1.966 for the complete data set (1409 records), pre-North-South line (359 records), post-North-South line 2018 (654 records), and post-North-South line 2019 (394 records), respectively [35].

Table 2: Results from the logit model of transfer location for the complete dataset with two different model specifications.

Baseline model with type of trip by period and tariffs by period					*Baseline model with type of trip by period and tariffs by type of trip*				
Coefficient	**Period**	Value	t-test	sig.**	**Coefficient**	**Period**	Value	t-test	sig.
Near origin	*All periods*	0.471	5.91	Yes	**Near origin**	*All periods*	0.484	5.98	Yes
Near origin, in-in*	*Post NZL '18*	-0.324	-1.41	No	**Near origin, in-in***	*Post NZL '18*	-0.265	-1.13	No
	Post NZL '19	-0.252	-0.96	No		*Post NZL '19*	-0.290	-1.07	No
Near origin, in-out*	*Post NZL '18*	0.645	2.51	Yes	**Near origin, in-out***	*Post NZL '18*	0.352	1.33	No
	Post NZL '19	1.19	3.67	Yes		*Post NZL '19*	0.755	2.31	No
Near origin, out-in*	*Post NZL '18*	-0.713	-4.53	Yes	**Near origin, out-in***	*Post NZL '18*	-0.496	3.17	No
	Post NZL '19	0.303	1.36	No		*Post NZL '19*	0.568	2.48	Yes
Near origin, tariff	*Post NZL '18 Summer*	-0.001	-0.01	No	**Near origin, tariff**	*All periods, in-in*	0.059	0.956	No
	Post NZL '18 Autumn	0.128	2.12	Yes		*All periods, in-out*	0.371	3.79	Yes
	Post NZL '19	0.045	0.89	No		*All periods, out-in*	-0.174	-3.15	Yes

* This value is compared to the dummy variable, transit near to destination, out-out, pre-North-South line.

** For significance level $\alpha = 0.05$ the following hypotheses are considered: $H_0 : \mu_i = \mu_0$ versus $H_1 : \mu_i \neq \mu_0$ for coefficient i [34], where μ_0 is the mean. Given $\alpha = 0.05$, H_0 is rejected (i.e. "sig." is "Yes") if the absolute t-value is greater than 1.962 for the complete data set (1409 records).

the parking tariffs and the measurement period. To find whether there is a difference between the commuter trip and a vacation trip, the post-North-South line measurements are split into a summer period (July and August) and an autumn period (September and October). Now positive significant effect on the parking behavior during the autumn period is observed. Because parking tariffs were not significant during the post-North-South line 2018 measurements (Table 1) this indicates that parking tariffs have an underlying bimodal distribution. For the commuter period, we can see that if the parking tariffs increase, more commuters tend to park near to origin. The right part of table shows impact of the combination between tariff and the type of trip on the parking behavior. Also here, the tariff variable is more significant compared to Table 1, hinting at a bimodal distribution of parking tariffs based on the type of trips. For the trips from Amsterdam to outside Amsterdam, an increase in tariffs also increases the tendency to park near to origin. A possible explanation for this behavior is that residents of Amsterdam have a parking permit. A negative effect of parking near to origin can be noted for travelers from outside Amsterdam to inside Amsterdam. However, trips inside Amsterdam are still not significant.

5. Conclusion

This paper presents a logit model to investigate the short-term and long-term impact of a new subway line, the North-South line, on the parking behavior in Amsterdam. The research sample consists of 1410 car to public transit trips in the Netherlands. The main conclusion is that in short-term more commuters tend to park in the city center close to the stations of this public transport line. Especially commuters from outside Amsterdam found with this public transport line a new alternative to directly connect with the city center. However, in 2019 this effect has faded as these commuters park closer to the location of origin, choosing for main transport mode a public transport mode over the car. Further, before the opening of the North-South line, an increase in the precipitation sum, and parking tariffs increase the tendency to park near to the location of destination. After the North-South line opening, weather and tariff coefficients were effectively random, which can be due to the small sample size.

In order to find whether the reduction of parked cars in Amsterdam in 2019 is caused by a tariff change in 2019, experiments with parking tariff cross-variable models are presented. These experiments reveal that parking tariffs consist of two underlying bi-modal distributions: the type of trip and whether the time period is a holiday or a commuter period. By splitting up the post North South line measures in 2018 to commuter period and holiday period, it is noted that an increase in parking tariffs positively increase parking near to origin. Another finding is that the parking behavior of travelers to and from Amsterdam is significantly affected by parking tariffs. These findings provide insight into the impact of a new subway line on parking behavior in the surrounding environment, and eventually indicate whether this line is effective in reducing environmental, social, and economic congestion problems in the city center. However, a few approximations have been made, meaning we have to be careful about drawing strong conclusions. A first approximation is the use of the cosine haversine distance function, instead of the road distance. In reality, the travel distance between point A to B is not a connection of a straight line but depends on the road and rail infrastructure. A second point of improvement is that two trips with the same trip characteristics can still be fundamentally different from each other. For example, we take two travelers from outside Amsterdam to inside Amsterdam that park near origin. The first trip is from Amstelveen, a suburban part of the metropolitan area of Amsterdam and the second trip is from Groningen, which is about 180 km travel distance from Amsterdam. These trips have the same characteristics according to this model. But "parking near to origin" can be completely different from the municipality of Amsterdam point of view. In the first case, the driver may still park inside Amsterdam, whereas in the second case the driver obviously parks outside Amsterdam. To improve this model, we need to distinguish directions from outside Amsterdam, and more specifically, include the exact distances in the logit model.

The interesting findings in the present paper have opened the door for future research. To tackle the above-mentioned inaccuracies, a shortest path algorithm can be applied for the distance calculation. Another improvement is incorporating the travel time to study the preference of traveling by public transport compared to car use. The underlying distributions from the parking tariffs can be further analyzed to find whether the changes in parking behaviour are indeed due to the parking tariff change. Other additions to the model are the inclusion of spatial characteristics (such as the walking distance to a public transport station), events and holidays, and the type of parking location, for instance if the commuter prefers to park off-street versus on-street. More specific analysis can be conducted into the neighbourhoods in Amsterdam. Eventually, the presented model will be extended to a hierarchical logit model, which can be implemented in a simulation model in order to find the impact of different policy decision scenarios. This can ultimately assist the policy maker in making effective policy decisions.

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