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Will good public transport substitute free-floating car sharing? A case study from Copenhagen

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ABSTRACT

Free-floating car sharing (FFCS) is an emerging mode of transport that enhances the mobility of individuals that do otherwise not have access to cars. This article investigates how the usage of FFCS is affected by the implementation of new high-class public transport. The analysis presents changes in spatiotemporal substitution patterns for FFCS and public transport usage after the opening of a high-class metro line in Copenhagen. A direct demand model is developed with the aim of modelling the FFCS demand and to associate this with land-use variables and public transport accessibility variables at level of zones. The results reveal that while generally increasing over time, the car sharing usage decreased in areas well-served by the new metro line after opening. Thus, it is suggested that FFCS usage and public transport are mainly substitutes and compete for the same costumer base. However, locally, there are signs that the two modes are complementary as well.

1. Introduction

Free-floating Car Sharing (FFCS) is a new alternative to private cars [ownership] and public transport (Becker et al., 2017). Contrary to stationary car sharing systems, where vehicles are located at fixed locations, FFCS systems provide more flexibility for users as vehicles can be picked up and dropped off at any location within the area of operation. However, due to its relatively recent addition to the transport system, its impact and interaction with other modes are not yet fully understood (Khan and Machemehl, 2017; Carrone et al., 2020). This is particularly true with respect to the interaction with the public transport system (Guirao et al., 2021). This interaction is increasingly important for the planning of sustainable urban transport systems in metropolitan areas. Although it has been suggested that the two systems compete for customers based on stated preference experiments (Carrone et al., 2020), it has also been suggested that FFCS is an enabler of public transport by serving access and egress trips (Shaheen and Chan, 2016). Some studies have suggested complementarity between FFCS and public transport through positive correlations between FFCS usage by travellers and public transport (Ceccato and Diana, 2021), and through a more frequent use of FFCS in areas with low coverage of public transport (Becker et al., 2017). While these studies have provided some information on the interactions between FFCS and public transport, no studies have specifically analysed how public transport could influence mode choice based on actual behaviour in a before- and after study context.

Motivated by this research question, this paper uses unique large-scale FFCS transaction data for the period 2017–2019 and investigates how demand for FFCS is affected by a new metro line. The case is a new 15.5 km circular high-class underground metro line called *Metro Cityring* connecting 17 stations in the city centre of Copenhagen, Denmark. The metro line operates in a dense urban area with high demand for FFCS services, providing a unique opportunity to investigate the substitution patterns between the demand for FFCS and high-quality public transport.

Specifically, the article contributes to the existing literature by presenting a unique before and after study that illustrates the relationship between the demand for FFCS and the quality of public transport. The analysis involves a presentation of changes in the spatial substitution patterns across FFCS and public transport usage after the opening of a high-class metro line. Subsequently, a direct demand model for FFCS demand is estimated, allowing for analysing explicitly how different factors contribute to FFCS usage. This includes data covering urban characteristics, sociodemographic characteristics and public transport characteristics in terms of accessibility to the new metro line, as well as existing bus services.

The paper is organised as follows. In Section 2, a review of the literature is provided. Section 3 presents the methodology. Section 4

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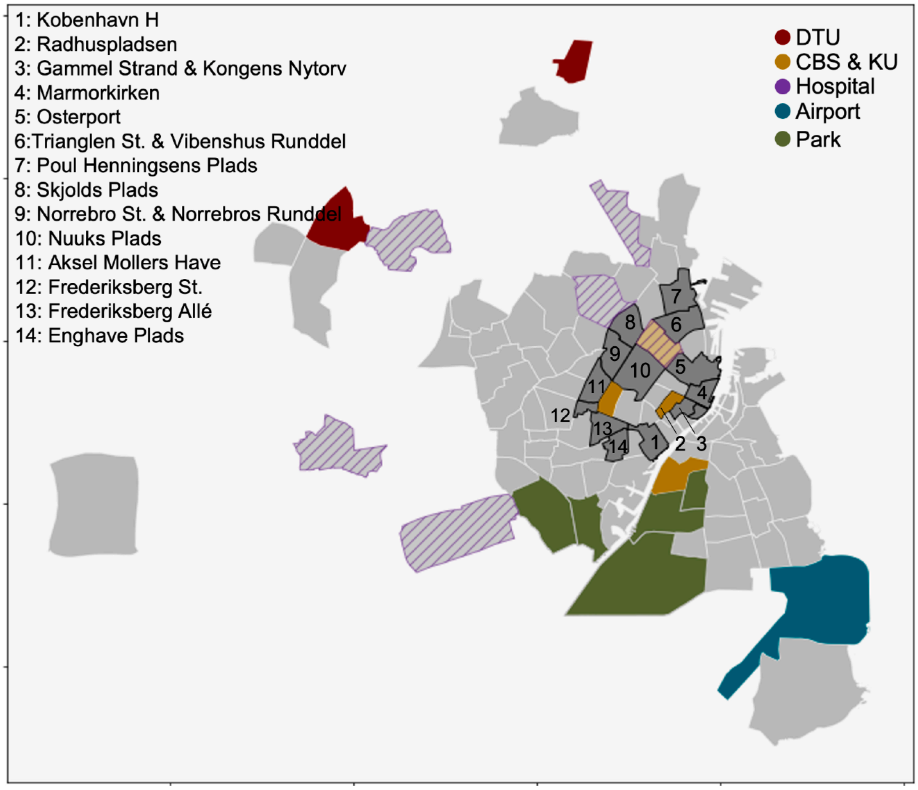

Fig. 1. Operational area of FFCS (light grey and colored zones), including the location of zones with new Metro Cityring stations (dark grey).

offers a description of data and details the data pre-processing. Section 5 presents the results of the direct-demand model, while Section 6 offers a discussion of the results and limitations. Finally, in Section 7, we conclude the paper by summarising the main findings and providing an outlook for future research.

2. Literature review

The drivers of demand for transport in cities in a wider perspective justify a few reflections to start with. As stated in Rodrigue (2020), cities are locations having a high level of accumulation and concentration of economic activities, which in turn demand transport across the infrastructures, including the transport systems. This is also why the business model of public transport and other transport services, such as free-floating transport services, are strongest in urban areas (Jochem et al., 2020; Hardt and Bogenberger, 2018; Shaheen and Cohen, 2013).

With an increasing amount of FFCS services offered to citizens in many cities (Sprei et al., 2019; Giordano et al., 4 2021.), there has been an increasing interest in studying the impact of such transport services have on the existing transport system, as well as factors that can affect the demand for such services in general.

2.1. Socio-demographic factors

Schmöller and Bogenberger (2014) and Schmöller et al. (2015) study how socio-demographic factors affect demand for car sharing services. They find that the car sharing is used primarily by young people living in small households. This is in line with Ceccato and Diana (2021), which identify car rental users as predominantly young men who live in small, high-income households. Recently, Muller et al. (2017) applied a negative binomial model to predict and explain the demand for FFCS services in Berlin, Germany. Their findings indicate that the average household income, accessibility and centrality of an area, as well as the lack of parking availability, are significant drivers of the use of FFCS. However, when applying their model to Munich and Cologne, it is shown how specific local conditions have great influence on the spatial demand for bookings.

2.2. Weather and spatio-temporal patterns

Schmöller and Bogenberger (2014) and Schmöller et al. (2015) studied how weather affect demand for car sharing services. They find that rainfall has a positive short-term impact on the use of car sharing. A similar conclusion was also found in Carrone et al. (2020) based on stated-preference data. Regarding day patterns, Giordano et al. (4 2021.) provided insights in a study of FFCS services in 23 cities in Europe and North America over a 14-month period. Thursday and Friday were revealed to be the days of the week with the highest demand in all cities. However, daily usage differed substantially between cities in North America and Europe. In Italian and Spanish cities, for example, utilisation increased during evening hours as opposed to several North American cities.

Regarding the spatial usage patterns, Giordano et al. (4 2021.) showed that usage was more homogeneously distributed in cities such as New York and Amsterdam, while it was concentrated in few zones in Milan and Vancouver. This suggests that the local geographical context is an important factor when analysing FFCS usage.

2.3. Mode competition

Only few studies analysed the competition between FFCS services and public transport. Some evidence is offered in Sprei et al. (2019) in an analysis of the usage of FFCS in 12 large European and US cities in the period 2014–17, with data from each city covering a period between three months and two years. While the analysis is mostly concerned with general usage patterns it also covers travel time savings by comparing the travel times of observed FFCS trips to similar travel times had those trips been carried out using other modes. In the study, FFCS have shorter travel times compared to public transport, with the smallest differences in European cities due to presumably better public transport systems. More specifically, the study found that as travel distance increases, public transport becomes more attractive. Similarly, Ceccato and Diana (2021) analyse interactions between FFCS and several competing modes using data from a travel survey distributed among 3,280 respondents in Turin, Italy. They find a positive correlation between being a user of FFCS and having a public transport pass, and the paper further suggests the existence of a positive correlation between choosing FFCS and the frequency of using public transport by bus, thus suggesting complementarity between FFCS and public transport. A similar conclusion is expressed by Guirao et al. (2021) in a study for the city of Madrid, Spain. In this study, they measure the demand for FFCS services near rail stations and find that demand remains high even in cases where there is limited parking space availability and alternative public transport options.

An opposite relationship has also been found in several studies. Becker et al. (2017) use a spatial regression model to study the effect of land use characteristics, as well as a mode choice model to analyse the influence of travel attributes on the choice of mode of travel. The demand for free-floating car sharing is found to be positively correlated with population density but negatively correlated with public transport accessibility, suggesting substitution effects between FFCS and public transport. Similar conclusions are presented in a study from Copenhagen, Denmark (Carrone et al., 2020). The study is based on a stated preference mode choice experiment aimed at analysing substitution patterns between free-floating car sharing, private cars, bikes, and public transport. The results, which are based on a mixed logit model, indicate that free-floating car sharing is a strong competitor to public transport and bike trips, but less of a competitor with respect to private car trips. However, it is concluded that while FFCS is primarily substituting public transport, the impact of the FFCS service on the total share of public transport trips is limited, as only 0.01 % of trips per year would change from public transport to car sharing for the respective case study.

Although the highlighted studies did analyse mode choice patterns and substitution effects, reaching quite different conclusions, no study did so using revealed preference data while controlling for public transport level of service over time. Hence, the present study will contribute to filling this specific gap in the literature.

3. Methodology

In this section, we describe the applied methodology for analysing the spatio-temporal usage pattern for the FFCS service before and after the opening of the circular Metro Cityring line. The analysis is based on FFCS log data over a three-year period from 2016–2019. The operational area of the FFCS is divided into 92 geographical zones, which is consistent with the zones of the Danish National Transport Model (Carrone et al., 2022; Rich and Hansen, 2016). The boundaries of the FFCS operating area are shown in Fig. 1. The operational area covers central Copenhagen as well as multiple satellite zones within the suburban area. The 17 new metro stations are located in 14 zones (dark grey) and are labelled with their respective names. Note that the stations *Gammel Strand* and *Kongens Nytorv*, *Trianglen* and *Vibenshus Runddel* as well as *Nørrebro Station* and *Nørrebros Runddel* are located within the same zone, respectively. The zones in which universities (DTU, CBS and KU), large parks, hospitals, or airports are located are highlighted using the different colours on the map. The specific landmarks and satellite areas typically attract a significant amount of FFCS trips although the direction of the trips (i.e., if these are going to or from the city centre) is very dependent on the day and time of day.

3.1. A model of direct demand

A direct demand model is developed with the aim of modelling the FFCS demand and to associate this with land-use variables and public transport accessibility variables at the level of zone pairs. The model allows accounting for changes in the public transport service level at the time of the opening of the metro and to verify statistically whether the usage pattern of FFCS changes due to the opening of the metro line.

The classic direct demand model is based on a multiplicative form (Talvitie, 1973; Yan et al., 2020). Using an appropriate logarithmic transformation, the model can be estimated using a standard ordinary least squares (OLS) model as described in Kepaptsoglou et al. (2017). As the dependent variable is essentially a trip count variable at the level of zone pairs, a Poisson model would apply as well. However, Choi et al. (2012) suggest that the multiplicative OLS model outperforms the Poisson regression model when explaining station-to-station ridesharing. Furthermore, it is noted in Yan et al. (2020) that the multiplicative model is simpler in terms of interpretation and inference compared to the Poisson model. The general model is presented in Eq. 1.

$$CS_{ijt} = \phi \prod_{p=1}^{P} X_{ipt}^{\alpha_{ipt}} \prod_{p=1}^{P} X_{jpt}^{\beta_{jpt}} \prod_{q=1}^{Q} Z_{ijqt}^{\gamma_q} \tag{1}$$

CS_{ijt} represent FFCS trips from zone i to zone j in time period t. In the study, we consider only two time periods, t, the before period and the after period. X_{ipt} represents the p^{th} independent variable for the origin zone i at time period t, while X_{jpt} represent the p^{th} independent variable for the destination zone j at time period t. Z_{ijqt} represent the q^{th} independent variable for zone pair i and j in time period t. In the model ϕ is the scale parameter, whereas $\alpha_{ipt}, \beta_{jpt}, \gamma_q$are the model parameters to be estimated. Variables included in the model include i) socioeconomic and demographic variables, ii) variables related to the built environment, iii) variables related to public transport supply, which may include zone-specific variables, e.g. accessibility variables, but also travel impedance variables (Yan et al., 2020; Zhao et al., 2014), and finally iv) temporal variables influencing the demand, e.g. day-of-week and year, hence explicitly considering that demand varies across days of the week and over time. With respect to the parameters for the temporal dimension, we only estimate main effects for the metro-zones in the two time periods after correcting for change in public transport supply. This is why γ_q is independent of the time dimension. Also note, that although α_{ipt} and β_{jpt} are formulated for all dimensions, for identification purposes, only a subset of dimensions are included in the estimated model.

Taking the natural logarithm, transforms Eq. 1 into a linear form as seen in Eq. 2.

$$ln(CS_{ijt}) = ln(\phi) + \sum_{p=1}^{P} \alpha_{ipy} ln(X_{ipt}) + \sum_{p=1}^{P} \beta_{jpt} ln(X_{jpt}) + \sum_{q=1}^{Q} \gamma_q ln(Z_{ijqt}) \tag{2}$$

It is here noted that explanatory variables will include a combination of continuous variables and categorical variables. For continuous variables, the estimated coefficients represent the constant elasticity of demand for FFCS with respect to changes in the corresponding variable. The exponential of the coefficients of dummy variables can be interpreted as the demand effect of the dummy variable compared to a reference level, all other things equal. As a consequence, the interpretability of the model is rather straightforward and thus the model serves the purpose of connecting the demand for zone-to-zone travel with various characteristics of the transport system (Talvitie, 1973).

The influence of the Metro Cityring is modelled by estimating the influence of station dummies in the before period (Jan 2017 to Sep 2019) and in the after period (Oct-Dec 2019). The opening of the Metro Cityring in October 2019 was indeed a "shock opening" where the entire new metro line was opened at once. Two weeks after the opening, there was an instant reorganisation of the remaining public transport system in that a number of competing bus lines were decommissioned. The two weeks between opening of the metro and the reorganisation of the bus network were excluded from the analysis. In the estimation we account for any change in the public transport travel time relative to changes in

Table 1
Variable descriptions.

Variable	Type	Description
Travel-impedance (Z)		
Av. trip duration	continuous	average trip duration in minutes
Av. trip distance	continuous	average trip distance in km
Av. $\frac{PT\_tt}{FFCS\_tt}$	continuous	ratio between public transport travel time and free-floating car sharing travel time for zone pair
Socioeconomic and demographic (X)		
Job density	continuous	jobs/sqkm at zone
Population density	continuous	population/sqkm at zone
Av. HH size	continuous	average number of residents per household
Av. HH income	continuous	average income per household
Av. HH car ownership	continuous	average number of cars owned per household
Shopping density	continuous	number of people employed in Shopping activity per sqkm
% HH with children	continuous	ratio of households with children
% Young adults	continuous	ratio of households with young adults
% Single HH	continuous	ratio of single households
% High education	continuous	ratio of households with at least one high educated member
Built-environment (X)		
Airport	dummy	dummy variable for the airport zone
Hospital	dummy	dummy variable that identifies zones with hospitals with more than 3000 employees
Park	dummy	dummy variable that identifies zones that correspond to Valbyparken and Amager Fælled
University Campus	categorical	Categorical variable with 3 levels: No University (reference), CBS & KU, DTU
Zone-location: main area	dummy	dummy variable that identifies the central zones of the area of operation, as defined by Carrone et al. (2022), as opposed to satellite zones
Temporal (X)		
Weekday category	categorical	Categorical variable with 3 levels: Working days (reference), Saturday, Sunday
Year	categorical	Categorical variable with 3 levels: 2017 (reference), 2018, 2019
Public tranport supply (X)		
Rail departure density	continuous	number of rail (train and metro) departures per sqkm in the zone
Bus departure density	continuous	number of bus departures per sqkm in the zone
Station_ID*	categorical	Categorical variable with 30 levels.

Station_IDs:

- Station_0 (reference) No M3 line station in the level 2 zone for 2017 and 2018 data
- Station_1 to Station_14: level 2 zones with M3 line metro station for 2017 and 2018 data
- Station_20: No M3 line station in the level 2 zone for 2019 data
- Station_21 to Station_34: level 2 zones with M3 line metro station for 2019 data

**Explanation of Station_ID*

1 & 21: København H; 2 & 22: Rådhuspladsen; 3 & 23: Gammel Strand & Kongens Nytorv; 4 & 24: Marmorkirken; 5 & 25: Østerport; 6 & 26: Trianglen St. & Vibenshus Runddel; 7 & 27: Poul Henningsens Plads; 8 & 28: Skjolds Plads; 9 & 29: Nørrebro St. & Nørrebros Runddel; 10 & 30: Nuuks Plads; 11 & 31: Aksel Møllers Have; 12 & 32: Frederiksberg St.; 13 & 33: Frederiksberg Allé; 14 & 34: Enghave Plads.

travel time by FFCS. This is necessary because several bus lines are being replaced by the new metro line after its opening. Further details on the different variables are offered in Section 4.

The dataset used for modeling is divided randomly in a training set (80 % of the data) and a test set (20 % of the data). Training data are used to estimate the model, while the test set is used to cross-validate the prediction performance of the estimated model (Bronshtein, 2017).

4. Data

4.1. FFCS data

The FFCS data in this article originates from the company Drive Now Copenhagen. The company was at the time of the data collection affiliated with BMW but was later merged with Mercedes in 2020, and is now part of the Share Now company. During the period of 2017–2020 the company operated around 300–400 vehicles. The fleet of vehicles did not suffer major changes during the studied period, but did have a daily variation in the number of operating vehicles due to maintenance and cleaning. Trips are generally rather short, with the majority of trips below 10 km. FFCS data constitute 2.5 million trips that have been registered during the period from January 2016 to December 2019 (refer to Fig. A.5 for a presentation of the geographical distribution of the actual number of trips). Hence, the data are unaffected by any impact that may result from the COVID-19 pandemic. Moreover, the area of operation has remained largely unchanged over the tracking period. The data consist of a large log-database containing timestamps (with a precision of seconds) and geographical coordinates for all trip origins and destinations. In addition, the data contains information about driven distance, prior reservation minutes of the vehicle, vehicle ID, customer ID and a trip purpose identifier, which specifies whether the trip has been a private or business trip or if the trip was carried out to relocate the vehicle or as part of maintenance. Furthermore, the data collected between January 2016 and December 2018 also include the age and gender of the users.

Before use, data underwent a major pre-processing and cleaning exercise. This included filtering trips with missing timestamps, unavailable trip purpose identifier, lack of origin and destination details, and invalid geographical coordinates. The filtering process also involved deletion of service and maintenance trips for, e.g. cleaning and relocation purposes. Trips with a recorded distance of zero kilometres were also removed as were trips starting or ending outside the operational area. For the remaining trips, travel time, trip length and average speed (km/h) was calculated based on the logged origins and destinations. These derived variables were then used to filter invalid or unreasonable trips (Antoniou et al., 2019). This included deletion of trips shorter than 1 min and longer than 120 min as well as trips with unrealistic speed profiles. In a final stage, only data for October, November, and December in the years 2016 to 2019 were selected for further processing to explicitly leave out possible seasonality effects. Hence, October to December in the years 2016 to 2018 represent the before period while October to December for 2019 represent the after period. After the processing of data, the three-month sample over the three years constitutes a total of 614,986 trips.

4.2. Geographical zone system

The coordinates of origins and destinations are geo-coded and matched with traffic zones defined in the Danish National Transport Model (Rich and Hansen, 2016). As a consequence, the area of operation area is divided into 92 urban zones (Carrone et al., 2022).

The zone system is also linked to the location of the 17 new Metro Cityring stations. As described briefly in Section 3, the 17 metro stations have been allocated to 14 zones.

4.3. Socio-economic and demographic data

As evidenced in the literature review in Section 2.1, socio-economic factors and specific geographical conditions play an important role for the demand of FFCS. As a result, we include several of such variables in the study. At the zonal level, we include average number of cars per household, share of single households, share of households with children, share of young adults (18 to 37 years), share of inhabitants with higher education and the number of people that are employed in

Fig. 2. The relative difference in FFCS demand between successive years (October-December). The vertical axis represents the absolute change in the number of trips.

Table 2
Implied change in demand due to change in dummy parameter estimates.

		Ratio of trip origins (%)			Ratio of trip destinations (%)		
ID	Station	Before	After	Change	Before	After	Change
0	No metro station		2.52	2.52		−0.88	−0.88
1	København H	−6.95	−16.32	−9.38	−7.75	−13.57	−5.81
2	Rådhuspladsen	50.95	27.77	−23.18	50.82	32.30	−18.52
3	Gammel Strand, Kongens Nytorv	−32.89	−34.41	−1.51	−36.93	−33.08	3.85
4	Marmorkirken	51.69	41.96	−9.73	52.73	36.92	−15.81
5	Østerport	14.96	13.70	−1.26	12.93	19.57	6.64
6	Trianglen St., Vibenshus Runddel	45.28	31.77	−13.51	38.85	34.08	−4.76
7	Poul Henningsens Plads	20.44	10.11	−10.33	20.60	13.62	−6.98
8	Skjolds Plads	23.99	8.37	−15.61	25.60	5.28	−20.31
9	Nørrebro St., Nørrebros Runddel	15.85	15.26	−0.59	24.30	12.54	−11.76
10	Nuuks Plads	48.65	45.79	−2.86	49.86	45.54	−4.31
11	Aksel Møllers Have	−7.78	−13.82	−6.04	−8.04	−13.15	−5.11
12	Frederiksberg St.	−38.03	−44.70	−6.67	−37.17	−45.18	−8.01
13	Frederiksberg Allé	25.51	21.11	−4.40	22.91	15.73	−7.18
14	Enghave Plads	16.14	−9.43	−25.57	12.84	−10.85	−23.69

% before/after calculation: $(e^{coef} - 1) \times 100$ *with respective coefs from Table C.4.*

different sectors. These data are based on data from the Danish National Transport Model (Rich and Hansen, 2016) and data from the Danish National Travel Survey (TU, Transportvaneundersgelsen) (Christiansen, 2018). In addition, we include the average household size and the average household income adopted from the COMPASS data set (MOE A/S, 2022).

4.4. Land-use variables and public transport supply data

As considered in Section 2.3, FFCS and public transport are competing transport services in urban areas. As a consequence, it is important to include the supply of public transport in the model.

Public transport supply variables represent the number of stops and service frequencies of bus and rail services operating within the FFCS area. Furthermore, information concerning zone-to-zone travel time using public transport has been used as well. The travel time is the accumulated travel time between the origin and destination. It consists of waiting time at the first vehicle, in-vehicle-time, and potential transfer times and waiting times at transfer locations (refer to Carrone et al. (2022) for more details).

Land use variables have been implemented to explicitly consider important points of interest. This includes the Copenhagen Airport zones, two large parks ("Valbyparken" and "Amager Fælled"), the Technical University of Denmark campus, and hospitals with more than

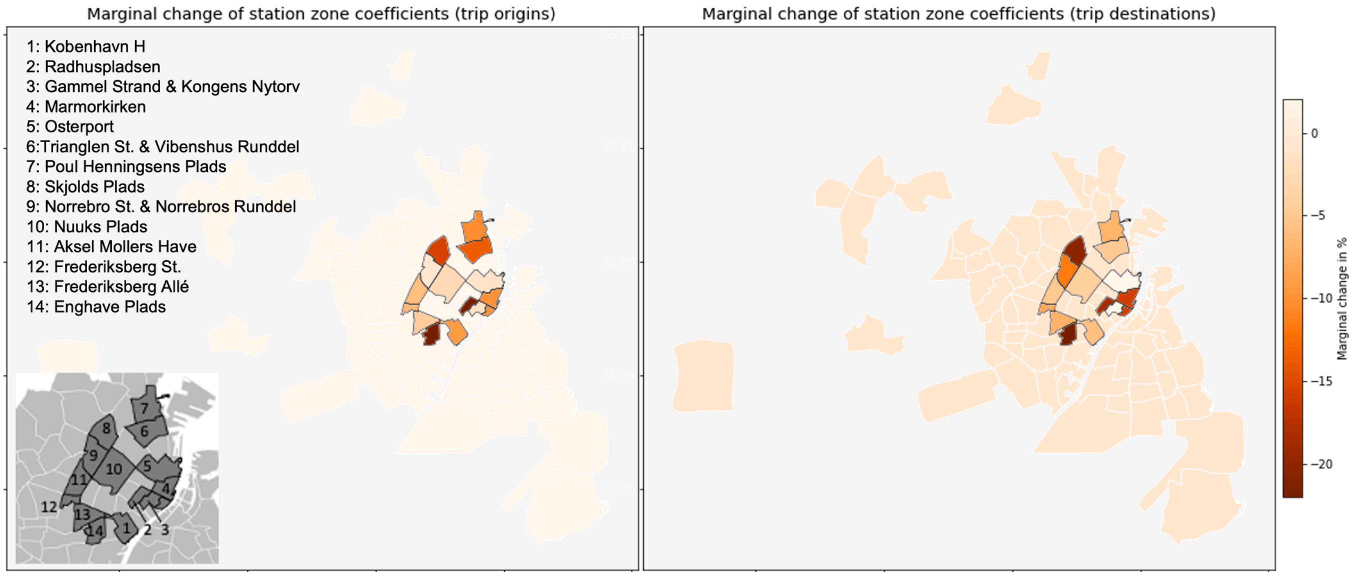

Fig. 3. Map of the marginal change of estimated metro zone coefficients from the before to the after period.

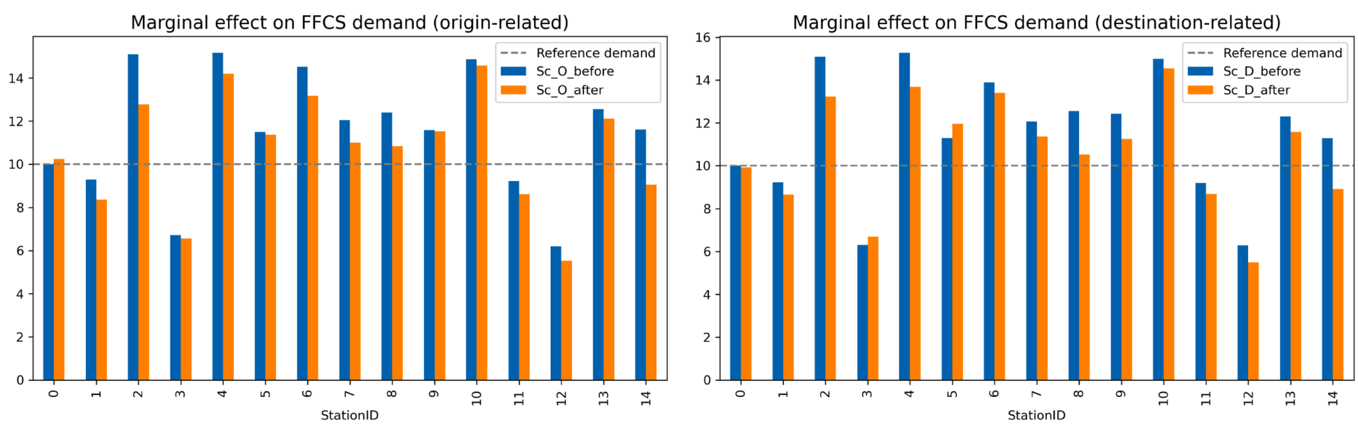

Fig. 4. Estimated effect of metro stations on FFCS demand.

3000 employees. Furthermore, a variable is introduced to determine whether a zone belongs to the main operational area (city centre and areas close to the city centre) compared to satellite areas or zones at the border of the operational area (Carrone et al., 2022), cf. Fig. 1.

A categorical variable (*Station_ID*) was created to analyse the influence of the new Metro Cityring stations on FFCS usage. As mentioned in Section 3, 14 zones have at least one Metro Cityring station within their zone boundary (three zones have two stations). Hence, the *Station_ID* variable has levels for each of the 14 Metro Cityring zones as well as one level if the zone does not have a Metro Cityring station. In addition, we differentiate between the before and after period, thus totalling 30 levels. In Table 1 the link between *Station_IDs* and Metro Cityring station names are stated, including the three zones, in which two stations are located. For ease of interpretation *Station_ID* has levels 0–14 and 20–34 representing the before and after period, respectively.

5. Results

This section presents the results of the direct demand model. The model is estimated using the Python libraries *scikitlearn* (Scikit-learn webpage, 2022) and *statsmodels* (Statsmodel webpage, 2022). Since the model includes a large number of characteristics, as mentioned in Section 4, only the main results are presented here. However, the complete list of estimated parameters can be found in C. As mentioned, the model is estimated on a training set consisting of 80% of the dataset and validated using the remaining 20%. The model performed well, showing an error of approximately 40% and an R^2 just below 0.50, suggesting that the model captures around 50% of the variation in the data. In the following, the before period denotes the years 2016–18 and the after period is 2019. However, before studying the model results, Fig. 2 illustrates the absolute changes in FFCS demand over the period. It is clear that while the demand for FFCS increased up to the fall 2019, we see a significant change in the after-period.

5.1. Model estimates

The main results in terms of the effects of the implementation of the Metro Cityring on the usage of FFCS are shown in Table 2. To compare the effect of metro zone dummies, the effect of the respective dummy coefficients has been translated into demand effect. The transformed coefficient of each dummy variable corresponds to the expected percent increase in FFCS demand compared to the reference level, which measures the level of zones without a Metro Cityring station in the previous period. The marginal change in the usage of FFCS is then calculated directly from the model as presented in Table 2.

The results clearly show a decreasing demand for FFCS for all trips originating in metro zones, and for most trips ending in metro zones in the after period. It is also shown that car sharing usage on average is 2.5% more likely to begin in a zone without a Metro Cityring station in the after period, and on average 0.88% less likely to end in a zone without a Metro Cityring station. As seen, the reference level of FFCS demand for zones without metro zones is significantly lower compared to most of the metro zones, hence suggesting that the metro zones are indeed important FFCS areas, probably due to being located in central areas with high travel demand.

A geographical visualisation of changes in FFCS demand is presented in Fig. 3 with darker colours representing decreasing demand. The greatest decrease is seen in the zones where the station *Enghave Plads* and *Radhuspladsen* are located, which before the Metro Cityring had relatively poor public transport services. The smallest decrease is in the zones in which *Norrebro St. and Norrebros Runddel*, *Osterport* stations and *Gammel Strand and Kongens Nytorv* are located. These zones have, prior to the Metro Cityring, been well connected by public transport.

To further examine the changes in demand with respect to metro zones, a small scenario is presented in Fig. 4. A reference demand is set to 10 FFCS trips for zones without a Metro Cityring station without accounting for unobserved fixed effects of the 14 metro stations (StationID = 0). The demand of the preceding period then represents the fixed effects of these 14 zones compared to the reference level. As can be seen, some zones have less than average demand in the before situation whereas others have more than average, as the demand level simply fluctuates across zones. The after-situation represents the situation where the fixed effect parameters are introduced. As can be seen, FFCS demand decreases across all zones in the after period for both the origin and destination zones except for trips with destination in the zone of Gl. Strand/Kgs. Nytorv (ID = 3) and Østerbro (ID = 5), thus highlighting the effect of vicinity to Metro Cityring stations on FFCS demand.

Finally, the estimated coefficients for the public transport-related variables further reveal that departure density for bus and rail services at origin and destination zones are negatively related to FFCS demand. More specifically, in the before period, FFCS demand decreases by 0.87%, or 0.052% when the bus, or rail departure density of the origin zone of a car sharing trip is increased by 10%. The effect is roughly the same when considering an increase in the density of bus or train departures from the destination zone, thus suggesting competition and substitution effects between FFCS and public transport.

5.1.1. *Travel-impedance variables*

As expected, the average travel distance of FFCS trips is negatively related to FFCS demand with a 10% increase in the average driving distance yielding a 4.4% decrease in car sharing demand. The average ratio between travel times using FFCS and public transport is also significant, i.e. an increase in FFCS demand can be expected if public transport travel time increases or if FFCS travel time decreases.

5.1.2. *Socio-economic and demographic variables*

First, FFCS usage is not surprisingly positively correlated with population density and the number of employed people in the shopping sector at both the origin and destination zone as commented in Section 2 and mentioned in Becker et al. (2017) specifically. Furthermore, an increase in FFCS demand is expected in zones with a higher proportion of households with young adults and children, and negatively correlated with the ownership of household vehicles, both in the origin and destination zone. This is in line with recent research findings as highlighted in Section 2. The average household size was only significant in reducing the use of FFCS in the destination zone. Similarly, FFCS usage was positively correlated with the percentage of highly educated people at the destination zone only.

5.1.3. *Built-environment variables*

The results showed that FFCS demand is much higher in the airport zone than in other zones. For the origin and destination zones containing hospitals and parks, demand is expected to be 9–10% (9–20%) higher than in the zones without hospitals or parks, respectively. For universities the effects are mixed. FFCS trips are expected to be higher (109,% for origins, 128,% for destinations) in DTU zones, compared to zones without a university campus. In contrast, the demand for car rentals is estimated to be 22–27,% lower for the origin and destination zones in which the CBS and KU universities are located. Despite controlling for a number of other characteristics, these findings might be influenced by the very different location of these campuses, as CBS and KU are located in the city centre of Copenhagen with very good public transport and bicycle access, whereas DTU is located more than 10 km north of Copenhagen, making it less accessible using public transport or bicycle.

5.1.4. *Temporal variables*

Finally, the temporal parameters indicate an increased FFCS demand over time, i.e. smallest demand in 2017 and largest in 2019. Not surprisingly, the demand for FFCS is higher during weekdays and lowest on Sundays.

6. Discussion

This paper analyses how usage of FFCS services are affected by large changes in the public transport system. Specifically, we look at how the implementation of a new high-class metro line in Copenhagen affects the geographical use pattern of FFCS services. Previous research has shown that FFCS and public transport can be both substitutes (Becker et al., 2017) and complementary goods (Shaheen and Chan, 2016). This study, however, clearly demonstrates that the two modes are by and large substitutes and compete for the same customer base. Similar findings were observed in Carrone et al. (2020) in a different study for Copenhagen based on Stated Preference data.

Although the results are clear and unambiguous, as demonstrated in the results section, it is relevant to discuss limitations, interpretability and research gaps further.

First, it is important to note that the supply of FFCS is limited. This is particularly true in a spatio-temporal context. Therefore, the observed demand depends on whether a user can find a vehicle close to the preferred origin at the preferred time. The current analysis of the transaction data does not account for the latent demand that would otherwise have resulted in trips had a vehicle been available (Gammelli et al., 2020). As a consequence, a decrease in FFCS demand in metro zones could be caused by other areas being more popular for FFCS trips, thereby reducing vehicle supply around metro stations. However, since the supply of vehicles has been increasing over the study period, this is not likely to influence the results.

A second interesting and slightly related observation is that although FFCS and public transport are mainly substitutes, we also find evidence of complementarity. For example, considering the stations in Østerbro, it appears that the demand for FFCS increases in the after-period when measured according to destination. It suggests that trips between central Copenhagen and the northern part of the city are using FFCS at an increasing rate. This is likely a rare example of complementarity in this transport system. Users will then travel to Østerbro and continue by the new Metro Cityring line rather than using FFCS. This makes sense because the congestion and parking options in the central parts of Copenhagen along the metro line are challenging.

A third observation point is that the direct demand model is indeed partly limited by data availability. Some data are extracted from external data sources and remain constant throughout the studied period. For example, socio-economic and demographic zone variables have been extracted from the Danish National Transport Model and based on the year 2016. These data are not updated from year to year, and the model thereby does not account for changes in these variables. However, considering that the study period only spans a few years, this assumption is expected to have a limited effect. Generally speaking, demographic changes and changes in the built environment occur at a slower pace. This is especially true in the central parts of the city, which have limited space for new buildings. Therefore, most of the urban development takes place outside the city and will thus have a more indirect effect on the results.

The data also do not allow a thorough analysis of why people choose metro over FFCS and how the substitution patterns play out at a very detailed level. However, one reason for the large degree of substitution could be that both services are mainly attracting high-income groups (refer to Section 2.1) in the city center. Note here that the metro appeals mainly to people that reside in the city, for which the household income is higher compared to the average. As a consequence, we should expect a slightly lower substitution towards other public transport services such as bus lines. Not least, because both bus and FFCS are affected by road congestion as opposed to the metro.

It is possible to analyse the change in ridership for different periods of the day before and after the demand for the metro service, including peak hours. This could shed light on the potential for a greater substitution towards the metro in these hours due to congestion effects. This, however, would add even more variables to the model and potentially mask the effect of other variables.

A final point worth mentioning is that the urban landscape and the transport flow in general, have been affected by the construction of the new metro line. Several roads have been closed during the construction period, resulting in reduced car accessibility until the opening of the metro. It is impossible to assess the precise impact, but the true demand for FFCS (without these limitations) would likely have been even higher in the before period. As a consequence, it may somewhat underestimate the effect of the metro line.

Regarding the political impact of the presented study, it is notable that FFCS services in many cities often are offered quite favorable conditions for operating their cars. One example is that they are offered discounts with respect to parking and this was also the case in Copenhagen at the time of the study. The argument from the municipality at the time was that FFCS services did complement the public transport system. However, based on the results in this paper, it is now evident that this is mostly not correct. While there can be local examples where FFCS complement specific stations, the two modes are mostly competing for the same costumer base. It suggests that planners and politicians should think carefully before favouring FFCS services, as it may end up increasing congestion and cannibalising public transport and bicycling. In this context, it is relevant to consider how other free-floating services, such as e-scooters or bicycles, interact with changes in public transport. It is expected that such services will substitute shorter public transport trips but also compete with free-floating car services.

7. Conclusion

This study analyses the usage of free-floating car sharing services in Copenhagen and studies how it is influenced by the development of a new metro line in the central part of the city. Three main conclusions stands out.

Firstly, by using large-scale FFCS transaction data before and after the opening of the metro line, we demonstrate that FFCS services are mostly a substitute for public transport. When public transport is notably improved, the demand for FFCS services is reduced. This suggests that these services compete for the same customers and that for the center of Copenhagen, FFCS is not a complementary good with respect to public transport.

Second, while the evidence of the products being complementary is weak when considering the overall pattern, it can emerge locally as a result of spatial substitution. An example of this is seen when studying the area of Østerbro, which in the after period experiences an increase in FFCS demand. In general, the change in FFCS demand varies substantially between zones, thus suggesting that the effect of metro accessibility varies with local accessibility and other urban conditions.

Third, by formulating and estimating a direct demand model, we are able to confirm many relationships between explanatory variables and FFCS demand that has been studied previously on the basis of smaller studies and often hypothetical data. Hence, a final conclusion is the affirmation of positive correlation between FFCS demand and population density, shopping opportunities, proportion of young adults, high education as well as special points of interests such as hospitals, parks and airports. Similarly, the confirmation that FFCS demand is negatively associated with travel distance, public transport opportunities as well as car ownership propensity.

CRediT authorship contribution statement

Jesper Bláfoss Ingvardson: Conceptualization, Methodology, Writing – original draft, Writing – review & editing. **Maresa Weisshaar:** Conceptualization, Methodology, Data curation, Software, Formal analysis, Investigation, Visualization, Writing – original draft. **Jeppe Rich:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Distribution of absolute number of trips over the years

See Fig. A.5.

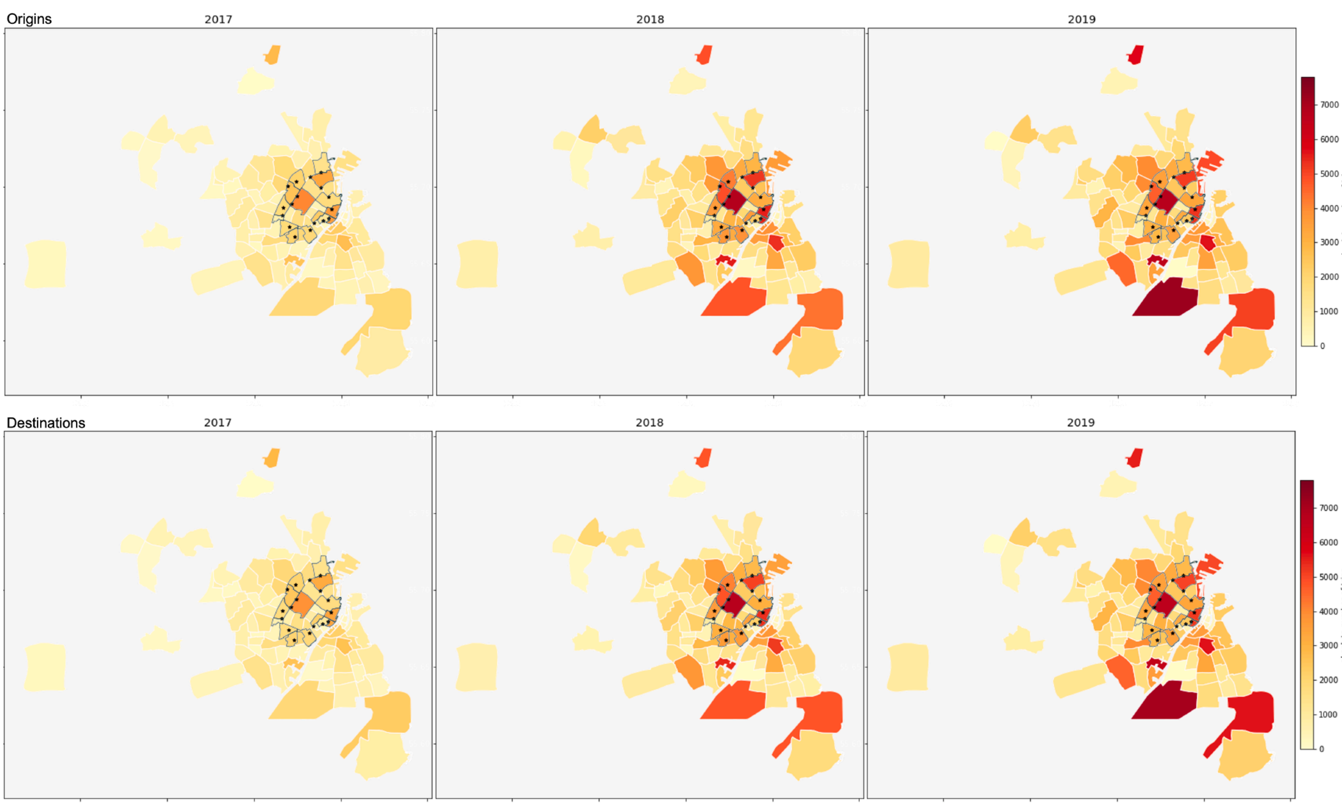

Fig. A.5. Geographical distribution of the absolute number of FFCS trips over the years. Black spots indicate the location of the metro stations.

Appendix B. Summary of aggregated variables

See Table B.3.

Table B.3
Summary of aggregated variables.

	Not transformed				Log-transformed			
	Mean	**Std**	**Min**	**Max**	**Mean**	**Std**	**Min**	**Max**
Dependent variable								
FFCS Tripcount	8,58	16,36	1,00	731,00	1,76	1,14	0,69	6,59
Independent variables								
Av. Trip duration *	29,27	11,18	2,00	120,00	3,31	0,37	0,69	4,79
Av. Trip distance	9,3	6,35	1,00	110,00	2,03	0,60	0,00	4,70
Av. PT_tt/FFCS_tt	0.59	0.25	0.01	4.71	−0.61	0.45	−3.98	1.55
O_PopDens	7858,99	6649,65	0,02	28292,45	8,33	1,91	−4,04	10,25
D_PopDens	7841,74	6654,03	0,02	28292,45	8,32	1,92	−4,04	10,25
O_AvHHsize *	1,80	0,22	1,00	2,37	0,59	0,12	0,10	1,00
D_AvHHsize	1,79	0,22	1,00	2,37	0,59	0,13	0,10	1,00
O_AvHHCarOwn	0,59	0,21	0,00	1,18	0,45	0,14	0,00	0,78
D_AvHHCarOwn	0,59	0,21	0,00	1,18	0,45	0,14	0,00	0,78
O_ShoppingDens	475,62	785,15	7,99	5691,83	5,29	1,36	2,08	8,65
D_ShoppingDens	475,62	783,41	7,99	5691,83	5,28	1,35	2,08	8,65
O_Perc_Child	0,31	0,11	0,00	0,56	0,27	0,09	0,00	0,44
D_Perc_Child	0,31	0,11	0,00	0,56	0,27	0,09	0,00	0,44
O_Perc_YoungAdults	0,43	0,16	0,00	1,00	0,43	0,16	0,00	1,00
D_Perc_YoungAdults	0,43	0,16	0,00	1,00	0,43	0,16	0,00	1,00
O_Perc_HighEd *	0,22	0,10	0,00	0,65	0,18	0,07	0,00	0,41
D_Perc_HighEd	0,22	0,10	0,00	0,65	0,18	0,07	0,00	0,41
O_Zoneloc:main_area *	0,78	0,42	0	1				
D_Zoneloc:main_area	0,77	0,42	0	1				
O_University	1,09	0,35	1	3				
D_University	1,09	0,35	1	3				
O_Hospital	0,06	0,23	0	1				
D_Hospital	0,06	0,24	0	1				
O_Park	0,06	0,24	0	1				
D_Park	0,06	0,24	0	1				
O_Airport	0,01	0,12	0	1				
D_Airport	0,01	0,12	0	1				
Weekday category			1	3				
Year			2017	2019				
O_BusDepDens	2646,92	2862,35	80,08	17371,09	7,35	1,13	4,38	9,76
D_BusDepDens	2618,75	2823,22	80,08	17371,09	7,34	1,13	4,38	9,76
O_RailDepDens	327,96	618,30	0,00	3645,06	2,93	3,09	0,00	8,20
D_RailDepDens	323,42	612,33	0,00	3645,06	2,92	3,09	0,00	8,20
O_Station_ID			0	34				
D_Station_ID			0	34				

* *Variable not included in the final model* O = Origin zone, D = Destination zone.

Appendix C. Parameter estimates of Direct Demand Model

See Table C.4.

Table C.4
Parameter Estimates of direct demand model.

	Training set			Test set		
Parameter	coef	std err	t-stats	coef	std err	t-stats
Const	1.5486	0.077	20.142	1.7416	0.156	11.158
Av_trip distance	−0.4368	0.007	−67.020	−0.4386	0.013	−33.086
Av_PT_tt/FFCS_tt	0.0249	0.008	3.130	0.0513	0.016	3.167
O_PopDens	0.0936	0.005	19.379	0.0786	0.009	8.287
D_PopDens	0.0878	0.005	17.994	0.0943	0.010	9.535
D AvHHsize	−0.1030	0.051	−2.018	−0.1531	0.103	−1.487
O_AvHHCarOwn	−0.2546	0.009	−27.128	−0.2444	0.019	−13.063
D_AvHHCarOwn	−0.2448	0.010	−24.550	−0.2797	0.020	−13.902
O_Shopping	0.1471	0.003	47.153	0.1388	0.006	22.339
D_Shopping	0.1385	0.003	44.086	0.1456	0.006	22.792
O_Perc_YoungAdults	0.2286	0.008	29.515	0.2344	0.015	15.235
D_Perc_YoungAdults	0.2152	0.010	22.011	0.2124	0.020	10.830
O_Perc_Child	0.0756	0.006	13.369	0.0757	0.011	6.611
D_Perc_Child	0.0718	0.006	12.338	0.0795	0.012	6.722
D_Perc_HighEd	0.0303	0.008	4.007	0.0413	0.015	2.719
O_RailDepDens	−0.0052	0.001	−8.595	−0.0060	0.001	−4.897
D_RailDepDens	−0.0050	0.001	−8.140	−0.0062	0.001	−4.916
O_BusDepDens	−0.0874	0.006	−15.605	−0.0802	0.011	−7.192
D_BusDepDens	−0.0925	0.006	−15.819	−0.1014	0.012	−8.479
O_Airport	1.6506	0.058	28.679	1.5939	0.112	14.202
D_Airport	1.8285	0.065	28.237	1.6383	0.123	13.269
O_Hospital	0.0978	0.015	6.697	0.1041	0.029	3.607
D_Hospital	0.1000	0.015	6.702	0.1208	0.030	4.041
O_Park	0.1962	0.016	12.437	0.1637	0.032	5.134
D_Park	0.1917	0.016	11.955	0.1415	0.033	4.355
D_zone_mainarea	−0.0163	0.010	−1.696	−0.0489	0.019	−2.522
O_University_CBS/KU	−0.2871	0.020	−14.597	−0.2929	0.038	−7.665
O_University_DTU	0.7490	0.037	20.066	0.7158	0.076	9.391
D_University_CBS/KU	−0.3305	0.020	−16.374	−0.3425	0.041	−8.323
D_University_DTU	0.7965	0.045	17.709	0.8222	0.089	9.250
Weekday_Saturday	−0.8978	0.008	−116.467	−0.9111	0.016	−58.408
Weekday_Sunday	−0.9867	0.008	−125.533	−10.130	0.016	−64.637
Year_2018	0.3957	0.008	49.065	0.4066	0.016	25.037
Year_2019	0.4717	0.017	27.387	0.5048	0.035	14.597
O_Station_1	−0.0742	0.037	−2.029	−0.0813	0.076	−1.073
O_Station_2	0.4118	0.042	9.901	0.4263	0.084	5.095
O_Station_3	−0.3989	0.038	−10.601	−0.3802	0.074	−5.133
O_Station_4	0.4167	0.036	11.675	0.4475	0.071	6.327
O_Station_5	0.1394	0.035	3.982	0.2268	0.079	2.862
O_Station_6	0.3735	0.036	10.420	0.3463	0.065	5.313
O_Station_7	0.1860	0.037	5.024	0.1720	0.069	2.491
O_Station_8	0.2150	0.035	6.120	0.2812	0.074	3.787
O_Station_9	0.1471	0.034	4.265	0.1911	0.079	2.431
O_Station_10	0.3964	0.035	11.202	0.3060	0.071	4.325
O_Station_11	−0.0810	0.036	−2.231	0.0672	0.068	0.982
O_Station_12	−0.4785	0.039	−12.172	−0.4851	0.082	−5.903
O_Station_13	0.2272	0.035	6.408	0.1919	0.076	2.530
O_Station_14	0.1496	0.034	4.342	0.1662	0.079	2.107
O_Station_20	0.0249	0.014	1.795	−0.0607	0.028	−2.155
O_Station_21	−0.1782	0.046	−3.841	−0.0371	0.096	−0.387
O_Station_22	0.2451	0.051	4.824	0.3371	0.096	3.504
O_Station_23	−0.4217	0.046	−9.096	−0.2500	0.098	−2.546
O_Station_24	0.3504	0.046	7.675	0.3198	0.095	3.371
O_Station_25	0.1284	0.049	2.643	0.2044	0.086	2.368
O_Station_26	0.2759	0.045	6.089	0.1854	0.097	1.920
O_Station_27	0.0963	0.047	2.067	0.1335	0.099	1.342
O_Station_28	0.0804	0.047	1.696	0.0407	0.091	0.446
O_Station_29	0.1420	0.047	3.024	0.0668	0.089	0.752
O_Station_30	0.3770	0.046	8.169	0.3261	0.088	3.717
O_Station_31	−0.1487	0.047	−3.194	−0.1571	0.090	−1.747
O_Station_32	−0.5924	0.051	−11.713	−0.5792	0.114	−5.083
O_Station_33	0.1915	0.046	4.149	0.1471	0.106	1.392
O_Station_34	−0.0991	0.046	−2.173	−0.1721	0.101	−1.712
D_Station_1	−0.0807	0.039	−2.075	−0.0801	0.074	−1.082
D_Station_2	0.4109	0.042	9.785	0.4260	0.084	5.101
D_Station_3	−0.4609	0.038	−12.079	−0.4616	0.076	−6.080
D_Station_4	0.4235	0.036	11.741	0.3750	0.072	5.218

(continued on next page)

Table C.4 (*continued*)

Parameter	Training set coef	Training set std err	Training set t-stats	Test set coef	Test set std err	Test set t-stats
D_Station_5	0.1216	0.036	3.372	0.1131	0.080	1.407
D_Station_6	0.3282	0.036	9.242	0.3562	0.064	5.531
D_Station_7	0.1873	0.036	5.151	0.1931	0.075	2.583
D_Station_8	0.2279	0.036	6.323	0.2081	0.072	2.910
D_Station_9	0.2175	0.035	6.132	0.0389	0.071	0.546
D_Station_10	0.4045	0.036	11.357	0.3846	0.070	5.497
D_Station_11	−0.0838	0.036	−2.353	−0.0808	0.075	−1.072
D_Station_12	−0.4648	0.040	−11.742	−0.4595	0.081	−5.653
D_Station_13	0.2063	0.036	5.712	0.2944	0.069	4.238
D_Station_14	0.1208	0.035	3.431	0.1866	0.072	2.575
D_Station_20	−0.0088	0.014	−0.633	0.0380	0.028	1.355
D_Station_21	−0.1458	0.048	−3.059	−0.1707	0.095	−1.792
D_Station_22	0.2799	0.052	5.392	0.2771	0.096	2.886
D_Station_23	−0.4016	0.047	−8.546	−0.4182	0.100	−4.192
D_Station_24	0.3142	0.048	6.598	0.2926	0.088	3.307
D_Station_25	0.1787	0.049	3.644	−0.0057	0.088	−0.064
D_Station_26	0.2933	0.046	6.399	0.2800	0.095	2.960
D_Station_27	0.1277	0.046	2.749	0.0771	0.099	0.776
D_Station_28	0.0515	0.047	1.084	−0.0066	0.092	−0.072
D_Station_29	0.1181	0.046	2.565	0.2685	0.094	2.851
D_Station_30	0.3753	0.045	8.392	0.3717	0.102	3.653
D_Station_31	−0.1410	0.046	−3.046	−0.1508	0.093	−1.618
D_Station_32	−0.6012	0.052	−11.568	−0.4213	0.104	−4.047
D_Station_33	0.1461	0.048	3.071	0.1496	0.097	1.539
D_Station_34	−0.1149	0.047	−2.451	−0.0766	0.088	−0.869

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