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Observed patterns of free-floating car-sharing use

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Abstract
Free-floating car-sharing (FFCS) services allow users to rent electric vehicles by the minute without restrictions on pick-up or drop-off locations within the service area of the rental company. Beyond enlarging the choice set of mobility options, FFCS may reduce congestion and emissions in cities, depending on the service's usage and substitution patterns. In this paper, we shed light on this by analyzing the universe of FFCS trips conducted through a leading company in Madrid during 2019. We correlate FFCS usage patterns with data on traffic conditions, demographics, and public transit availability across the city. We find complementarities between FFCS and public transport in middle-income areas with scarce public transport options. Moreover, we find that the use of FFCS peaks earlier than overall traffic and is broadly used during the summer months. This suggests that FFCS may have smoothed road traffic in Madrid, contributing to a reduction in overall congestion.

1 Introduction

Road transport is associated with several types of negative externalities, including traffic accidents (Edlin and Karaca-Mandic 2006), congestion (ECA 2019), and pollution, such as fine particulate matter ($PM_{2.5}$) (ECA 2019; Böhm et al. 2022; Li and Managi 2021). These pollutants, in turn, have been linked to increased mortality among adults

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and infants (Currie and Neidell 2005; Deryugina et al. 2019; Gehrsitz 2017; Lelieveld et al. 2015) through a variety of mechanisms, ranging from respiratory (Wu et al. 2018; Wei and Tang 2018) to cardiovascular diseases (Al-Kindi et al. 2020; Sanidas et al. 2017). The transport sector also accounts for approximately 23% of energy-related CO_2 emissions globally (IEA 2022). Additionally, car ownership in cities may lead to inefficient land use. On average, private cars are parked 96% of the time, or 23 h per day, thus having relatively low usage rates (Nagler 2021). This inefficiency is exacerbated by the increasing single-occupancy vehicle commuting rates (Machado et al. 2018).

Worldwide, a breadth of policies are being implemented to mitigate these externalities, including congestion pricing (Anas and Lindsey 2011; Börjesson et al. 2012), subsidies for electric vehicle purchases (Rapson and Muehlegger 2023), or low-emission zones in cities (Galdon-Sanchez et al. 2022; Börjesson et al. 2021), among others. Reliance on these policies is expected to grow as countries seek to comply with their commitments to achieve net-zero emissions by 2050 (European Commission 2020; U.S. DoS and EOP 2021). To improve their effectiveness, we still need a deeper understanding of the benefits and costs of the various policy options. For equity purposes, we must also understand who benefits and who is harmed by those policies. Significant headway has been made in some fronts (Parry 2002), yet little is known about the potential impacts of some rapidly proliferating technologies. This study contributes in this direction by analyzing the characteristics of users and usage patterns of one such technology, free-floating car-sharing (FFCS).

In part thanks to advances in communications and tracking technologies, as well as the widespread adoption of smartphones, companies are now able to rent cars by the minute, at rates ranging from approximately 0.19 €/min to 0.31 €/min.[1] In earlier stages of the deployment of these services, users were required to drop off the vehicles at specific locations or at charging stations. However, in recent years, there has been a rapid growth of demand for FFCS services allowing users to pick up the vehicle and drop it off at any place within the service area of the rental company (Ampudia-Renuncio et al. 2020a). Importantly, the companies providing these services often do so with electric vehicles.

Therefore, FFCS can potentially affect congestion and environmental externalities in opposing directions, depending on which mode of transport it is substituting. On the one hand, FFCS may alleviate urban congestion and pollution through the extensive and intensive margins, i.e., if they reduce car ownership (car shedding) or the number of trips with private polluting cars (Bucsky and Juhász 2022). This possibility is supported by the fact that shared vehicles are mostly electric and have much higher utilization rates than private vehicles (Habibi et al. 2017). On the other hand, car-sharing may increase congestion if used as a substitute for public transport, walking, or cycling (Machado et al. 2018). Whether one effect or the other dominates is an empirical question related to the usage patterns of FFCS.

As a starting point for shedding light on the welfare effects of FFCS, this study provides a comprehensive description of car-sharing usage patterns, seasonality of

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[1] Rates published on the websites of the main FFCS companies operating in Madrid (Emov, ShareNow, WiBLE, Zity), as of December 2023.

use, users' incomes, and primary usage purposes. In particular, we investigate the correlations between the variables of interest without claiming causation. While most of the early literature on car-sharing has focused on German cities,[2] or relied mostly on survey data (Amirnazmiafshar and Diana 2022; Müller et al. 2017; Schmöller et al. 2015; Kopp et al. 2015), in this paper, we provide new evidence based on thousands of observed trips in the city of Madrid. According to surveys across several European and North-American cities (Sprei et al. 2019; Habibi et al. 2017), Madrid had the highest FFCS utilization rate (between 17 and 21.6% of the time when cars can be potentially driven per day). Additionally, together with Amsterdam, Madrid is one of the only cities in Europe where the FFCS fleet is fully electric (Ampudia-Renuncio et al. 2020a).

One of the strengths of this study is that it combines a rich set of data sources. Importantly, we have access to a unique proprietary database of the universe of car-sharing trips (more than 1,500,000) carried out in 2019 by one of the leading FFCS companies operating in Madrid.[3] To correlate car-sharing usage patterns with socio-demographic characteristics, we use neighborhood-level data on population, income, car ownership, public transport network, and parking availability data. We also analyze daily road traffic data, comparing it against the seasonality of car-sharing trips.

Our main dataset contains precise geo-referenced data on the car-sharing trip timing, origin, and destination but lacks information on the customers' demographics. In particular, while we can track users through unique identifiers, we do not observe where they live. Hence, we developed a strategy to impute users' neighborhood of residence based on repeated trips from and to the same destination during commuting times. Our approach constitutes an improvement relative to the previous literature, which was restricted to analyzing the characteristics of the place of origin/destination of trips (Schmöller et al. 2015; Ampudia-Renuncio et al. 2020a) and therefore abstracted away from users' place of residence. Besides imputing members' residences, we also exploit the hourly frequency of repeated origins and destinations to infer the trips' purposes, as either commute or leisure. These strategies allow us to match the trip data and the socio-demographics to study the determinants of car-sharing usage and the differences across income groups.

We obtain meaningful insights into the usage patterns and characteristics of the FFCS users. First, we find that car-sharing users mostly live in middle- and high-income neighborhoods. This finding is partly driven by the service area restriction from the FFCS company (Fig. 1), revealing that FFCS companies expect to have greater demand in higher-income areas. Hence, lower-income neighborhoods do not have access to FFCS, which is a strong force toward a positive correlation between neighborhood income and car-sharing use. Usage intensity in the covered neighborhoods provides a different picture, as the most loyal users tend to live in middle-income

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[2] Some earlier studies within Madrid exist (e.g., Ampudia-Renuncio et al. 2020b), however, with a shorter period of analysis and smaller coverage area. The data used in those studies were obtained from the companies' websites.

[3] During the period that we analyze, the company charged fixed prices per minute, such that total costs depended exclusively on the trip duration. There was no price discrimination across users and no rebates for frequent users.

Fig. 1 Coverage area of the car-sharing service, in 2019. *Notes* The figure presents the study area of this paper and the coverage area of the car-sharing service, i.e., the area in which customers can start or end a trip. Users are allowed to drive outside the coverage area and leave the car in standby mode if they need to make a stop outside the coverage area. All territorial units represented are neighborhoods inside Madrid Municipality, except for the darker shaded units: Alcobendas, Coslada, Pozuelo de Alarcón, and San Sebastian de los Reyes municipalities

Car sharing coverage area
Neighborhoods inside Madrid Municipality
Outside Madrid Municipality
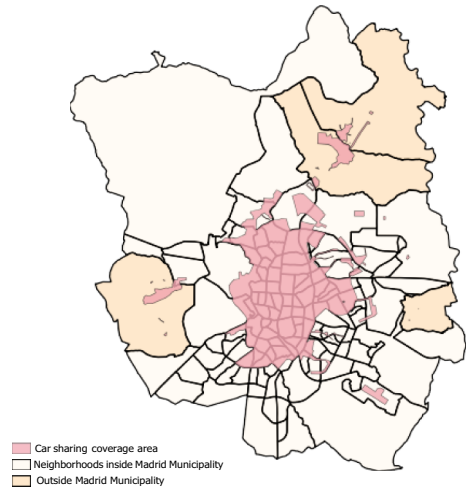
neighborhoods, i.e., conditionally on having access to FFCS, there is a negative correlation between neighborhood income and the frequency of car-sharing use.

Based on the timing of use, we also provide evidence on the purposes of car-sharing trips. We are able to classify almost 536 thousand commuting trips and 386 thousand leisure trips. This allows us to explore heterogeneity along these dimensions. For example, we find that income is positively correlated with commuting with car-sharing but negatively correlated with leisure trips.

Since most loyal customers live in neighborhoods with high car ownership rates and fewer public transport options, our analysis suggests that these customers use the service to complement public transport. If car-sharing members are car owners who prefer to leave their car at home, or even eventually sell it, FFCS would imply an overall reduction of vehicles in the city and, consequently, reduced use of parking space, decreased road traffic, and improved air quality.

Additionally, we find that the seasonality of car-sharing trips closely matches the trends of other motorized vehicles, although car-sharing usage peaks slightly earlier. Moreover, while road traffic decreases during the summer months, the number of car-sharing trips increases in the months of July and September. These patterns suggest that FFCS contributes to smoothing overall traffic and, thus, reducing congestion in the city. Importantly, during summer months, usage by the highest-income customers decreases substantially. We see a higher usage of the car-sharing service during workdays, particularly on Fridays. During weekends, trips are less frequent but longer. Overall, car-sharing trips are generally short, both regarding the duration and distance.

Finally, we implement gravity-type regression specifications to uncover potential frictions or facilitators for adopting car-sharing across the city. This analysis is performed at the level of Madrid's "transport zones" ("zonas de transporte," in Spanish), which are smaller than neighborhoods but larger than census tracts. We observe nearly 500 transport zones within the car-sharing company's area, corresponding to about 250

thousand origin/destination pairs (or dyads). Our results suggest that the likelihood of taking a car-sharing trip decreases with the distance between origin and destination. This could be due to the high costs associated with long car-sharing trips. Conversely, the likelihood of car-sharing is higher for origin/destination dyads that are poorly connected by public transit (i.e., dyads with long expected travel times by public transit).

2 Data sources

Table 1 provides a summary of the main variables used in this study, including sample sizes and data sources. We describe each data source in detail below.

2.1 Free-floating car-sharing trips

We use the universe of car-sharing trips made through one of the leading companies operating in Madrid during 2019. This database, which the company provided directly to the authors, contains unique vehicle and customer IDs, the starting and ending time and location of each trip, and the duration and distance traveled. During the analyzed sample period, the company had a fleet of 656 operating electric vehicles, which virtually remained constant throughout the year 2019 (Fig. 11). We excluded trips by company employees and focused only on trips made by customers. We exclude trips that last less than 2 minutes or more than 180 minutes. We further excluded observations for which the same member used the service more than 6 times on the same day.[4]

2.2 Demographics

In terms of demographics, we primarily use data on population and income, obtained from the Madrid City Council (AM 2018c) and the National Statistics Institute (INE 2018a; b). This entails combining data at different spatial aggregation levels. For the city of Madrid, we obtain neighborhood-level demographics for its 131 neighborhoods. We also collect municipality-level data for the other municipalities that are part of the Community of Madrid (metropolitan area). We also collect data on other demographic variables, such as gender and age. However, we find no significant heterogeneity along those dimensions, such that they are omitted from the remainder of this paper. Note that we do not directly observe demographics of the car-sharing users, which limits the scope of our heterogeneity analysis. Regardless, in Sect. 3 we present a proposal for imputing demographics.[5]

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[4] These are outlier cases that may represent bugs in the recording of trip durations.

[5] Previous studies, mostly relying on survey data, found that car-sharing users are predominantly male, high-income, and young (Amirnazmiafshar and Diana 2022; Vine and Polak 2020). Similarly, Schmöller et al. (2015) argue that car-sharing services can be especially appealing to young adults, since owning a private car is becoming less valuable now, compared to the past.

Table 1 Descriptive statistics

Variable	Obs	Mean	Std. Dev	Min	Max	Source	Year
Individual-level data							
Full sample of FFCS trips							
Number of trips	1,474,287					Trip data	2019
Number of customers	143,315					Trip data	2019
Customer loyalty							
No. of days used in 2019	143,315	8.224	14.239	1	344	Trip data	2019
No. of times used in 2019	143,315	10.287	20.306	1	726	Trip data	2019
Percentage of days used in 2019[1] (%)	143,315	4.027	7.212	.274	100	Trip data	2019
Weighted no. of days used in 2019[2]	143,315	14.699	26.323	1	365	Trip data	2019
Sub-sample of trips with identified residence							
Number of identified neighborhoods	95					Trip data	2019
Number of trips	511,070					Trip data	2019
Number of customers	12,143					Trip data	2019
Annual net income (€)[3]	12,143	20,994	5,247	8,758	31,239	AM, INE	2018
Customer loyalty							
No. of days used in 2019	12,143	31.925	28.209	1	344	Trip data	2019
No. of times used in 2019	12,143	42.088	43.256	1	724	Trip data	2019
Percentage of days used in 2019[1] (%)	12,143	10.74	9.45	0.28	94.25	Trip data	2019
Weighted no. of days used in 2019[2]	12,143	39.21	34.48	1.01	344	Trip data	2019
Survey sample of EDM [4]							
Number of cars per household	28,922	0.96	0.80	0	5	EDM	2018
Inadequate public transport (%)[5]	36,030	21.34	37.85	0	100	EDM	2018
% individuals with driving license	119,423	0.64	0.48	0	1	EDM	2018

Table 1 (continued)

Variable	Obs	Mean	Std. Dev	Min	Max	Source	Year
Neighborhood/municipality averages							
Neighborhood population size	135	26,589	17,971	1,176	116,037	AM, INE	2018
Average annual net income *per capita* (€)	135	17,425	6,318	6,712	32,242	AM, INE	2018
Average age	135	43.60	3.58	32	48.91	AM, INE	2018
Percentage of females (%)	135	53.31	1.86	48.30	58.22	AM, INE	2018
Average number of cars per household	135	0.95	0.31	0.42	1.91	EDM	2018
% individuals with driving license	135	59.58	8.83	32.13	78.71	EDM	2018
Inadequate public transport (%)[5]	135	18.74	8.45	3.44	52.17	EDM	2018
No. of metro stations per km^2	135	1.51	2.26	0	15.73	CRTM	2018
No. of train stations per km^2	135	0.15	0.40	0	2.58	CRTM	2018
No. of bus stations per km^2	135	24.6	12.05	0.12	53.16	CRTM	2018
No. of regulated parking slots per car[6]	48	0.36	0.35	0.12	2.55	AM	2018
Neighborhoods in the study area							
Car sharing member density (%)	95	0.56	0.58	0.01	3.66	Trip data	2019
Neighborhood population size	95	27,471	18,994	1,176	116,037	AM, INE	2018
Average annual net income *per capita* (€)	95	19,220	5,783	8,758	31,239	AM, INE	2018
Average age	95	44.04	3.40	32.5	48.91	AM, INE	2018
Percentage of females (%)	95	53.66	1.92	48.30	58.22	AM, INE	2018
Average number of cars per household	95	0.96	0.29	0.42	1.71	EDM	2018
% individuals with driving license	95	61.72	8.04	32.13	78.71	EDM	2018
Inadequate public transport (%)[5]	95	17.65	8.33	5.69	52.17	EDM	2018

Table 1 (continued)

Variable	Obs	Mean	Std. Dev	Min	Max	Source	Year
No. of metro stations per km^2	95	1.74	2.08	0	13.07	CRTM	2018
No. of train stations per km^2	95	0.11	0.37	0	2.58	CRTM	2018
No. of bus stations per km^2	95	26.2	11.2	1.7	53.16	CRTM	2018
No. of regulated parking slots per car[6]	48	0.36	0.35	0.12	2.55	AM	2018

[1] Computed as the number of days the customer used the car-sharing service divided by the total number of days left in 2019 since the first day they used the service. [2] Computed as the percentage of days a customer used the car-sharing service, multiplied by total number of days in a year. [3] Assuming all residents in a certain neighborhood have an annual net income equal to the annual income *per capita* of that same neighborhood. [4] Survey data from EDM 2018, restricted to our four municipalities of analysis (Madrid, Alcobendas, Coslada, Pozuelo de Alarcón, and San Sebastian de los Reyes). The observation units of the variable "% individuals with driving license" correspond to an individual, for "number of cars per household" to a household, and for "inadequate public transport" to a trip made by car by one of the survey respondents. [5] Using survey data from EDM 2018, we created a measure of adequacy of the public transport network. It measures the percentage of trips, out of total trips made by car, in which the respondents of EDM affirm using this travel mode because they have no public transport alternative. [6] Number of slots from the city's regulated parking service (Servicio de Estacionamiento Regulado, SER), normalized by the number of registered vehicles. In 2018, only 48 neighborhoods in the Municipality of Madrid were covered by the SER

2.3 Mobility-related data

Another key data source is Madrid's Mobility Survey (*Encuesta Domiciliaria de Movilidad*, CRTM 2018b). This is a recall survey of over 58 thousand households, aiming to assess mobility patterns in the Community of Madrid during working days.[6] The mobility survey includes information on the number of cars per household, which we use to proxy car ownership in each neighborhood. Moreover, using trip data from the mobility survey, we build a measure of the adequacy of the public transport network to assess the degree of complementary and substitutability between the car-sharing service and public transport (see Sect. 3 for further details).

We also downloaded data from Madrid's Regional Transport Consortium (*Consorcio Regional de Transportes de Madrid*, CRTM 2018a) containing the geographical coordinate of each metro, train, and bus station in the Madrid Autonomous Community, to measure neighborhood-level density of public transport stations in Madrid and neighboring municipalities. The Consortium also provides detailed georeferenced

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[6] Respondents were asked to describe all of their trips from the day prior to the interview. Data are representative for trips taken from Monday to Thursday.

information about all public transit stops and schedules in GTFS format (General Transit Feed Specification).[7] We use these to estimate public transit travel times, which are later used in our gravity-type specifications (Sect. 3.5).

To study the influence of parking availability, we use data from the regulated parking service, obtained in Madrid City Council's open data portal (AM 2018b). In Madrid, the parking policy was designed to contribute to the air quality improvement objectives. The Regulated Parking Service (*Servicio de Estacionamiento Regulado, SER*) covers the more congested areas of the city and differentiates parking fares according to vehicle technology and the daily pollution levels. The City Council establishes base prices for parking in each location of the city and provides discounts for low-emission vehicles. In high pollution periods, the base price increases, as an incentive to opt for public transport or low-emission travel modes. Importantly, electric vehicles receive a 100% discount, being exempted from parking fares. This exemption applies to car-sharing services; thus, car-sharing members are allowed to park for free and without restrictions in Madrid Municipality. The current SER coverage area was established in 2021 and extends through the so-called Central Almond. However, during our year of analysis, the coverage area was considerably narrower. In 2018, SER comprised 47 neighborhoods in Madrid Municipality, with a total of 153,082 parking slots. We collected data on the number of SER parking slots in each neighborhood, in 2018. To normalize the number of parking slots, we further downloaded data on the number of cars registered in each neighborhood. Figure 10 portrays the spatial distribution of SER parking slots, normalized by the number of cars.

Finally, we rely on daily road traffic data in Madrid (AM 2018a) and compare it against the seasonality of car-sharing trips.

3 Methodology

3.1 Imputing users' residences

In the absence of demographic information on each car-sharing member, we established a strategy to impute users' potential neighborhood of residence. Using this methodology, we are able to study socioeconomic determinants of car-sharing usage. We can do this thanks to access to precise geo-referenced data on the trip timing, origin, and destination, as well as unique user identifiers.

Our strategy exploits the frequency with which the same member starts and ends a trip in the same location. To achieve our preferred specification, we explored distinct frequencies, starting times, and days of the week. Notably, we explored trips for which the morning origin (with time intervals ranging from 6 am to 12 pm) and evening (from 1 pm to 8 pm) or night destination (from 9 pm to 5 am) coincide for at least 4, 5, and 10 times.[8] The criteria used are presented in Table 2. Using a frequency of 5,[9] we

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[7] This is a standardized file format created by Google to facilitate the sharing of information about public transit across cities. More details in https://developers.google.com/transit/gtfs.

[8] One potential concern is that workers providing services (e.g., cleaners, technicians, gardeners, etc.) might use car-sharing to travel from one household to another. This would contaminate the data given that their socio-demographics need not coincide with those of the neighborhoods where they work. However,

Table 2 Methodology to impute users' residence location

Criteria			Number of	Additional number of
Start Time	End Time	Day of week	Customers captured	Customers captured
6:00 am–9:59 am	1:00 pm–8:59 pm	Work days	4051	4051
6:00 am–9:59 am	1:00 pm–8:59 pm	Any day	5964	1918
6:00 am–9:59 am	9:00 pm–5:59 am	Work days	734	178
6:00 am–9:59 am	9:00 pm–5:59 am	Any day	1336	198
10:00 am–12:59 pm	1:00 pm–8:59 pm	Work days	1090	580
6:00 am–9:59 am	5:00 pm–5:59 am	Weekend	76	10
10:00 am–12:59 pm	5:00 pm–5:59 am	Weekend	97	65
6:00 am–9:59 am	–	Work days	9139	3941
6:00 am–9:59 am	–	Any day	11,563	1235
Total				12,176

The table summarizes the criteria used to identify FFCS users' residence location. The neighborhood/municipality of residence is identified if a user starts and/or ends their trips at least 5 times according to the criteria presented in the table

were able to identify the residence of 12,176 members (8.4% of the total number of users), which sum 511,070 trips (34.7% of the total number of trips). This sub-sample was used to infer socio-demographic determinants of car-sharing members. For this purpose, we used data on population and net annual income for all neighborhoods and municipalities of analysis, as explained in Sect. 2.3.

In all regressions that incorporate demographics, we restrict our analyses to this sub-sample of users with identified residence, always excluding those living in the neighborhoods where the main train stations (Atocha and Chamartín, the latter located in Castilla neighborhood) and airport (Aeropuerto) are located. These members are most likely multi-modal passengers, rather than residents in the Atocha, Castilla, and Aeropuerto neighborhoods, which have the smallest population size in our study area (1100–1800 inhabitants).

Our approach constitutes an improvement relative to the previous literature, which was restricted to analyzing the characteristics of the place of origin/destination of trips (Schmöller et al. 2015; Ampudia-Renuncio et al. 2020a) and therefore abstracted away from users' place of residence.

Footnote 8 continued

our approach is not subject to this bias given that it imputes residencies according to the early morning trip and late evening trips, without using the trips that might occur in between.

[9] When choosing the number of occasions for which we require a common origin and destination, there is a trade-off: enlarging it means greater confidence in the neighborhood imputation, but also a smaller set of users with imputed residences. We have chosen a frequency of 5 because it allows us to strike a balance between these two objectives.

3.2 Measure of customer loyalty

We construct a measure of customer loyalty that is intended to capture the number of days that a given customer uses the FFCS service within a full year. We use the following formula:

$$L_i = 365 \times \frac{N_i^{used}}{N_i^{samp}}$$

where L_i is the measure of loyalty for customer i. The count N_i^{used} is the number of days that customer i used the service during the whole year of 2019. The count N_i^{samp} is the total number of days elapsed between the first date when customer i used the service in 2019 and the last day of the year. The fraction on the right-hand side thus serves as a normalization that takes into account that some customers became aware and started using the FFCS service at different points within the year.

3.3 Inferring the purpose of trips

We exploit the frequency of repeated origins and destinations to categorize trips into two purposes: commuting and leisure. Firstly, we considered all trips occurring during the week, where the member leaves their residence in the morning (from 6:00 am to 9:59 am), or returns to their residence at lunchtime (2:00 pm to 3:59 pm) or afternoon (6:00 pm to 8:59 pm, excluding Fridays) as commuting trips. We exclude trips happening between 6 pm and 9 pm on Fridays because many Spaniards do not work on Friday afternoons. With regard to leisure, we considered all trips where members leave/return to their residences during the weekend.

To cross this information with demographic characteristics (in particular, income), we need to restrict the analysis to our sub-sample of members with imputed residence. Nevertheless, we are aware that the criteria that we established to impute members' residence strongly influence the determined trip purpose. Hence, in Table 3, we include descriptive statistics for both the full sample and sub-sample, to compare the percentage of trips classified as commuting and leisure. For the full sample, we considered any trip happening in the aforementioned time intervals, regardless of the trip's origin and destination. In Table 3, we show the fractions of trips according to their purpose, comparing the sample of all customers versus the sub-sample of customers with identified residence. We find that the sub-sample with identified residence is relatively more likely to represent commuting trips, such that our results need to be interpreted accordingly. This is expected, given that both our strategies for imputing residence and classifying commuting trips partially rely on observing customers who take a trip in the morning and return to the same location in the evening, for example.

3.4 Measuring the availability of public transport

We measure the density of public transport stations in each neighborhood and municipality using the geographical data from Madrid Regional Transport Consortium.

Table 3 Identifying trip purpose—commuting or leisure

Purpose of trip	Obs	%
Full sample		
Commute	535,990	58.11
Leisure	386,333	41.89
Trips with identified purpose	922,323	100
Observations in the full sample	1,474,287	
Sub-sample with identified residence location		
Commute	199,051	68.83
Leisure	90,158	31.17
Trips with identified purpose	289,209	100
Observations in sub-sample with identified residence	511,070	

However, since the number of stations is not informative of the degree of connection between different destinations, we created a measure of the adequacy of the public transport network. For this purpose, we use the Mobility Survey of 2018 (*Encuesta Domiciliaria de Movilidad, EDM*), the most recent mobility survey available for Madrid, which comprises a questionnaire that aims to assess mobility patterns during weekdays. To build our measure of the adequacy of the public transport network, we make use of a question in the EDM 2018 that asks respondents which travel mode they choose for a particular trip. If the chosen travel mode was not public transport, EDM proceeds to ask the reason for not picking a public transport alternative. Among the possible answers, we are interested in two: *(i)* improper connection and *(ii)* non-existence of a public transport option. Exploiting this question from the mobility survey, we create an index for inadequate public transport network, which measures the percentage of trips for which the respondents declare to use a car because there is no public transport alternative (improper connection or non-existence), out of the total number of trips made by car, to or from their neighborhood of residence. Finally, we aggregate the microdata from EDM 2018 to obtain an average measure for each of the 95 geographical units where we identified car-sharing members.

3.5 Gravity model

We estimate gravity-type specifications in order to provide insight about potential frictions or facilitators of car-sharing trips across the city. Note that gravity specifications are typically based on linked origin/destination pairs or "dyads." In our case, working with specific origin/destination points is computationally intractable and results in too many unique dyads for which a single trip is observed. Rather, we aggregate the car-sharing trips data to the level of Madrid's "transport zones."[10] We focus on the

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[10] These zones were established by Madrid's Regional Transport Consortium (CRTM, 2018a). The zones are at a level of aggregation typically smaller than neighborhoods, but larger than census tracts. More details at https://datos.crtm.es/datasets/crtm::zonificacionzt1259/about.

500 transport zones within the coverage area of the car-sharing company from which we have data, corresponding to about 250 thousand origin/destination dyads.

In terms of frictions or facilitators, we consider two factors: (i) geographical distance between origins/destinations; and (ii) the travel time between origins/destinations that is expected under Madrid's current public transit system. For the former, we take the straight-line distance between the centroids of the transport zones. For the latter, we rely on data from Madrid's Regional Transport Consortium (CRTM 2018a). In particular, we take the georeferenced data (in GTFS format) from all stops and schedules of metro, train, and bus routes across the Community.[11] These serve as inputs for the r5r R package, which identifies optimal public transit itineraries and associated travel times between specified origin/destination pairs (Pereira et al. 2021). We focus on the optimal travel times. That is, we compute how long would a trip would take between each of the 250 thousand relevant origin/destination pairs in our sample, in case that trip was taken by public transit. The r5r router incorporates factors such as waiting time required when switching transit lines, for example, and accommodates multi-modal trips (details in Pereira et al. 2021). The router requires choosing a "representative" starting date/hour for the trips (as optimal itineraries may change depending on the starting hour). We choose a non-holiday Wednesday at 10am for our main specification, and we show that our results are not sensitive to this choice.[12]

The outcome variable for this analysis is the count of car-sharing trips that we observed between each of the dyads in our sample. That implies that we aggregate the trips that we observe to the dyad level, considering all of the observations for the year 2019. Specifically, we implement the following regression:

$$[\#\text{Trips}]_{od} = \beta_1[\text{LogDistance}]_{od} + \beta_2[\text{PTTravelTime}]_{od} + \gamma_o + \gamma_d + \varepsilon_{od}, \quad (1)$$

where $[\#\text{Trips}]_{od}$ represents the count of car-sharing trips between origin o and destination d in 2019; $[\text{Log Distance}]_{od}$ are distances in log; $[\text{PT Travel Time}]_{od}$ are public transit travel times in minutes; γ_o are origin fixed effects; γ_d are destination fixed effects; and ε_{od} is an idiosyncratic error term.

Regression specification (1) is implemented with dyad-level data. With the origin and destination fixed effects, we control for location-specific factors that explain car-sharing adoption and which are fixed over time. The implication is that this analysis does not allow us to explore heterogeneity by demographics, which in our sample are fixed over time. Nevertheless, the specifications implicitly control for those factors, to some extent. The coefficients of interest are β_1 and β_2 which capture, respectively, how the frequency of car-sharing trips is affected by dyad distances and optimal public transit travel times.

Note that our outcome of interest is a count variable which may also include some zeroes. For this reason, following recommendations from the trade literature (e.g., Silva and Tenreyro 2006; Buggle et al. 2023), we estimate specification (1) through Poisson pseudo-maximum-likelihood (PPML). More specifically, we use the ppmlhdfe

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[11] The currently available GTFS public transit data for Madrid are representative for the year of 2022. We use that as a proxy of public transit availability in 2018.

[12] Specifically, we use the itineraries that were possible at 10am on April 27th, 2022. Results are similar when we use 8am, 12 pm, 2 pm, 4 pm, 6 pm, 8 pm, or 10 pm as the reference starting hour (Table 8).

package by Correia et al. (2020). We cluster standard errors at the dyad level. We also implement variants of specification (1), restricting the sample to either commuting or leisure trips, or for observations at different time windows throughout a day.

4 Results

4.1 Geographical distribution of car-sharing members

Based on our approach to infer the neighborhood of residence of each user in our sample, we explore the socio-demographic determinants of car-sharing.

In Fig. 2 panel (a), we present car-sharing members' geographical distribution, normalized by the number of inhabitants living in the respective neighborhood. Figure 2 panel (b) portrays the average member loyalty per neighborhood. Panel (a) shows that car-sharing members are concentrated in two axes. First, we note a high concentration of users along the main road connecting the city from south to north (Paseo de la Castellana), around which significant businesses and tourist attractions are located. Second, there is a high concentration of users in the northern peripheral neighborhoods of Madrid. Conversely, the Central District exhibits the lowest car-sharing member density. According to our methodology, the neighborhood with the highest member density is Atocha (3.65%). However, this density might be overestimated since that neighborhood houses Madrid's central train station. It is thus plausible that many trips

(a) Member density (%)   **(b)** Member loyalty (days used)
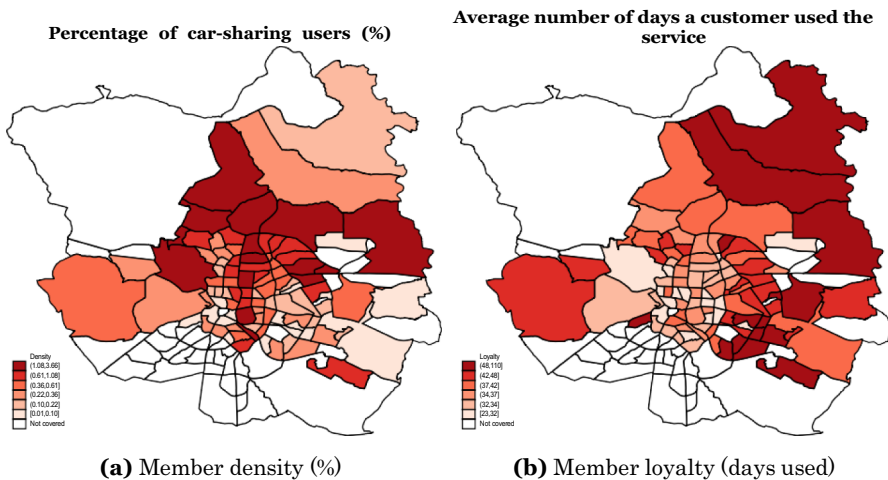
Fig. 2 Geographical distribution of car-sharing members. *Notes* Panels (**a**) and (**b**) provide neighborhood averages of the car-sharing data. Panel (a) shows the density of car-sharing users living in each neighborhood (i.e., the number of users divided by the population). Panel (b) portrays the weighted average number of days the members living in the neighborhood used the service in 2019. This loyalty measure is computed by taking the total number of days each customer used the service, weighted by the total number of days left in 2019 since they first used the service, and multiplied by the total number of days in a year. All territorial units represented are neighborhoods inside Madrid Municipality, except for the municipalities of Alcobendas, Coslada, Pozuelo de Alarcón, and San Sebastian de los Reyes

that start or end in Atocha are multi-modal. For example, users might take a train to Atocha and, from there, take the car-sharing service to their final destination. Thus, as explained in Sect. 3, we exclude Atocha from our analyses. Likewise, we exclude the Castilla and Aeropuerto neighborhoods, which are almost entirely occupied by the Chamart´ın train station and Madrid-Barajas Airport. According to our methodology, the Castilla and Aeropuerto neighborhoods would be the 7th and 5th areas with the highest member density (1.52 and 1.66%, respectively).

Figure 2 panel (b) shows that more loyal car-sharing members live in the periphery of our study area, particularly in the four municipalities outside Madrid and the southeastern neighborhoods. A comparison of panels (a) and (b) reveals that neighborhoods with a higher percentage of car-sharing customers have a lower loyalty to the service, which might suggest that those customers use the service for distinct purposes. The sections below explore this further.

4.2 Income distribution

Prior literature suggests that FFCS in Madrid is about three times more expensive than public transport when considering single-trip fares (Ampudia-Renuncio et al. 2020b). The availability of monthly passes for public transportation increases the cost difference. However, car-sharing is cheaper than ride-hailing and, depending on the usage intensity, car-sharing can be a more affordable option than owning a car. The implication of these cost differences is that car-sharing might not be accessible or attractive to some income groups while appealing to others.

In this section, we provide insights into how income relates to car-sharing usage in the city of Madrid. Having identified the users' residence location through the car-sharing usage patterns, we then impute their income based on neighborhood-level data (see Table 1). This shows that the average annual net income of car-sharing users in our sample is close to €20 thousand, which is substantially higher than the average income per capita for the entire municipality of Madrid (€16,700) (INE 2018b).[13] This is in line with the fact that the car-sharing service area (Fig. 1) excludes some of the lowest-income neighborhoods in the city. Our findings are consistent with prior literature showing that car-sharing users tend to have an above-average income (Amirnazmiafshar and Diana 2022; Caulfield and Kehoe 2021).

Although our data suggest the existence of a positive correlation between car-sharing member density and income, we would expect to find a negative correlation between member loyalty and income, given that, as discussed in Sect. 4.1, neighborhoods with a higher percentage of car-sharing customers seem to have a lower loyalty to the service. We formally test these relationships with regressions as follows:

$$Y_i = \alpha + \sum_{g=2}^{4} \beta_g 1\big[i \in \text{income quartile } g\big] + \varepsilon_i \tag{2}$$

where Y_i is the outcome of interest (customer density or loyalty) for the unit of analysis i; the unit of analysis is the neighborhood for the density variable, and the customer

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[13] The average annual income per capita of the four municipalities of the study area (Madrid, Alcobendas, Coslada, Pozuelo de Alarcon, and San Sebastian de los Reyes) was €17,425.

for the loyalty variable; α is a regression constant; the indicators $1[i \in$ income quartile $g]$ are equal to one when i belongs to a given income quartile, zero otherwise; note that the 1st quartile (income from €8000–€14,500) is the omitted comparison group; and ε_i is an idiosyncratic error term. The coefficients β_g thus capture how density or loyalty changes depending on the income quartiles of neighborhoods or customers.

Regression estimates from Eq. (2) are presented in Table 4. Column (1) shows that the highest-quartile neighborhoods have a member density of about 0.72 p.p. higher than the lowest-quartile neighborhoods. Conversely, column (2) suggests that the higher-income customers are less loyal, i.e., they use the service almost 6.6 days less than the lower-income customers. In Figs. 3 and 4, panel (a), these opposite relationships are evident. While neighborhoods with higher income tend to have a higher proportion of car-sharing users, those with the lowest income in our study area concentrate the most loyal members. Regardless, in results presented in appendix (see Table 11), we show that both loyalty and income are positively correlated with the probability of taking a car-sharing trip.

Table 4 Regression results for purpose of trip: trip level (sub-sample with identified residence)

		Member loyalty		
	Member density	Days used	Times used	Days used (weighted)
	(1)	(2)	(3)	(4)
Annual net income (€)				
14,500–19,500€	0.104	−2.443**	−4.129***	−4.439***
	(0.071)	(0.960)	(1.498)	(1.190)
19,500–24,000€	0.379***	−4.920***	−8.565***	−8.597***
	(0.106)	(0.878)	(1.366)	(1.072)
+24,000€	0.722***	−6.601***	−11.286***	−10.385***
	(0.118)	(0.848)	(1.305)	(1.045)
Observations	92	11,818	11,818	11,818
R^2	0.358	0.007	0.008	0.011

Standard errors in parentheses: $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

The above linear regressions are restricted to the sub-sample of car-sharing users with identified residence, excluding those living in Atocha, Aeropuerto, and Castilla neighborhoods. The regressions provide correlations between car sharing member density and loyalty with the neighborhood income quartiles, using as base category the lowest quartile: €8,000–€14,500. Column (1) uses neighborhood observations, while in columns (2–4) each observation represents a customer

The outcome variable in column (1) measures the percentage of car-sharing users in a neighborhood, i.e., total number of users divided by total resident population

Columns (2–4) provide different measures of member loyalty. The dependent variable in column (2) Measures the total number of days a customer used the car-sharing service in 2019, while column (3) Measures the number of times she/he used the service. In column (4), the outcome variable measures the weighted number of days used, given by the number of days the customer used the car-sharing service, weighted by the total number of days left in 2019 since the first day they used the service, multiplied by total number of days in a year
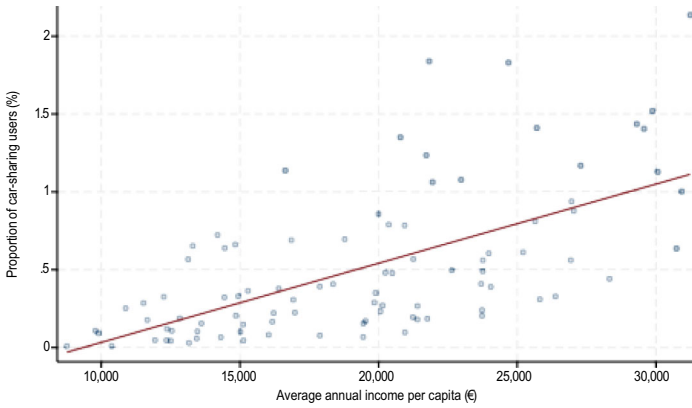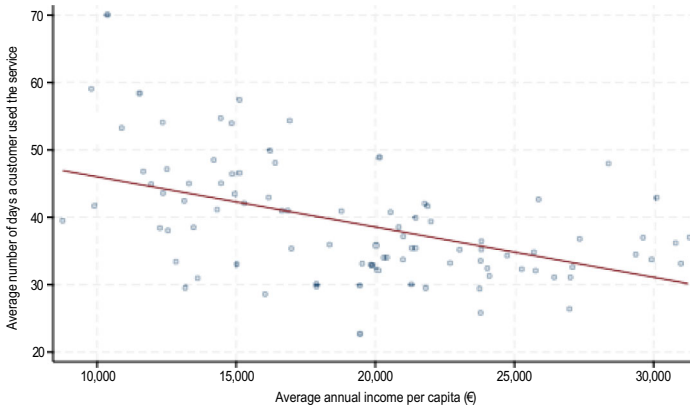
(a) Average annual income
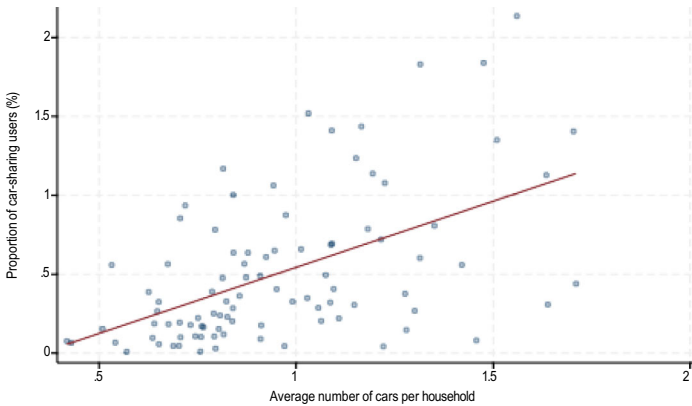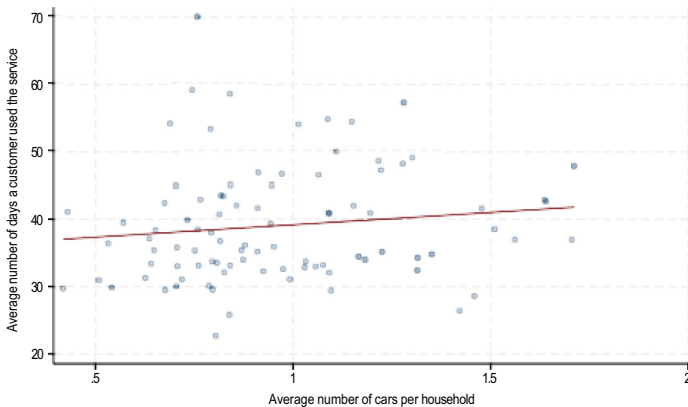

(b) Car ownership

Fig. 3 Correlation plots between member density and neighborhood-level attributes. *Notes* The scatter plots correlate car-sharing member density with two neighborhood attributes. Member density is computed as the number of car-sharing users living in each neighborhood, weighted by the total population. Panel (**a**) correlates member density with the average annual net income *per capita* (INE 2018b; AM 2018c), while panel (**b**) provides the correlation with the average number of cars per household (CRTM 2018b) in each neighborhood of the study area. We exclude the neighborhoods of Atocha and Castilla (where the main train stations are) and Aeropuerto.

4.3 Effect on mobility patterns

One crucial factor to consider when assessing the implications of FFCS in cities is the impact of the car-sharing service on mobility patterns. For example, fully electric FFCS cars could accelerate the decarbonization of cities through car shedding. In this scenario, the majority of car-sharing members would be car owners considering

(a) Average annual income

(b) Car ownership

Fig. 4 Correlation plots between member loyalty and neighborhood-level attributes. *Notes* The scatter plots correlate car-sharing member loyalty with two neighborhood attributes. Member loyalty is measured as the weighted average number of days the members living in the neighborhood used the service in 2019. This loyalty measure is computed by taking the total number of days each customer used the service, weighted by the total number of days left in 2019 since they first used the service, and multiplied by the total number of days in a year. Panel (**a**) correlates member loyalty with the average annual net income *per capita* (INE, 2018b; AM, 2018c), while panel (**b**) provides the correlation with the average number of cars per household (CRTM, 2018b) in each neighborhood of the study area. We exclude the neighborhoods of Atocha and Castilla (where the main train stations are) and Aeropuerto. We also exclude the Pavones neighborhood, which exhibits outlier loyalty above 100

the possibility of selling their vehicle and using the car-sharing service as an alternative (Jochem et al. 2020; Becker et al. 2018).[14] This may be particularly likely for households owning more than one car. Another potential mechanism is that drivers may switch their polluting vehicle for an electric one following a positive car-sharing experience. In that case, even when shedding is limited, car-sharing may contribute to reducing pollution by accelerating the electrification of the fleet. Moreover, FFCS might prevent future vehicle purchases if drivers consider that the FFCS service already fulfills their needs.

Besides the effect on car ownership, however, it is essential to analyze the relationship between the use of car-sharing services and public transport. On the one hand, if users consider them to be substitutes, FFCS could reduce the use of collective public transport, leading to an overall increase in the number of cars in the city. For instance, users may see FFCS and public transportation as substitutes for short trips between nearby areas, for which the travel time by public transport is generally higher than by car (Ampudia-Renuncio et al. 2020b). However, when considering the time required to reach the vehicle and to find a parking slot, the travel time difference between FFCS and public transport may not be significant (Sprei et al. 2019). Indeed, this outcome is unlikely, according to prior literature (Habibi et al. 2017; Becker et al. 2018; Tyndall 2019).

On the other hand, FFCS could be a complement to public transport, particularly in areas where the public transport network is scarce (Vine and Polak 2020). In this case, FFCS would prevent the use of private vehicles, contributing to reduced land occupancy and lowering emissions. However, even where car-sharing complements incomplete public transport networks, FFCS services must be implemented where alternative transport modes exist, given the uncertainty regarding the availability of cars for the return trip (Ampudia-Renuncio et al. 2020a). This is another important source of complementarity.

Building on data from several sources, we provide insights into which of the above mechanisms is more likely to dominate in Madrid. We relate FFCS usage with car ownership and the public transport network in the city. To measure the availability of public transport services, we first focus on the density of metro, train, and bus stations/stops, i.e., the number of stations/stops per Km^2 in each neighborhood. Since the presence of several stations might not imply a proper connection between different destinations, we further created a measure of public transport adequacy based on a question from Madrid's Mobility Survey (see Sect. 3).

We assess the correlation between car-sharing usage and mobility patterns through the following regression:

$$Y_i = \gamma + X'\theta_i + \varepsilon_i, \tag{3}$$

[14] According to a survey conducted among car-sharing users in 11 European cities (Jochem et al. 2020), the share of survey participants selling a car after trying the service ranged from 3.6% to 16.0%, with the lowest value being found in Madrid. However, compared to station-based car-sharing, FFCS members are less likely to decrease vehicle ownership, as these users see the FFCS service as a complement rather than a replacement for their private car (Amirnazmiafshar and Diana 2022).

where Y_i is the outcome of interest (customer density) for the neighborhood i; γ is a regression constant; X is a vector of explanatory variables; and ε_i is an idiosyncratic error term. The coefficients θ_i capture how car-sharing member density changes according to neighborhood characteristics and amenities, notably, the annual income *per capita*, rate of car ownership, and adequacy of the public transport network.

Table 5 provides the results for the above regression. Firstly, we note that neighborhoods with higher rates of car ownership tend to have a higher percentage of car-sharing members (see also panel (b) of Fig. 3). In particular, columns (1) and (5) suggest that an additional car per household is associated with a 0.56 p.p. increased member density. Since these regressions already control for the income level of the neighborhood, these results suggest that car-sharing users are car owners, substituting their private vehicle for a shared one, when using the service. In column (2) we test the influence of the public transport network on car-sharing usage. The estimates indicate that neighborhoods with fewer metro and bus stops per Km^2 have a higher density of car-sharing members.

In Table 9 in appendix, we estimate Eq. 3 for a different outcome variable: member loyalty. In this specification, θ_i captures changes in customer loyalty, for customer i, according to the same neighborhood characteristics and amenities. The results support our previous conclusions, neighborhoods with fewer public transport stations/stops per Km^2 and with more complaints of inadequate public transport network have the most loyal customers. However, these effects are muted once we control for car ownership, which is negatively correlated with the availability of public transport. These results suggest that car-sharing might be used in Madrid as a substitute for private vehicles, and to complement the existing public transport network. In fact, the negative correlation between car ownership and the availability of public transport could indicate that residents in areas with poorer public transport networks own a car to counter insufficient public transport options. Our findings could imply that FFCS services decrease commuting/travel times, improve connections, and promote car shedding.

In Table 10 in appendix, we estimate the original Eq. 3, extending the previous analysis to all neighborhoods in Madrid municipality. In neighborhoods where we did not identify car-sharing members, we impute a member density of zero. Our results are robust to this sample modification.

For the complete decarbonization of the city, preference should be given to more sustainable travel modes, such as walking, cycling, and public transport. The first two modes are not feasible for long distances, and expanding the public transport network is generally costly and requires a long implementation period. In this sense, electric free-floating car-sharing services might be an optimal solution to complement the existing public transport network. It is important to stress that these shared vehicles are considerably more efficient than private cars. Firstly, the FFCS fleet in Madrid is fully electric. Secondly, FFCS provides more efficient use of the scarce space in cities, particularly parking. On average, a private car is parked 23 hours a day, translating into a usage rate of 4% (Nagler 2021). By being shared among several individuals, FFCS vehicles have a higher utilization rate. In our data, vehicles' average usage rate was 23%, measured by the total number of hours each car was used, divided by the maximum number of hours it could have been used. Habibi et al. (2017) and Sprei

Table 5 Regression results for mobility patterns: neighborhood level (sub-sample with identified residence)

	Member density			No. trips at destination		
	(1)	(2)	(3)	(4)	(5)	(6)
Log annual net income (€)	0.739***	0.933***	0.877***	0.906***	0.737***	32.742***
	(0.198)	(0.123)	(0.213)	(0.126)	(0.200)	(6.908)
Avg. no. of cars per household	0.561***		0.298		0.568**	
	(0.212)		(0.244)		(0.218)	
% of residents with driving license	−0.003		−0.004		−0.003	
	(0.009)		(0.010)		(0.009)	
No. metro stations per km^2		−0.033**	−0.021			
		(0.013)	(0.015)			
No. train stations per km^2		0.030	0.048			
		(0.082)	(0.092)			
No. bus stations per km^2		−0.009**	−0.006			
		(0.004)	(0.004)			
Inadequate public transport network (%)				0.008	−0.001	
				(0.006)	(0.006)	
No. of parking slots per car						0.573***
						(0.051)
Observations	92	92	92	92	92	47
R^2	0.459	0.467	0.480	0.376	0.459	0.715

Standard errors in parentheses: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

Notes The linear regressions use neighborhood observations. Columns (1) to (5) are restricted to the sub-sample of car-sharing users with identified residence, excluding those living in Atocha, Aeropuerto, and Castilla neighborhoods. The outcome variable in columns (1) to (5) measures the neighborhood member density, i.e., the percentage of car-sharing users in each neighborhood, out of the total resident population. These regressions provide correlations between car-sharing membership and the characteristics and amenities of the neighborhood. The dependent variable in column (6) measures the total number of trips ending in each neighborhood, weighted by the resident population, while the independent variable is given by the number of parking slots per car. These parking slots are integrated within the Regulated Parking Service (SER), which, in 2018, only covered 48 neighborhoods in the Municipality of Madrid. Regression (6) provides the correlation between the number of trips and parking availability at the destination

et al. (2019), which studied FFCS in several European and North-American cities, concluded that Madrid had the highest usage rate of all cities analyzed.

4.4 Seasonality and purpose of car-sharing usage

Figure 5 shows the temporal distribution of car-sharing trips. For graphs on the left-hand side, we use the full sample of car-sharing trips in 2019. Right-hand side graphs are for a restricted sample of trips for which we identified users' residences, such that we can correlate seasonality patterns with demographic characteristics (income).

For graphs on the left, we contrast the car-sharing trip seasonality with road traffic on the main highway (M-30) and in urban areas inside the municipality. We observe that the seasonality of car-sharing trips closely follows the pattern of other motorized vehicles in Madrid. We see a higher usage during peak hours (morning and afternoon) on weekdays (panel a). In Madrid, there is a third peak hour at lunchtime, between 2 pm and 5 pm, when many stores close (Ampudia-Renuncio et al. 2020b; Habibi et al. 2017). Nonetheless, we notice that the morning peak for car-sharing users happens earlier, between 6 am and 7 am, with the number of car-sharing trips dropping significantly during the usual morning peak, between 8 am and 9 am. This might suggest that car-sharing users avoid high congestion hours to avoid paying higher bills, since the car-sharing service is charged by the minute. Additionally, car-sharing trips exhibit a higher peak at lunchtime than road traffic. According to the graphs on the right, during both these peaks, most car-sharing members are above the medium income of all car-sharing users. There are only two peaks at lunchtime and in the afternoon on weekends (panel b). Similarly, the peaks for car-sharing users happen slightly earlier than usual road traffic.

Looking at the patterns by day of the week (panel c), we see higher usage of the car-sharing service on weekdays, particularly on Fridays. We also note that trips during the weekend are dominated by below-average income customers, while during weekdays, especially at peak hours, higher-income users are more prevalent. These figures suggest that higher-income customers use the service for commuting rather than leisure. This is in line with findings for Germany, where most free-floating car-sharing trips happen on Saturday, and the peak usage hours happen considerably later than those of private cars, particularly during the afternoon (Schmöller et al. 2015). The seasonality of car-sharing trips seems to be city-specific, especially when comparing workdays versus weekends (Sprei et al. 2019).

Regarding the distribution of trips throughout the year (panel d), July and September show more car-sharing usage. However, road traffic, which is relatively consistent throughout the year, sees a drop in these months, intensifying in August. Although we see the same drop in August for car-sharing trips, the reduction is much less pronounced, suggesting that tourists also use this service. A study in Berlin and Munich found a drop in car-sharing utilization between June and September, arguing that during these months, users opt for other travel modes, such as walking and cycling (Schmöller et al. 2015). The right-hand side graph of panel (d) is consistent with higher-income customers leaving the city during the summer for holidays.
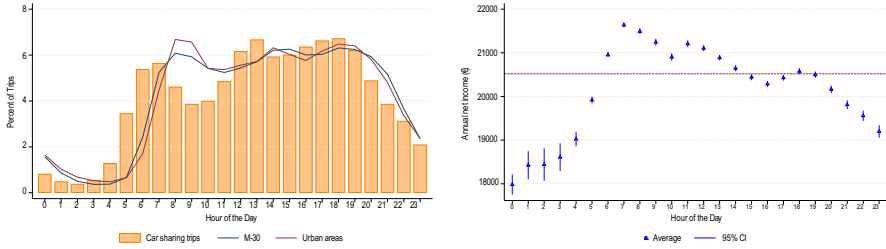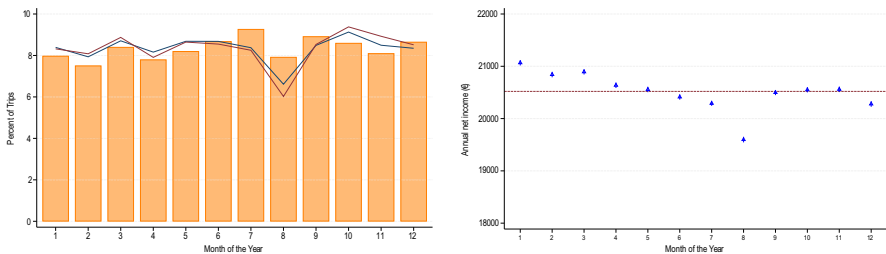
(a) Patterns by Hour of Day – weekdays
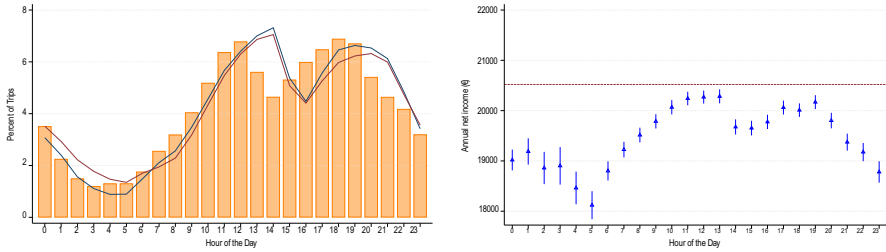
(b) Patterns by Hour of Day – weekends
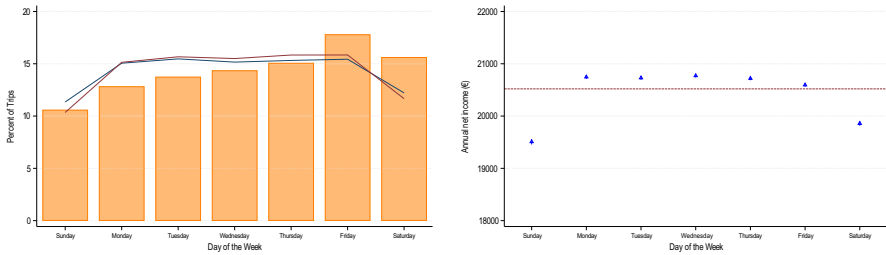
(c) Patterns by Day of Week

(d) Patterns by Month of Year

Fig. 5 Seasonality of car-sharing trips. *Notes* Left-hand side figures use the full sample, while right-hand side figures are restricted to the sub-sample of members with identified residence. The blue and red lines in the left-hand side figures represent road traffic seasonality in the main highway (M-30) and in urban areas of the municipality of Madrid, respectively (AM 2018a). The red lines in the right-hand side figures represent the imputed average annual net income of the car-sharing members with identified residence, excluding those living in Atocha, Aeropuerto, and Castilla neighborhoods (20,435€) (INE 2018b; AM 2018c)

To test the hypothesis that higher-income customers predominantly use the service to commute, we categorized trips according to their purpose, based on the frequency of usage at different times of the day and the week (see Sect. 3). With this specification, we could categorize 56% of the trips from members with an identified residence. Of those, 68.8% were commuting trips, while 31.2% had a leisure purpose. The regression estimates from Table 6 suggest that higher-income customers are more likely to take car-sharing trips to commute and less likely to use this service for leisure purposes.

According to Becker et al. (2017), who focus on the case of Switzerland, "free-floating car-sharing is mainly used for discretionary trips, for which only substantially inferior public transportation alternatives are available." Schmöller et al. (2015) find that car-sharing services in Berlin and Munich are used predominately for shopping and social-recreational activities. In Vine and Polak (2020), the authors argue that the purpose of car-sharing usage differs according to car ownership status. Car owners are more likely to use the service for business purposes (for instance, meetings), while non-car owners use the service for shopping purposes.

Finally, Fig. 6 represents the seasonality of trips according to their distance and duration. Car-sharing trips were generally short as a function of distance and travel time. The average figures were 23 minutes and 7 Km per trip (in line with previous studies, e.g., Ampudia-Renuncio et al. 2020b; Sprei et al. 2019). As expected, trips take longer during peak hours due to heavier road traffic. On weekends and Fridays, trips are relatively longer in distance and time traveled. Additionally, over time, customers started to take longer trips (in terms of distance).

4.5 Gravity specifications

Tables 7 and 8 present results from estimation of gravity-type models such as Eq. (1). Table 7 is for baseline specifications. In the first column, we show results when only log distance is included as a friction variable, ignoring the availability of public transit. We find that car-sharing trips become less likely with increased distance between origin/destination pairs. According to our preferred specification (column 3), the point estimate is (-0.47). Given our Poisson specification, this coefficient needs to be transformed for ease of interpretation. For example, if the distance between origins/destinations were to double, then the number of car-sharing trips would drop by almost 28% $[= exp(-0.47 \times log2)-1]$. This may be partly explained by the fact that the costs of car-sharing trips can also increase significantly with distance (as the trip duration increases, and rentals are paid by the minute).

In terms of the impact of public transit travel times, note that column (2) of Table 7 suggests a negative elasticity, while column (3) suggests a positive elasticity. However, the negative elasticity from column (2) may be confounded by the effect of distances. Column (3) is the preferred specification in the sense that it estimates the elasticity of car-sharing with respect to public transit travel times, while simultaneously controlling for the distance between the origins/destinations of the trips. In that case, the elasticity becomes positive, such that car-sharing is more likely as origins/destinations are less well-connected through public transit. The point estimate is (0.0037), which can be interpreted as follows: if travel time by public transit increases by 10 minutes, then

Table 6 Regression results for purpose of trip: trip level (sub-sample with identified residence)

	Commute			Leisure		
	(1)	(2)	(3)	(4)	(5)	(6)
Log annual net income (€)	−0.00924***	0.00891***	0.00748***	−0.02009***	−0.01358***	−0.01394***
	(0.00046)	(0.00045)	(0.00044)	(0.00030)	(0.00029)	(0.00028)
Member loyalty[1]		0.00147***	0.00150***		0.00053***	0.00051***
		(0.00001)	(0.00001)		(0.00000)	(0.00000)
Controls for month and day of week	No	No	Yes	No	No	Yes
Observations	3,550,020	3,550,020	3,550,020	3,550,020	3,550,020	3,550,020
R^2	0.000	0.044	0.075	0.001	0.016	0.064

Standard errors in parentheses: $*p < 0.1$, $**p < 0.05$, $***p < 0.01$

Notes This table provides regressions results using linear probability models. For columns (1–3), the dependent variable is an indicator equal to 1 when a customer takes a car-sharing trip for commuting and 0 otherwise. For columns (4–6) the dependent variable is equal to 1 for leisure trips and 0 otherwise. The dependent variables are set to missing for all dates prior to the first usage date of a given customer. These variables therefore measure the probability of taking a car-sharing trip after trying the service for the first time in 2019. The sample is restricted to car-sharing users with identified residence, excluding those living in Atocha, Aeropuerto, and Castilla neighborhoods
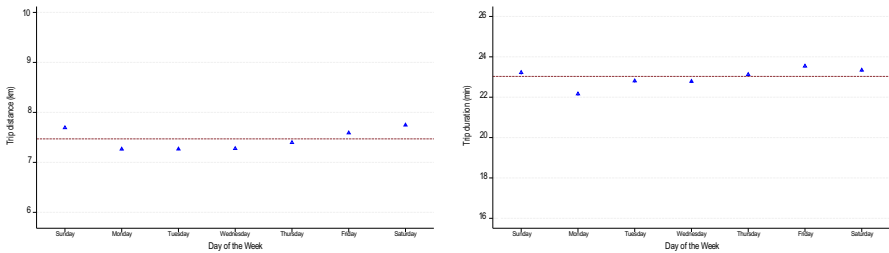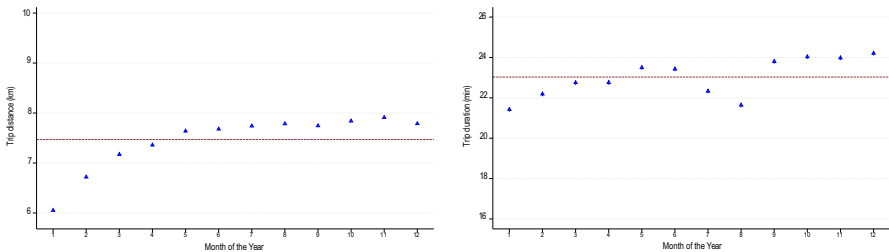[1]Weighted number of days a customer used the car-sharing service in 2019
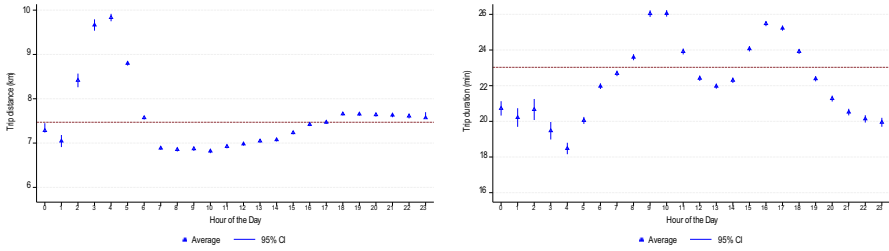
(a) Patterns by Hour of Day – week days
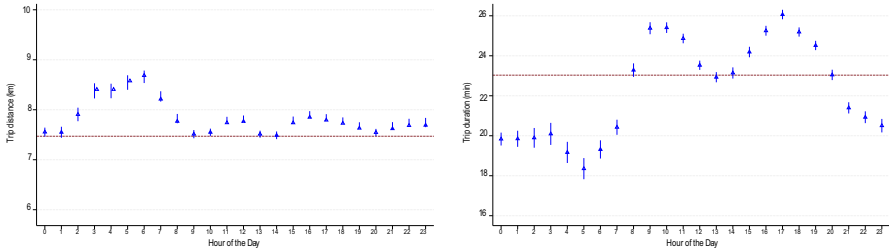
(b) Patterns by Hour of Day – weekends

(c) Patterns by Day of the Week

(d) Patterns by Month of the Year

Fig. 6 Seasonality of car-sharing trips, according to trip distance and duration. *Notes* Both columns use the full sample of car-sharing trips. The red lines represent the average travel duration (in minutes) and distance (in kilometers), respectively

Table 7 Results from baseline gravity-type specifications

	All trips			Commute	Leisure
	(1)	(2)	(3)	(4)	(5)
Log distance	−0.3845***		−0.4671***	−0.4460***	−0.4932***
	(0.0085)		(0.0117)	(0.0142)	(0.0109)
Public transit travel time		−0.0094***	0.0037***	0.0036***	0.0042***
		(0.0003)	(0.0003)	(0.0004)	(0.0003)
Observations (dyads)	250,170	250,167	250,167	170,556	176,954
Pseudo-R-squared	0.752	0.727	0.754	0.612	0.569

Standard errors in parentheses: $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Results from pseudo-maximum-likelihood specification relating the count of car-sharing trips with covariates of interest (Eq. 1). All specifications control for origin and destination fixed effects. Standard errors are clustered at the dyad level

Table 8 Results from gravity-type specifications for different hours of the day

	7 am–9 am	9am–11am	11am–1 pm	1 pm–3 pm
Log distance	−0.4019***	−0.5394***	−0.4638***	−0.4631***
	(0.0163)	(0.0127)	(0.0132)	(0.0141)
Public transit travel time	0.0025***	0.0046***	0.0035***	0.0041***
	(0.0003)	(0.0004)	(0.0004)	(0.0004)
Observations (dyads)	135,879	135,315	137,905	139,021
Pseudo-R-squared	0.467	0.434	0.461	0.446
	3 pm to 5 pm	5 pm to 7 pm	7 pm to 9 pm	9 pm to 11 pm
Log distance	−0.4940***	−0.4969***	−0.4633***	−0.5168***
	(0.0137)	(0.0127)	(0.0136)	(0.0153)
Public transit travel time	0.0037***	0.0045***	0.0043***	0.0034***
	(0.0005)	(0.0004)	(0.0004)	(0.0004)
Observations (dyads)	152,267	145,007	134,478	92,146
Pseudo-R-squared	0.457	0.458	0.433	0.395

Standard errors in parentheses: $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Results from pseudo-maximum-likelihood specification relating the count of car-sharing trips with covariates of interest. Specifications are variants of Eq. (1), restricting the sample to car-sharing trips at different hours of the day. All specifications control for origin and destination fixed effects. Standard errors are clustered at the dyad level

the likelihood of car-sharing trips increases by approximately 3.7% [= ($exp(0.0037 \times 10)-1$]. Overall, these results are consistent with those from prior sections, suggesting that car-sharing is relatively more likely in neighborhoods that are not well-connected through public transit options.

Columns (4) and (5) of Table 7 present the elasticities associated with commuting and leisure trips, respectively. Results are similar to those using the full sample. We note only a slight decrease in elasticities for the commuting trips. Finally, in Table 8 we show elasticities for different hours of the day. Point estimates are generally similar to those from baseline specifications. It seems that elasticities are only lower for trips from 7am to 9am, which may be mostly considered commuting trips. This is consistent with an interpretation that during the early hours of the day, when there is an urgency to arrive at work on time, car-sharing customers are less sensitive to variations in distance and public transit availability.

5 Conclusions

Free-floating car-sharing (FFCS) services allow users to rent electric vehicles by the minute without restrictions on where to pick them up or drop them off within the company's service area. Beyond enlarging the choice set of mobility options, FFCS can reduce congestion and emissions in cities as they promote higher utilization rates of green vehicles. However, whether this potential is fully realized depends on the service's usage and substitution patterns. In this paper, we analyze these patterns through the lens of a unique dataset comprising the universe of FFCS rentals from a leading company in Madrid during 2019.

We contribute to answering the critical question of whether users view FFCS as a complement or substitute for public transport, cycling, or walking. If viewed as a complement, the increased demand for FFCS will promote public transport, cycling, or walking, reducing the use and sales of private vehicles and thus lowering congestion and local pollution. On the contrary, if viewed as a substitute, FFCS will lower public transport use and increase private vehicle use, thus increasing urban congestion.

Our analyses suggest that the most loyal customers, i.e., those who use the service more often, live in middle-income neighborhoods with relatively limited public transport options, making FFCS more appealing. These customers also typically live in neighborhoods with high pre-existing car ownership rates. Further, with a gravity model, we find that an increase in public transit travel times leads to an increased likelihood of car-sharing trips. Conversely, car-sharing is less likely for longer trips, possibly due to the substantial associated costs (as rentals are paid by the minute).

Taken together, our results are better aligned with a hypothesis that FFCS serves as a substitute for private vehicles, and as a complement to public transport, especially in areas with limited public transport options. We also find that many customers take FFCS for leisure purposes. Therefore, even if these users are unable or unwilling to pay for car-sharing for their regular commutes, the service is still a valuable option for them for leisure trips, in the absence of public transport alternatives.

We also analyze how FFCS usage patterns compare with those of privately owned vehicles. We note that FFCS can contribute to reducing congestion even when used

as substitutes for private vehicles, through a process of smoothing out the time at which drivers choose to start their trips. We find that the use of FFCS peaks earlier than overall traffic and is more broadly used during the summer months. This may be partly explained by the fact that FFCS users wish to avoid peak hours and congestion which can result in substantially higher expenses.

Last but not least, FFCS can have distributional implications depending on who uses the service most frequently. We find that FFCS companies tend to cover mostly high- and middle-income neighborhoods, thus reducing the possibility for lower-income individuals to use the service. Indeed, the average annual net income of car-sharing users in our sample is close to €20,000, thus substantially higher than the average net income for the entire municipality of Madrid (€16,700). The expansion of FFCS on the intensive margin (within currently covered neighborhoods) may therefore exacerbate inequality in mobility options.

We conclude by acknowledging some limitations of this study. For example, the methodology used to impute users' neighborhoods of residence allows for insights not previously explored but might suffer from classification errors. In particular, there is classification uncertainty for FFCS users who live close to the borders of neighborhoods, as they may choose to park on either side of the border. Also, our methodology only allows classifying a fraction of all trips. This may limit the applicability of our findings to a broader population. We have shown that results depend on several variables that might be time and location-specific. For instance, usage depends on the availability of other modes of transport, and their monetary and time costs, which in turn depend on traffic conditions and the availability of parking. Therefore, some of our findings do not necessarily extend to other municipalities or other moments in time. Nevertheless, our framework can well be implemented within other contexts, to strengthen the body of evidence regarding the benefits and costs of FFCS.

Data availability Data are available at https://doi.org/https://doi.org/10.5281/zenodo.7707902. This excludes the proprietary car-sharing trips data.

Code availability All code is available at https://doi.org/https://doi.org/10.5281/zenodo.7707902.

Declarations

Appendix

See Tables 9, 10, 11, 12 and Figs. 7, 8, 9, 10, 11.

Table 9 Regression results for mobility patterns: customer level (sub-sample with identified residence)

	Member loyalty				
	(1)	(2)	(3)	(4)	(5)
Log annual net income (€)	−14.351***	−13.774***	−13.307***	−13.873***	−14.840***
	(1.577)	(1.255)	(1.714)	(1.257)	(1.596)
Avg. no. of cars per household	13.212***		10.403***		14.189***
	(1.279)		(1.928)		(1.387)
% of residents with driving license	−0.291***		−0.283***		−0.289***
	(0.074)		(0.075)		(0.074)
No. metro stations per km^2		−0.567**	−0.169		
		(0.221)	(0.241)		
No. train stations per km^2		−3.182**	−1.562		
		(1.251)	(1.291)		
No. bus stops per km^2		−0.152***	−0.052		
		(0.035)	(0.041)		
Inadequate public transport network (%)				0.126***	−0.065
				(0.039)	(0.043)
Observations	11,818	11,818	11,818	11,818	11,818
R^2	0.020	0.018	0.020	0.012	0.020

Standard errors in parentheses: $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

The linear regressions use customer observations and are restricted to the sub-sample of car-sharing users with identified residence, excluding those living in Atocha, Aeropuerto, and Castilla neighborhoods. The loyalty measure, used as outcome variable, measures the weighted number of days a customer used the car-sharing service, given by the total number of days used, weighted by the total number of days left in 2019 since the first day they used the service, multiplied by the total number of days in a year. The regressions provide correlations between the characteristics and amenities of the neighborhood and the loyalty/intensity of usage of the resident customers

Table 10 Regression results for mobility patterns: neighborhood level (full sample)

	Member density					
	(1)	(2)	(3)	(4)	(5)	(6)
Log annual net income (€)	0.745*** (0.110)	0.935*** (0.329)	0.841*** (0.128)	1.001*** (0.259)	0.761*** (0.114)	0.948*** (0.326)
Average no. of cars per household		0.474 (0.307)		0.218 (0.294)		0.358 (0.264)
% of residents with driving license		−0.020 (0.021)		−0.014 (0.014)		−0.018 (0.019)
No. metro stations per km^2			−0.047* (0.027)	−0.035* (0.020)		
No. train stations per km^2			0.443 (0.315)	0.379 (0.230)		
No. bus stations per km^2			−0.002 (0.004)	−0.002 (0.005)		
Inadequate public transport Network (%)					0.013 (0.011)	0.007 (0.010)
Observations	135	135	135	135	135	135
R^2	0.241	0.307	0.348	0.368	0.279	0.316

Standard errors in parentheses: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

These regressions provide correlations between density of car-sharing membership and the characteristics and amenities of neighborhoods. The linear regressions use neighborhood-level observations and include all neighborhoods of the municipality of Madrid in addition to the four municipalities covered by our study area. The outcome variable measures the neighborhood member density, i.e., the percentage of car-sharing users in each neighborhood, out of the total resident population. This density is set to zero for neighborhoods where we did not identify car-sharing members

Table 11 Regression results for probability of trip happening, linear probability model: trip level (extended sub-sample with identified residence)

	Probability of taking a car sharing trip		
	(1)	(2)	(3)
Log annual net income (€)	−0.03777***		−0.00210***
	(0.00063)		(0.00060)
Member loyalty[1]		0.00275***	0.00275***
		(0.00001)	(0.00001)
Control for weekly seasonality	Yes	Yes	Yes
Control for monthly seasonality	Yes	Yes	Yes
Observations	3,682,648	3,682,648	3,682,648
R^2	0.015	0.101	0.101

Standard errors in parentheses: $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

The table provides regressions results using a linear probability model, where the dependent variable is an indicator equal to 1 when a customer takes a car-sharing trip and 0 otherwise. We use customer-by-date observations. The dependent variable is set as missing for all dates prior to the first usage date of a given customer. This variable therefore measures the probability of taking a car-sharing trip after trying the service for the first time in 2019

[1] Weighted number of days a customer used the car-sharing service in 2019, computed as the number of days the customer used the car-sharing service weighted by the total number of days left in 2019 since the first day they used the service, multiplied by total number of days in a year

**Table 12** Regression results for trip duration and distance: trip level (sub-sample with identified residence)

	Trip distance			Trip duration		
	(1)	(2)	(3)	(4)	(5)	(6)
Log annual net income (€)	−2.10846***	−2.01185***	−1.93357***	−3.77156***	−3.85011***	−3.81258***
	(0.02620)	(0.02639)	(0.02640)	(0.10407)	(0.10492)	(0.10528)
Member loyalty[1]		0.00379***	0.00249***		−0.00308***	−0.00467***
		(0.00014)	(0.00014)		(0.00054)	(0.00055)
Control for weekly seasonality	No	No	Yes	No	No	Yes
Control for monthly seasonality	No	No	Yes	No	No	Yes
Observations	497,009	497,009	497,009	497,011	497,011	497,011
R^2	0.013	0.014	0.023	0.003	0.003	0.005

Standard errors in parentheses: $*p < 0.1$, $**p < 0.05$, $***p < 0.01$

Notes The linear regressions use trip observations and are restricted to the sub-sample of car-sharing users with identified residence, excluding those living in Atocha, Aeropuerto, and Castilla neighborhoods. The outcome variables are trip distance [in kilometers, for columns (1) to (3)] and trip duration [in minutes, for columns (4) to (6)]
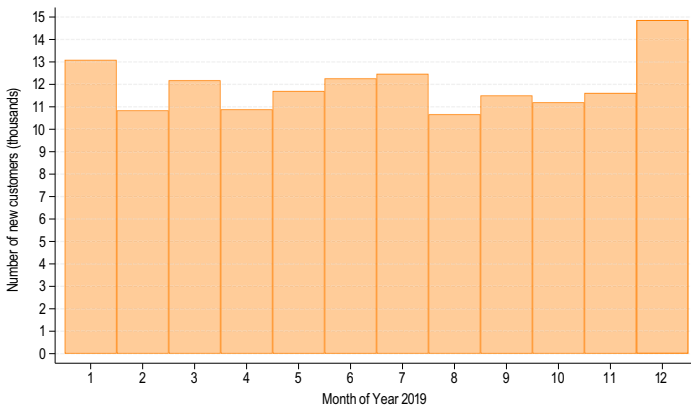[1] Weighted number of days a customer used the car-sharing service in 2019

Number of customers using the service
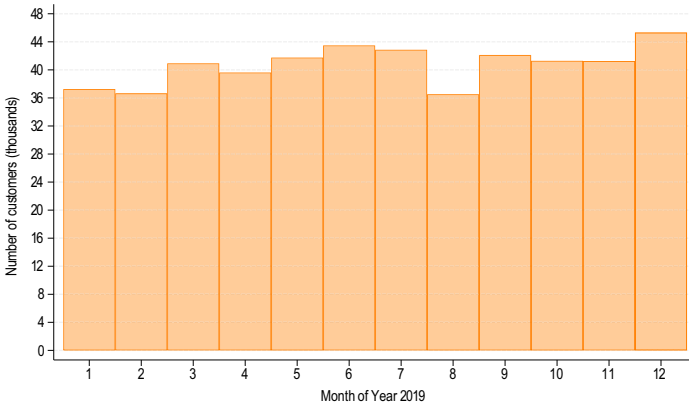
(a) All users

Number of new customers joining the service

(b) New users

Fig. 7 Number of car-sharing customers per month, in 2019. *Note* The figure portrays the number of car-sharing customers in 2019. Panel (**a**) shows the total number of customers that used the service in each month of the year, while panel (**b**) presents the number of new customers joining the car-sharing service for the first time, in each month
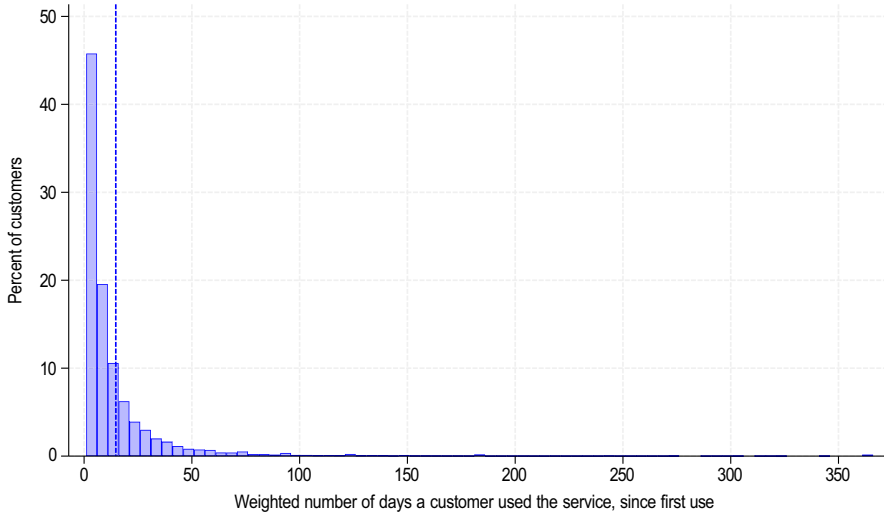
Fig. 8 Frequency distribution of member loyalty. *Note* The figure shows the frequency distribution of the weighted member loyalty measure, which is given by the number of days a customer used the car-sharing service, weighted by the total number of days left in 2019 since the first day he/she used the service, multiplied by the number of days in a year. The vertical lines give the average loyalty of the full sample of customers (14.7 days). The median loyalty is 6.8 days
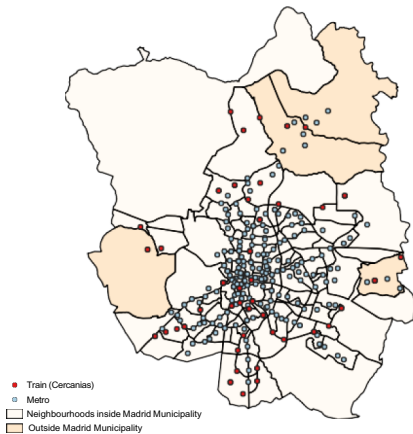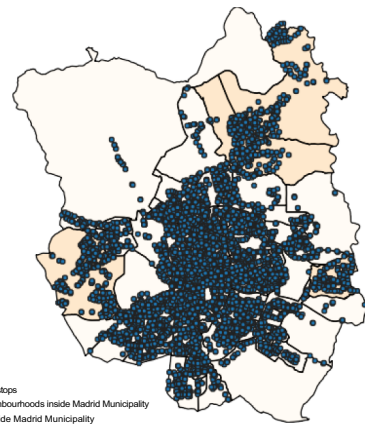
(a) Train and metro   **(b)** Bus

Fig. 9 Public transport network (metro, train, and buses). *Note* The figures show the geographical location of each metro, train, and bus station/stop in the municipalities of our study area (CRTM 2018a). All territorial units correspond to neighborhoods inside Madrid Municipality, except for the dashed units: Alcobendas, Coslada, Pozuelo de Alarcón, and San Sebastian de los Reyes municipalities
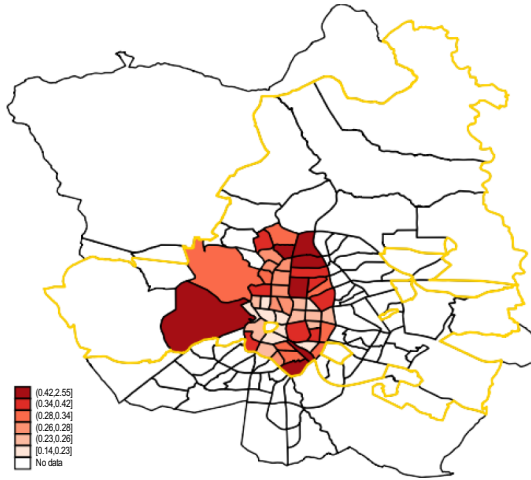
Fig. 10 Regulated parking slots, in 2018. Note: The figure portrays the number of regulated parking slots, weighted by the number of registered vehicles in each neighborhood. These parking slots are integrated within the Regulated Parking Service (*Servicio de Estacionamiento Regulado, SER*). In 2018, only 48 neighborhoods in the Municipality of Madrid were covered by the SER. All territorial units represented are neighborhoods inside Madrid Municipality, except for the municipalities of Alcobendas, Coslada, Pozuelo de Alarcón, and San Sebastian de los Reyes. The yellow line delimits our car-sharing study area
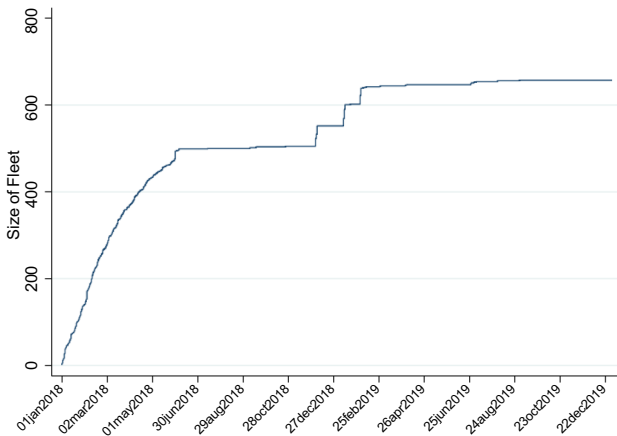

Fig. 11 Fleet of car-sharing company. *Note* The figure shows the FFCS rental company's cumulative number of cars (fleet) operating in Madrid during 2018/2019. Note that our main analyses are performed for the year of 2019, when the fleet was already stabilized

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