Factors associated with round-trip carsharing frequency and driving-mileage impacts in London

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Abstract

This study draws on respondents from Greater London within the 2016/17 wave (n=2,640) of Britain's Annual Survey of carsharing users, which we enrich with external data from the 2011 England and Wales Census and small-area income estimates. Focusing on round-trip carsharing users, we present multivariate analyses of frequency-of-usage of carsharing vehicles and impacts on annual vehicle miles travelled (VMT). Published attribute effects from other geographic and contextual circumstances are compiled and compared (where direct comparison is possible) with the specific attribute effects that we report in this paper. We demonstrate a statistically significant link between customer satisfaction with proximity of carsharing vehicles and VMT impacts. Car ownership (both current, and changes upon joining a carsharing service) is shown to have intuitive structural impacts. We find that frequent usage is associated *ceteris paribus* with increasing VMT after joining a carsharing service, and that subscribing to multiple types of carsharing is associated with frequent carsharing usage and a reduction in VMT. Interestingly, we did not find any significant effect of household income on either frequency-of-usage or VMT impacts.

Keywords: Carsharing, Travel behaviour, Frequency of usage, Vehicle miles travelled

1. Introduction

Carsharing (termed “car clubs” in the UK vernacular) is a form of shared-mobility in which a user accesses a vehicle to use for a relatively brief period (shorter on average than car rental; typically in units of minutes/hours rather than days). There are estimated to be 1.4 million members of such services in the US (Roberts, 2017) and 245,000 in the UK, with 79% of the UK total (193,500) based in Greater London (Carplus, 2017).

The expansion of shared mobility has in many cities taken place alongside supportive public policy, notably the provision of priority access to on-street parking. There is therefore a public interest in developing the evidence base regarding user behaviour, in order to maximise the public benefit. Due to this need, these research questions have attracted increasing focus from the transport research community (discussed in detail in Section 2).

The body of literature on the impact of carsharing has studied various aspects, including car ownership levels (Martin, Shaheen and Lidicker, 2010; Giesel and Nobis, 2016; Namazu and Dowlatabadi, 2018), impacts on vehicle miles travelled (VMT) (Cervero, 2003; Cervero and Tsai, 2003; Cervero, Golub and Nee, 2007), usage of alternative modes of transport (Martin and Shaheen, 2011b; Wang, MacKenzie and Cui, 2017), and environmental impacts such as pollutant emissions (Firnkor and Müller, 2011; Martin and Shaheen, 2011a; Chen and Kockelman, 2015). Usage pattern of carsharing members have also received attention, including Niels and Bogenberger (2017), Morency et al. (2011) and Habib et al. (2012).

This study focuses on the usage and impact of round-trip carsharing in Greater London as of 2016. London presents an interesting policy context, as strategic transport policy is the responsibility of London’s regional government, with direct responsibility for managing much of the street network held at the subregional municipal (“borough”) level of government. Due to the importance of on-street parking to carsharing services, each of London’s 33 boroughs therefore has great influence in determining which services operate within their boundaries and under which terms and conditions.

We employ data from Britain's Annual Survey of carsharing users. Results from the Annual Survey are traditionally (since inception in 2007) employed to track the growth and impacts (driving mileage, car ownership, emissions, etc) of carsharing activity. Documenting such impacts is important as many carsharing vehicles are stored on-street with the explicit permission of the relevant borough, and this permission depends in some cases on demonstrating that carsharing activity contributes to achieving the borough's goals for the transport sector. Therefore, the primary focus of the published results from the Annual Survey is to document system-wide effects, reported as a consistent time series in each edition of the Annual Survey.

Though not traditionally employed for purposes of identifying factors associated with carsharing user behaviour, the Annual Survey data are suitable for such purposes. The motivation for the present research is therefore to extend the usual descriptive statistical analyses via multivariate analyses of the survey's microdata (to allow identification of *ceteris paribus* effects) focusing on two of the principal dimensions of carsharing user activity: Frequency-of-usage and Impact of carsharing subscription on users' annual driving mileage.

The remainder of this paper is organised as follows: Section 2 synthesises the relevant background literature, and Section 3 introduces the individual analyses, with Section 4 concluding the paper.

2. Background

In the presentation of results (Section 4), we compare parameter effects that we obtained in this study with analogous effects from the literature. This discussion of the relevant background is therefore oriented around the two statistical analyses that we performed: Section 2.1 discusses prior studies of carsharing users' frequency of using the services, and Section 2.2 reviews studies on the carsharing impact of users' vehicle miles travelled.

2.1 Frequency of usage

One important stream of carsharing research addresses how the frequency-of-carsharing-usage is influenced by the characteristics of users, the type of carsharing, the existence of other modes of transport, and the land-use. This is an important dimension of carsharing user behaviour, as the number of users (which is widely quoted; see the 1st paragraph of the Introduction) and their frequency of usage combine to yield aggregate carsharing usage.

Table 1 summarises the body of literature that has investigated frequency of carsharing usage. Table 2 consists of only studies that have employed multivariate regression techniques, and which therefore reported parameter effects that are amenable to comparison with our results (presented in Section 4).

Table 2 presents studies that modelled either (or both) round-trip carsharing (in which a vehicle must be returned to its starting point) and one-way carsharing services (in which a vehicle may be returned anywhere within a designated operating zone), with common variables as columns. Age, population density, density of businesses, and public transport access are the explanators considered most frequently by researchers. In general, users who are younger and living in areas with higher density of users tend to use carsharing more frequently, and vice versa for high income users. The effects of other parameters are mixed, and the literature does not provide any clear guidance regarding different influences on usage frequency of round-trip versus one-way carsharing.

Another set of studies (shown only in Table 1, rather than also in Table 2) has investigated patterns of variation amongst carsharing users. Examples here include Morency et al. (2011), in which operational data allowed for examination of the repetitiveness of usage patterns over the length of a user's membership. The authors indicate that a large share of carsharing members used the service on an infrequent basis. Two other studies from China shown in Table 1 also employed clustering techniques to identify segments of carsharing users defined by usage patterns (Hui, Ding, Zheng, *et al.*, 2017; Hui, Wang, *et al.*, 2017).

Four of the studies shown in Table 2 analysed round-trip (as opposed to one-way) carsharing. Costain et al. (2012) found that the typical member makes fewer than 30 trips per year via carsharing, with a low male-female ratio and living in a lower median income household associated with higher frequency of carsharing usage. Habib et al. (2012) found the opposite effect for gender, and that younger members were more frequent users. Kang et al. (2016) found a similar result with respect to age, and de Lorimier and El-Geneidy (2011) found a consistent result as Costain et al. (2012) with respect to household income.

2.2 Impacts on driving mileage

The body of literature on the impact of carsharing on users' vehicles miles travelled (VMT) generally finds that users experience on average a decrease in VMT, though the aggregate effect masks wide variation. Martin and Shaheen (2011), for instance, demonstrate that the majority of users increase their VMT but by a small amount, and this is outweighed by the minority who decrease their VMT and do so by a larger average magnitude.

Much of the VMT-impacts literature consists of relatively early studies, and employ simple descriptive statistics rather than multivariate regression approaches (see Table 3). Several studies (Cervero et al., 2007; Costain et al., 2012) however have employed regression techniques to relate change in driving mileage with user characteristics; these are summarised in Table 4.

Consistent with Martin and Shaheen (2011), earlier longitudinal studies by Cervero and colleagues Cervero et al. (Cervero, 2003; Cervero and Tsai, 2003; Cervero et al., 2007) also indicate that the impact of VMT is non-linear. Cervero reported that carsharing users (in the San Francisco Bay area) tended to increase their VMT early in their carsharing membership, and then tended to switch to a net reduction of VMT in the longer term. The largest reduction of carsharing users' VMT was found to occur in the first year of becoming a carsharing member, and forgoing their current private vehicles or a planned car purchase are major explanatords for individuals reducing their VMT.

It is worth noting the extent of diversity in the types of data that researchers have employed to analyse these research questions. As noted previously, studies such as Morency et al (2011) have employed operational data from a carsharing service, in which each user's recorded usage over a long period (including date, time, duration, location, etc. of each usage episode) can be correlated with their characteristics. A more common type of data is user surveys; examples include Becker et al. (2017), Martin and Shaheen (2011), and the series of studies by Cervero and colleagues. The latter type of approach (which was taken for the present study, as described in the next section) is limited by considerations of sampling errors and biases, and recording of carsharing usage with much less information than the usage-episode-specific information that is in principle available through operational datasets. Operational datasets have limitations as well, however, including limited demographic details and a lack of information about journey characteristics such as purpose and whether the journey involved transporting any large items (luggage, etc.). Operational datasets also do not generally capture information on carsharing members' usage of other forms of transport, and their travel behaviour prior to joining the carsharing service, which is needed to perform analysis of VMT impacts.

3. Data

An Annual Survey of carsharing users in the UK has been undertaken each year since 2007 (Carplus, 2017). The data employed for this study are sourced from the tenth edition, with field data collection during Autumn 2016. The survey was administered via a CASI protocol, with all 'active' carsharing subscribers invited to participate via email by the operator of the service to which they subscribe (the definition of an active member is made individually by each operator).

The response rate within Greater London was 2% (4,023 / 193,500); single-digit response rates are not uncommon in bespoke surveys of shared-mobility users, and in the case of this specific survey the low response rate could be linked to the decentralised definition of

‘active’ with some carsharing operators applying looser criteria than others. The UK’s National Travel Survey (Lepanjuuri et al., 2017) and the US’s National Household Travel Survey (NHTS, 2016) (as well as various regional travel surveys in each of these countries) have both begun collecting data on shared-mobility in recent years, which will in due course provide the opportunity to evaluate whether (and in which ways) the Annual Survey’s data are or are not statistically representative.

The Annual Survey contains an “operator survey” completed by each carsharing operator directly, as well as the “member survey”; the latter is the data employed in this research. The operator survey contains data such as the emissions-classification of their vehicle fleet.

After removing participants surveyed by one-way carsharing operators and respondents with incomplete data, the database used for analysis in this research consists of 2,640 respondents living in Greater London. The Annual Survey data contains the following data points used in this research²:

- The year of joining carsharing
- The membership of other types of carsharing
- The time, purpose, and number of adults and children travelled with in the last carsharing trip
- The alternative mode if there was no carsharing in the last carsharing trip
- Carried large item or not in the last carsharing trip
- The reason for using carsharing in the last carsharing trip
- The frequency of using different modes of transport including carsharing
- Car ownership before and after joining carsharing
- The vehicle miles travelled change after joining carsharing

² The survey questionnaire is accessible via (Carplus, 2017).

- Satisfaction of the proximity, availability, and quality and condition of the carsharing vehicles

Variables employed in this study are summarised in Table 5, along with descriptive statistics (mean and standard deviation). A correlation matrix of the variables is available from the authors on request.

Due to the focus of the Annual Survey on system-wide monitoring rather than the user-specific determinants of carsharing activity, demographic characteristics of respondents and the spatial context of their residence are notable omissions. The Annual Survey dataset contains the full residential postcode³ of each respondent, which we drew on to enrich it with external data. The external data were average household income (London Datastore, 2015) and the following variables from the most recent England and Wales Census (Office for National Statistics, 2011b, 2011a, 2011c), all joined to the Annual Survey data at the “Lower-Layer Super Output Area” geographic unit (average population ~1,500):

- Level of education (expressed as percentage of adults with bachelor’s or higher degree)
- Household composition (expressed as percentage of households having at least one child under age 16)
- Population density (persons per hectare)
- Housing tenure (expressed as percentage of households that own their dwelling unit)

4. Numerical analysis

The analyses consisted of two sets of linear regression models (self-reported frequency of usage and impact-of-carsharing subscription on annual VMT). The remainder of this section

³ UK postcodes are much smaller than US zip codes; each residential UK postcode covers ~15 dwelling units.

presents these two analyses in turn. We note that the parameter estimates do not indicate causality, therefore our speculation in this section (and the Conclusions section which follows) regarding possible interpretations employs conditional language ('may', 'could', 'suggests', etc.) and should be viewed as informed guesswork rather than demonstration of causality.

4.1 Frequency of usage

Frequency of carsharing usage was collected via a five-point scale (3+ times/week, 1-2 times/week, At least once per month, At least once per year, Never), with user responses converted into usage episodes per year via the midpoint of each category (the 3+ times/week category which does not have a midpoint was converted at the rate of 3 uses/week = 156 uses/year).

Table 6 contains the results from the analysis of frequency of usage. We report two sets of parameters: Model #1a includes all parameters, and Model #1b is a reduced-form model of only parameters with p-values less than 0.15 (i.e. highly-insignificant parameters are excluded).

Model #1b demonstrates that being a newer user (i.e. having joined recently) is associated with frequent usage of the carsharing service, which may suggest that longer-term users' needs for car-based mobility tend to reduce over time. Having an additional subscription to a one-way carsharing also positively associated with the frequency of using round-trip carsharing, which suggests that the presence of the newer one-way form of carsharing is complementary (rather than a substitute) to how frequently subscribers use round-trip carsharing. This is somewhat different than the findings of Becker et al. (2017), who report that membership in a round-trip carsharing system has a negative effect on the frequency of one-way carsharing usage.

Having carried heavy luggage during the most recent carsharing usage was negatively associated with frequency-of-usage, which may reflect that this type of travel need is

relatively infrequent, and other non-carsharing modes are typically used by subscribers who use carsharing for this type of journey. Having shed a private car upon joining carsharing is positively linked with frequency-of-usage, perhaps indicating that such users have latent high demand for automobility which manifests as frequent carsharing usage. Current ownership of a car is, however, strongly negatively linked with frequency-of-carsharing-usage. This is intuitive, as carsharing usage fees are generally charged at average cost (which must include a component for recovery of fixed capital costs) whereas car owners only face [lower] marginal costs when using a private household car. For carsharing members that own a car, circumstances that may serve as motivators for acquiring their carsharing membership could be the unavailability of their household vehicle at specific times, or their desire to use carsharing as a 'last-mile' mode of travel as part of a multimodal journey employing public transport for the longest leg of the journey, or as a form of "mobility insurance" in case their personal car becomes out of service unexpectedly.

A user indicating that their most recent carsharing journey would have been made by bicycle or walking if carsharing were unavailable is another factor that we found to be positively linked with the frequency of usage. We do not have a clear interpretation for this result; it suggests that for at least some carsharing journeys the nearest substitute modes of transport are walking or cycling.

We found a positive link between shared-vehicle occupancy and frequency-of-usage, which is consistent with (Cervero and Tsai, 2003). This effect is statistically significant for both adults and children as car occupants, with a larger magnitude for children. The journey purposes most strongly associated with frequency-of-usage are Commuting and travel-to-Education, with Personal Business and Leisure comparatively weakly linked with frequent usage.

The bottom row of Table 2 compares our results to common correlates of carsharing frequency-of-usage reported in the literature. The only directly comparable effect for which

we report a statistically significant effect is the effect of car ownership; our negative effect is consistent with the finding of Müller et al. (2017) (which was in the context of free-floating carsharing), but the opposite sign of the results found by Becker et al. (2017).

4.2 Impacts on annual driving mileage

Table 7 presents the regression results of the impact of round-trip carsharing subscription on each user's annual VMT (including all cars whether owned privately, rented, accessed from the carsharing operator or a family member, etc.). Consistent with earlier literature (e.g. (Martin and Shaheen, 2011a)), the UK's Annual Survey has consistently over time found that there is a net negative impact (i.e. reduction) on annual VMT (570 miles/person/year in 2016/17 in London), which arises from a small proportion of users decreasing their VMT each by a large amount, and a larger proportion increasing their VMT but by a much smaller amount.

The results shown in Table 7 arise from a simple transformation of the VMT impacts, in which we capped the impacts at +5,000 miles/yr (for increases) and -5,000 miles/yr (for decreases). We retain the small number of people ($n=70$) with VMT impacts larger than $\pm 5,000$ miles in the analysis; we simply recoded their VMT impact to the capped value. This reduction in the impact of outliers in the data improves goodness-of-fit from an adjusted r^2 of 0.10 to 0.17. All parameter effects retain their sign; results from the 'uncapped' regressions are available from the authors on request.

Table 7 shows that fewer variables in this analysis are statistically significant, compared to the analysis of frequency of carsharing usage (Table 6). We find that being a member of both round-trip and one-way carsharing is associated with having reduced one's annual VMT. The only statistically significant effect (negative) due to journey purpose of most recent carsharing activity is for the Visiting Friends/Relatives purpose. We do not have a hypothesis for this result pertaining to this journey purpose; further research will be needed to determine whether this result is robust across different contexts, and if so why it is found. Carrying

heavy luggage on one's most recent carsharing journey was positively associated with VMT impacts; this suggests that such journeys might have otherwise been performed by non-driving forms of travel. How frequently one uses a taxi was found to be positively linked with frequency of usage (Table 6), but negatively linked with VMT impacts. This could indicate that taxi usage and carsharing usage are complementary and taken together serve as a combined substitute for private car travel. Also, as would be expected, having decreased one's private car ownership upon subscribing to a carsharing is very strongly linked with also decreasing one's annual VMT.

Finally, the level-of-satisfaction of carsharing subscribers with the proximity of the carsharing vehicles to their home is associated with VMT reductions, which suggests that a greater density of carsharing vehicles may be linked with larger VMT reductions.

In comparison to previously published regression analyses of VMT impacts (Table 4), the effects that we report are neither strictly consistent nor strictly inconsistent with the existing published literature, because either our results or those in the literature (or both) are statistically insignificant for effects which are common across studies.

5. Conclusions

In order to analyse how carsharing users in London use the service and its impact of on their car usage, we performed multivariate analysis of the 2016/17 wave of Britain's Annual Survey of carsharing users, focusing on residents of Greater London that are subscribers of round-trip carsharing. The regression analyses that we undertook of frequency of carsharing usage and impacts on annual VMT allow *ceteris paribus* attribute effects to be estimated. We then compare the effects we obtained for London in 2016 with results from prior studies in other contexts.

Our results build on those of earlier studies in several notable ways. In some instances Britain's data resources allow us to identify effects that are intuitive but not previously

reported in the literature, such as using carsharing to transport bulky items (“luggage”) being associated with infrequent carsharing usage. We also find that, rather intuitively, using carsharing for Commuting and Travel-to-Education are more strongly associated with frequency-of-carsharing than other trip purposes (e.g. Leisure and conducting Personal Business). In other instances we find results that diverge from earlier literature, for instance with regard to the effect of car ownership on usage frequency of round-trip carsharing. The only earlier study to report such an effect (Kang et al. 2016) found car ownership to be positively associated with carsharing usage frequency; we report the opposite. One possibility is that this divergence with previously published results reflects that the causal mechanisms underpinning the effect are context-dependent, such as varying with differences in the cost structures of private car ownership and public policies towards automobility. Further accumulation of empirical results will be needed to answer this question.

With regard to impacts on driving mileage upon joining round-trip carsharing, we find that the trip purpose most significantly associated with a decrease in VMT is use of carsharing to Visit Friends/Relatives. It may be that these journeys tend to take place at times and in places where public transport is less competitive than, for instance, traditional commuting patterns. This result may therefore indicate that carsharing members that use the service for Visiting Friends/Relatives have reduced their driving mileage by switching from driving for other types of journeys where non-car forms of transport are more competitive.

Interestingly, we found that income, traditionally one of the strongest predictors of travel behaviour, was not significantly associated with either carsharing usage frequency or driving mileage impacts. There is evidence of income decreasing in recent years in its salience as an explanator of driving behaviour, with car use declining most sharply for higher income groups (see, e.g., Fig. 14 in Goodwin (2012)). Other studies have found that income is negatively associated with usage frequency of carsharing (Costain et al. 2012; de Lorimer and El-Geneidy, 2013) and linked with positive (i.e. increasing) VMT impacts upon joining a

carsharing service. One possibility is that the data fusion approach that we employed to impute an income level to each survey respondent based on average income of their neighbourhood could cause our approach to fail to detect a 'true' but weak income effect. Further research will be needed to either provide further support for these earlier findings or for the lack-of-significant effect that we found in the present study.

We were able to link between users self-reported satisfaction with various aspects of their carsharing service and frequency-of-usage/VMT-impacts. The only statistically significant relationship that we found is with respect to the proximity of the service's vehicles to one's home: we found that higher satisfaction with the proximity of vehicles is associated with larger declines in driving mileage. This suggests that monitoring and ensuring high levels of vehicle availability within carsharing service areas may be a sensible strategy to encourage reductions in VMT.

It is hoped that further findings will emerge in the near future to either confirm or contrast with the results that we present here, and that the results we present in this study will be useful to future researchers as well as both practitioners in the carsharing industry and public sector staff that set policies relating to carsharing.

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Tables

Table 1: Previous studies of frequency of carsharing usage

Citation	Data source	Methodology	Notable findings
(Müller, Correia and Bogenberger, 2017)	DriveNow Berlin (free-floating); Census	Negative binomial model	Free-floating carsharing has higher demand in higher-income areas
(Becker, Ciari and Axhausen, 2017)	A free-floating carsharing operator in Basel, Switzerland; Canton of Basel-Stadt; Canton of Basel-Land	Linear Cliff-and-Ord-type SARAR model; Conditional logit model	Free-floating carsharing mainly used for discretionary trips; Station-based one-way carsharing depends more strongly on public transport, whereas free-floating carsharing serves to “fill in gaps” in the public transport network
(Morency, Trépanier and Agard, 2011)	Communauto (round-trip)	k-mean cluster analysis	Many low-frequency members; Frequency and travel distance are highly correlated; Members found to have similar recurring weekly patterns approximately two thirds of the time
(Costain, Ardron and Habib, 2012)	AutoShare Toronto (round-trip) Census;	Binary logit model; Log-logistic hazard model; Negative binomial model; Multinomial logit model; Multivariate regression	Accessibility to the service an important determinant of membership growth and frequency of usage; Members make less than 30 trips per year on average, and more than half travel less than 40 km by carsharing; Most trips for non-work purpose; Most trips short-distance and during off-peak periods; usage is higher on weekends; Low pricing and high perceived savings lead to longer membership duration; Carsharing members generally environmentally conscious and willing to pay for carbon offset; Membership duration and frequency of usage are lower in dense neighbourhoods
(Habib <i>et al.</i> , 2012)	Communauto Montreal (round-trip)	Hazard model; Binomial probit model; Ordered probit model;	Likelihood of unsubscribing in any given period is negatively linked with increasing membership duration; Increasing number of cars at stations does not influence the decision of remaining members, however does increase frequency of usage; Membership duration increases with zonal population but decreases with zonal household car ownership
(de Lorimier and El-Geneidy, 2011)	Communauto Montreal (round-trip)	Multilevel regression model; Logistic regression model	Size of carsharing station (# of vehicles) has a large impact on both availability and usage of the carsharing service; Seasonal impact on both availability and usage; Carsharing stations close to metro stations have low availability but high usage; Users prefer newer cars

(Kang, Hwang and Park, 2016)	GreenCar Seoul (round-trip)	Linear regression	Carsharing demand is high in business areas and areas with many young residents (20s and 30s), high car ownership and low underground train access
(Hui, Ding, Qian, <i>et al.</i> , 2017)	Chefenxiang Hangzhou (round-trip)	Clustering LARge Applications (CLARA)	5 clusters of users are identified, and carsharing is heavily used for commuting in 4 of the segments; Having "open-minded" residents is important; Central areas and areas with "good availability of parking lots" have higher demand
(Hui, Wang, <i>et al.</i> , 2017)	Chefenxiang Hangzhou (round-trip)	Cluster analysis (specifics not stated)	Long-term users classified into 4 clusters by the frequency of usage, weekly usage pattern, and time of pick-up and returning the car
(Schmöller <i>et al.</i> , 2015)	A free-floating carsharing operator in Berlin and Munich, Germany; Infas	k-mean; linear regression	Demand highly concentrated in small number of temporal peaks and spatial "hot spots"; Weather significantly impacts demand; Density of businesses and rent price ratio both positively impact demand

Table 2: Parameters of regression models in the literature of carsharing usage frequency

Citation	Gender (Male)	Income	Population density	Age	Car ownership	Tenure (rent)	Household with children	Density of businesses	Public transport access	Carsharing member density
(Müller, Correia and Bogenberger, 2017) (free-floating)			Negative**	Positive* for presence of children (up to age 14) and adults aged 25- 49; negative for other age bands	Negative*			Positive*		
(Becker, Ciari and Axhausen, 2017) (free-floating)			Positive**		Positive			Negative***	Positive	Positive***
(Costain, Ardron and Habib, 2012) (round-trip)	Negative*	Negative*	Negative**							
(Habib <i>et al.</i> , 2012) (round-trip)	Positive***			Negative***						
(de Lorimier and El-Geneidy, 2013) (round-trip)		Negative*						Negative***	Positive*	Positive***
(Kang, Hwang and Park, 2016) (round-trip)				Negative***	Positive***				Negative***	
(Schmöller <i>et al.</i> , 2015) (free-floating)				Negative (significance not stated)		Positive (significance not stated)	Positive (significance not stated)	Positive (significance not stated)		
Our result (round-trip)		Positive	Positive		Negative*	Positive	Negative			

Note: *, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

Table 3: Previous studies of carsharing subscription impacts on vehicle miles travelled

Citation	Data source	Methodology	Notable findings
(Martin and Shaheen, 2011a)	Survey of members of 11 carsharing services in North America	Descriptive	Members decrease VKT/year by 27%; Mean observed impact of carsharing on greenhouse gas emission is -0.58 ton/year; full impact is -0.84 ton/year
(Costain, Ardron and Habib, 2012)	AutoShare Toronto (round-trip) Census;	Binary logit model; Log-logistic hazard model; Negative binomial model; Multinomial logit model; Multivariate regression	See row describing this study in Table 1
(Cervero, 2003)	Survey of City Carshare San Francisco Bay Area (round-trip) members	Binomial logit model;	VMT of carsharing members decreases less than a control group
(Cervero and Tsai, 2003)	Survey of City Carshare San Francisco Bay Area (round-trip) members	Binomial logit model; Multiple regression	VMT of carsharing members decreases more than non-members (0.09 average decrease for members and 6.37 increase for non-members); 73.3% of members shed or opt not to purchase a vehicle, compared to 42.9% of non-members
(Cervero, Golub and Nee, 2007)	Survey of City Carshare San Francisco Bay Area (round-trip) members	Multinomial logit model; Binomial logit model; Ordinal logit model; Multiple regression	Members' mean mode-adjusted VMT decreases by 67% over the 4 years; Users 12% more likely to shed a private vehicle than non-members; Complementarity between public transport and carsharing
(Martin and Shaheen, 2016)	Survey of Car2go (free-floating) members in 5 cities in North America	Descriptive	Most members walk more frequently and use public transport and taxi less frequently; FFCS affects a small number of users' decision to shed or postpone vehicle purchasing, but net impact on car ownership is a decrease; The minority who sell/discard vehicles contribute most to VMT reduction, and net VMT reduction of car2go members
(Chen and Kockelman, 2015)	Summary of published literature		"Potential carsharing users" reduce energy use and greenhouse gas emission 48% upon joining carsharing. Reduction would be 5% of household VMT if scaled up to all US households; VMT can be reduced by 33% to 69% if "potential users" join carsharing

Table 4: Parameters of regression models in the literature of VMT change

Citation	Gender (Male)	Income	Population density	Age	Car ownership	Car decrease	Tenure (rent)	Household with children
(Costain, Ardron and Habib, 2012) (round-trip)	Positive	Positive**	Positive**					
(Cervero, Golub and Nee, 2007) (round-trip)				Quadratic (with age being negative and age squared being positive)	Negative			
Our result		Positive	Positive		Negative	Negative***	Positive	Positive

Note: *, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

Table 5: List of variables and descriptive statistics

Variable name (as appears in subsequent tables)	Description	Mean	Standard deviation
Frequency: Carsharing	Frequency of using carsharing, per year	30.47	35.14
Impact on VMT	Vehicle miles travelled change after joining carsharing	-563.99	2,466.28
Impact on VMT (trimmed)	Vehicle miles travelled change after joining carsharing (trimmed at -5000 and 5000 miles)	-368.39	1,473.89
HH income	Zonal-average household annual income in GBP/10000	£57,293	£18,173
% of adults with degree	Zonal-fraction of people having level 4+ degrees	0.46	0.14
% of HHs with children	Zonal-fraction of household with children	0.26	0.09
% of HHs that own residence	Zonal-fraction of household owning properties	0.39	0.17
Population per hectare	Zonal population density	127.49	65.54
# years of membership	Number of years of membership (before 2016)	3.02	3.16
Member of one-way carsharing	1 if the respondent subscribes both round-trip and one-way carsharing and 0 otherwise	0.08	0.27
Purpose: Business	1 if the purpose of the last carsharing trip is business and 0 otherwise	0.08	0.27
Purpose: Education	1 if the purpose of the last carsharing trip is education and 0 otherwise	0.02	0.15
Purpose: Shopping	1 if the purpose of the last carsharing trip is shopping and 0 otherwise	0.27	0.45
Purpose: Pers. Bus	1 if the purpose of the last carsharing trip is personal business and 0 otherwise	0.35	0.48
Purpose: Visit	1 if the purpose of the last carsharing trip is visit friends/family and 0 otherwise	0.02	0.15
Purpose: Leisure	1 if the purpose of the last carsharing trip is leisure and 0 otherwise	0.23	0.42
Purpose: Commuting	The purpose of the last carsharing trip was commute (binary)	0.03	0.16
# adult (age 16+) pax	The number of adults travelled with in the last carsharing trip	1.19	0.89
# child (under age 16) pax	The number of children travelled with in the last carsharing trip	0.29	0.66
Luggage	1 if the respondent carries luggage in the last trip (binary)	0.49	0.50
	If carsharing was not available in your last carsharing trip...	0.30	0.46
Journey cancelled	...1 if the respondent would not make the trip and 0 otherwise	0.09	0.28
Journey by walk/bicycle	...1 if the respondent would choose to walk or bike and 0 otherwise	0.40	0.49
Journey by PT	...1 if the respondent would take public transport (bus, underground train or train) and 0 otherwise	0.33	0.47
Journey by taxi	...1 if the respondent would take taxi or on-demand taxi and 0 otherwise	0.23	0.42
Journey by car	...1 if the respondent would choose car and 0 otherwise	0.50	0.50
PT service poor	1 if the reason of using carsharing in the last carsharing trip is because of the inconvenience of public transport and 0 otherwise	157.41	79.70
Frequency: Walk/bicycle	Frequency of walk or bike per year	257.19	128.80
Frequency: PT	Frequency of taking public transport (bus, underground train or train) per year	51.77	65.31
Frequency: Car	Frequency of using car per year	42.56	48.77
Frequency: Taxi	Frequency of using taxi or on-demand taxi per year	0.32	0.47
Car ownership decrease	1 if the car ownership was decreased after joining carsharing and 0 otherwise	0.23	0.42
Own car now	1 if the respondent still has a car now and 0 otherwise	4.08	1.13
Satisfaction: Proximity	Level of satisfaction with the proximity of carsharing vehicles to one's residence (5 is the highest and 1 is the lowest)	3.90	1.01
Satisfaction: Availability	Level of satisfaction with the availability (temporal) of carsharing vehicles (5 is the highest and 1 is the lowest)	4.14	0.94
Satisfaction: Quality/Condition	Level of satisfaction with the quality and condition of carsharing vehicles (5 is the highest and 1 is the lowest)	0.54	0.50
Used carsharing last month			

Table 6: Regression results of frequency of carsharing usage per year

	Model #1a (full model)		Model #1b (variables with p>0.15 excluded)	
	Coefficient	p-value	Coefficient	p-value
Intercept	35.694***	<0.001	34.198***	<0.001
HH income (£/year)	4.920	0.439	-	-
% of adults with degree	-25.751***	0.010	-10.125*	0.056
% of HHs with children	-19.592	0.147	-	-
% of HHs that own residence	-3.633	0.565	-	-
Population per hectare	0.006	0.640	-	-
# years of membership	-0.695***	0.007	-0.734***	0.002
Member of one-way carsharing	11.600***	<0.001	11.029***	<0.001
Purpose: Business	18.366***	<0.001	14.678***	<0.001
Purpose: Education	22.316***	<0.001	27.228***	<0.001
Purpose: Shopping	11.350***	<0.001	10.864***	<0.001
Purpose: Pers. Bus	5.687***	0.002	4.892***	0.004
Purpose: Visit Friends/Relatives	2.648	0.608	-	-
Purpose: Leisure	4.949**	0.013	4.062**	0.027
Purpose: Commuting	33.906***	<0.001	30.703***	<0.001
# adult (age 16+) pax	1.673*	0.063	1.594*	0.059
# child (under age 16) pax	2.079*	0.082	2.163*	0.054
Luggage	-9.241***	<0.001	-8.710***	<0.001
Journey cancelled	-0.922	0.679	-	-
Journey by walk/bicycle	4.592	0.110	4.632*	0.080
Journey by PT	-1.285	0.513	-	-
Journey by taxi	0.640	0.738	-	-
Journey by car	-1.447	0.501	-	-
PT service poor	0.200	0.901	-	-
Frequency: Walk/bicycle	-0.026**	0.011	-0.025***	0.008
Frequency: PT	0.009	0.173	-	-
Frequency: Car	0.031*	0.052	-	-
Frequency: Taxi	0.101***	<0.001	0.101***	<0.001
Car ownership decrease	3.868**	0.027	3.878**	0.017
Own car now	-5.632**	0.019	-4.131**	0.026
Satisfaction: Proximity	1.152	0.176	-	-
Satisfaction: Availability	0.783	0.406	-	-
Satisfaction: Quality/Condition	-1.737*	0.055	-1.248	0.115
Adjusted r^2	0.162		0.146	

Note: *, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

Table 7: Regression results of VMT change ('capped' at -5,000 and +5,000 miles/yr)

	Model #2a (full model)		Model #2b (variables with p>0.15 excluded)	
	Coefficient	p-value	Coefficient	p-value
Intercept	-256.422	0.549	326.515**	0.020
HH income (£/year)	374.224	0.223	-	-
% of adults with degree	497.472	0.329	-	-
% of HHs with children	672.116	0.322	-	-
% of HHs that own residence	-514.494	0.109	-	-
Population per hectare	0.117	0.860	-	-
# years of membership	0.070	0.996	-	-
Member of one-way carsharing	-406.442***	0.006	-336.256***	0.006
Used carsharing last month	-74.061	0.389	-	-
Purpose: Business	-91.178	0.531	-	-
Purpose: Education	-259.147	0.372	-	-
Purpose: Shopping	-45.683	0.632	-	-
Purpose: Pers. Bus	-7.045	0.938	-	-
Purpose: Visit Friends/Relatives	-416.500	0.109	-539.736**	0.021
Purpose: Leisure	110.731	0.264	-	-
Purpose: Commuting	-73.412	0.792	-	-
# adult (age 16+) pax	-21.834	0.632	-	-
# child (under age 16) pax	-16.481	0.783	-	-
Luggage	180.353**	0.037	132.669**	0.048
Journey cancelled	144.329	0.202	-	-
Journey by walk/bicycle	-14.914	0.918	-	-
Journey by PT	211.723**	0.031	-	-
Journey by taxi	49.981	0.598	-	-
Journey by car	21.049	0.845	-	-
PT service poor	-50.544	0.525	-	-
Frequency: Carsharing	-0.554	0.698	-	-
Frequency: Walk/bicycle	0.309	0.532	-	-
Frequency: PT	-0.062	0.843	-	-
Frequency: Car	-0.020	0.979	-	-
Frequency: Taxi	-1.855	0.046	-1.305*	0.067
Car ownership decrease	-1296.944***	<0.001	-1,285.514***	<0.001
Own car now	-3.284	0.978	-	-
Satisfaction: Proximity	-101.874**	0.015	-65.144**	0.033
Satisfaction: Availability	4.739	0.918	-	-
Satisfaction: Quality/Condition	44.592	0.313	-	-
Adjusted ρ^2	0.170		0.173	

Note: *, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively