Electric and conventional vehicle usage in private and car sharing fleets in Germany

Wolfgang Habla, Vera Huwe, Martin Kesternich

Angaben zur Veröffentlichung / Publication details:

Habla, Wolfgang, Vera Huwe, and Martin Kesternich. 2021. "Electric and conventional vehicle usage in private and car sharing fleets in Germany." *Transportation Research Part D: Transport and Environment* 93: 102729. https://doi.org/10.1016/j.trd.2021.102729.

Electric and conventional vehicle usage in private and car sharing fleets in Germany

Wolfgang Habla[a,*], Vera Huwe[a], Martin Kesternich[a,b]

[a] ZEW – Leibniz Centre for European Economic Research, Mannheim, Germany
[b] Department of Economics, University of Kassel, Germany

1. Introduction

Electric vehicles are considered to be a key technology for developing future transport systems, particularly due to their ability to reduce road noise, local air pollutants, and tailpipe carbon emissions (e.g., BMVI, 2019). However, whether battery electric vehicles (EVs) are able to actually decrease the total amount of carbon emissions being released during their lifetime as compared to vehicles with internal combustion engines (ICEVs) depends on various factors including the production process of the battery, the electricity mix, as well as the degradation and recycling or reuse of the battery. A major factor affecting the carbon footprint after the purchasing decision are the actual usage patterns, i.e., how many kilometers EVs are actually driven over their lifetime. Recent studies suggest that only when the total vehicle kilometers traveled (VKT) are sufficiently large do EVs have an advantage over ICEVs in terms of greenhouse gas emissions (e.g., Hoekstra and Steinbuch, 2020).

From an environmental economic point of view, an important question is whether EV usage (partly) substitutes the total VKT of existing or replaced ICEVs within a given household (which would not necessarily increase the total VKT within this household) or whether it serves as a complement to ICEV usage (which would increase the total VKT of this household). As the purchase of EVs is heavily subsidized in many countries, the post-purchase use (Hasan and Simsekoglu, 2020) of EVs is critical for evaluating the environmental effectiveness of these subsidies. If, in the end, EVs are driven much less than ICEVs, either because they are often used as a second car instead of replacing an existing ICEV or because EV drivers per se use their car less than ICEV drivers, then the granted subsidies for the purchase of an EV imply very high marginal costs of abating CO_2, indicating an ineffective (and inefficient) policy.

* Corresponding author.

https://doi.org/10.1016/j.trd.2021.102729

Finally, if EVs exhibit much higher VKT than ICEVs, e.g., due to lower operating costs and potential rebound effects (Sorrell and Dimitropoulos, 2008; Gillingham et al., 2016), then their increased usage will worsen other problems, such as congestion and low utilization of public transit. It is therefore of utmost importance to monitor the post-purchase use of EVs as compared to that of ICEVs.

For consumers, EVs differ from ICEVs in a number of ways that potentially affect their use. Apart from slightly different driving characteristics, important differences persist with respect to costs (including purchase, maintenance and running costs) and cruising ranges. While EVs tend to be more expensive with respect to the purchase price than comparable ICEVs, even after deducting the abovementioned subsidies, they typically have lower variable costs per km, as electricity usually comes at a lower cost than fossil fuels. This could potentially increase VKT. By contrast, EVs still suffer, despite recent technological advances, a disadvantage as compared to ICEVs with respect to cruising range due to the lower energy density of batteries compared to fossil fuels. Also, the network of publicly available charging stations is currently much less dense than the network of petrol stations.[1] As a result, non-monetary costs associated with EV use, e.g., time costs for trip planning and recharging or psychological costs, may arise (e.g., Hasan and Simsekoglu, 2020; Alkhalisi, 2020). Furthermore, drivers might suffer from behavioral lock-in effects, cognitive biases or range anxiety – factors which speak against the (extensive) use of EVs. Range anxiety describes the fear that a vehicle has insufficient range to reach the driver's desired destination and thus strands its occupants. It is often presumed that range anxiety constitutes a major barrier to the adoption of EVs, suggesting that EVs and ICEVs may not yet be perceived to provide substitutable services.

In this paper, we focus on the post-purchase use of EVs as compared to that of ICEVs. We first discuss the monetary incentives for using an EV vs. an ICEV based on the underlying cost structures for two different types of ownership, namely privately owned and shared cars. We also examine potential non-monetary costs related to EV usage. We then confront the resulting predictions with car-level micro data from Germany. To investigate the use of EVs and ICEVs for both ownership types, we bring together car-level micro data on privately owned vehicles from the most recent German National Travel Survey (Mobilität in Deutschland 2017) and booking data from Flinkster, the largest stationary car sharing provider in Germany. Together, these datasets cover two important pillars of individual mobility demand and convey a very detailed picture of the current state of EV use in one of the largest car markets in the world. We provide empirical evidence on how observed usage differs between EVs and ICEVs both for daily and annual usage for both ownership types.

The comparative analysis between privately owned and shared vehicles is important for a variety of reasons. First, EV penetration is substantially higher in the car sharing fleet than in the private car fleet (5.3% vs. 0.002% in our data). Secondly, car sharing clients who frequently or exclusively rent EVs are more likely to buy an EV instead of an ICEV (e.g., Burghard and Dütschke, 2019). And, thirdly, the monetary incentives users face differ in a substantive manner depending on the ownership type. Specifically, driving costs (per km and hour) are identical for car sharing customers across all engine types (electric vs. conventional) within a certain car segment. This identical cost structure offers a unique opportunity to examine EV usage in a setting where no additional monetary barriers for usage in contrast to ICEV usage exist. This setting enables us to gain new insights into whether usage differences persist beyond monetary incentives. If so, the remaining difference in usage may result from non-monetary barriers, behavioral lock-in effects or preferences.

Among the various non-monetary barriers to EV adoption, range anxiety is considered key (e.g., Tate et al., 2009; Neubauer and Wood, 2014). Building on observed single-day mileages, we examine in the last part of this paper whether range anxiety is justified for the trips taken with ICEVs in our sample. Given different EV cruising range assumptions, we investigate which share of the observed single-day trips (and single-booking trips, respectively) made with an ICEV could be completed with an EV without any adaptation required. We further discuss in detail potential selection effects relevant for the interpretation of our results.

The paper is organized as follows. Section 2 reviews the related literature. Section 3 discusses the incentives to choose an EV vs. an ICEV based on monetary and non-monetary costs. Section 4 outlines potential selection effects into EV usage, with important implications for the interpretation of our results. We describe the datasets used in Section 5, and Section 6 presents our empirical analyses. Section 7 concludes.

2. Literature review

This paper contributes to several strands of literature. First, it contributes to the literature comparing the use of EVs and ICEVs in terms of distances traveled both daily and annually. Second, it adds to the literature on the potential of substituting ICEVs with EVs, which crucially depends on actual cruising ranges of EVs and users' mobility demand.

The literature analyzing the use of EVs is still relatively sparse. Davis (2019) uses nationally representative data from the United States to analyze differences in the mileage of EVs and ICEVs. He finds that, on average, EVs are driven considerably fewer miles per year than gasoline-powered vehicles. The difference is highly statistically significant and holds for both all-electric and plug-in hybrid electric vehicles, for both single- and multiple-vehicle households, and both inside and outside California. Hasan and Simsekoglu (2020) surveyed both EV and ICEV owners in Norway to examine EV use. They find that perceived economic aspects (in particular

[1] Germany, the country that we focus on in our analysis, was not among the top performers in terms of the charging station density in the past. For example, in 2017, there were 70.43 EV charging points per 100,000 urban inhabitants in Germany, while there were, e.g., 259.91 in the Netherlands, 197.41 in Denmark, 130.60 in Austria, 94.25 in Sweden and 86.64 in France (see https://ec.europa.eu/transport/facts-fundings/scoreboard/compare/energy-union-innovation/ev-charging-points_en; last accessed: 18/12/2020). In comparison with Italy (9.44 charging stations per 100,000 urban inhabitants), Spain (16.97) or the UK (29.01), Germany had a higher charging station density but especially the comparison with Italy or Spain should take into account the differences in the general economic performance of these countries, especially in recent years, which probably explains delays in public investments in charging infrastructure.

long-term cost savings for EVs as compared to ICEVs) are statistically significant in explaining VKT of sole battery electric vehicle (BEV) owners. By contrast, perceived operating barriers related to EVs, such as the long time it takes to charge an EV or the limited range of EVs, are statistically significant in explaining EV VKT of drivers owning both types of vehicles. Two recent papers compare the use of EVs and ICEVs in car sharing fleets. Using data on free-floating car sharing services in 12 European and US cities, Sprei et al. (2019) find that rental time is shorter and the number of rentals per car and day are slightly fewer for EVs as compared to ICEVs. Langbroek et al. (2019) compare travel patterns of shared EVs and ICEVs in a case study on the island of Gotland in Sweden. They find that the driving patterns of EVs do not seem to indicate serious limitations regarding driving distance, parking time, and the destinations visited, as compared to the driving patterns of conventional rental cars.

Regarding the potential for substitution, a large number of studies have shown that, at least with current battery technologies and EV cruising ranges, the majority of trips could easily be made with an EV instead of an ICEV. For instance, using high-resolution data on the use of gasoline vehicles in 13 US states, Pearre et al. (2011) find that a significant (but still low) fraction of transportation needs could be covered with EVs without adaptation. In particular, if drivers were willing to make adaptions on only two days per year, a 100-mile (approx. 160 km) range car would satisfy the mobility demand of 17% of all drivers. For a sample of motorists in Sydney, Greaves et al. (2014) conclude that EVs with a range of as low as 60 km would be able to accommodate well over 90% of day-to-day driving, assuming a home-based charging set-up. Combining information from travel surveys with high-resolution GPS data, Needell et al. (2016) estimate the energy requirements of personal vehicle trips across the US. They find that existing, affordable EVs could meet the energy requirements of 87% of vehicle-days. Jakobsson et al. (2016) analyze driving patterns in Sweden and Germany based on survey data, concluding that a range of 230 km is required for half of all vehicles, and thus EVs are better suited to serve as second cars in a household. Based on a simulation model with Swiss and Finnish survey data, Melliger et al. (2018) find that 85–90% of all trips could have already been made with EVs in 2016. Vial and Schmidt (2019) find that 89% of the vehicles of a taxi fleet in Hamburg could drive fully electric. Some recent studies determine optimum EV cruising ranges based on observed trip lengths. For instance, Tamor (2019) shows that optimal fleet-average ranges are approximately 175 km but that those could be reduced if users could choose the battery range that best matches their needs. Shi et al. (2019) use travel data from private vehicles and taxis in Beijing, concluding that nearly 80% of both types of vehicles have an optimal battery range of less than 300 miles. Meinrenken et al. (2020) use GPS-based trip data for 412 cars in Ann Arbor, Michigan, to compute all-electric ranges that achieve maximum GHG emission reductions. Based on this, they estimate that between 66% and 86% of all total distances could be covered with EVs (if these EVs have optimum range). These studies predominantly either use survey data or GPS data to estimate the share of trips for which ICEVs could be substituted by EVs, mostly for private vehicles.

We contribute to this literature by focusing on the monetary incentives for using an EV vs. an ICEV, with a detailed view on the two different types of ownership, namely privately owned and shared vehicles. We advance the literature by confronting our predictions derived from economic theory with empirical evidence from rich micro data covering both ownership types in one of the world's most important automotive markets. Furthermore, the data from the two sources overlap in the time of data recording, which reduces the threat of time effects which could otherwise bias our results. Finally, in contrast to previous studies, we extensively discuss the economic incentives of using EVs and ICEVs, and the selection issues that plague any empirical analysis of EV use (and adoption more generally).

3. The economics of using EVs vs. ICEVs

In order to guide our empirical analysis, we first outline the monetary incentives for using an EV vs. an ICEV, before discussing potential non-monetary costs and behavioral aspects related to vehicle use.

Economic theory suggests that the purchase, i.e., adoption, of a certain vehicle or type of vehicle (such as an EV or ICEV) depends, among others, on its perceived attributes, its expected mileage and the (expected) total costs of ownership (TCO), which are highly correlated with mileage. According to this line of reasoning, one would expect that individuals with higher mobility demand purchase car types that have low TCO given their expected mileage. Recent research suggests that TCO of EVs as compared to ICEVs have significantly decreased in the last two decades (Palmer et al., 2018), though EVs might still not be cost competitive despite of fuel savings and generous subsidies (Breetz and Salon, 2018). Scorrano et al. (2020) show for Italy that with recent purchase subsidies, the cheapest EVs have become competitive in terms of TCO as compared to diesel cars but not as compared to petrol cars, unless very high annual distances are driven (more than 12,500 km). Therefore, the choice between an EV and an ICEV and its later use may already be prone to selection (such selection issues are discussed in the next section), although information on TCO might not be readily available to potential buyers and might thus not influence a buyer's decision too much. Furthermore, high uncertainty exists regarding, e.g., maintenance costs and depreciation of EVs, which might hinder their adoption. It has also been found that vehicle TCO are in general heavily underestimated by individuals (Andor et al., 2020).

Once a fully rational individual has bought a certain vehicle, the purchase costs should, however, be (close to) sunk and, theoretically, not influence the owner's mileage (use) decision. Sunk cost effects can be attributed to loss aversion, an aversion to regret, post hoc rationalization and psychological commitment (e.g., Arkes and Blumer, 1985). While, as reported by Ho et al. (2018), sunk costs might affect vehicle use, we argue that variable costs per km (and possibly the price of alternative mode choices) should play a decisive role for the decision on how far to drive. The variable costs, which mostly consist of "fuel" costs including taxes but also of costs related to periodic control and maintenance as well as insurance, are typically lower for EVs than for ICEVs, at least when EVs are charged at home or at the workplace.[2] For instance, Sivak and Schoettle (2018) find cost ratios for annual fuel costs of driving a typical gasoline vehicle vs. driving a typical battery electric vehicle in US states (in which gasoline prices are historically much lower than, e. g., in most EU countries) of between 1.364 and 3.602, with an average of 2.304. W*e thus expect, based on monetary incentives alone, an EV to be used at least as much as an ICEV.*

Regarding different fuel types (diesel and gasoline), diesel cars are more fuel-efficient than gasoline cars and, in addition, diesel is more heavily subsidized than gasoline in Germany (a fact that is often referred to as "diesel privilege"). By contrast, diesel cars have higher purchase prices than gasoline-powered cars. As a result, diesel cars are cheaper in terms of TCO – beyond a certain mileage – and cheaper in terms of variable costs than gasoline-powered vehicles (e.g., Belzowski, 2015). Based on monetary incentives, *we thus expect that diesel cars are driven longer distances than gasoline-powered vehicles.*

Furthermore, it is conceivable that a car owner has taken into consideration the available recharging opportunities as well as the required mileage before making the purchase decision and only chooses an EV if it is considered adequate given the conditions and constraints she faces. Therefore, limited recharging opportunities or range restrictions should not severely constrain mileage choice.

In contrast to a private owner, a car sharing user can choose between an EV and an ICEV for each trip, given that both types of cars are available at a particular station at the moment of booking. Moreover, the monetary incentives differ significantly for a car sharing customer compared to a private car owner. While different payment types exist for different car sharing fleets, members of the car sharing service for which we have data do not incur any fixed costs. Notably, variable costs are differentiated by vehicle category but not by fuel and engine type. Within each category, costs only depend on the distance traveled and the duration of the booking (for the price list see Table 6 in the Appendix). As a result, these variable costs are identical for EVs and ICEVs within one vehicle category. Considering monetary incentives only, *we expect that shared EVs, if chosen, are driven similar distances as shared ICEVs.*

It is important to note that, in addition to monetary costs, the decision to buy, use or book an EV vs. an ICEV may be influenced by non-monetary costs, in particular psychological or time costs, as well as preferences (e.g., Hasan and Simsekoglu, 2020). Some users might prefer an EV over an ICEV because of its driving features (fast and steady acceleration, low noise levels), its environmental features (no local pollution emissions, possibly lower carbon footprint beyond a certain mileage; see Chu et al., 2019), or because an EV is associated with a certain self-image and status in terms of being environmentalist or tech-savvy (Axsen et al., 2018). In line with behavioral lock-in tendencies, other users might prefer more "convenient" or familiar engines and thus ICEVs. They might also incur psychological costs of switching from the conventional to the electric vehicle technology. In addition, psychological or time costs may arise from finding a charging station if none is conveniently located close to home or the workplace (in case of private owners) or in the vicinity of the car sharing station. Finally, individuals might suffer from a status quo bias (Samuelson and Zeckhauser, 1988), where they take the status quo, i.e., the ICEVs that they have driven in the past, as a reference point from which any change is perceived as a loss. They might also suffer from (justified or unjustified) range anxiety (e.g., Alkhalisi, 2020). Unjustified range anxiety could be due to a lack of information on typical cruising ranges. Overall, *we expect that EVs are more likely to be chosen for shorter trips than for longer ones if range anxiety is a common concern among users.*

4. Selection issues

In addition to unobservable non-monetary costs and preferences for a particular engine type, a variety of selection mechanisms may be at work for an individual's decision to choose one type of car over the other. Selection into EV ownership or usage is relevant for the interpretation of our results if it occurs based on characteristics that are directly related to mobility demand. This holds, for instance, when individuals who self-select into EV ownership or usage reveal a different mobility demand than ICEV users per se. As this paper mainly follows a descriptive approach, we cannot fully explore the potential channels on self-selection issues directly. Nevertheless, as selection may confound the comparison of usage patterns, we discuss potential selection issues upfront in detail. In the empirical analysis, we differentiate the sample according to a variety of criteria prone for selection whenever possible.

For private households, it has been established that (i) households select into car ownership (e.g., Van Wee, 2009; Wu et al., 2020), and that (ii) EV owners represent a non-random subset of car owners. As we work with German data, we briefly review the literature with particular attention paid to the German context. With respect to selection into car ownership, Nobis and Kuhnimhof (2018) identify, among others, differences in ownership among German households depending on the household's economic status, regional type, province, and household type. With respect to EV adoption, a vast and non-conclusive set of sociodemographic characteristics as well as attitudinal variables have been found to relate to EV ownership (e.g., Potoglou and Susilo, 2008; Anable et al., 2011; Hidrue et al., 2011; Plötz et al., 2014; Vassileva et al., 2017; Morton et al., 2018; Sovacool et al., 2018; and Huwe and Gessner, 2020, for a review). For the German context, Plötz et al. (2014) provide evidence for a relationship between intention to adopt an EV and gender, family size, full-time employment as well as regional type. Besides sociodemographic characteristics, they also identify pro-environmental attitudes and openness to technology to be related to the intention to adopt. Several recent contributions investigate the motivational drivers of EV adoption more closely. Studying EV-owning households in Vancouver, Axsen et al. (2018) classify the motivations for EV adoption as financial (in terms of cost savings), functional (in terms of improved driving experience with EVs),

[2] Charging station providers sometimes charge relatively high prices per kWh or even a lump-sum amount, irrespective of how much electricity is actually consumed. For an overview of the different charging schemes in use in Germany, see https://www.mobilityhouse.com/de_de/ratgeber/elektroauto-oeffentlich-laden-welcher-ladetarif-ist-der-richtige-fuer-mich#gelegenheitslader-tarif [last accessed: 25/11/2020].

Table 1
Numbers of households with different combinations of ICEVs (gasoline and diesel combined) and EVs (source: MiD 2017).

# of EVs (vertical)/# of ICEVs (horizontal)	0	1	2	3+	Sum
0	–	55	8	1	**64**
1	74,365	206	9	0	**74,580**
2	48,006	107	0	0	**48,113**
3+	12,962	0	0	0	**12,962**
Sum	**135,333**	**368**	**17**	**1**	**135,719**

societal/environmental as well as symbolic (in terms of status and being seen as an ambassador for new technologies). Reviewing 75 studies, Daramy-Williams et al. (2019) obtain similar conclusions. Given that a significant degree of consumer stratification is present in the emerging market for EVs, Morton et al. (2017) find that the reasons to be attracted to or repelled from EV purchase also vary greatly for different EV market segments.

An important limitation of the literature is that not all of the studies consider data from actual EV owners but inquire hypothetical choices or intention to adopt (exceptions are Vassileva et al., 2017, and Morton et al., 2018). As an intention-behavior gap has been well documented (e.g., Sheeran, 2002), intention to purchase may only serve as an indicator of actual purchase and usage. Secondly, several of the characteristics identified are also likely to reveal a direct relation with general mobility demand. For instance, households with strong pro-environmental attitudes may also have lower mobility demand than the overall population. Consequently, the established knowledge cannot be considered causal. Moreover, as the institutional settings with respect to EV infrastructure, purchase incentives etc. have varied greatly over time and space, country-specific findings may not be generalizable.

For car sharing, there is selection into i) car sharing membership in the first place and ii) EV use among car sharing members subsequently. Regarding i), car sharing users have been found to have more positive environmental attitudes than non-users (Schaefers, 2013; Kawgan-Kagan, 2015; Clewlow, 2016). As argued earlier, such attitudes may be associated with lower mobility demand (and also lower demand for motorized individual transport). Regarding ii), the selection among members into EV usage may be based on preferences for a certain engine type (as outlined in Section 3), availability of EVs/ICEVs at a particular station, and trip characteristics, especially required mileage. The availability of EVs or ICEVs at a particular station may be the result of strategic business considerations which could in fact have an impact on the observed usage of different engine types. EVs are likely to be placed in regions in which they are also expected to be more intensively used, e.g. because of a higher likelihood of shorter trips. Burghard and Dütschke (2019) provide some evidence on the two selection mechanisms. Making use of a survey with 947 individuals from field trial regions in Germany on electric mobility, they analyze sociodemographic characteristics of EV users in car sharing fleets. They find that shared EVs are particularly attractive for younger individuals who live as a couple and do not own cars or who are starting a family and use car sharing services as a supplement to their own cars. Furthermore, the surveyed car sharing users represent a specific subgroup of the population: A large share are employed and highly-educated men living in small households.

In our analysis pertaining to car sharing, we also distinguish between one-time and frequent users as these are likely to be different from each other. First, there may be individuals signing up for car sharing who need to move around individually but do not have access to a car, for instance because they travel in a city other than their home town. These individuals are likely to be one-time (or infrequent) users. Second, individuals may decide to use car sharing repeatedly and frequently, possibly in order to get access to a car without owning a car themselves (or owning one car less in their household). Both groups may differ in their mobility demands from the overall population of private car users.

5. Data

In the empirical part of this paper, we use car-level micro data from Germany from two different data sources. The data reflect two ownership types, namely privately owned vehicles and vehicles owned by a stationary car sharing provider. Private car data is self-reported while car sharing data is retrieved from booking data. We uniquely identify each car as either electric or conventional. Measures of both single-day and annual mileage are reported or can be calculated based on the available data. In the following, we describe the two datasets in detail.

5.1. Privately owned cars

For privately owned vehicles, we use micro data from the most recent German National Travel Survey, *Mobilität in Deutschland 2017* (MiD), published by the German Federal Ministry for Transport and Digital Infrastructure (BMVI).[3] The MiD is a large-scale household survey with detailed information on mobility patterns, household characteristics, and vehicles owned. Households are recruited based on the national register of residents as well as landline and mobile phone numbers. Households report engine and fuel type (gasoline,

[3] According to the information being available on the MiD website (http://www.mobilitaet-in-deutschland.de/pdf/MiD2017_StudySummary.pdf, last accessed: Nov 25, 2020), after 2002 and 2008, the Federal Ministry of Transport and Digital Infrastructure commissioned the infas Institute for Applied Social Sciences to carry out the Mobility in Germany study for the third time in 2017. No new MiD wave has been announced as of January 2021.

Table 2
Average individual and household-level characteristics of our sample of the MiD 2017

# of individuals	# of households	% female	Age	Monthly household income	# of household cars	% living in urban region
281,671	134,053	51	48.9	€3,600–4,000	1.7	34

diesel, gas, electric, hybrid) as well as annual vehicle mileage for up to three vehicles. If households own more than three cars, they are only required to report the data for three of their cars. We restrict the analysis to gasoline- and diesel-powered conventional cars and battery electric vehicles. In addition, we exclude all gas cars for comparability and all hybrids, as they are not classifiable as either conventional hybrids or plug-in hybrids (PHEVs). We also exclude cars with missing information on engine type. The distribution of EVs and ICEVs across households that own at least one car is presented in Table 1.[4] The majority of these households (65.0%) owns one car, mostly an ICEV. Among EV households, the majority also owns one or more ICEVs.

For the analysis of annual vehicle mileage, we use the data at the car level and all vehicles for which engine type and annual VKT is reported (which also allows us to re-include observations where no household data was available and therefore had been excluded in Table 1, as discussed in footnote 4). In total, we observe 204,920 such cars owned by 134,053 households. Information on average individual and household-level characteristics for this sample can be found in Table 2. 408 vehicles are EVs, which amounts to 0.002% of the observed fleet. The low share of EVs in the sample is only slightly below the overall market penetration rate of EVs in Germany in 2019. In order to capture single-day mobility patterns in the MiD, a household is assigned to a record date based on statistical sampling methods.[5] Record dates cover all dates between June 13, 2016, and September 12, 2017, and include both weekdays and weekends. For a subsample of vehicles, record-day mileage is available at the car level, while for the largest share no car-specific information is available at the household level. Record-day mileage aggregates the distances traveled across all trips taken with the car on the record date. Moreover, we exclude cars with missing values for single-day mileage as well as cars that have not been used on the record date (0 km), as we are only interested in drivers who actually use their car on the record date. We observe single-day mileage for 6,740 vehicles (distributed across 5,282 households), thereof 16 EVs, 4,282 gasoline-powered cars, and 2,442 diesel cars. Due to the large sample size, reported record-day mileage can be used as a measure of single-day mileage on an average day.

5.2. *Vehicles in car sharing fleet*

For shared vehicles, we use booking data from Flinkster, the largest stationary car sharing provider in Germany. The data covers the period from January 01, 2014, to December 31, 2016.[6] Customers and vehicles are uniquely identifiable. We assume here that one customer ID is used by only one individual and not several individuals. For each car, the engine type and the vehicle model are reported. For ICEVs, we can further distinguish between fuel types (diesel and gasoline).

We observe 1,727 distinct vehicles, thereof 91 EVs (5.3% of the observed fleet). 15 PHEVs are excluded due to lack of comparability with privately owned cars. We report that fleet size and composition change over time. We also classify vehicles into three car segments based on model type. All segments include EVs, yet the larger segments offer very limited numbers of EVs.[7] For each booking, we observe the customer (id), the vehicle booked, start and end time, date, rental station, as well as the distance traveled. Note that for stationary car sharing, cars are borrowed and returned at the same rental station. For annual mileage, we aggregate the distances traveled over all bookings made with a particular vehicle within one year. Importantly, only 31% of the vehicles are available throughout an entire year. We define a vehicle to be available throughout a particular year if at least one booking per month can be observed for this vehicle. Note that the subsample of vehicles available throughout an entire year is substantially smaller than the full sample, especially for gasoline-powered cars. In our analysis, we consider the full sample unless noted otherwise. For single-day mileage, we restrict the sample to single-day bookings, i.e., bookings for which the car is borrowed and returned on the same day. For some of our analyses, we group stations according to engine type availability: stations where only EVs are available (EV stations), stations where only ICEVs are available (ICEV stations), and stations with both EVs and ICEVs (mixed stations). Engine type

[4] We exclude all households who own at least one gas-powered or hybrid car or do not report the engine type.

[5] The exact sampling methods for the MiD are described in "Mobilität in Deutschland – MiD Methodenbericht", available at: http://mobilitaet-in-deutschland.de/pdf/MiD2017_Methodenbericht.pdf.

[6] Available at https://data.deutschebahn.com/dataset/data-flinkster. Upon request, DB Flinkster indicated that the data covers the universe of bookings made during that period except those made with cars of partner providers, which can also be booked via the DB Flinkster application or booking portal. While data principally is available until May 15, 2017, we use only the data for full calendar years due to our analysis of annual mileage.

[7] Small: Citroen C-Zero (EV) and DS3 (ICEV), Fiat 500 (ICEV), Ford Fiesta and Ka (both ICEVs), Mitsubishi i-MiEV (EV), Opel Corsa (ICEV), Peugeot iOn (EV), Toyota Aygo (ICEV); medium: Nissan Leaf (EV), Ford Focus (ICEV), Mercedes C-Klasse (ICEV), Opel Astra (ICEV), Renault Kangoo (ICEV); large: Ford Transit Custom (ICEV), Mercedes Sprinter and Vito (both ICEVs), Nissan eNV200 (EV), VW T5 (ICEV). Small vehicles: 1,269 ICEVs, 80 EVs; medium vehicles: 368 ICEVs, 9 EVs, large vehicles: 26 ICEVs, 2 EVs.

Table 3
Numbers of bookings, customers, vehicles and locations of Flinkster

Year	Bookings	Single-day bookings	Customers	Vehicles	EVs	Stations	Mixed stations	EV stations
2014	182,155	152,285	30,265	1121	84	75	13	61
2015	161,333	133,876	28,615	922	79	73	11	62
2016	136,084	111,602	26,534	1006	64	66	10	49

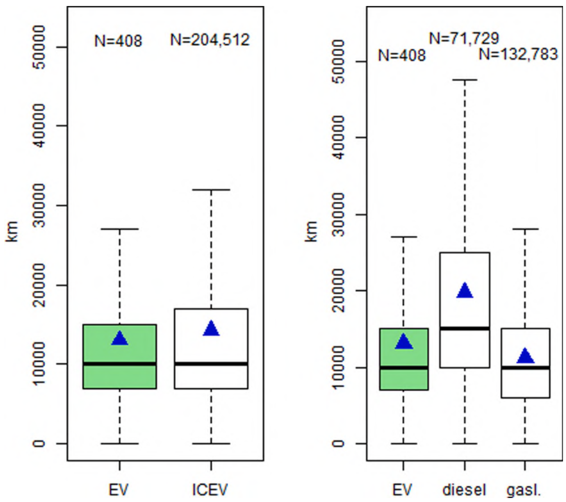

Fig. 1. Boxplots of annual mileage for EVs and ICEVs in the MiD, excluding outliers (the triangle indicates the mean, the bold line the median).

availability at a particular station changes over time for some stations.[8] Importantly, we do not check for mixed stations whether an EV or ICEV was *actually* available at the time when the booking was made but only whether the booking falls into a period when at least one EV or ICEV was available at the station in general. For each rental station, we assign EV (ICEV) availability to the time period between the first day an EV (ICEV) is booked and the last day an EV (ICEV) is booked at that particular station. At stations where both EVs and ICEVs are offered, the average share of EVs among the provided vehicles is 40%. Table 3 summarizes the dataset. In total, we observe 52,467 customers making 479,572 bookings within the three years of our observation period. The number of bookings, customers, EVs and rental stations decreases over time.[9] 31.6% of all customers are one-time customers.

6. Results

In this section, we analyze both annual and single-day mileage by engine and ownership type. Moreover, we examine which share of ICEVs could complete their single-day mileage with an EV under different cruising range scenarios.

6.1. Annual mileage

6.1.1. Private car fleet

For privately owned vehicles, we observe substantial heterogeneity in annual mileage both *within* and *between* engine types. In particular, EVs reveal 8.4% lower average annual mileage than ICEVs, as Fig. 1 (left panel) demonstrates. While the average annual mileage is 13,052 km for EVs, ICEVs are driven 14,243 km. The difference in means is statistically significant at the 1% level (Welch's test, $p = 0.006$). Our comparisons rely on the results of a Welch's *t*-test, which is more reliable for testing two samples with unequal variances and/or sample sizes than a conventional Student's *t*-test. The median annual mileage is identical (10,000 km for both EVs and ICEVs). Accordingly, the mileage distribution reveals that the difference in means is driven by a particularly large share of high-mileage vehicles among ICEVs.

[8] Changes with respect to the (full-year) availability of engine types occurred at 15 stations. The patterns were as follows: EV→ICEV: 1 change; ICEV→EV: 0 changes; EV→mixed: 0 changes; ICEV→mixed: 7 changes; mixed→EV: 3 changes; mixed→ICEV: 4 changes. Nearly half of all changes thus concerned ICEV stations at which EVs were added. At the same time, at 7 mixed stations, the availability of engine types was restricted to either EVs or ICEVs. Reasons for expanding the availability of engine types to EVs could be (expected) increasing demand by users – though we also observe that the total number of EVs in the Flinkster fleet declined over time, as did the number of stations.

[9] As we do not observe bookings made with partner companies, which are also available on the Flinkster booking platform, a decrease in booking frequency only represents a decrease in booking frequency with Flinkster vehicles and not necessarily a decrease in car sharing usage.

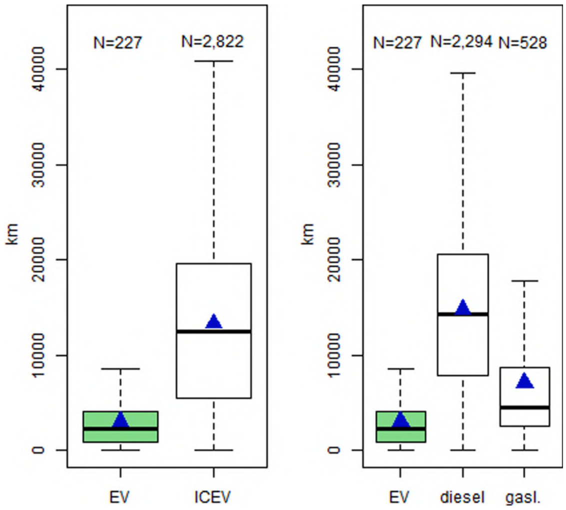

Fig. 2. Boxplots for annual mileage of EVs and ICEVs in car sharing fleet, excluding outliers.

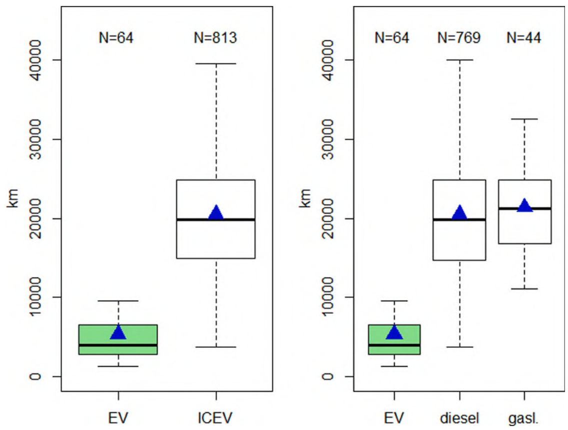

Fig. 3. Boxplots for annual mileage of EVs and ICEVs available throughout an entire year in car sharing fleet, excluding outliers.

When further differentiating ICEVs by fuel type (Fig. 1 right panel), we do not find a statistically significant difference in means between EVs and gasoline cars (Welch's $p = 0.99$). Moreover, the distributions of annual mileages are similar, indicating that gasoline cars are indeed used similarly as EVs, which is in strong contrast to what we would expect based on the monetary incentives. By contrast, diesel-powered cars exhibit significantly higher annual mileage than EVs (and thus also than gasoline cars), both in terms of means (Welch's $p = 0.00$) and medians. As EVs typically have lower variable costs than diesel cars, the fact that diesel cars are still the preferred choice for high mileages indicates that other impediments to EV usage exist for high-mileage demand individuals. Range anxiety is likely to be a major concern if a large share of trips is high-mileage. Among ICEVs, the data confirms that diesel cars are used more intensely than gasoline vehicles, which is in line with behavior based on monetary incentives.

To provide suggestive evidence on potential selection effects, we differentiate our analysis by the number of cars in a household. While an analysis keeping the number of cars fixed clearly cannot fully circumvent potential selection effects (e.g., due to unknown household preferences), we focus on single-vehicle households as the group for which mobility demand can plausibly be assumed to be more similar on average, irrespective of engine type. Comparing EVs and ICEVs for single-vehicle households, we do not observe a statistically significant difference in annual mileage between vehicles of different engine types (Welch's $p = 0.47$). Yet, differences exist in multi-vehicle households (Welch's $p = 0.00$, see Fig. 10 in the Appendix). In these households, which constitute the majority in our sample (see Table 1), EVs seem to be more likely to be used as second (or third) car (or be purchased as an additional car) and are driven less than the first car. This finding is in line with, e.g., Klöckner et al. (2013), Figenbaum and Kolbenstvedt (2016), Jensen and Mabit (2017), and Bauer (2018).

6.1.2. Car sharing fleet

For shared vehicles, we also find that EVs are, on average, driven less than ICEVs (Welch's $p = 0.00$; see Fig. 2 left panel). Average annual EV mileage amounts to a mere 23% of average annual ICEV mileage. The difference is thus substantially more pronounced than

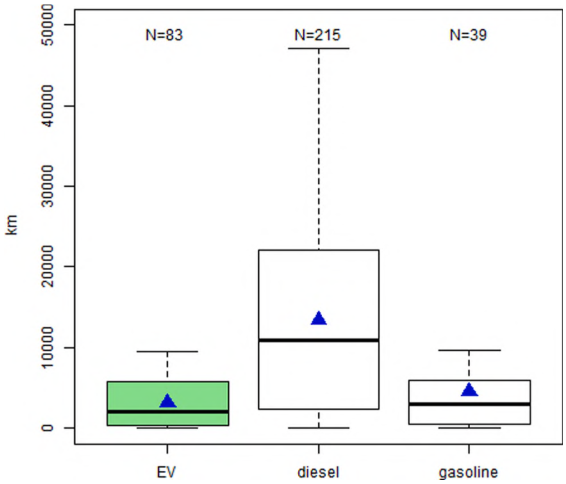

Fig. 4. Boxplots for annual mileage of EVs and ICEVs in car sharing fleet at stations where both EVs and ICEVs are available on the day of booking, excluding outliers.

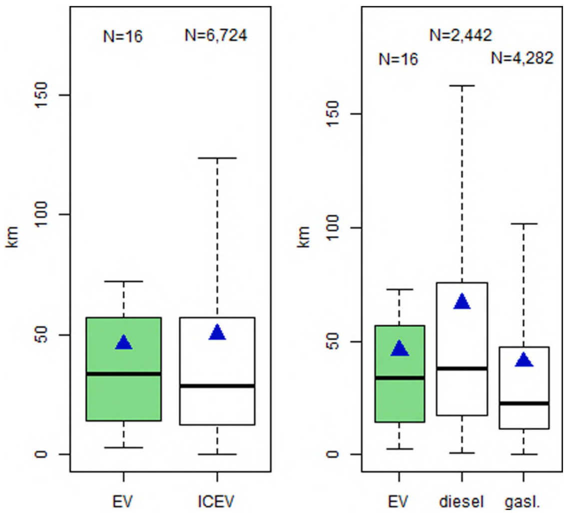

Fig. 5. Boxplots for single-day mileage of private EVs and ICEVs, excluding outliers.

for private car ownership and prevails not only with respect to diesel cars but also with respect to gasoline cars (both $p = 0.00$; see Fig. 2 right panel).

Lower annual mileage for shared EVs might result both from lower mileage per booking and/or from lower usage intensity as reflected by the booking frequency per car. Both channels are going to be examined in Section 6.2. Thirdly, the difference may partly result from differences in the length of availability of vehicles of different engine and fuel types. Fig. 3 therefore plots the distribution of annual mileages for vehicles that have been available throughout an entire year only. For all engine and fuel types, the average annual mileage is much higher than before, indicating that the substantial share of vehicles that is not available throughout an entire year drives down the observed travel distances at the annual level. The general pattern is, however, very robust. The difference in means between EVs and ICEVs is even more pronounced for vehicles available throughout an entire year, while diesel and gasoline cars are used almost identically (in terms of the mean).

As mentioned earlier, EV or ICEV availability at a station may be strategically chosen by the car sharing provider. Thus, station-specific effects could drive the difference in annual mileage between EVs and ICEVs. We address this concern by only comparing the mileage of EVs and ICEVs at rental stations where both types of cars are hypothetically available on the day of the booking. We find a very similar picture as before (Fig. 4), although the difference between EVs and gasoline cars is much smaller now, though still statistically significant (Welch's $p = 0.06$).

We can also compare annual mileage of privately owned and shared vehicles. We restrict the car sharing data to vehicles that were available throughout an entire year (see Table 7 in Appendix for summary statistics of the sub-sample). We find that conventional cars reveal substantially higher average mileage when shared compared to private ownership (Welch's $p = 0.00$ for gasoline, $p = 0.06$ for

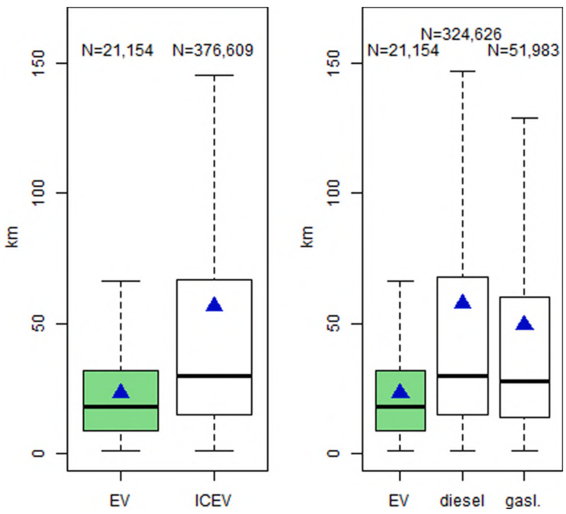

Fig. 6. Boxplots for single-day mileage of EVs and ICEVs in car sharing fleet, excluding outliers.

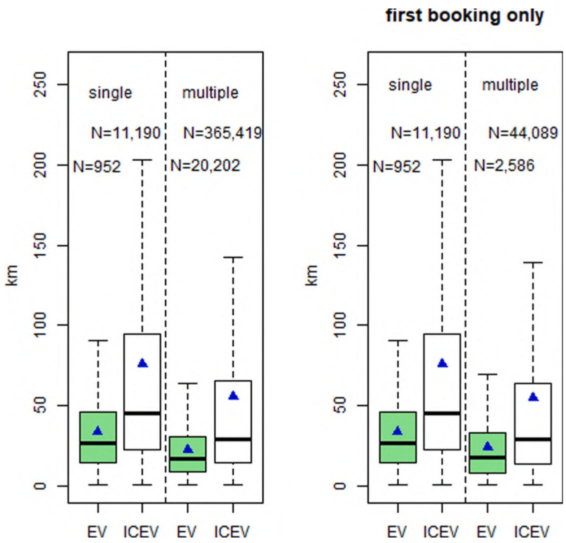

Fig. 7. Boxplots for single-day mileage of shared EVs and ICEVs, differentiated by one-time and multiple-booking customers, excluding outliers. Left panel all bookings, right panel first booking only.

diesel). By contrast, EVs are driven significantly fewer kilometers per year when shared (Welch's $p = 0.00$). These results suggest that car sharing achieves an intensification of car usage only for ICEVs. This observation should, however, be treated with caution, as we cannot infer about the large majority of car sharing vehicles which are not available throughout the entire year.

Summarizing our observations on annual driving patterns, we formulate our first result as follows:

Result 1 (annual mileage): *In the aggregate, EVs exhibit lower average annual mileage than ICEVs both in the private and in the car sharing fleet. The difference in means is driven by a higher share of high-mileage cars among ICEVs, particularly among diesel cars. Diesel cars are driven much longer annual distances than EVs, irrespective of ownership type. By contrast, differences between gasoline cars and EVs can only be observed in the car sharing setting. Car sharing intensifies car usage for conventional cars only.*

6.2. Single-day mileage

It is important to compare mileage not only at the annual level but also at the daily level (for private cars) and the booking level (for shared cars), because EV adoption may be hindered if an EV's battery range is insufficient to cover the required mileage at the day or trip level.

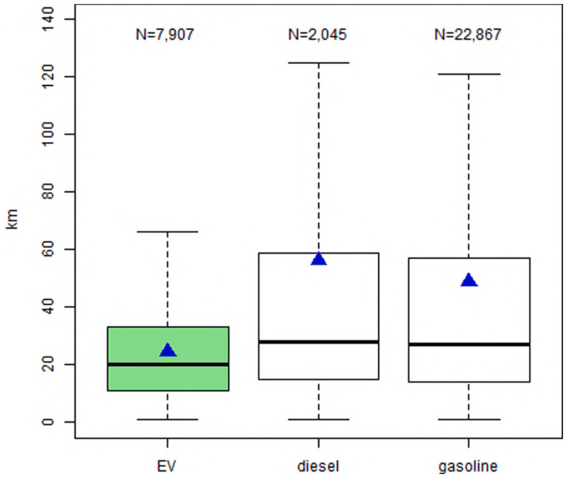

Fig. 8. Boxplots for single-day mileage of shared EVs and ICEVs at mixed stations, excluding outliers.

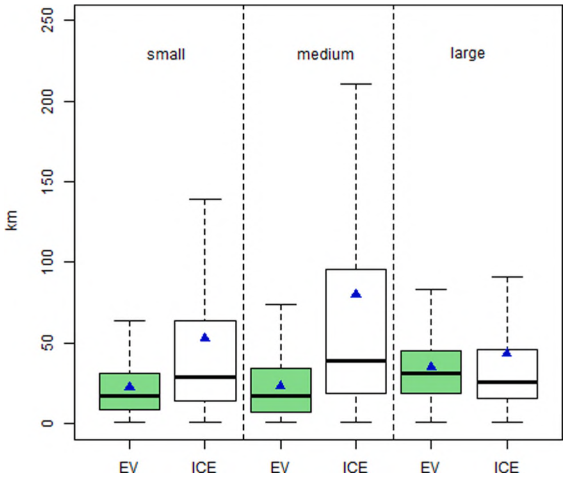

Fig. 9. Boxplots for single-day mileage of EVs and ICEVs in car sharing fleet by vehicle category, excluding outliers.

6.2.1. Private car fleet

Among privately owned vehicles, EVs are, on average, driven 45.95 km per day, while ICEVs are driven slightly longer distances (50.13 km, Fig. 5 left panel). Diesel cars show a substantial number of high-mileage trips in comparison with EVs and gasoline-powered cars (Fig. 5 right panel). We refrain from a more formal statistical test due to the very low number of EVs in the sample for which single-day mobility patterns are recorded in the MiD (N = 16). The patterns observed on the daily level are thus reminiscent of the patterns observed for annual distances traveled.

6.2.2. Car sharing fleet

For shared vehicles, we observe almost 400,000 distinct single-day bookings. The left panel of Fig. 6 illustrates that large differences exist for average single-day (single-booking) mileages between EVs and ICEVs (the latter are driven distances that are more than twice as long as those driven by EVs). Interestingly, despite being offered at equal costs, differences in single-day mileage exist for both ICEV types compared to EV usage (Fig. 6 right panel). Again, the difference in means is driven by a large share of high-mileage trips, while the medians are more similar across engine and fuel types. Strikingly, the distribution of mileage is more similar for gasoline-powered and diesel cars in the car sharing fleet compared to the private car fleet. This is in line with expectations based on monetary incentives, since diesel cars do not have a cost advantage for the user in this setting.

In the following, we further differentiate our analysis by user type, station type, and car segment in order to shed light on potential selection effects. To this end, we first split the sample according to these criteria and present the respective distribution of single-day mileage. In a second step, we investigate the relationship between fuel type and single-day mileage econometrically while controlling for car segment and both user and station type.

First, one-time customers may differ from frequent users with respect to their required mileage demand. We observe that, as before,

Table 4
Annual booking frequency per car during the whole observation period (cars available all 12 months of a year)

	All stations			EV stations	Mixed stations			ICEV stations	
	EV	Gasoline	Diesel	EV	EV	Gasoline	Diesel	Gasoline	Diesel
Mean	188	367	259	146	178	226	205	357	249
Standarddeviation	138	107	115	135	146	177	177	117	116
N (cars)	64	44	769	53	24	2	60	44	749

single-day travel distances are, on average, significantly lower for EVs both among single- and multiple-booking users as compared to ICEVs (both Welch's $p = 0.00$, cf. Fig. 7 left panel). This may reflect that individuals select into EV or ICEV choice based on the mileage required for their trip. Importantly, both EVs and ICEVs exhibit higher average distances traveled among one-time customers than among multiple-booking customers (one-time customers ICEVs 78.3 km, EVs 33.2 km, multiple-booking customers ICEVs 55.5 km and EVs 22.6 km). This result supports the conjecture that one-time users may be different from recurring, long-term users with respect to their mobility demand. One potential explanation for this observation is that many one-time customers book a shared vehicle when there are strikes or bad weather events at Deutsche Bahn (the German railway company) or at local public transit providers in order to get to their final destination, as rental stations of Flinkster (a Deutsche Bahn company) are often close to train stations.

As a further robustness check, we only use the first booking of multiple-booking customers (Fig. 7 right panel). The results are quite robust (average mileage for multiple-booking customers now 52.2 km for ICEVs and 23.3 km for EVs) and thus provide suggestive evidence that multiple-booking users do not change their usage behavior in terms of trip distance over time. This constitutes an interesting finding, as it has been found that practical driving experience with EVs can reduce range stress perceived by drivers (Rauh et al., 2020) and thus might lead to longer distances driven.

Next, we compare single-booking distances across station types (see Table 8 in the Appendix and Fig. 8 for mixed stations only). Again, median mileages are almost identical across engine, fuel, and station types, but EVs reveal lower mean single-day mileage than gasoline and diesel cars. EVs are used for similar single-day distances at EV stations and mixed stations. The same holds true for ICEVs at ICEV stations and mixed stations. Overall, these results provide little evidence of strategic placement effects of the rental stations by the car sharing provider.

Lastly, we differentiate by car segment in order to compare mileages of vehicles of the same or similar size. This is justified on the grounds that vehicles of different segments differ in their variable costs per hour and per km. We find that differences in single-day mileage between EVs and ICEVs prevail within all three vehicle segments (see Fig. 9).

As noted earlier, lower annual mileage of EVs in the car sharing fleet compared to the private fleet can be due to either lower mileage per booking, a lower number of bookings, i.e., a lower usage intensity, or both. For the analysis of booking frequencies, we restrict the sample to cars that were available throughout the entire year, i.e., for which at least one booking can be observed for every month of the year. Over all stations and years, EVs are, on average, booked 188 times per year, while gasoline and diesel cars are booked 367 and 259 times, respectively. Table 4 summarizes annual booking frequencies at the car level by station type. EV booking frequencies are significantly lower than those of both gasoline and diesel cars (both Welch's $p = 0.00$). In general, gasoline cars reveal the highest average booking frequencies, irrespective of the station type. Interestingly, EVs have a higher booking frequency at mixed stations than at EV stations, while the opposite holds true for ICEVs. This pattern may be explained by station-specific characteristics. For instance, EVs and ICEVs might be provided jointly in particularly favorable locations, i.e., at stations with very high demand, whereas EV only stations might be placed in neighborhoods in which environmental awareness is expected to be particularly high. In these neighborhoods, residents might have lower mobility demand per se, which translates to lower EV booking frequencies than at heavily frequented mixed stations where car sharing users might have to switch to EVs in case all ICEVs are booked.

Taken together, we confirm the findings of Sprei et al. (2019) for the case of stationary car sharing, though we find quite significant differences between EVs and ICEVs not only for rental times (respectively trip lengths) but also for the number of bookings. Though we do not have information on personal characteristics (nor attitudes) of car sharing users in our sample, our finding of lower mileage and a lower number of bookings for EVs as compared to ICEVs may be partly explained by more environmentally aware individuals with lower overall mobility demand who select themselves into EV rather than ICEV usage.

Comparing private and shared cars in terms of single-day mileage, a mixed picture emerges. Privately owned gasoline cars are driven shorter distances than their shared counterparts (Welch's $p = 0.00$). The opposite holds true for diesel cars (Welch's $p = 0.00$). We do not formally test for differences between EVs of different ownership type due to the low number of EVs in the private fleet for which we observe single-day mileage.

When controlling for vehicle segment, station and user type simultaneously in an OLS regression, we find that single-day mileage is 74% (66%) higher for diesel (gasoline) cars than for EVs (see Table 9 in the Appendix). The coefficients are significantly different from zero (both $p = 0.00$) as well as from one another ($p = 0.00$) and are robust across different specifications.[10] This result confirms that diesel cars are driven more than EVs and more than gasoline cars, even when controlling for all available potential confounders.

We summarize our results from this section as follows.

[10] With a mean variance inflation factor of 1.78, multicollinearity does not seem to be major issue in our models.

Table 5
Percentage of single-day trips made with ICEVs that are below the assumed EV ranges

	Conservative (93 km)	Intermediate (182 km)	Average 2016 (271 km)
Gasoline (privately owned)	92%	98%	99%
Diesel (privately owned)	82%	93%	96%
Gasoline (shared)	86%	96%	99%
Diesel (shared)	83%	94%	98%

Result 2 (single-day mileage): *For both ownership types, EVs reveal lower single-day mileage on average than ICEVs. Again, a higher share of high-mileage vehicles among ICEVs than among EVs drives the difference. While gasoline cars are driven similarly in the private fleet as compared to EVs, they reveal higher mileage in the shared fleet. Diesel cars reveal higher single-day mileage in both settings. The results persist when controlling for user type, station type or car segment. Furthermore, EVs are booked less often than ICEVs on average, irrespective of station type.*

Overall, the same patterns emerge from Results 1 and 2. When it comes to choosing between different types of ICEVs, car users clearly respond to price incentives. In line with differences in TCO, private diesel cars are driven higher annual mileage than gasoline-powered cars. However, the difference decreases substantially once cost differences disappear, i.e., in the car sharing setting.[11] In terms of single-day mileage, diesel and gasoline-powered cars are used even more similarly in the car sharing fleet.

By contrast, observed EV usage patterns are not in line with the predictions based on monetary incentives**.** EVs reveal lower annual and single-day mileage both in the private and shared fleet. While the higher purchase costs may detain private households from EV adoption, substantially lower travel distances of EVs are also observed in the car sharing setting for which costs are identical. Our results suggest that higher purchase costs do not constitute the sole impediment to EV penetration. Shared EVs reveal lower annual mileage not only because they are booked less frequently, but they are also driven lower distances (both compared to shared ICEVs as well as compared to privately owned EVs). An identical cost structure obviously does not suffice to encourage customers to switch from ICEVs to EVs.

Two different channels may explain this finding. First, important non-monetary costs might matter for engine type choice in a way that possibly counteracts cost incentives. One can only speculate whether information asymmetries (e.g., unjustified range anxiety), switching or learning costs or status quo bias may lead customers to continue choosing ICEVs rather than EVs. Furthermore, environmental concerns obviously do not push car sharing customers towards using EVs, despite equal costs. Secondly, the results may reflect selection effects, i.e., EVs may be chosen by individuals who reveal lower mobility demand per se. We cannot disentangle the two possible explanations by means of our descriptive analysis.

6.3. Theoretical substitution possibilities between EVs and ICEVs

In this section, we examine whether the difference in usage patterns between EVs and ICEVs could be due to justified range anxiety. In particular, we analyze for which share of ICEVs the observed single-day distance falls within the typical range of an EV. In the analysis, we consider three different range scenarios for EVs: i) a conservative scenario with a range of 93 km to cover small and older EVs[12], ii) a range scenario of 271 km that reflects the average range of all EVs sold in Germany in 2016[13] under optimal conditions (see Horvarth and Partners 2019), and iii) an intermediate range of 182 km to account for the case of imperfect weather and adverse operating conditions (cold weather, etc.). We choose 182 km as equidistant from the conservative and the average scenario. This assumption reflects a rather strong impairment of EV range due to weather conditions etc. Furthermore, the average range refers to vehicles registered in a particular year (here: 2016), hence it does not apply to vehicles that have been in operation at the beginning of the time period covered by our data. Therefore, it seems appropriate to consider lower ranges in our analysis, as well.

Furthermore, we make two assumptions regarding EV charging opportunities and travel demand, both of which are explicitly conservative to cover the complete set of potential cases of (theoretically possible) EV substitution. First, following Pearre et al. (2011), we assume that EVs are charged once a day, typically at home or at the workplace for privately owned vehicles and at the car sharing station for shared vehicles. We assume that the battery is fully charged before the first trip of the day and that no recharging is being done during the day. This is a conservative assumption that allows us to cover the most extreme case when the car cannot be charged during the course of a day. In practice, however, car sharing users are provided with cards to recharge their vehicle during the trip. Second, by using observed single-day travel distances completed with ICEVs, we implicitly assume that drivers do not change their travel demand when switching to an EV. This is again a conservative assumption as adjustments of travel behavior are conceivable when switching to an EV. Such adjustments include, e.g., trip planning (adjustment of travel distance to battery capacity or available

[11] Note that this result does not take into account whether the vehicle has been available throughout the entire year. The share of vehicles available for an entire year differs between gasoline and diesel cars.

[12] For the conservative range scenario, we use the range of the Smart EQ Fortwo, which had (in its 2017 version), according to http://web.archive.org/web/20200417041133/https:/www.automobilemag.com/news/electric-vehicle-range-ev-cars-mileage-best-worst/ (last accessed 14/12/2020), the lowest range of all listed cars and an official US-EPA (Environmental Protection Agency) certified range of 58 miles (93 km), see, e.g., https://www.caranddriver.com/smart/eq-fortwo/specs/2017/smart_fortwo-electric-drive_smart-fortwo-electric-drive-hatchback_2017 (last accessed 14/12/2020). We take this model to represent the type of models with small battery ranges as of 2017.

charging opportunities), time budget (budgeting of more time during the trip for recharging), or the choice of the means of transport (switching to trains for longer distances). As mentioned earlier, it would also be possible that privately owned EVs are driven longer distances because the lower variable costs per km make additional trips or substitution away from other means of transport attractive.

6.3.1. *Private car fleet*

Building on the cumulative distribution function (see Fig. 11: upper panel in Appendix), 82–92% of all single-day trips made by privately owned ICEVs could be completed with an EV in the most conservative range scenario, depending on the fuel type (Table 5). Given average EV cruising ranges in 2016, range restrictions would not be binding for 96–99% of all ICEV single-day trips under optimal conditions and only negligibly fewer (93–98%) under suboptimal conditions. Obviously, this share would be even higher for vehicles at the technological frontier. The magnitude of our results is well in line with what the previous literature has established. The average range scenario under optimal conditions is on the upper edge of previous estimates.

6.3.2. *Car sharing fleet*

With respect to shared vehicles, we find that 83–86% of all single-day ICEV trips could be completed with an EV under the conservative range assumption, depending on the fuel type considered (Table 5, Fig. 11: lower panel in the Appendix). In the case of an EV with 2016 average range and good weather conditions, this share rises to 98–99%. Again, the loss under suboptimal conditions is negligible. The results are thus almost the same for privately owned and shared vehicles.

We summarize the results of this section as follows.

> ***Result 3 (substitution potential):*** *The large majority of single-day ICEV trips could be made with an EV without any trip adjustment, irrespective of the cruising range scenario. This result holds both for privately owned and shared vehicles.*

Our analysis provides evidence that cruising range limitations – even though being still perceived as a major obstacle towards the adoption of EVs both in private and shared car fleets – affect only a minority of single-day trips. We conclude that either unjustified range anxiety persists for single-day mileage or that few days with higher-than-average mileage requirements, which are not captured by our measure of single-day mileage requirement, impede EV adoption. This consideration seems most relevant for one-vehicle households which cannot easily switch to an ICEV. Furthermore, even though most single-day trips can be made with EVs instead of ICEVs, there is still a high likelihood that a car owner experiences one or several days per year with out-of-range mobility demand. In that case, EV adoption depends on the car owner's willingness to make trip adjustments (e.g., by stopping more often during the trip to charge the battery) or switch to other modes of transport.

7. Conclusion

In this paper, we document differences in usage patterns between conventional and electric cars for both privately held as well as shared vehicles in Germany. Comparing usage patterns between these ownership types offers the unique opportunity to gain insights into the relative importance of monetary and non-monetary barriers to EV usage. If monetary incentives are identical for different engine types (as is the case for car sharing), differences in usage patterns can be ascribed to non-monetary costs, behavioral lock-in effects, preferences for different engine types, or may additionally or alternatively reflect self-selection.

We find that car users seem to respond to monetary incentives when choosing among conventional cars. Diesel cars are used for longer distances than gasoline cars in the private fleet, which is plausible given that both types of cars have very similar driving features but differ with respect to costs. Differences in usage between these two types of cars disappear for shared vehicles for which the usage price is identical. By contrast, EV usage is clearly not in line with monetary incentives. Our analyses reveal that EVs exhibit lower average distances traveled than conventional cars both at the annual level as well as on a single day, in both fleets. This result stands in contrast to previous findings by, e.g., Davis (2019) and provides evidence that relevant non-monetary barriers exist with respect to EV adoption and usage. Such barriers include psychological and time costs, which may be, among others, related to a low density of the charging station network. Additionally, behavioral lock-in effects may exist. Focusing on range anxiety as one potential barrier, we find that most single-day mobility demands currently satisfied with ICEVs could be met easily with an EV, even under very conservative range assumptions. As a result, range anxiety is not justified for the majority of single-day trips. In light of these results, policy-makers, car manufacturers, and car sharing providers who want to encourage EV adoption may address unjustified range anxiety by providing more information on real-world cruising ranges or by offering opportunities to gain first-hand experience with EVs.

As our measure of single-day mileage for private cars reflects a randomly chosen record day, one may argue that it may not sufficiently capture heterogeneity in mobility demand throughout the year. Many individuals may experience some high-mobility demand days per year on selected days, e.g., when they use their car to go on vacation. It is conceivable that very few high-mobility demand days per year are perceived as a strong barrier to adopting an EV. Among private households, the concern is particularly relevant for one-vehicle households which cannot switch to an ICEV. To circumvent this problem, car manufactures could try to make ICEV rentals over longer time periods (e.g., during a vacation of one or two weeks) or access to long-distance rail transport easily and cheaply available to EV owners, possibly in form of a voucher. Such short-term rentals could also offer an interesting market for car rental companies. Of course, the increased dispersion of EV charging station availability and higher cruising ranges due to improved battery technology also help to resolve the problem. Among car sharing users, individual days with particularly high mobility demand should not pose a problem for EV adoption as a car sharing membership allows users to flexibly choose between different engine types

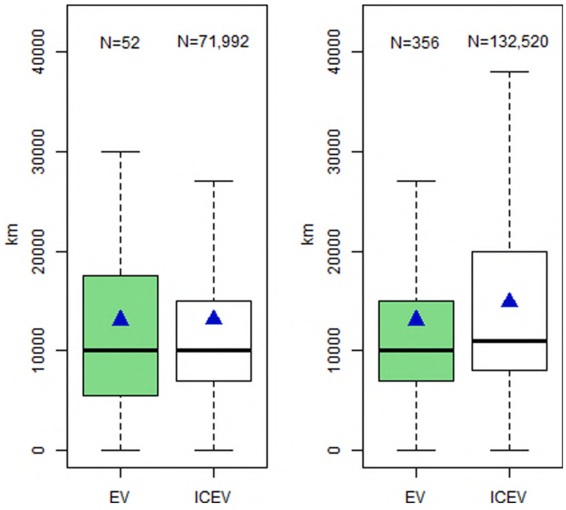

Fig. 10. Boxplots for annual mileage of EVs and ICEVs by number of household cars in the private fleet, excluding outliers. Left panel cars in single-vehicle households, right panel cars in multi-vehicle households.

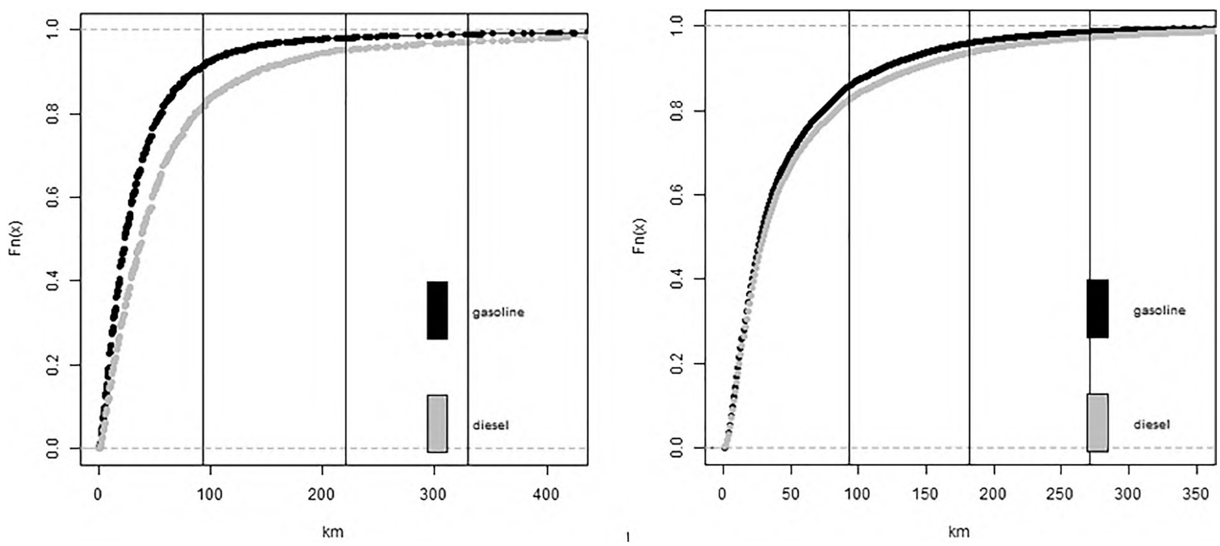

Fig. 11. Cumulative distribution function single-day mileage (for diesel cars in grey and gasoline cars in black). Left panel private cars, right panel shared cars.

for every single trip (although rentals over a couple of days might become very expensive).

Despite higher market penetration of EVs in the car sharing fleet than in the private fleet, we also found that EVs are utilized less as compared to ICEVs. Shared EVs are not only driven fewer kilometers per trip, but they are also booked less frequently than ICEVs throughout the year. This finding implies that there is potential to increase EV usage in the car sharing fleet by financially incentivizing users or motivating them in other ways to switch from ICEVs to EVs.

More generally, to increase the uptake and use of EVs, policies should continue to address the expansion of the public charging station network but should also subsidize the installation of private charging points (as has been implemented in Germany in 2020). Furthermore, the public procurement of EVs (in particular buses) could increase the visibility of this technology in the public and reflect trust in daily usage while further decreasing production costs. Finally, the standardization of charging technologies and billing schemes for public charging points could significantly increase users' trust towards EV technology.

Our analysis captures usage patterns of EVs in a period of time in which EVs have not reached the mass market yet (at least in Germany). It thus remains to be seen how these patterns will change when better charging infrastructure is provided and EVs are not only used by early adopters with potentially lower mobility demand than the average car owner. It seems likely that EVs will then be used more intensely than now, also compared to ICEVs. Due to lower variable costs and a potentially "greener" conscience of the drivers, overall mileage might not necessarily be reduced with higher EV adoption rates.

Table 6
Flinkster price list (valid between 2014 and 2020; obtained from Flinkster's website)

Car segments	Example cars	Hourly price 10 pm-8am	Hourly price 8am-10 pm	Day price Day 1	Day price From Day 2	Price per km
Mini (without GPS)	Toyota Aygo	€1.50	€2.30	€39.00	€29.00	€0.18
Small (partly without GPS)	Citroen C-Zero, Opel Corsa, Peugeot Ion, Ford Fiesta, VW Polo, Peugeot 207, MINI-E	€1.50	€5.00	€50.00	€29.00	€0.18
Compact	VW Golf, Opel Astra, Ford Focus Turnier, Peugeot 307	€1.90	€6.00	€60.00	€39.00	€0.18
Middle	VW Passat, Ford Mondeo, MB C-Klasse, Toyota Prius Plug-In PHV, Audi A4, Opel Ampera	€1.90	€7.00	€70.00	€49.00	€0.20
Transporter (partly without GPS and with more seats)	Ford Transit, MB Sprinter, Opel Movano, VW T5	€1.90	€8.00	€80.00	€59.00	€0.20
High	Volvo XC 60	€2.50	€8.00	€90.00	€69.00	€0.22
Luxury	Volvo XC 90	€3.00	€9.50	€110.00	€89.00	€0.22

Table 7
Summary statistics annual mileage car sharing vehicles available throughout an entire year

	Mean	Standard deviation	N
EV	5361	4408	64
Diesel	20,490	7678	769
Gasoline	21,390	5482	44
ICEV aggregate	20,540	7575	813

Table 8
Summary statistics for single-day mileage with shared cars by station type

	EV stations	Mixed stations			ICEV stations	
	EV	EV	Gasoline	Diesel	Gasoline	Diesel
Mean	22	20	49	57	49	58
Standard deviation	20	19	66	83	59	76
N	13,247	7907	2034	22,867	49,949	301,759

Table 9
Regression results (dependent variable: ln mileage at the booking level; p-values in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$). Our OLS estimation results are derived from the following econometric model: $\ln(y_i) = \alpha + \boldsymbol{x_i}^T \boldsymbol{\beta} + u_i$. The dependent variable y_i denotes the mileage driven (during one booking i); x_i is a vector of different explanatory variables including: a binary variable diesel which equals one if the shared vehicle is a diesel vehicle; a binary variable gasoline which equals one if the shared vehicle is a gasoline vehicle; the binary variables medium-sized car and transporter which are based on the categorization of vehicles in Footnote 7; the binary variable mixed station if at least one EV and one ICEV was theoretically available when the booking was made; and the binary variable regular customer which equals one for users with at least two bookings in the whole observation period. The parameterα depicts the constant, while β is the vector of coefficients. Finally, u_i is the error term and assumed to follow a normal distribution.

	(1)	(2) Vehicle category	(3) Station type	(4) Customer type
Diesel	0.79***	0.73***	0.73***	0.74***
	(0.00)	(0.00)	(0.00)	(0.00)
Gasoline	0.63***	0.66***	0.66***	0.66***
	(0.00)	(0.00)	(0.00)	(0.00)
Medium-sized car		0.52***	0.52***	0.51***
		(0.00)	(0.00)	(0.00)
Transporter		−0.05***	−0.05***	−0.08***
		(0.00)	(0.00)	(0.00)
Mixed station			0.00	−0.00
			(0.78)	(0.64)
Regular customer				−0.51***
				(0.00)
_cons (α)	2.87***	2.84***	2.84***	3.33***
	(0.00)	(0.00)	(0.00)	(0.00)
N	479,572	479,572	479,572	479,572

Declaration of Competing Interest

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

Acknowledgements

The authors thank the Associate Editor Dimitris Potoglou, two anonymous referees, Elisa Rottner, Martin Achtnicht and Andreas Ziegler for valuable comments and suggestions, and Kathrin Schwörer, Johannes Gessner, Paula Beck and Marina Schwab for excellent research assistance. Huwe and Kesternich acknowledge the generous financial support of the Federal Ministry of Education and Research (BMBF) through the project INTEGRATE (FKZ: 01LP1928B), Habla acknowledges the financial support of MISTRA through the program Carbon Exit and of the Leibniz Science Campus MannheimTaxation. The study made use of data provided by DB Connect GmbH (https://data.deutschebahn.com/dataset/data-flinkster).

Appendix

See Figs. 10 and 11.
See Tables 6–9.

References

Alkhalisi, A.F., 2020. Creating a qualitative typology of electric vehicle driving: EV journey-making mapped in a chronological framework. Transp. Res. Part F 69, 159–186.

Anable, J., Skippon, S., Schuitema, G., Kinnear, N., 2011. Who will adopt electric vehicles? A segmentation approach of UK consumers. European Council for an Energy Efficient Economy.

Andor, M.A., Gerster, A., Gillingham, K.T., Horvath, M., 2020. Running a car costs much more than people think – stalling the uptake of green travel. Nature 580, 453–455.

Arkes, H.R., Blumer, C., 1985. The psychology of sunk cost. Org. Behav. Human Decis. Process. 35 (1), 124–140.

Axsen, J., Cairns, J., Dusyk, N., Goldberg, S., 2018. What drives the pioneers? Applying lifestyle theory to early electric vehicle buyers in Canada. Energy Res. Social Sci. 44, 17–30.

Bauer, G., 2018. The impact of battery electric vehicles on vehicle purchase and driving behavior in Norway. Transp. Res. Part D 58, 239–258.

Belzowski, B.M., 2015. Total cost of ownership: a diesel versus gasoline comparison (2012–2013). Technical Report UMTRI, 2015-20.

BMVI, 2019. The future of mobility is electric. Available at: https://www.bmvi.de/SharedDocs/EN/Dossier/Electric-Mobility-Sector/electric-mobility-sector.html. German Federal Ministry for Transport and Digital Infrastructure. Last accessed: 21/02/2020.

Breetz, H.L., Salon, D., 2018. Do electric vehicles need subsidies? Ownership costs for conventional, hybrid, and electric vehicles in 14 U.S. cities. Energy Policy 120, 238–249.

Burghard, U., Dütschke, E., 2019. Who wants shared mobility? Lessons from early adopters and mainstream drivers on electric carsharing in Germany. Transp. Res. Part D 71, 96–109.

Chu, W., Im, M., Song, M.R., Park, J., 2019. Psychological and behavioral factors affecting electric vehicle adoption and satisfaction: a comparative study of early adopters in China and Korea. Transp. Res. Part D 76, 1–18.

Clewlow, R.R., 2016. Carsharing and sustainable travel behavior: results from the San Francisco Bay Area. Transp. Policy 51, 158–164.

Daramy-Williams, E., Anable, J., Grant-Muller, S.M., 2019. A systematic review of the evidence on plug-in electric vehicle user experience. Transp. Res. Part D 71, 22–36.

Davis, L.W., 2019. How much are electric vehicles driven? Appl. Econ. Lett. 26 (18), 1497–1502.

Figenbaum, E., Kolbenstvedt, M., 2016. Learning from Norwegian battery Electric and Plug-in Hybrid Vehicle Users. Institute for Transport Economics, Oslo.

Gillingham, K., Rapson, D., Wagner, G., 2016. The rebound effect and energy efficiency policy. Rev. Environ. Econ. Policy 10, 68–88.

Greaves, S., Backman, H., Ellison, A.B., 2014. An empirical assessment of the feasibility of battery electric vehicles for day-to-day driving. Transp. Res. Part A 66, 226–237.

Hasan, S., Simsekoglu, Ö., 2020. The role of psychological factors on vehicle kilometer travelled (VKT) for battery electric vehicle (BEV) users. Res. Transp. Econ. 82, 1–8.

Hidrue, M.K., Parsons, G.R., Kempton, W., Gardner, M.P., 2011. Willingness to pay for electric vehicles and their attributes. Resour. Energy Econ. 33 (3), 686–705.

Ho, T.-H., Png, I.P.L., Reza, S., 2018. Sunk cost fallacy in driving the world's costliest cars. Manage. Sci. 64 (4), 1761–1778.

Hoekstra, A., Steinbuch, M., 2020. Comparing the lifetime greenhouse gas emissions of electric cars with the emissions of cars using gasoline or diesel. Technical report. Available at: https://www.oliver-krischer.eu/wp-content/uploads/2020/08/English_Studie.pdf Last accessed: 30/10/2020.

Horvath & Partners, 2019. Faktencheck E-Mobilität Update 2018/2019.

Huwe, V., Gessner, J., 2020. Are there rebound effects from electric vehicle adoption? Evidence from German household data. ZEW Discussion Paper 20–048.

Jakobsson, N., Gnann, T., Plötz, P., Sprei, F., Karlsson, S., 2016. Are multi-car households better suited for battery electric vehicles? – Driving patterns and economics in Sweden and Germany. Transp. Res. Part C 65, 1–15.

Jensen, A.F., Mabit, S.L., 2017. The use of electric vehicles: a case study on adding an electric car to a household. Transp. Res. Part A 106, 89–99.

Kawgan-Kagan, I., 2015. Early adopters of carsharing with and without BEVs with respect to gender preferences. Eur. Transp. Res. Rev. 7 (4), 33.

Klöckner, C.A., Nayum, A., Mehmetoglu, M., 2013. Positive and negative spillover effects from electric car purchase to car use. Transp. Res. Part D 21, 32–38.

Langbroek, J.H.M., Cebecauer, M., Malmsten, J., Franklin, J.P., Susilo, Y.O., Georén, P., 2019. Electric vehicle rental and electric vehicle adoption. Res. Transp. Econ. 73, 72–82.

Meinrenken, C.J., Shou, Z., Di, X., 2020. Using GPS-data to determine optimum electric vehicle ranges: a Michigan case study. Transp. Res. Part D 78.

Melliger, M.A., van Vlietb, O.P.R., Liimatainen, H., 2018. Anxiety vs reality – Sufficiency of battery electric vehicle range in Switzerland and Finland. Transp. Res. Part D 65, 101–115.

Morton, C., Anable, J., Nelson, J.D., 2017. Consumer structure in the emerging market for electric vehicles: identifying market segments using cluster analysis. Int. J. Sustain. Transp. 11, 443–459.

Morton, C., Anable, J., Yeboah, G., Cottrill, C., 2018. The spatial pattern of demand in the early market for electric vehicles: evidence from the United Kingdom. J. Transp. Geogr. 72, 119–130.

Needell, Z.A., McNerney, J., Chang, M.T., Trancik, J.E., 2016. Potential for widespread electrification of personal vehicle travel in the United States. Nat. Energy 1 (9), 16112.
Neubauer, J., Wood, E., 2014. The impact of range anxiety and home, workplace, and public charging infrastructure on simulated battery electric vehicle lifetime utility. J. Power Sources 257, 12–20.
Nobis, C., Kuhnimhof, T., 2018. Mobilität in Deutschland – MiD: Ergebnisbericht.
Palmer, K., Tate, J.E., Wadud, Z., Nellthorp, J., 2018. Total cost of ownership and market share for hybrid and electric vehicles in the UK, US and Japan. Appl. Energy 209, 108–119.
Pearre, N.S., Kempton, W., Guensler, R.L., Elango, V.V., 2011. Electric vehicles: how much range is required for a day's driving? Transp. Res. Part C 19, 1171–1184.
Plötz, P., Schneider, U., Globisch, J., Dütschke, E., 2014. Who will buy electric vehicles? Identifying early adopters in Germany. Transp. Res. Part A 67, 96–109.
Potoglou, D., Susilo, Y.O., 2008. Comparison of vehicle-ownership models. Transp. Res. Rec. 2076 (1), 97–105.
Rauh, N., Günther, M., Krams, J.F., 2020. Positive influence of practical electric vehicle driving experience and range related knowledge on drivers' experienced range stress. Transp. Res. Part F 71, 182–197.
Samuelson, W., Zeckhauser, R., 1988. Status quo bias in decision making. J. Risk Uncert. 1 (1), 7–59.
Schaefers, T., 2013. Exploring carsharing usage motives: a hierarchical means-end chain analysis. Transp. Res. Part A 47, 69–77.
Scorrano, M., Danielis, R., Giansoldati, M., 2020. Dissecting the total cost of ownership of fully electric cars in Italy: The impact of annual distance travelled, home charging and urban driving. Res. Transp. Econ. 80.
Sheeran, P., 2002. Intention-behavior relations: a conceptual and empirical review. Eur. Rev. Soc. Psychol. 12 (1), 1–36.
Shi, X., Pan, J., Wang, H., Cai, H., 2019. Battery electric vehicles: what is the minimum range required? Energy 166, 352–358.
Sivak, M., Schoettle, B., 2018. Relative costs of driving electric and gasoline vehicles in the individual U.S. states. Report SWT-2018-1.
Sorrell, S., Dimitropoulos, J., 2008. The rebound effect: microeconomic definitions, limitations and extensions. Ecol. Econ. 65 (3), 636–649.
Sovacool, B.K., Kester, J., Noel, L., de Rubens, G.Z., 2018. The demographics of decarbonizing transport: the influence of gender, education, occupation, age, and household size on electric mobility preferences in the Nordic region. Global Environ. Change 52, 86–100.
Sprei, F., Habibi, S., Englund, C., Pettersson, S., Voronov, A., Wedlin, J., 2019. Free-floating car-sharing electrification and mode displacement: travel time and usage patterns from 12 cities in Europe and the United States. Transp. Res. Part D 71, 127–140.
Tamor, M.A., 2019. Examining the case for long-range battery electric vehicles with a generalized description of driving patterns. Transp. Res. Part C 108, 1–11.
Tate, E.D., Harpster, M.O., Savagian, P.J., 2009. The electrification of the automobile: From conventional hybrid, to plug-in hybrids, to extended-range electric vehicles. SAE Int. J. Passenger Cars Electron. Electr. Syst. 1 (1), 156–166.
Van Wee, B., 2009. Self-selection: a key to a better understanding of location choices, travel behaviour and transport externalities? Transp. Rev. 29 (3), 279–292.
Vassileva, I., Campillo, J., 2017. Adoption barriers for electric vehicles: Experiences from early adopters in Sweden. Energy 120, 632–641.
Vial, A., Schmidt, A., 2019. Quantifying the potential of electrification with large-scale vehicle trajectory data. Transp. Res. Procedia 41, 577–586.
Wu, N., Song, X.B., Yao, R., Yu, Q., Tang, C., Zhao, S., 2020. A Bayesian sample selection model based on normal mixture to investigate household car ownership and usage behavior. Travel Behav. Soc. 20, 36–50.