Access to charging infrastructure and the propensity to buy an electric car

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Abstract

The policies for supplying charging infrastructure will be an important issue for the accel-eration of electrification of cars. In Sweden most early adopters of chargeable vehicles have been residents in detached houses. Residents in apartment buildings will be more dependent on public charging. This paper therefore examines how access to public charg-ing can affect the probability of buyers of new cars to choose a chargeable car. The main results indicate that the density of public charging stations close to home and work has a small but significant effect for buyers of private cars, as well as for buyers of other com-pany cars. We cannot however show any effect for the acquisition of Benefit In-Kind (BIK) company cars, but this could be due to incomplete data on charging access at the workplace. The socio-economic control variables are household income, having more than one car in the household, residence in a detached house, and that the owners of the apart-ment building received a grant for installing charging infrastructure close to the apartment building. These variables all have strong effects in the model. In the models of company cars, type of industry has strong effects for some industries.

Keywords
Car type choice, Discrete choice modelling, Electric vehicle adoption, Electrification and decarbonization of transport, Revealed preference, Charging infrastructure

JEL Codes
H54, R42

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ABSTRACT

The policies for supplying charging infrastructure will be an important issue for the acceleration of electrification of cars. In Sweden most early adopters of chargeable vehicles have been residents in detached houses. Residents in apartment buildings will be more dependent on public charging. This paper therefore examines how access to public charging can affect the probability of buyers of new cars to choose a chargeable car. The main results indicate that the density of public charging stations close to home and work has a small but significant effect for buyers of private cars, as well as for buyers of other company cars. We cannot however show any effect for the acquisition of Benefit In-Kind (BIK) company cars, but this could be due to incomplete data on charging access at the workplace. The socio-economic control variables are household income, having more than one car in the household, residence in a detached house, and that the owners of the apartment building received a grant for installing charging infrastructure close to the apartment building. These variables all have strong effects in the model. In the models of company cars, type of industry has strong effects for some industries.

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1. INTRODUCTION

Many countries, including Sweden, want to speed up the transition towards electric vehicles (EV). In this context, it is important to increase the knowledge about which polices that most cost efficiently could speed up electrification by incentivising car buyers to choose EVs.

Several previous studies investigated who buys an electric car. Recently, Archsmith et. al (2022) utilized car buyer data from the U.S. and showed that buying an EV is correlated with high income, high education, being 35-45 years old and living in more liberal states. Plötz et al. (2014) showed that the group of early EV owners in Germany were mainly men with families in suburbs or rural areas who value the environment and with a high vehicle kilometres travelled per year. Fevang et al. (2020) investigated Norwegian register data from 2011-2017 and found that EV owners were more likely to be families with children, high income, high education level and live in central areas. Trafikanalys (2023) used detailed Swedish register data from 2020 and identified high income, high education level, living at the outskirts of an urban area, living in detached house, being male and having Swedish background as explanatory factors for buying an EV. Trafikanalys also compared the results to 2016 and found that the importance of detached house and high income had diminished somewhat. Two further studies pointed out that early EV owners are a special niched group but that EV buyers with time become more similar to car buyers in general and that this development can go pretty fast, around 4-5 years (Bjørge et al., 2022; Fevang et al., 2020; Trafikanalys, 2023). None of the above papers directly examined the influence of accessibility to charging infrastructure on the choice of car type, but the issue of charging is often noted.

Of the studies explicitly considering charging infrastructure, the perhaps most cited study is Springel (2021), already available as a working paper in 2017, which used a two-sided market framework and Norwegian data from 2010 to 2015 to compare the different impacts of subsidies to car purchases and charging infrastructure. Estimates indicated that a dollar spent on charging infrastructure resulted in more than twice as many EV purchases as a dollar spent on vehicle purchase subsidies. Furthermore, this relation was found to revert as spending on charging infrastructure increased. Schulz and Rode (2022) used an event study approach to study Norwegian highly resolved data on location of public charging and the ownership rate of BEVs in 356 municipalities from 2009 to 2019 thus having four more years than Springel. They concluded that charging infrastructure had a stimulating effect on the number of EVs, although the direction of causality was not obvious. Illman and Kluge (2020) estimated the effect of increasing availability of public charging infrastructure on the likelihood of buying an EV. The results indicated a positive long-run relationship but on “a rather low scale”. Dixon et al. (2020) investigated the inconvenience of EV charging compared to fuelling of an internal combustion engine vehicle (ICEV) in the UK, and found a much larger potential EV charging inconvenience for those who cannot charge at home. Egnér and Trosvik (2018) estimated an aggregate relationship between EV adoption and public charging infrastructure supply at municipal level in Sweden and found that, especially in urban municipalities, EV adoption increased with an increased number of public charging points. Haustein et al. (2021) used three surveys in Denmark and Sweden from 2017, 2018 and 2019 to model purchase intentions. They found that intentions were stable. A significant effect of new fast chargers was found in Denmark but not in Sweden. Patt et al. (2019) used a randomized survey and found that people who own their parking space stated that they were almost twice as likely to purchase an EV as those parking in streets and 50% more likely than those who park in communal parking or in a garage.

The aim of this paper is to investigate the influence of accessibility to public charging facilities in Sweden (also considering private charging) on the choice of a new car type and the likelihood of buying an EV, both fully electric vehicle (BEV) and plug-in hybrid (PHEV), controlling for other factors. This is done by estimating a Swedish car type choice model based on previous research using 2019 demand data including socio-economic information for households, the supply of cars in 2019, and the supply of public charging infrastructure in the same year. We also use data on established charging facilities in housing cooperatives, as well as sparse data on charging facilities at workplaces. The data sources imply that we analyse cross-section data for one year. We also compare the 2019 estimation results with results of a limited model estimation on 2022 data which is richer in electric vehicle choices but does not include socio-economic and charging infrastructure information.

In the analysis, we define car buyers in three segments having different car attribute preferences. The segments are private car buyers, company cars bought by companies for private use and other cars bought by companies. The employee benefit of having a company car bought for private use is taxed as a Benefit-In-Kind (BIK), and for short we refer to company cars as either BIK company cars or other company cars.

The research questions of this paper are:

1) Did accessibility to public charging infrastructure influence the choice of car type in 2019?
2) If so, in what way and to which extent did accessibility to public charging infrastructure influence the choice of buying an electric car in 2019?
3) Did the influence of accessibility to charging infrastructure differ between fully electric vehicles and plug-in hybrids in 2019?
4) Did the influence of accessibility to public charging infrastructure differ between the segments private cars, BIK company cars, and other company cars in 2019?

A main drawback associated with electric vehicles is the time it takes to charge the vehicle. This is related to the vehicle as well as the user and the charging infrastructure. The need to charge has different implications for daily car use and less frequent longer distance trips. Daily use is less demanding regarding range and speed of charging, and more demanding regarding accessibility to charging infrastructure close to dwelling location. For long-distance travel, range and charging speed are important, as well as the location of charging infrastructure. The daily use and long-distance travel components therefore imply different variable formulations.

To summarize, previous literature has looked at a more aggregate zonal level and found that charging infrastructure has an impact on electric vehicle adoption. There are however few or no studies that look in detail how accessibility to public charging infrastructure, for daily use as well as long-distance travel, impacts the car type choices of individual buyers and compare the impacts for three different segments private cars, BIK company cars, and other company cars. This is thus the research gap which we address in this paper.

2. METHOD

2.1. Hypotheses

Before conducting the analysis, we formulate several hypotheses regarding the influence of accessibility to charging infrastructure, for daily use as well as for long-distance travel.

2.1.1 Variables associated with daily use

We hypothesize that important factors related to daily use charging for the propensity to buy an electric car (BEV and PHEV) are:

H1 Access to public charging infrastructure close to home if you live in an apartment without access to easy home charging (private cars),
H2 Access to public charging infrastructure close to work (all segments),
H3 Living in a detached house as a proxy for easy home charging (private cars),
H4 Living in an apartment where the housing cooperative or landlord has received a grant for installing charging infrastructure as a proxy for easy home charging (private cars).

For BEVs limited range has been, and continues to be, an issue to be considered by car buyers. For PHEVs this issue is less important. We therefore test the hypothesis that households owning more than one car are more likely to choose a BEV, than households owning only one. Regarding differences between fully electric cars and plug-in hybrids we hypothesize that:

H5 There is no significant difference in the importance of access to public charging infrastructure close to home (private cars),
H6 Access to local public charging infrastructure close to work is more important for plug-in hybrids compared to fully electric cars given the shorter electric range of plug-in hybrids (all segments),
H7 Having more than one car in the household is an important explanatory factor for choosing a fully electric car (private cars).

2.1.2 Variables associated with long-distance travel

Charging requirements for long-distance trips depend on trip lengths. Depending on the range of the vehicle, charging might not even be required when the trip length is less than the (real) range of the vehicle. For that reason, pure range may be a very coarse descriptor of the disutility of the charging requirement. We therefore also test another measure, called the logsum, which is built on the expected travel pattern for long distance trips.

So, we test two versions of long-distance charging disutility – pure range, and the logsum range constraint. These measures are mainly used to describe long distance effects, but we do not rule out the possibility that range may also influence the choice of PHEV. This results in the following hypotheses:

H8 Range affects the propensity to buy an electric vehicle (BEV and PHEV)
H9 The range constraint on long-distance travel accessibility affects the propensity to buy an electric vehicle (BEV only)

2.2. Car type choice models

In this paper, three multinomial logit (MNL) models (Ben-Akiva & Lerman, 1985; McFadden, 1974) for passenger car type choice are estimated for the segments private cars, BIK company cars, and other company cars. The difference between the two company-owned segments is that BIK company cars is used as a proxy for company cars used also for private car travel, whereas other company cars are supposed to be used only while working. We build on previous work with the Swedish car type choice model (Engström et al., 2019), but estimate the model on data from year 2019 and add variables related to both private and public charging infrastructure. Year 2019 is chosen due to broken supply chains in the years during and after the Covid-19 pandemic, which led to long delays in delivery of new cars. Buyers wanting a new car reasonably fast did thus often not have the possibility to choose their first-choice car type. We later realised that there is a trade-off between using data unaffected by the pandemic and data from a later year when the market share of electric cars is higher. Therefore, we also estimate car type choice models on year 2022 data (without socioeconomic and charging infrastructure information), which was to some extent affected by the pandemic, but with a much larger share of electric cars bought.

In the model, car alternatives are defined by make, fuel type and fuel consumption class. There are 32 makes, 9 fuel types (Table 1) and 50 fuel consumption interval classes.

Table 1: Car type choice model fuel types.

Fuel type	Definition
Petrol	Petrol only
Diesel	Diesel only
BEV	Fully electric car
HEVPetrol	Petrol car with electric nonchargeable engine
HEVDiesel	Diesel car with electric nonchargeable engine
PHEVPetrol	Petrol car with electric chargeable engine
PHEVDiesel	Diesel car with electric chargeable engine
Gas	CNG car
E85	Petrol and Ethanol car

The model is an MNL model, defined by Equation 1 and 2.

$$P_{ijk} = \frac{e^{V_{ijk}}}{\sum_{ijk} e^{V_{ijk}}} \qquad \text{Eq. (1)}$$

$$V_{ijk} = \sum_m \beta_m x_{ijkm} \qquad \text{Eq. (2)}$$

P_{ijk} denotes the probability to choose car type of make i, fuel type j and fuel consumption class k and V_{ijk} is a sum of car attribute variables multiplied with parameters to be estimated, expressing the observed utility of the car type alternative.

2.3 Data

Four different sources of data are used in estimation:

1) Choice data in the form of register data on all new cars bought by a private household or a company during 2019. The choice data on private cars includes socio-economic information on the household of the buyer. This information includes home zone (typically a

square of 250m x 250m, but in sparser areas a square of 1km x 1km), work zone[1], household income, type of housing (detached house or apartment), and the number of cars owned by the household. We divide private car buyers into five classes depending on household income before tax (see Table 2) and estimate separate purchase price parameters for each household income class, to capture the effect of sensitivity to price decreasing with increasing household income. The choice data on company-owned cars only includes socio-economic information in the form of type of industry and work zone. We do not have access to information on the user of the car. For all three segments, the data on the type of car bought includes information about brand, fuel type, and fuel consumption.

2) Supply data consisting of price, benefit value, operation cost, range, rust guarantee, number of seats, weight, safety classification for each of the 597 car types was formed from all cars sold during 2019. Each car type is categorized by a brand, a fuel type, and a fuel consumption class, i.e. there are several car models averaged into one car type. One of the brand categories is 'other', where several rare brand choices are included. For 2022, a corresponding dataset was established also including data on the number of chosen car types in each of the 24 counties in Sweden.
3) Public charging infrastructure data on the location of charging stations in Sweden in 2019 and how many outlets there were at each station.
4) Data from *Klimatklivet* on apartment building locations where the housing cooperative has received a grant in 2019 or earlier for installing charging infrastructure.

Table 2: Lower and upper bound for household income classes, with household income measured as kSEK/year before taxes.

Household income class	Lower bound	Upper bound
HI1	0	400
HI2	401	800
HI3	801	1600
HI4	1601	2400
HI5	2401	-

[1] The workplace data is not complete. For the three segments, work zone is missing for 2% of private car observations, 43% of BIK company car observations and 22% of other company car observations.

2.4 Charging infrastructure accessibility measures

2.4.1 Private charging close to home

The user of an electric car obviously must have reasonable access to a charging facility. An advantage is that charging does not require the driver to be present, which makes charging over night or during another activity of the driver possible. The most convenient solution is of course to have a charging facility where the user prefers to park the vehicle over-night. Other solutions are also possible (but less convenient), like publicly available charging facilities. We therefore think that an important variable would be whether there is access to charging close to the dwelling place of the user. For persons living in houses of their own, it can be said that this possibility exists. Therefore, we introduce a binary variable for persons living in a house of their own (*DetachedHouse*) which is a proxy for easy home charging.

For persons living in apartment houses, a similar charging possibility will exist only if the landlord or housing cooperative has installed private charging posts. The data on apartment building locations where the housing cooperative or landlord has received a grant for installing charging infrastructure were matched to car buyer home zones. We introduce a binary variable called *Grant* which is 1 if the home zone of the buyer could be matched to a zone where an housing cooperative has received a grant for installing charging infrastructure.

2.4.2 Public charging close to home

From the data on location of public charging infrastructure and on location of the home of the car buyer we construct a variable (*PublicChargingHome*) which comprises number of charging stations within one kilometre from the home. Since home zone is only available for car buyers of private cars, this variable can only be constructed for this segment.

The process of matching the number of stations to an observation involves first identifying the centre of the home zone square. From this central point, we draw a circle with a radius of 1 km. The locations of charging stations are then compared to this circle, and the number of charging stations within its perimeter is attributed to the observation.

2.4.3 Public charging close to work

From the data on location of public charging infrastructure and on location of the workplace we construct a variable (*PublicChargingWork*) which comprises number of charging stations within one kilometre from the workplace. The matching process equals that of identifying public charging stations close to home, with the primary distinction being the use of the work zone square instead of the home zone square.

For company-owned cars, work zone is not as adequately determined as the place of residence of the owner of private cars. The municipality where the company car was bought is given. If the company only has one office in the municipality, then we assume that the 250x250m square where the company is located is the location of the owner's workplace. However, sometimes a company has multiple workplaces in the same municipality and then we use an average of number of charging stations within 1km from these offices. Information about work zone is missing if the company has no office in the given municipality. It should be noted that BIK company cars are often used in the vicinity of the home of the benefit taker, which we have no information about.

2.4.4 Charging accessibility for long-distance travel

As described above, we test two variables describing long-distance charging disutility: pure range (*Range*) and a logsum range constraint (*Logsum*). The logsum measure uses a model for long-distance trips developed for the national Swedish travel forecasting model Sampers (Beser & Algers, 2002). This model also comprises the mode and destination choices, giving a car mode trip matrix for long-distance car travel. That matrix is based on travel costs and travel times as well as attraction variables like population and number of employees in different economic industries. It reflects the accessibility to different activities varying with the dwelling zone of the car user. The model is a logit model (Ben-Akiva & Lerman, 1985), and the accessibility to desired activities can therefore be measured by the so called logsum of the destination alternatives.

For electric car users, charging may be required for some of the long-distance destinations. This means that the logsum measure needs to be adjusted for electric cars. This adjustment will depend on the range of the vehicle, but also on the location of public charging infrastructure. If public charging points can be found along the route assumed for the travel time calculation, the adjustment is straight forward using range and charging speed of the vehicle. But if deviations from the assumed route are necessary, additional travel time should be added, requiring recalculation of travel time with respect to necessary route deviations. In this project, travel recalculations have not been available.

It may also be that for long-distance travel the availability of charging facilities is not well known to the user, adding a degree of uncertainty to travel to destinations beyond the range limit. We have therefore tested a formulation of the logsum adjustment by making destinations requiring charging unavailable (which does not require travel time recalculation). The description of how the logsum measure is calculated can be found in the Appendix (A.1).

2.5 Model estimation

As the register data needs to stay on the Statistics Sweden's server MONA[2], all estimations are performed on the server. The software R/Apollo (Hess & Palma, 2019a, 2019b) is used for model estimation. Due to long estimation run times, a sample needs to be made from the choice data. For private cars, all fully electric cars (3343 BEVs) and all plug-in hybrids (2203 PHEVs) are included in a stratified sample, with random sampling of the other vehicle types up to a sample size of 15000 observations. In the stratified sample of 15000 observations, 396 observations were matched as having received a grant for installing charging infrastructure. For company cars (both BIK and other), there are more observations of electric car purchases during 2019 and thus stratified sampling is not necessary. To account for the stratification of the sample of car alternatives for private cars, weights depending on fuel type are used in estimation. Weighting has a large impact on estimation run time, which for the private model increases from 8 hours to around 50 hours when including weighting, even though the estimation has access to more than 100 GB of RAM.

[2] https://www.scb.se/en/services/ordering-data-and-statistics/ordering-microdata/mona--statistics-swedens-platform-for-access-to-microdata/

3 DESCRIPTIVE STATISTICS

In this chapter we show descriptive statistics about the data used in the car type choice modelling and compare between the three segments private cars, BIK company cars, and other company cars, as well as between the total population and BEV buyers.

3.1 Choice data

As choice data we use observations of all cars bought in Sweden in 2019. Table 3 shows the number of observations for each segment. From the total number of observations (the total population) we sample 15000 observations for each segment to reduce run time of the car type choice model estimation. As described in section 2.5, the private sample is stratified and therefore needs to be weighted in estimation, whereas the BIK company car and other company car samples are randomly selected.

Table 3: Number of observations per segment in 2019 choice data. BEV and PHEV sample is weighted for private cars.

Segment	Total pop	BEV pop	PHEV pop	BEV sample	PHEV sample
Private cars	100739	3343	2203	496	327
BIK company cars	110011	6677	11367	931	1560
Other company cars	61172	2223	5153	532	1250

Brand distributions are shown in Figure 1 - Figure 3. Volvo and Volkswagen are the two most popular brands in all segments, but the pattern is most pronounced for leasing cars where Volvo and Volkswagen alone make up for around 45 percent of the observations. For all segments, there are very minor differences between the brand distribution of the total population and the sample.

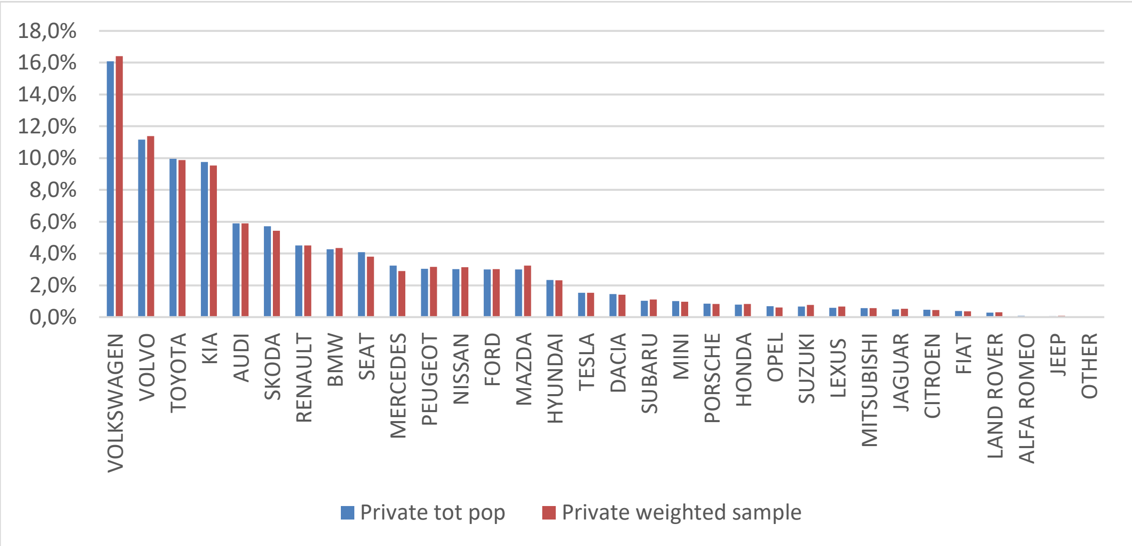

Figure 1: Brand distribution for private cars bought in 2019.

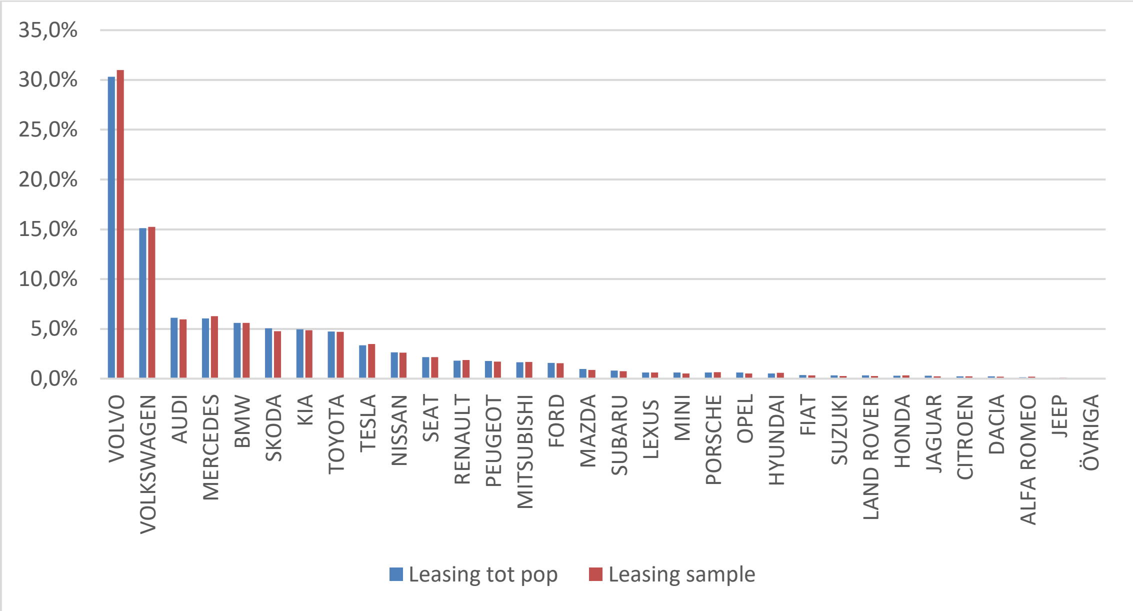

Figure 2: Brand distribution for BIK company cars bought in 2019.

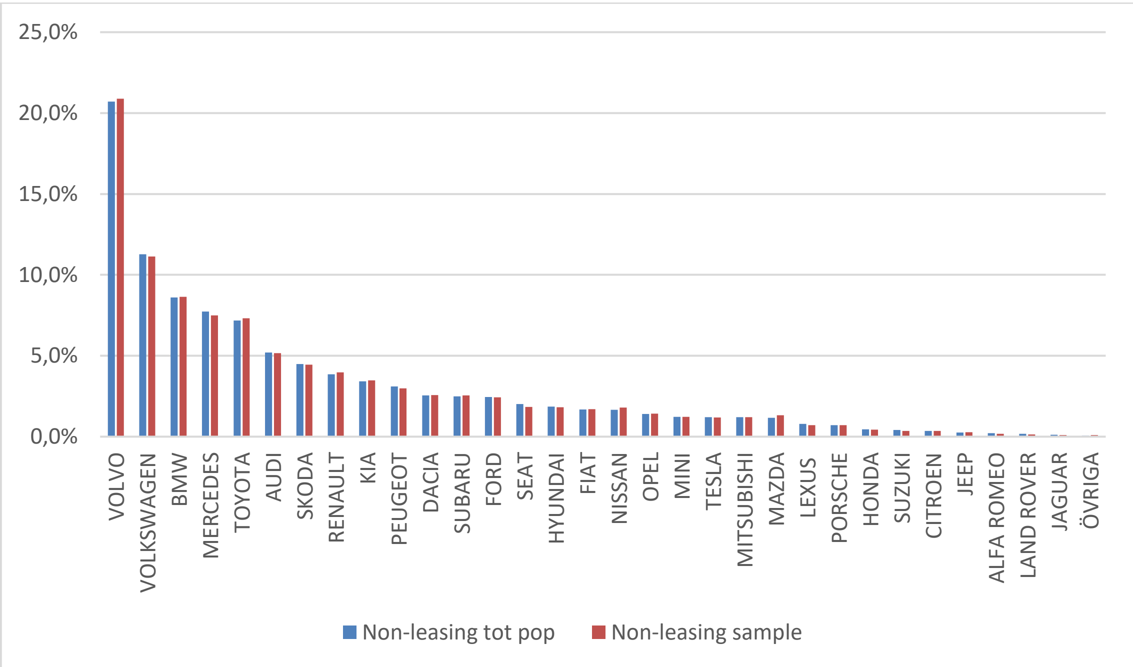

Figure 3: Brand distribution for other company cars bought in 2019.

Figure 4 shows that the differences are small between total population and sample also for the fuel type distribution. Most private cars are petrol cars, whereas diesel has a larger share for company-owned cars. BEVs and PHEVs are most common for leasing cars compared to the other segments.

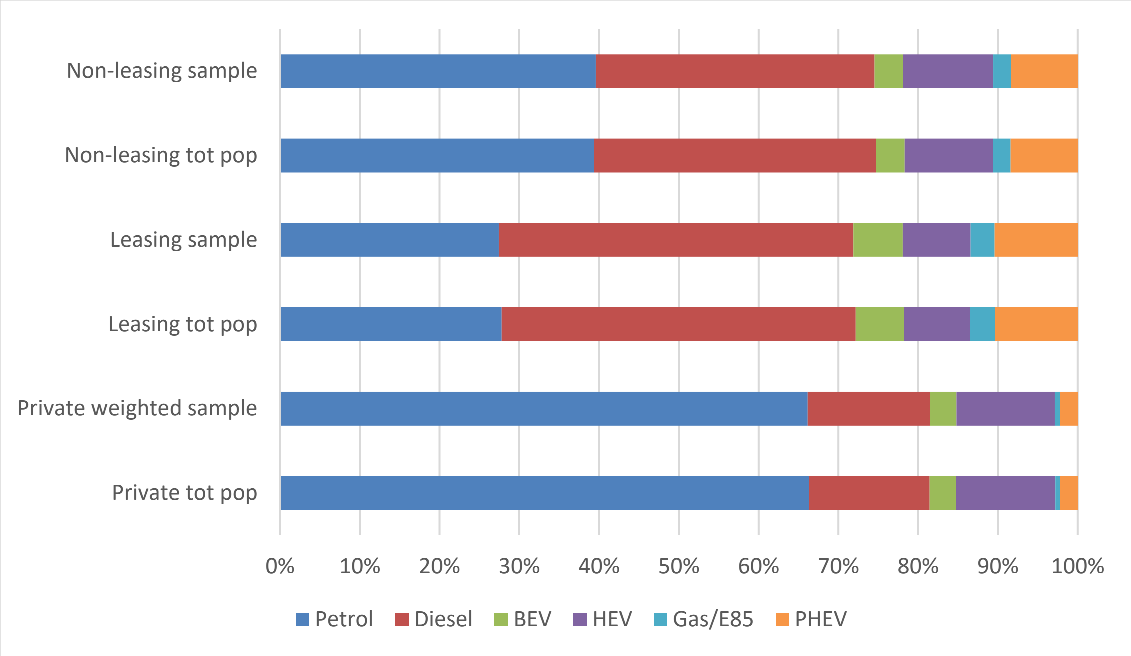

Figure 4: Comparison of fuel type distributions for cars bought in 2019.

For private cars, the choice data includes socio-economic information, i.e. household information about the car buyer.
Table 4 shows descriptive statistics about the socio-economic variables that are included in the car type choice model for private cars. From the data it is clear that the 2019 BEV buyer population differs quite a lot from the general car buyer population. The 2019 BEV buyer population are categorized by that they to a greater extent than the average in the total car buyer population:

- live in a detached house or an apartment where the landlord received a grant for installing charging infrastructure,
- have more than one car in the household,
- live in a large city or rural area,
- have a higher average household income.

In this paper, we use small areas (DESO-areas) defined by Statistics Sweden. These small areas are classified by area type defined as large city, small city, and rural area. An area is classified as a large city area if it is part of a city with more than 60000 inhabitants or a municipality which is part of the same continuous urban area as a large city. Correspondingly, an area is classified as a small city area if it is part of a city with less than 60.000 inhabitants that is the central urbanity in its municipality. All other small areas are classified as rural.

Table 4: Socio-economic characteristics of buyers of private cars in 2019.

Variable	Description	Total population	BEV population
DetachedHouse	Car buyer living in a detached house	62	78
Apartment	Car buyer living in an apartment	38	22
Grant	Car buyer living in an apartment where the landlord received a grant for	2	3

	installing charging infra-structure.		
ManyCarsHH	Car buyer belonging to a household with more than one car.	47	64
RuralArea	Car buyer living in rural area	24	28
SmallCity	Car buyer living in a small city	27	18
LargeCity	Car buyer living in a large city	49	54
Household-Income	Average household in-come in SEK per year (be-fore tax)	1 196 585	2 774 656

Figure 5 shows that fuel type choice depends on household income. Disregarding the two lowest income classes (in reality their household income is not zero), it is a clear pattern that diesel cars, BEVs and PHEVs become more common as household income increases.

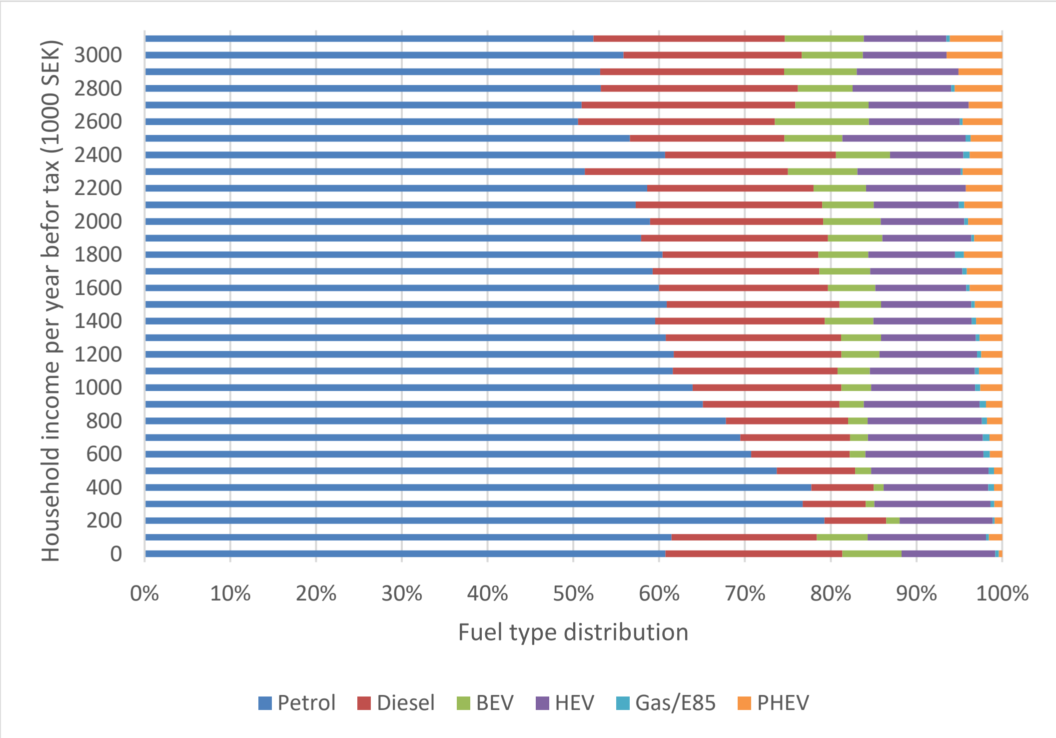

Figure 5: Fuel type distribution per household income class for private cars bought in 2019.

3.2 Supply data

In the supply data, car type alternatives are defined by brand, fuel type and fuel consumption interval. These alternatives are aggregates of “real” car alternatives, i.e., cars that are actual cars bought. By choosing this level of aggregation, it is hoped to describe the alternative attributes as precise as possible. Data sets including several different car attributes for each “real” car sold on the Swedish market are commercially available, and we use a data source from the company

Bilvision to obtain our data sets. Definitions of attributes that we have used in estimation are provided in the estimation sections.

To give an idea of the 2019 market, data on the distribution of some characteristics can be shown. We first show the distribution of car type alternatives on fuel types Figure 6. Supply was in 2019 dominated by petrol and diesel car types. There were only 34 BEV alternatives and 60 PHEV alternatives.

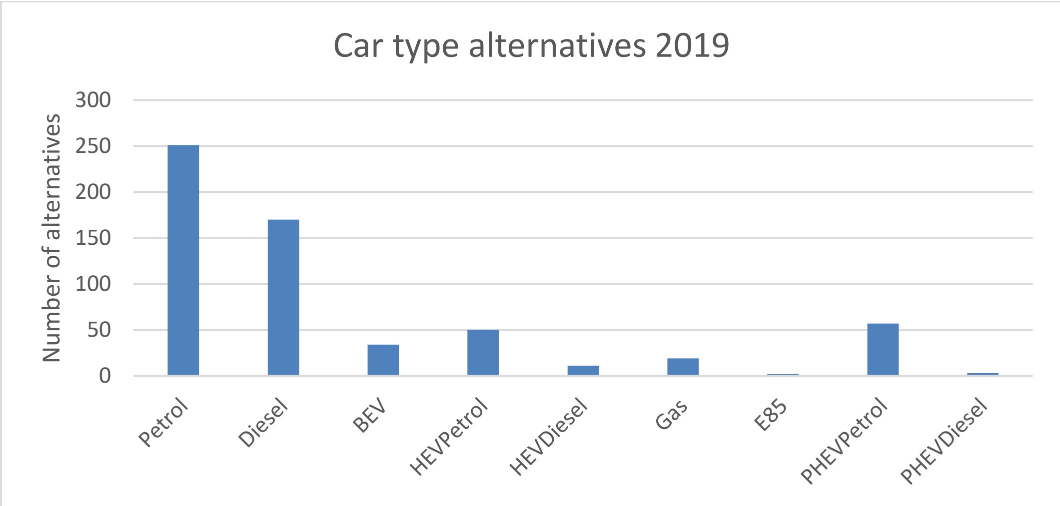

Figure 6: Number of car type alternatives distributed on fuel type 2019.

Range is a central variable for electric vehicles, and Figure 7 gives the distribution of BEV alternatives on range.

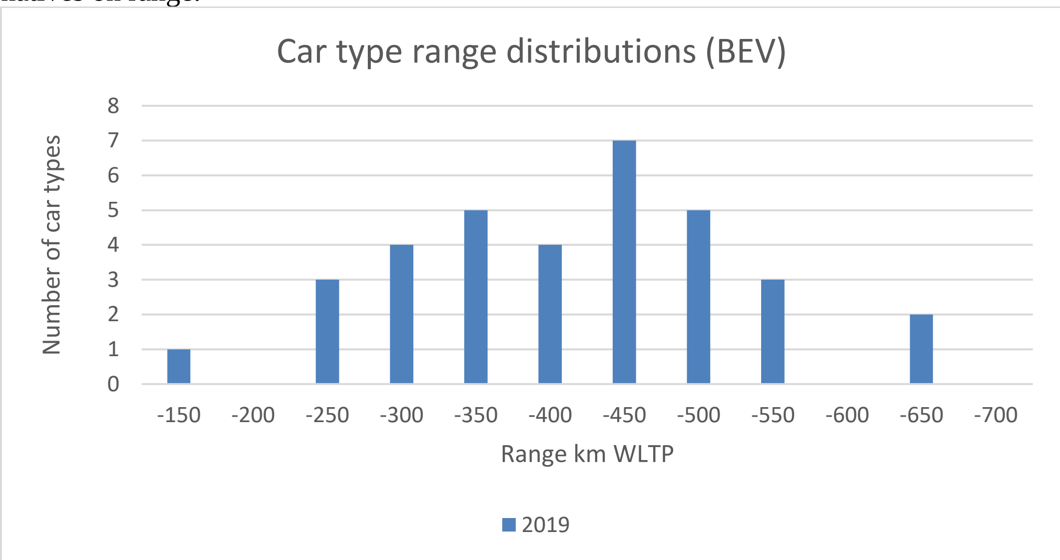

Figure 7: Number of BEV car type alternatives distributed on range 2019.

The most frequent range is between 400 km and 450 km (WLTP), but the majority of alternatives has a shorter range. Range also has a price. In Table 5, the number of alternatives as well as the average purchase price in each range interval is shown. It is obvious that price and range are quite correlated.

Table 5: Average purchase price per range category for BEV alternatives in 2019.

Range km	Number of BEV car type alternatives	Average price (kSEK)
-150	1	235
200-250	3	399
250-300	4	407
300-350	5	443
350-400	4	545
400-450	7	786
450-500	5	706
500-550	3	629
600-650	2	857

3.3 Public charging infrastructure data

Figure 8 shows the distribution of number of public charging stations 1km from home in 2019 for all buyers compared to BEV buyers, where both groups live in an apartment which did not receive a grant for installing charging infrastructure. Many car buyers living in an apartment (27.3%) did not have any public charging station within 1km from home in 2019. For BEV buyers living in apartments this number was lower but still substantial (19.2%). As we noted above, this does not necessarily mean that they do not have access to private charging on the premises of their apartment, or for that matter that there may be public charging for which we lack data close to the location. This indicates however that a significant number of BEV owners living in apartments can solve their charging needs without observed public charging in the vicinity. A larger share of BEV buyers living in apartments had 11-20 as well as more than 20 public charging stations in their vicinity (14.3% and 6.2% respectively) compared to the general car buyer population living in apartments (8.0% and 2.0% respectively).

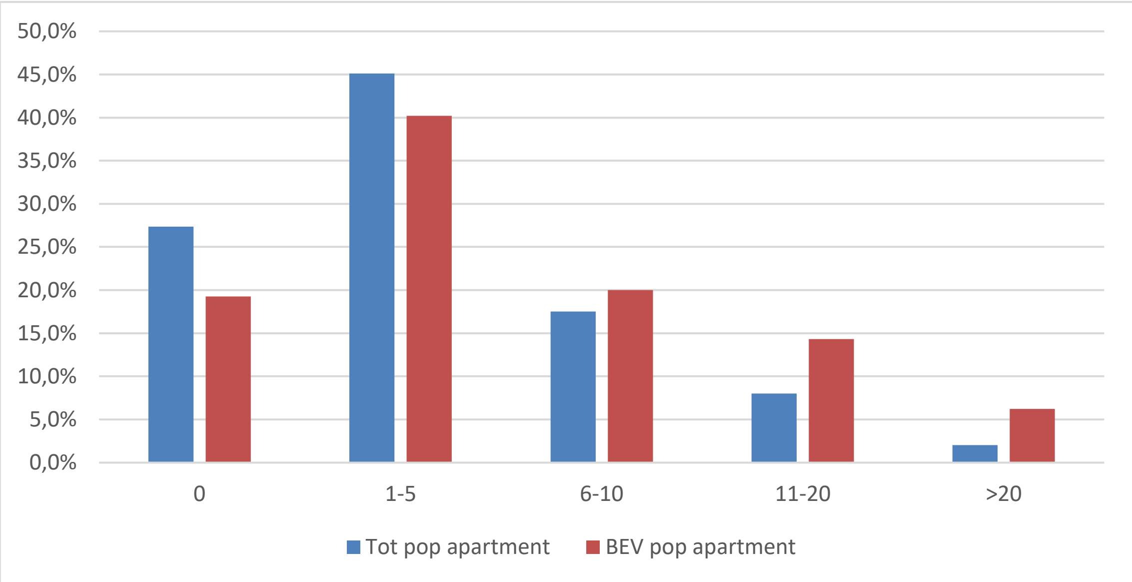

Figure 8: Public charging station density in the vicinity of private car buyer homes for those living in an apartment without known access to private charging.

Figure 9 shows that for the total population, 49% have no charging station close to their workplace, whereas for BEV buyers the percentage is lower, 39%. Furthermore, the figure shows that as much as 8% of buyers of private BEV cars have more than 20 charging stations within 1km from their workplace.

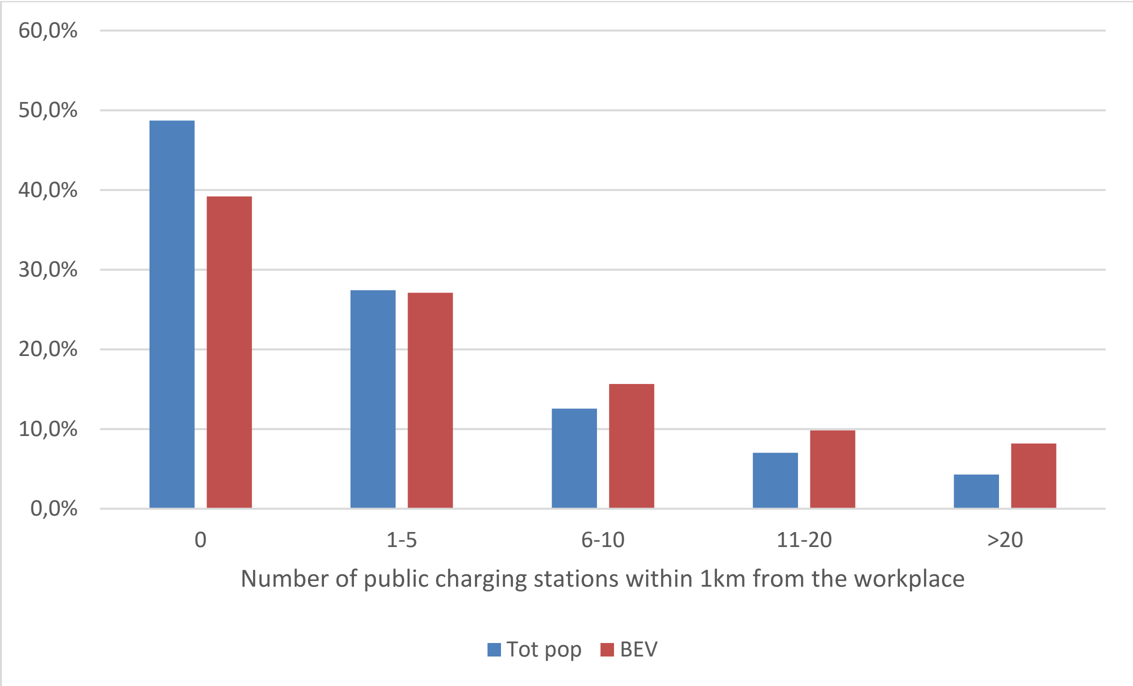

Figure 9: Public charging station density in the vicinity of private car buyer workplaces.

4 ESTIMATION RESULTS

4.1 Estimation on year 2019 data

4.1.1 Private cars in 2019

The result of estimation of a car type choice model for private cars for year 2019 and including measures of access to charging infrastructure is shown in Table 1. The model includes explanatory variables typically used in car type choice models such as price, operation cost, safety classifications, rust guarantee, and size category of the car type. These variables are mostly significant and have expected sign. The estimation of separate price parameters for household income class *HI1* to *HI5* (see Table 2) shows that sensitivity to purchase price decreases with household income, which is expected. For the size-dummies, the reference size is *Small* (also including the category *VerySmall*), and for the fuel-type-dummies the reference fuel type is *Petrol*. Dummiy-variables for Brand (e.g. Volvo) are also estimated but are not included in the table for readability. There are 32 brand categories in the model and the reference brand is *Other*, a category which includes for example Ferrari and Bentley. *ManyCarsHH* is a binary variable which is 1 if the buyer has more than one car in the household and this binary variable is only included for BEV alternatives.

Table 6 shows that, for persons living in an apartment, the number of public charging stations within 1km from home (PublicChargingHome) significantly increases their probability of buying an electric car, even though the magnitude of the effect is smaller than that of DetachedHouse and Grant. There is no significant difference in the effect for BEV and PHEV. The number of public charging stations within 1km from work (*PublicChargingWork*) also has a significant effect on the probability of buying an electric car. Just as with public charging close to home, the magnitude of the effect of public charging close to work is rather small compared to the effect of *DetachedHouse* and *Grant* and there is no significant difference between effects for BEV and PHEV. The result also shows that persons living in a detached house has a higher probability of buying an electric car. The effect is not significantly different between BEV and PHEV. The same goes for persons living in an apartment where the housing cooperative or landlord has received a grant for installing charging infrastructure (*Grant*). It should however be noted that even if the effect of *Grant* is strong, this variable only applies to a limited number of buyers. Furthermore, the result shows that the probability of buying a BEV increases if there are more than one car in the household. Likely, this is due to BEV cars having a shorter range and are often bought as a second car utilized for regional travel.

Table 6: Result of car type choice model estimation for private cars in 2019.

Variable name	Unit	Utility functions	Parameter value	T-value
Price_HI1	kSEK	All	-0.010	-27.2
Price_HI2	kSEK	All	-0.0067	-28.1
Price_HI3	kSEK	All	-0.0038	-19.5
Price_HI4	kSEK	All	-0.0018	-7.6
Price_HI5	kSEK	All	0.00025	1.3
OpCost	kSEK/year	All	-0.052	-13.4
RustGuarantee	#years	All	0,506	14,9
PassengerSafety	index 0-100	All	0,005	3,2
SafetySystems	index 0-100	All	0,008	7,1
SafetyInfoMissing	Binary 0/1	All	-1,105	-5,6
SizeMid	Binary 0/1	All	0,783	27,6
SizeLarge	Binary 0/1	All	1,112	38,5
SizeSport	Binary 0/1	All	-0,568	-5,7

PHEVDiesel	Binary 0/1	All	-4,008	-6,2
PHEVPetrol	Binary 0/1	All	-2,635	-19,2
E85	Binary 0/1	All	-0,432	-3,3
Gas	Binary 0/1	All	-3,946	-19,2
HEVDiesel	Binary 0/1	All	-1,144	-13,1
HEVPetrol	Binary 0/1	All	-0,515	-12,9
BEV	Binary 0/1	All	-2,158	-13,9
Diesel	Binary 0/1	All	-1,087	-42,7
ManyCarsHH	Binary 0/1	BEV	0,272	2,8
DetachedHouse	Binary 0/1	BEV, PHEV	0,614	5,4
Grant	Binary 0/1	BEV, PHEV	0,477	2,0
PublicChargingHome	#stations	BEV, PHEV	0,022	2,0
PublicChargingWork	#stations	BEV, PHEV	0,011	2,9
WorkInfoMissing	Binary 0/1	BEV, PHEV	0,114	0,4
SmallCity	Binary 0/1	BEV, PHEV	-0,380	-4,0
AreaInfoMissing	Binary 0/1	BEV, PHEV	0,164	0,3
Obs	*15000*			
Rho square	*0.136*			
Final LL	*-82798*			

Accessibility to public charging close to home/work can be measured in different ways. We started out by measuring it using distance from home/work to the closest public charging station. However, these variables were not significant in model estimation. As shown above, changing to number of public charging stations within 1km from home/work turned out to be significant. We also tried number of public charging outlets within 1km from home/work (there are often many outlets at one charging station), which resulted in similar estimation results as using number of public charging stations. These results indicate that density of public charging stations is more important than distance to the closest station.

It was not possible to obtain reasonable parameters using year 2019 data for variables that are more relevant for the long-distance use of BEV, i.e., range and long-distance accessibility measures. We describe possibilities to obtain more reasonable parameters for range and accessibility using 2022-year data in section 4.2.

To get a sense of the magnitude of the effects implied by the estimated model, we conduct four scenarios where we apply the model after making changes in supply (Table 7). Increasing the number of public charging stations close to home by 10% increased the likelihood of choosing a BEV by 0.2% in 2019. The corresponding increase in likelihood for public charging stations close to work is 0.6%, i.e. the effect is larger at the workplace compared to close to home. Note however that this calculation excludes all areas where the initial number of charging stations are zero. Decreasing the price of BEV and PHEV by 10% leads to large effects in the model with increases of around 20%, implying an elasticity of around -2. The effects of decreasing operating costs are not as large as price decreases, but still substantial with a 3% increase in BEVs chosen and around 5% increase in PHEVs chosen.

Table 7: Changes in private BEVs and PHEVs when changing supply variables.

Supply variable change	Increase in BEVs	Increase in PHEVs
PublicChargingHome (+10%)	0,2% (496.4 → 497.5)	0,2% (327.1 → 327.9)
PublicChargingWork (+10%)	0.6% (496.4 → 499.3)	0,6% (327.1 → 329.0)
BEV/PHEV Price (-10%)	20.5% (496.4 → 598.3)	20.4% (327.1 → 394.0)
BEV/PHEV OpCost (-10%)	2.6% (496.4 → 509.1)	5.4% (327.1 → 345.0)

4.1.2 BIK company cars in 2019

The results of the car type choice model estimation for BIK company cars are shown in Table 8. Remember that for these cars we do not have data on the user of the BIK company car. It should be noted that binary variable for Brand (e.g. Volvo) are also estimated but are not included in the table for readability. Since this model concerns BIK company cars, the benefit value is used instead of the list price. The reference class for Size is *VerySmall*, for Fuel type it is *Petrol* and for Brand it is *Other*. As expected, the probability of choosing a certain car type decreases with increasing benefit value (*BenefitValue*) and operating cost (*OpCost*) and increases with more years of rust guarantee (*RustGuarantee*) and size (*SizeSmall*, *SizeMid*, *SizeLarge*) of the car up till a point where the largest cars (*SizeVeryLarge*) are slightly less popular as BIK company car compared to the second largest category.

Public charging infrastructure close to work did not have any significant effect in this model. This could be due to the large amount of missing data about workplace when it comes to BIK company cars in our data material or that benefit cars are often used close to the home of the benefit taker (which we have no information about).

Type of industry has however an effect in the model. Compared to other types of industries, choosing a BEV as a BIK company car is more common for *HotelRestaurant*, *Communication*, *Insurance*, and *RealEstate*, and less common for *Commerce*. Compared to other types of industries, choosing a PHEV as a BIK company car is more common for *Communication*, *Insurance*, and *RealEstate*, and less common for *Commerce*, *Defense*, *Education*, and *HealthCare*.

Table 8: Result of car type choice model estimation for BIK company cars in 2019.

Variable name	Unit	Utility functions	Parameter value	T-value
OpCost	SEK/year	All	-0.078	-22.5
BenefitValue	SEK/year	All	-0.026	-16.9
RustGuarantee	#years	All	0.222	9.7
SizeSmall	Binary 0/1	All	0.311	4.3
SizeMid	Binary 0/1	All	0.701	10.0
SizeLarge	Binary 0/1	All	1.441	20.8
SizeVeryLarge	Binary 0/1	All	1.216	17.1
PHEVDiesel	Binary 0/1	All	-1.783	-11.9
PHEVPetrol	Binary 0/1	All	-1.396	-21.3
E85	Binary 0/1	All	0.282	1.4
Gas	Binary 0/1	All	0.218	3.8
HEVDiesel	Binary 0/1	All	-0.688	-10.3
HEVPetrol	Binary 0/1	All	-0.386	-8.4
BEV	Binary 0/1	All	-1.728	-18.4
Diesel	Binary 0/1	All	0.279	9.8
WorkInfoMissing	Binary 0/1	BEV, PHEV	0.280	5.4
Commerce	Binary 0/1	BEV	-1.021	-7.5
HotelRestaurant	Binary 0/1	BEV	0.815	2.0
Communication	Binary 0/1	BEV	1.652	11.4
InsuranceRealEstate	Binary 0/1	BEV	1.125	7.4
Commerce	Binary 0/1	PHEV	-0.465	-5.3
Communication	Binary 0/1	PHEV	1.084	7.5

Insurance	Binary 0/1	PHEV	1.340	9.7
RealEstate	Binary 0/1	PHEV	0.806	3.5
Defense	Binary 0/1	PHEV	-2.254	-3.2
EducationHealthCare	Binary 0/1	PHEV	-0.892	-3.6
Obs	*15000*			
Rho square	*0.136*			
Final LL	*-82867*			

To get a sense of the magnitude of the effects implied by the estimated model, we conduct two scenarios where we apply the model after making changes in supply. Table 9 shows that decreasing the BEV and PHEV benefit value by 10% has an effect in the model, increasing the number of BEVs and PHEVs chosen by around 7%. Decreasing the operating cost by 10% has a substantial effect especially for PHEVs, where the number of PHEVs chosen increases by almost 13%, whereas BEVs only increase by around 5%.

Table 9: Changes in BIK company BEVs and PHEVs when changing supply variables.

Supply variable change	Increase in BEVs	Increase in PHEVs
BEV/PHEV BenefitValue (-10%)	6,8% (931.0 → 994.6)	7,4% (1560.0 → 1675.2)
BEV/PHEV OpCost (-10%)	4,7% (931.0 → 974.9)	12,7% (1560.0 → 1757.9)

4.1.3 Other company cars in 2019

Table 10 shows the results of the car type choice model estimation for other company cars. For Size, the reference class is *Very small* cars. The reference for fuel type and brand is, just as for the other segments, fuel type *Petrol* and brand *Other*. As expected, the probability of choosing a certain car type decreases with increasing list price (*Price*) and operating cost (*OpCost*) and increases with more years of rust guarantee (*RustGuarantee*) and size (*SizeSmall*, *SizeMid*, *SizeLarge*) of the car.

When it comes to choosing an electric car type, public charging infrastructure within 1 km from the company (*PublicChargingWork*) increases the probability of choosing BEVs and PHEVs alike (no significant difference between the two). Compared to other types of industries, the industries *Build*, *Communication*, *RealEstate*, *Education*, and *HealthCare* have a higher probability of choosing BEVs. The industries *Manufacturing*, *Carrier*, *Insurance*, *CompanyServices*, and *HealthCare* have a higher probability of choosing PHEVs, whereas the industry *Agriculture* has a lower probability of choosing PHEVs.

Table 10: Result of car type choice model estimation for other company cars in 2019.

Variable name	Variable type	Utility functions	Parameter value	T-value
Price	SEK	All	-0,002	-13,7
OpCost	SEK/year	All	-0,047	-22,8
RustGuarantee	#years	All	0,262	13,8
SizeSmall	Binary 0/1	All	1,152	14,0
SizeMid	Binary 0/1	All	1,469	17,7
SizeLarge	Binary 0/1	All	2,039	24,7
SizeSport	Binary 0/1	All	0,972	8,3
PHEVDiesel	Binary 0/1	All	-1,556	-12,2

PHEVPetrol	Binary 0/1	All	-1,962	-24,1
E85	Binary 0/1	All	0,450	3,5
Gas	Binary 0/1	All	-0,966	-14,6
HEVDiesel	Binary 0/1	All	-0,494	-8,7
HEVPetrol	Binary 0/1	All	-0,374	-9,3
BEV	Binary 0/1	All	-1,630	-16,2
Diesel	Binary 0/1	All	0,022	1,0
PublicChargingWork	#stations	BEV, PHEV	0,014	3,3
WorkInfoMissing	Binary 0/1	BEV, PHEV	0,806	11,8
Build	Binary 0/1	BEV	0,972	2,3
Communication	Binary 0/1	BEV	1,878	3,8
RealEstate	Binary 0/1	BEV	1,678	4,1
Education	Binary 0/1	BEV	1,114	3,2
HealthCare	Binary 0/1	BEV	1,358	4,4
Agriculture	Binary 0/1	PHEV	-1,315	-2,3
Manufacturing	Binary 0/1	PHEV	2,043	10,4
Carrier	Binary 0/1	PHEV	0,638	3,6
Insurance	Binary 0/1	PHEV	1,197	6,5
CompanyServices	Binary 0/1	PHEV	0,974	12,9
HealthCare	Binary 0/1	PHEV	0,834	2,8
Obs	*15000*			
Rho square	*0.085*			
Final LL	*-87775*			

To get a sense of the magnitude of the effects implied by the estimated model, we conduct three scenarios where we apply the model after making changes in supply. Table 11 shows that decreasing the BEV and PHEV price by 10% has a substantial effect in the model, increasing the number of BEVs and PHEVs chosen by around 10%. Decreasing the operating cost by 10% has a substantial effect especially for PHEVs, where the number of PHEVs chosen increases by almost 8%. In the last scenario, the number of charging stations within 1km from the company is increased by 10% (note that observations with zero stations within 1km in the base case will still have zero stations in the scenario). This has only a small effect in the model with number of BEVs and PHEVs chosen increasing with less than 1%.

Table 11: Changes in other company BEVs and PHEVs when changing supply variables.

Supply variable change	Increase in BEVs	Increase in PHEVs
PublicChargingWork (+10%)	0,6% (532.0 → 535.2)	0,9% (1250.0 → 1261.1)
BEV/PHEV Price (-10%)	10,3% (532.0 → 586.8)	9,3% (1250.0 → 1366.7)
BEV/PHEV OpCost (-10%)	3,5% (532.0 → 550.6)	7,9% (1250.0 → 1349.3)

4.2 Estimation on year 2022 data

In this section we present results from estimating car type choice models on car register data from 2022. The specification is as close as possible to the models estimated on 2019 data except for socioeconomic data and data on charging infrastructure that were not available for 2022. The reason for presenting 2022 results is that data on range and logsum appeared to give counter intuitive results in the form of negative signs in the 2019 models, assuming a car buying behaviour consistent with appreciating longer range and higher accessibility when controlling for other factors. A possible reason for these results is that supply and demand was still in early stages 2019, but swiftly evolving in the period up to 2022. First, we show the differences in demand between year 2019 and 2022 (Figure 10).

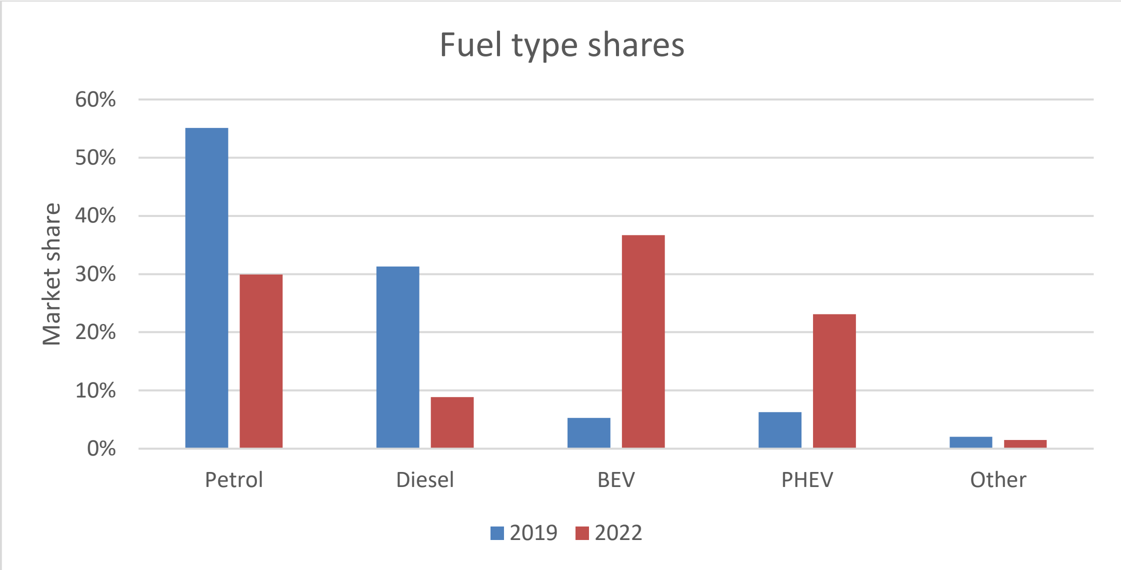

Figure 10: Fuel type shares in 2019 and 2022.

The increase of BEV car sales is quite large. Also, PHEV cars have a higher market share in 2022, but has decreased compared to 2021. The increase is partly due to the increase in the number of BEV car type's supply. Figure 11 shows the number of car models compiled by Mobility Sweden from 2019 to 2022.

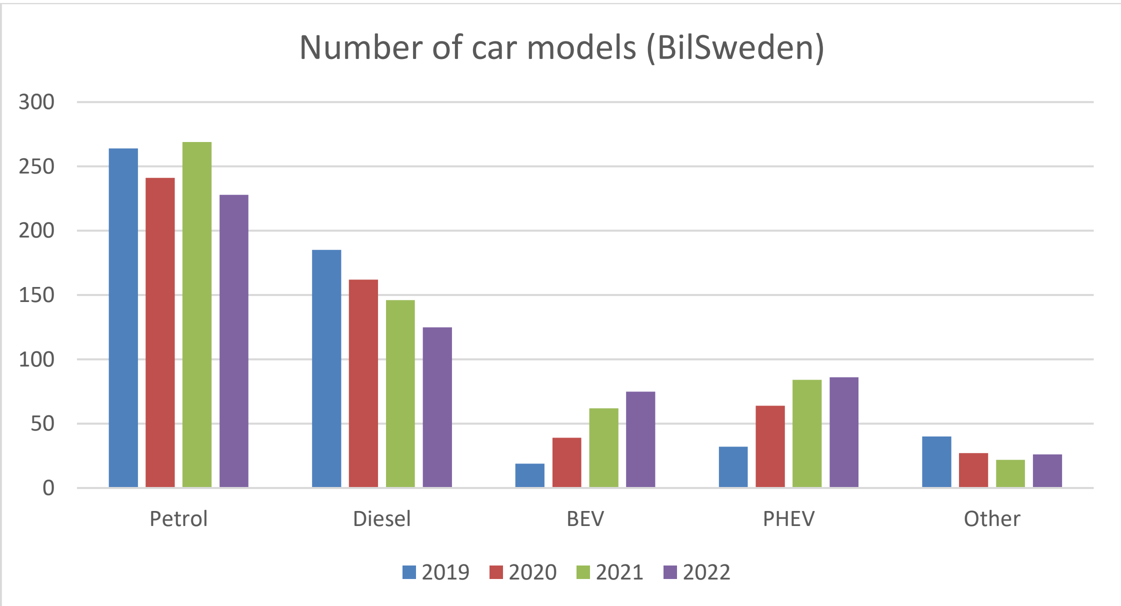

Figure 11: Number of car types by fuel (Mobility Sweden).

The much larger number of BEV and PHEV buyers in 2022 compared to 2019, and the large increase in the number of BEV and PHEV models provide richer data for estimation of choice models involving specific BEV and PHEV variables. The evolution of BEV has also affected the distribution of car types on purchase prices. Figure 12 shows the car types in 2019 and 2022 distributed on purchase prices (price level of 2019 and 2022 respectively).

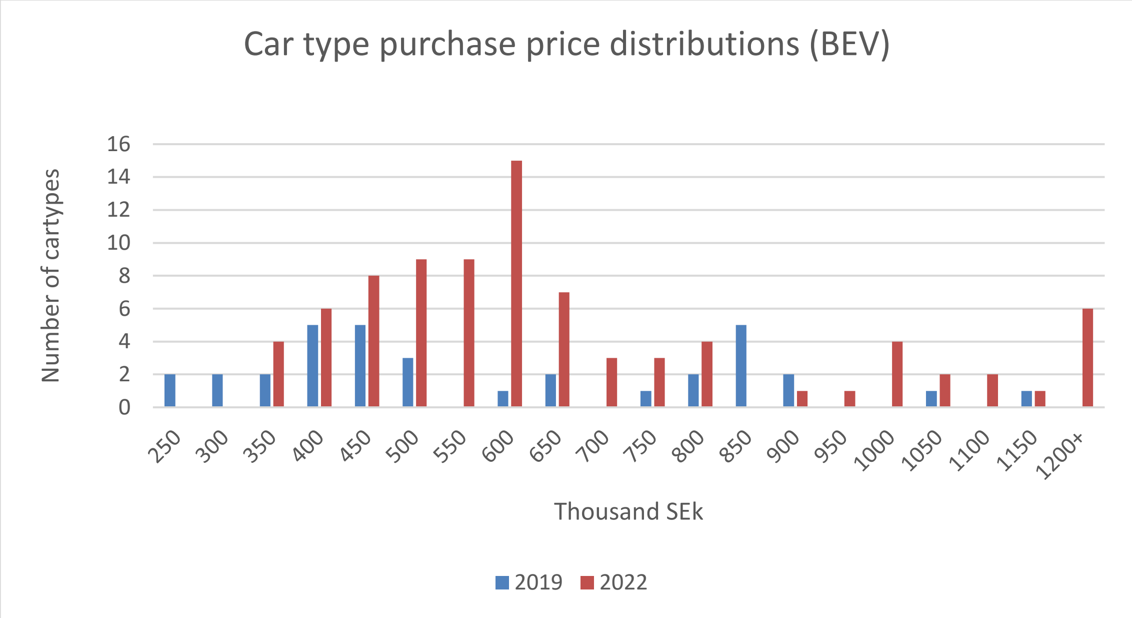

Figure 12: Distribution of car types on purchase prices 2019 and 2022.

4.2.1 Private cars in 2022

Results of estimating the car type choice model on year 2022 data without socio-economic information and public charging infrastructure data is shown in Table 12.

Table 12: Estimation results for private cars in 2022.

		Range model		Logsum model	
Variable name	**Unit**	**Parameter value**	**T-value**	**Parameter value**	**T-value**
Price	SEK	-0.0051	-77.4	-0.00451	-74.3
OpCost	SEK/year	-0.0502	-28.2	-0.08488	-47.6
PassengerSafety	Index 0-100	0.0372	45.1	0.03509	43.2
SizeMid	Binary 0/1	0.6921	57.6	0.72075	59.2
SizeLarge	Binary 0/1	0.3882	35.0	0.48083	43.4
SizeSport	Binary 0/1	0.0413	2.7	0.11891	8.0
PHEVDiesel	Binary 0/1	-2.8516	-21.1	-0.62326	-10.8
PHEVPetrol	Binary 0/1	-3.0056	-22.4	-0.54347	-16.0
HybridPetrolEthanol	Binary 0/1	0.1155	2.9	-0.19385	-4.9
HybridPetrolGas	Binary 0/1	-2.6767	-31.4	-2.84208	-33.3
HybridDieselElectric	Binary 0/1	0.0664	3.0	-0.03785	-1.7
HybridPetrolElectric	Binary 0/1	0.2771	24.2	0.17303	15.6
BEV	Binary 0/1	-9.1549	-9.6	1.14572	33.4
Diesel	Binary 0/1	-1.4803	-63.0	-1.54768	-65.7
Log Range BEV	log(km)	1.7042	8.7	-	-
Log Range PHEV	log(km)	0.7692	23.4	-	-

Range BEV	km	0.0014	2.6	-	-
Logsum	utility	-	-	9.09413	36.2
Obs		*129928*		*129392*	
Rho square		*0.136*		*0.133*	
Final LL		*-725357*		*-724706*	

In the range model, BEV range is included in linear as well as log forms. The parameters are significant with expected positive signs. The formulation with a linear and a log form component corresponds to a Box-Cox transformation of range, giving a simple way to find the optimal functional form (Daly, 2010). The Box-Cox transformation takes the following form for x > 0:

$$x^{(\lambda)} = \begin{cases} \frac{x^{\lambda} - 1}{\lambda} & if\ \lambda \neq 0 \\ \ln(x) & if\ \lambda = 0 \end{cases}$$

Fridström (2022) also used the Box-Cox formulation to find the shape of range utility on Norwegian data. Fridström finds the Box-Cox transformation parameter λ to be -0.5, which can be compared to the parameter found here, which would be 0.3 implying a slower decline in range utility compared to the Norwegian case.

The PHEV range is significant with an expected positive sign. In Figure 13 and Figure 14, the form of the range variables is shown.

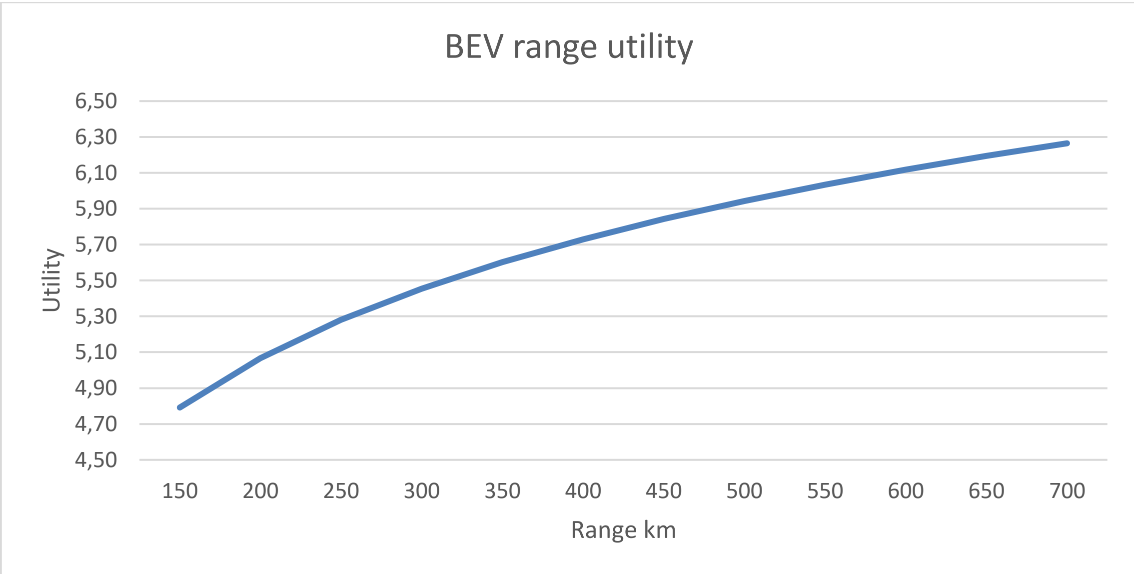

Figure 13: BEV range utility function for private cars.

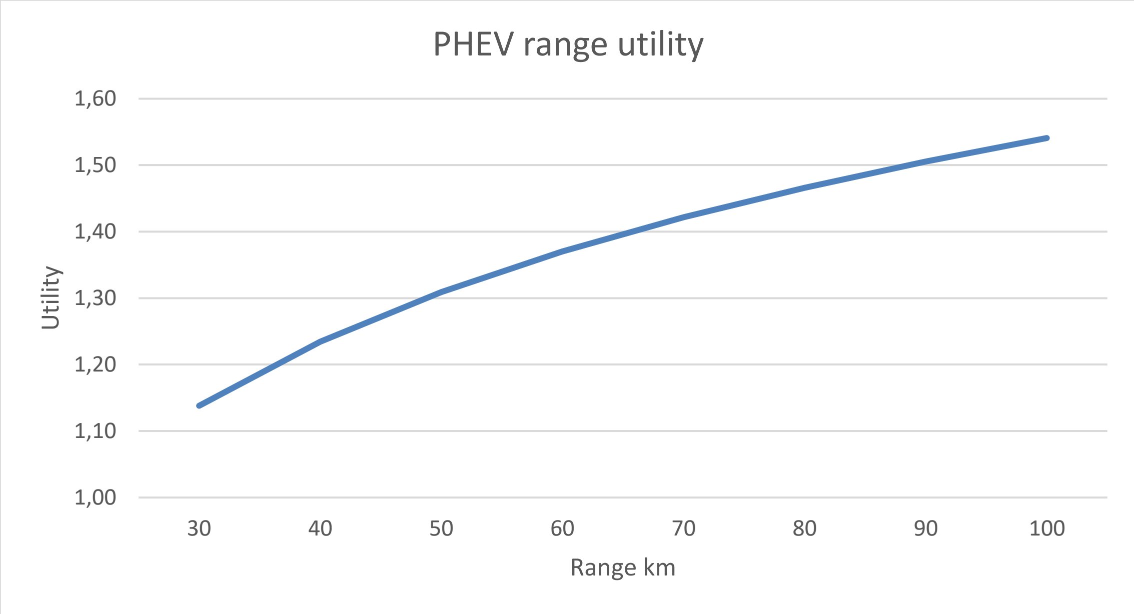

Figure 14: PHEV range utility function for private cars.

In the logsum model, the logsum variable also shows a significant effect with an expected positive sign. In this specification, the logsum specification is based on assuming that destinations that cannot be reached without charging are unavailable. A specification in which these destinations are still available, but where travel times are considering charging time might be preferable. Such a specification would require modelling detour travel time, which has not been possible in this project. This would also enable calculating effects of charging infrastructure development. Assuming that charging would be possible when needed would be possible to include in the specification but would of course be incorrect. To be able to take real advantage of the logsum formulation for forecasting, available techniques to model charging behaviour must be used.

4.2.2 BIK company cars in 2022

As for private buyers, range and logsum parameters are significant with the expected signs (Table 13). The range variables are transformed to logarithms also for this consumer segment. Figure 15 and Figure 16 show the range utility function shapes.

Table 13: Estimation results for BIK company cars in 2022.

		Range model		Logsum model	
Variable name	**Unit**	**Parameter value**	**T-value**	**Parameter value**	**T-value**
BenefitValue	SEK/year	-0.0061	-34.9	-0.0027	-16.6
OpCost	SEK/year	-0.0533	-36.9	-0.0975	-65.1
RustGuarantee	#years	0.0000	0.0	0.0000	
PassengerSafety	Index 0-100	0.0092	7.3	0.0094	7.3
SizeMid	Binary 0/1	1.0075	54.4	1.0804	58.6
SizeLarge	Binary 0/1	0.6260	35.8	0.7167	40.9
SizeSport	Binary 0/1	-0.0247	-1.0	0.2989	13.5
PHEVDiesel	Binary 0/1	-7.8138	-62.5	-1.1873	-23.1

PHEVPetrol	Binary 0/1	-8.2779	-69.6	-1.4580	-36.6
HybridPetrolEthanol	Binary 0/1	-0.1820	-2.8	-0.7605	-11.0
HybridPetrolGas	Binary 0/1	0.2232	6.9	0.1374	4.2
HybridDieselElectric	Binary 0/1	0.7361	35.2	0.5503	26.4
HybridPetrolElectric	Binary 0/1	0.0045	0.3	-0.1640	-9.3
BEV	Binary 0/1	-23.1956	-68.1	-0.4347	-10.8
Diesel	Binary 0/1	0.1245	6.2	-0.0707	-3.5
Log Range BEV	Log(km)	3.8530	68.5	-	-
Log Range PHEV	Log(km)	1.9342	61.6	-	-
Logsum	utility	-	-	47.2016	23.3
Obs		*74846*		*74654*	
Rho square		*0.125*		*0.119*	
Final LL		*-423202*		*-425037*	

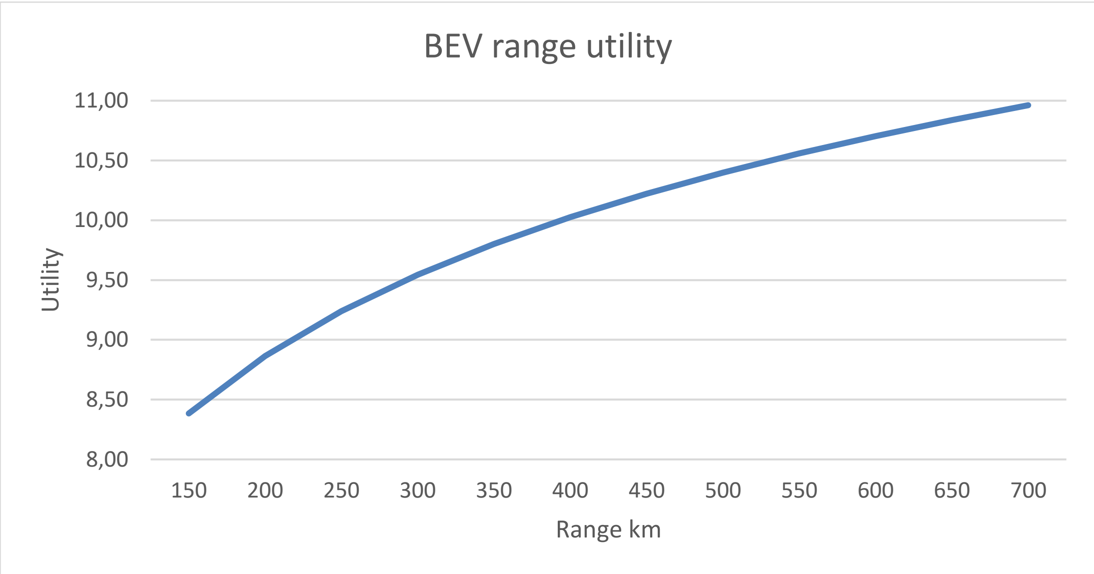

Figure 15: BEV range utility function for BIK company cars.

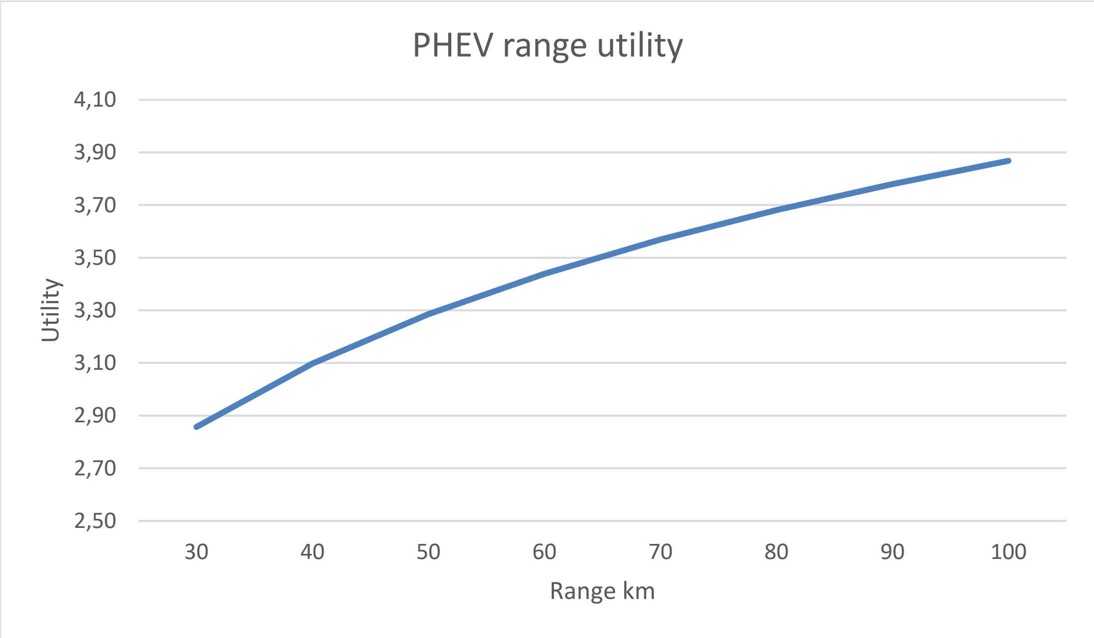

Figure 16: PHEV range utility function for BIK company cars.

4.2.3 Other company cars in 2022

As for private cars and BIK company cars, range and logsum parameters are significant with the expected signs (Table 14). The range variables are transformed to logarithms also for this consumer segment. Figure 17 and Figure 18 show the range utility function shapes.

Table 14: Estimation results for other company cars in 2022.

Variable name	Unit	Range model Parameter value	Range model T-value	Logsum model Parameter value	Logsum model T-value
Price	SEK	-0.00307	-39.6	-0.00247	-32.8
OpCost	SEK/year	-0.01208	-5.0	-0.04996	-17.9
RustGuarantee	#years	0.02762	12.1	0.03109	14.2
PassengerSafety	Index 0-100	0.87184	26.0	0.90008	27.1
SizeMid	Binary 0/1	0.58041	19.3	0.63774	21.4
SizeLarge	Binary 0/1	-0.19617	-4.9	0.06711	1.7
SizeSport	Binary 0/1	-7.24389	-28.7	0.69547	6.4
PHEVDiesel	Binary 0/1	-7.96165	-33.9	0.23501	2.7
PHEVPetrol	Binary 0/1	-1.14392	-5.7	-1.77417	-8.4
HybridPetrolEthanol	Binary 0/1	0.70844	12.7	0.51133	9.3
HybridPetrolGas	Binary 0/1	1.45841	40.1	1.32669	36.6
HybridDieselElectric	Binary 0/1	0.39484	12.2	0.23567	7.2
HybridPetrolElectric	Binary 0/1	-21.70139	-33.4	1.28313	14.5
BEV	Binary 0/1	0.58096	16.7	0.45383	12.9
Diesel	Binary 0/1	3.91357	36.3	-	-
Log Range BEV	Log(km)	2.27575	40.0	-	-

Log Range PHEV	Log(km)	-	-	37.28405	13.9
Logsum	utility	-0.00307	-39.6	-0.00247	-32.8
Obs		*23138*		*23111*	
Rho square		*0.128*		*0.120*	
Final LL		*-130413*		*-131457*	

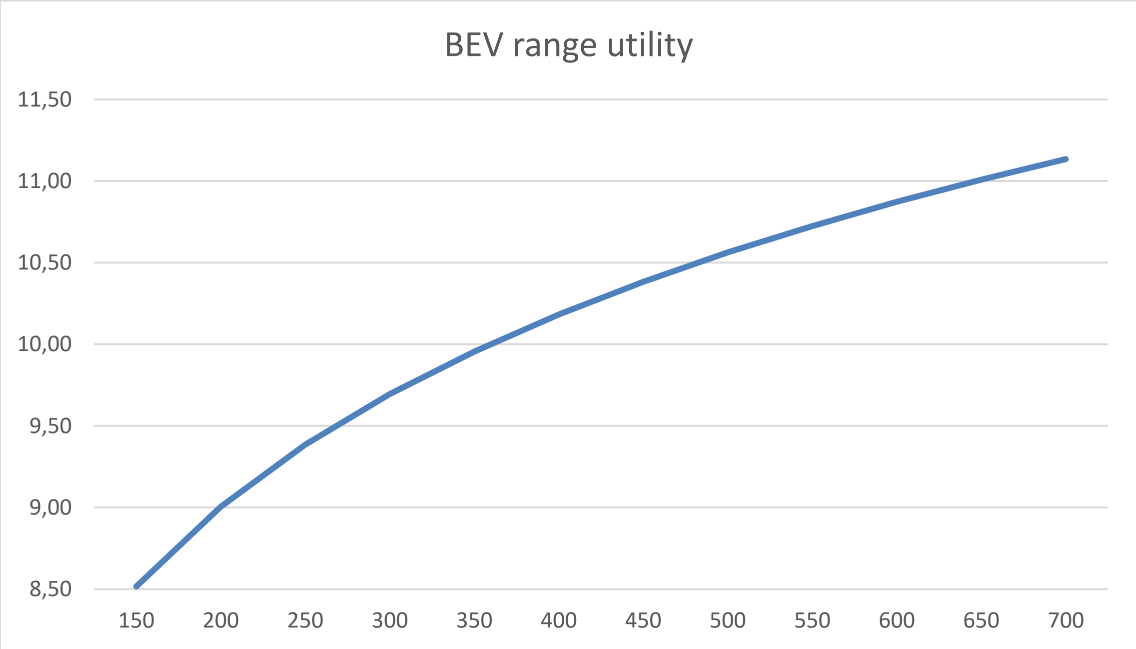

Figure 17: BEV range utility function for other company cars.

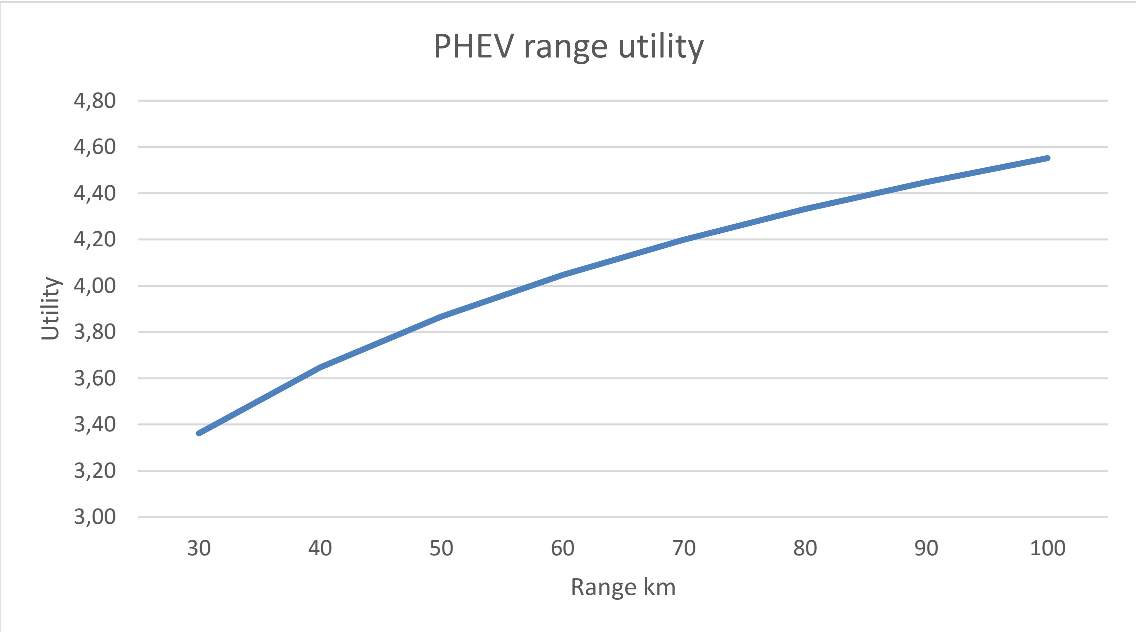

Figure 18: PHEV range utility function for other company cars.

5. DISCUSSION

The appropriate design of policies for a fast increase in the number of EVs will be highly dependent on the effects of charging provision on the acquisition of new EVs. In this paper we focus on the analysis of the effects of accessibility to public charging had on the probability to choose an EV in 2019. In future studies we hope to study where further charging facilities are most likely to increase purchases of EVs the most.

In this study we cannot compare car buyers at different points in time, but we can compare households that chose BEVs, PHEVs and fossil fuelled cars in the same year. The descriptive statistics in section 3 indicated that private EV buyers in 2019 in Sweden differed substantially from the general car buyer population. This is likely to change in view of the results presented for Norway and Sweden in (Bjørge et al., 2022; Fevang et al., 2020).

The electrification of the car fleet is rapidly developing. The development of supply is an important factor and will continue to be so for a long time. The differences in results between 2019 and 2022 suggest that it would be useful to use more recent data to be able to provide more adequate models for charging infrastructure analysis.

A disturbing fact is the outcome of our estimations where we were unable to find a model that yielded expected and significant estimates of the value of increased range and accessibility as represented by logsums. Estimations with car sales data from 2022, however, indicate that these problems may be rectified with data from later sales.

In 2023, public charging infrastructure measured as charging points increased by close to 90 percent in Sweden (https://powercircle.org/). We have no official records on how many of these points were established on a purely commercial basis and how many were subsidized. If a large share of these points were commercial investments this may indicate that the commercial development has gained sufficient momentum. If on the other hand there is an important side effect in terms of more electric vehicles being bought, then this may indicate the presence of a network benefit. In that case subsidization may still be economically justified.

If subsidization is justified this has clear implications for policies for extending the charging network. The effects of increases in supply are likely to differ considerably with the income groups and types of housing dominating a neighbourhood. In areas with high incomes and high shares of detached housing, more public charging is likely to have less impact than in areas with high incomes and high shares of apartment dwellings. Therefore, more resolved analyses could be motivated. We would like to do this for private purchases. For the company-owned cars it is less obvious that the estimations will show clear effects.

Operators of charging networks are likely to invest in new capacity if they can expect the new infrastructure to be profitable. A simplified assessment can be done by considering the capacity utilization of existing infrastructure. There is, however, a risk that commercial operators underestimate the growth of the number of electric vehicles and therefore the charging demand that may come about as a result of increasing the supply of infrastructure.

6. CONCLUSIONS

In this paper we investigate if, in what way, and to what extent access to public charging infrastructure influences the propensity to buy an electric car. We estimate car type choice models for three types of car buyers on revealed preference data from Sweden in 2019. Hypotheses H1 and H2 are confirmed. Access to public charging close to home influences households living in apartment buildings. We find that they have a small but statistically significant higher propensity to buy an electric car compared to persons living in an apartment without public charging nearby. Increasing the number of public charging stations close to apartment residents by 10% is estimated to have increased the likelihood of them choosing a BEV by 0.2% in 2019. Note however that this calculation excludes all areas where the initial number of charging stations are zero. Nevertheless, this small effect raises some doubts about the importance of large subsidies to public charging points. Maybe increased efforts to provide private charging close to apartment buildings is a better strategy. This is also underpinned by the strong effect in the model of receiving a grant for installing charging infrastructure in an apartment building, which is almost as strong as the impact of living in a detached house. Regarding access to public charging close to work, this has somewhat larger effects (0.6%) compared to access to public charging close to home. Hypothesis H5 is also confirmed, i.e., the results show no significant differences between the effect for fully electric vehicles and plug-in hybrids when it comes to access to charging close to home, regardless of whether it is public charging or home charging. However, hypothesis H6 needs to be rejected, i.e., access to public charging infrastructure close to work does *not* seem to be more important for plug-in hybrids compared to fully electric cars.

We also examine the influence of control variables. Most of the variables associated with price and quality are estimated to have the expected outcomes. Exceptions are variables for range and accessibility represented by logsums. Thus, for 2019 data, the hypotheses H8 and H9 are rejected, i.e., range and the range constraint on long-distance travel accessibility do not seem to affect the propensity to buy an electric car, neither BEV nor PHEV. However, using data from 2022, both range and the range constraint on long-distance travel accessibility become significant in the model. We find that access to private charging infrastructure does influence the propensity to buy an electric car in several ways. Hypothesis H3 and H4 are both confirmed, i.e., persons living in a detached house or in an apartment in a housing cooperative which has received a grant for installing charging infrastructure, have a large and significant propensity to buy an electric car. Furthermore, we find that households owning more than one car are more likely to choose a BEV as a second car when upgrading their cars, thus confirming hypothesis H7. Other control variables that matter are the area type where the household reside and type of industry for company-owned cars.

To summarize, the results indicate that public charging infrastructure contribute to increase the propensity for private buyers to choose an electric car, both for the choice of fully electric vehicles and plug-in hybrids. Control variables for easy home charging have large and significant effects in the model, whereas density of public charging stations in the vicinity of home and work both have significant effects in the model but of a smaller magnitude. In future research, one would also want to test different measures of access to public charging infrastructure during long-distance travel on the propensity to buy an electric car. It was not possible to obtain reasonable parameters using year 2019 data for variables that are more relevant for the long-distance use of BEV, i.e., range and long-distance accessibility measures. A test on year 2022 data without socioeconomic variables and other charging infrastructure variables showed however that such variables were well estimated in that context, and we believe that it would be useful to extend the reported analysis from 2019 data to 2022 data (or possibly 2023 data).

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APPENDIX

A.1 Calculating the logsum differences with respect to fuelling infrastructure

In Sampers there are models for mode and destination choice for different travel purposes. Destination choice is at the lowest choice level for all travel purposes. This implies that cost and travel time variables are included in the utility function, together with size variables in an MNL form. The logsum over destination alternatives given a specific travel mode (like car) reflects the expected maximum utility of using the mode for the specific travel purpose of each model.
If we want to create a logsum for a given car type, we can modify travel costs and travel times accordingly, resulting in a different logsum. Current travel costs and travel times in the mode and destination choice models are based on cost and time averages and are not particular to any car type. They are also depending on traveller related variables, like income. It would therefore be possible to define a logsum conditional on car type and user, requiring a lot of calculations.
Modifying theses variables implies subtracting the current cost and time variables and adding fuel specific costs and time for each car type.
Changes in travel time and cost will affect the logsum, and hence the car utility. Differences in costs and times due to fuelling can therefore be represented in the logsum measure, also implying different travel patterns depending on fuel type and car type. A question is then how this can be calculated.
We first describe the calculation approach theoretically.
The destination choice model can be formulated as in eq 1 and 2:

Eq (1) $$P_{ij} = \frac{e^{V_{ij}}}{\sum_j e^{V_{ij}}}$$

where P_{ij} denotes the probability of choosing destination j from origin I and V_{ij} is the utility function.

Eq (2) $$V_{ij} = \alpha * c_{ij} + \beta * t_{ij} + \gamma * s_j$$

In the utility function, α is the cost parameter for travel cost from I to j, β ist the travel time parameter for travel time from I to j and γ is a parameter for size variables in destination j.
The logsum LS_i of the model for origin i is (Eq 3)

Eq (3) $$LS_i = ln\left(\sum_j e^{V_{ij}}\right)$$

We then want to obtain car type specific logsums, representing different car type alternatives. The utility associated with time and cost variables Vij will therefore be replaced by Vij + dVkij. A car type k specific logsum LS'_i can be formulated (Eq 4)

Eq (4) $$LS_{ki} = ln\left(\sum_j e^{V_{ij}+\Delta V_{kij}}\right)$$

where $V_{ij} + \Delta V_{kij}$ is the car type specific time and cost. The car type specific logsums can be calculated by recalculating the utility functions in the destination choice model part. This requires access to these variables, implying a lot of calculations. A simpler approach would be to start from the Sampers car travel output, being the result of the mode and destination choice models. This output has been generated using the car type average car travel costs and car travel times. Then for each car type a logsum difference from the logsum implied from the anticipated total car travel model can be calculated. The logsum difference can be calculated in the following way.

We start from the total car travel matrix, defined by T_{ij}

We first calculate P_{ij} by $$P_{ij} = \frac{T_{ij}}{\sum_{ij} T_{ij}} \qquad \text{Eq (5)}$$

We then recognise that

$$LS_i = ln\left(\sum_j e^{V_{ij}}\right) = \ln\left(\frac{e^{V_{ij}}}{P_{ij}}\right) = V_{ij} - \ln\left(P_{ij}\right) \qquad \text{Eq (6)}$$

We also recognise that

$$LS_{ki} = ln\left(\sum_j e^{V_{ij}+\Delta V_{kij}}\right) = \ln\left(\frac{e^{V_{ij}+\Delta V_{kij}}}{P_{kij}}\right) = V_{ij} + \Delta V_{kij} - \ln\left(P_{kij}\right) \qquad \text{Eq (7)}$$

The expected utility difference between the average cost and time logsum and a specific car type logsum is then $LS'_i - LS_i$.

$$LS'_i - LS_i = V_{ij} + \Delta V_{ij} - \ln\left(P'_{ij}\right) - \left(V_{ij} - \ln\left(P_{ij}\right)\right) \qquad \text{Eq (8)}$$

We now recall the definition of the incremental logit model, allowing forecasting choice probabilities using only the initial choice probabilities and the changes in utilities caused by changes in the utility function variables (cost and time in our case).

$$P_{kij} = \frac{P_{ij} * e^{\Delta V_{kij}}}{\sum_j P_{ij} * e^{\Delta V_{kij}}} \qquad \text{Eq (9)}$$

After substituting Pk_{ij} with the above expression, we get

$$LS'_i - LS_i = \ln\left(\sum_j P_{ij} * e^{\Delta V_{ij}}\right) \qquad \text{Eq (10)}$$

This means that we can calculate the logsum differences just by knowing the T_{ij} matrix and the changes of cost and time that we want to make in the utility function for each car type. The logsum difference can then be used as a variable in the car type choice utility function, representing vehicle differences regarding fuel type, fuel costs and fuelling time.

Another issue is which cost and time parameters that should be used. The Sampers mode and destination choice models are, as mentioned earlier, based on average cost and time variables. At least theoretically, these models could be reestimated conditioning cost and time on car type (and even on user income), providing more adequate parameter values. This is however not suggested here, as it would imply a lot of work and would also not be so relevant because of the lack of electric cars in the 2005 survey data.

We therefore suggest a more general approach. The Sampers system has two levels of geographical resolution, one for regional travel (<100 km single trip), and a coarser one for long distance travel. Given that BEV ranges have increased in recent years, recharging may not be necessary for a day's normal travel. For PHEVs, recharging may still be necessary. On the other hand, the necessity for PHEVs is only conditioned on the desire to use electric fuel. For longer trips, recharging is likely to be necessary for many BEV trips. For PHEVs, driving on electric fuel for longer trips cannot really be regarded an option, because of the need for frequent charging sessions and long charging times.

As range is more vital for long distance travel, we suggest that the logsum based approach be used for long distance trips. Range is however not the only aspect of owning an electric car. An electric car obviously must have as much access to a charging facility to be used at all. An advantage is that charging does not require the driver to be present, which makes charging over night or during another driver activity possible. The most convenient solution is of course to have

a charging facility at the overnight parking place of the vehicle, and/or at the workplace. Other solutions are also possible (but less convenient), like publicly available charging facilities.
We therefore think that an important variable would be whether there is access to charging posts in association with the dwelling place of the owner. For persons living in houses of their own, it can be said that this possibility exists. For persons living in multiflat houses, the possibility will exist only if the landlord decides on installing charging posts.

To be able to include the accessibility to overnight charging for persons living I houses of their own, we need information on dwelling type. For persons living in multiflat houses, addresses could be matched to authority information on house owners that have obtained subsidies to establish charging posts. In other cases, a distance measure could be established using addresses or coordinates for the person and the charging post register. This would correspond to the basic requirement of being able to charge overnight.

To further include utility effects of vehicle range for daily travel, it would be possible to use the logsum based approach. To make this manageable, we propose to use a simplified model, not segmented by travel purpose.