THESIS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

The Role of Plug-in Hybrid Electric Vehicles in Electrifying Personal Transport

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Abstract

The Paris Agreement emphasizes the importance of greenhouse gas mitigation in the transport sector to address climate change and create a sustainable future with lower carbon emissions. Plug-in hybrid electric vehicles (PHEVs) can be helpful in reducing greenhouse gas emissions in transportation when combined with efforts to decarbonize the electricity sector. PHEVs combine an electric engine with a conventional one, so they have rechargeable battery packs as well as fuel tanks. The unique position of PHEVs as a vehicle that can utilize two different energy sources makes their role in electrifying personal transport highly debated. This thesis uses various sets of real-world PHEV charging and driving data and investigates the role of PHEVs in electrifying personal transport with a focus on how much their kilometers are electrified through analysis of (1) their charging behavior and how this behavior impacts fuel consumption and tail-pipe CO_2 emissions, (2) how they are driven within the household context and (3) how they are driven differently across countries.

This thesis develops a new method to identify charging events and analyze PHEV charging behavior for large samples that only have driving data. Using this method, results show that the possibility to charge overnight has a bigger effect than additional charging during the day on increasing the share of electrified kilometers of PHEVs and reducing their fuel consumption and tail pipe emissions. Therefore, it is important to ensure adequate access and incentives for users to plug-in every night to make sure PHEVs can contribute to a reduction of CO_2 emissions; and policies for PHEVs should prioritize easy access to overnight charging. Results also show that PHEVs with a range of at least 56 km (35 miles) have the potential to electrify a similar share of total household miles as some short-range battery electric vehicles (BEVs) —which only have an electric engine—, or can reach up to 70% as much electrification as some long-range BEVs (e.g. Tesla Model S). On the other hand, results also show that PHEVs have poor environmental performance across the globe compared to set standards: lower share of electrified kilometers compared to type approval values and higher fuel consumption than e.g. European Union targets. However, lower electricity price to gasoline price ratio can lead to an increase in the share of electrified kilometers of PHEVs.

This thesis shows that PHEVs can considerably contribute to the share of electrified kilometers in the transport sector and play an important role in decarbonizing it if the debate regarding PHEVs is focused on maximizing their environmental benefits.

Keywords: PHEV (Plug-in hybrid electric vehicle), eVMT, eVKT, utility factor, charging behavior, fuel consumption, greenhouse gas (GHG) emissions

List of appended papers

I **Mandev** A., Plötz P., Sprei F., & Tal G. (2022). Empirical charging behavior of plug-in hybrid electric vehicles. *Applied Energy*, 321, 119293. doi:https://doi.org/10.1016/j.apenergy.2022.119293

II **Mandev** A., Plötz P., Sprei F. (2021). The effect of plug-in hybrid electric vehicle charging on fuel consumption and tail-pipe emissions. *Environmental Research Communications* 3 081001. https://doi.org/10.1088/2515-7620/ac1498

III **Mandev** A., Sprei F., & Tal G. (2022). Electrification of vehicle miles traveled and fuel consumption within the household context: a case study from California, U.S.A. *World Electric Vehicle Journal*, 13(11), 213. https://doi.org/10.3390/wevj13110213

IV **Mandev** A., Sprei F. (2023). Plug-in hybrid electric vehicle driving behavior: the differences in the share of electrified kilometers between countries. *To be submitted to International Journal of Sustainable Transportation*.

V **Mandev** A., Plötz P., Sprei F. (2023). Factors impacting real-world fuel economy of plug-in hybrid electric vehicles in Europe – An empirical analysis. *Working manuscript*.

Author Contributions

Paper I: AM, PP and FS designed the study. AM analyzed the data. AM wrote the original draft. All authors reviewed, edited, and approved the final version of the manuscript.

Paper II: AM, PP and FS designed the study. AM analyzed the data. AM wrote the original draft. All authors reviewed, edited, and approved the final version of the manuscript.

Paper III: AM, FS and GT designed the study. AM analyzed the data. AM wrote the original draft. All authors reviewed, edited, and approved the final version of the manuscript.

Paper IV: AM designed the study. AM analyzed the data. AM wrote the original draft. All authors reviewed, edited, and approved the final version of the manuscript.

Paper V: AM, PP and FS designed the study. AM and PP analyzed the data. AM and PP wrote the original draft. All authors reviewed, edited, and approved the final version of the manuscript.

List of conference papers

I **Mandev** A., Sprei F., (2023). Plug-in hybrid electric vehicle usage in the world: the differences in the share of electrification between countries. In *36th Electric Vehicle Symposium (EVS36)*, Sacramento.

II **Mandev** A., Sprei F., Tal G. (2023). Electrification of vehicle miles travelled and fuel consumption within the household context: a case study from California, USA. In *Transportation Research Board 102nd Annual Meeting*, Washington DC.

III **Mandev** A. Sprei F. (2022). Plug-in hybrid electric vehicle usage in the world: analyzing the differences in the share of electrification between countries. In *Swedish Transportation Research Conference 2022*, Lund.

IV **Mandev** A., Sprei F., Tal G. (2022). Electrification of vehicle miles travelled within the household context: a case study from California, USA. In *35th Electric Vehicle Symposium (EVS35)*, Oslo.

V **Mandev** A. Sprei F. (2021). Electrification of vehicle miles travelled within the household context: a case study from California, USA. In *Swedish Transportation Research Conference 2021*, Malmö.

VI **Mandev** A., Plötz P., & Sprei F. (2020). Empirical recharging behavior of plug-in hybrid vehicles. In *33rd Electric Vehicle Symposium (EVS33)*, Portland. http://doi.org/10.5281/zenodo.4023325

VII **Mandev** A., Sprei F., Tal G. (2020). Electrification of vehicle miles travelled within the household context. In *Transportation Research Board 99th Annual Meeting*, Washington DC.

VIII **Mandev** A., Sprei F., Tal G. (2019). Electrification of vehicle miles travelled within the household context. In *32nd Electric Vehicle Symposium (EVS32)*, Lyon.

IX **Mandev** A., Sprei F., Tal G. (2018). What impacts the electrified miles travelled (eVMT) of Plug-in Electric Vehicles (PEVs) within the household context? In *Swedish Transportation Research Conference 2018*, Gothenburg.

The Road goes ever on and on
Down from the door where it began.
Now far ahead the Road has gone,
And I must follow, if I can

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Göteborg, June 2023

Ahmet Mandev

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List of commonly used abbreviations

AER:	All-electric-range
BEV:	Battery electric vehicle
EDS:	Electric driving share
EV:	Electric vehicle
eVKT:	Electric vehicle kilometers travelled
eVMT:	Electric vehicle miles travelled
FCEV:	Fuel cell electric vehicle
gVKT:	Gasoline vehicle kilometers travelled
gVMT:	Gasoline vehicle miles travelled
HEV:	Hybrid electric vehicle
ICEV:	Internal combustion engine vehicle
MPG:	Miles per gallon
OEM:	Original equipment manufacturer
PEV:	Plug-in electric vehicle
PHEV:	Plug-in hybrid electric vehicle
ROC:	Receiver operating characteristic
UF:	Utility factor
VKT:	Vehicle kilometers travelled
VMT:	Vehicle miles travelled
WLTP:	Worldwide harmonized light-duty vehicles test procedure

1. Introduction

The Paris Agreement emphasizes the importance of greenhouse gas mitigation in the transport sector to address climate change and create a sustainable future with lower carbon emissions. One way to achieve this is by shifting towards electric vehicles for personal transportation, which can reduce emissions by avoiding the use of fossil fuels and relying more on renewable energy sources. Plug-in hybrid electric vehicles (PHEVs) can be helpful in reducing greenhouse gas emissions in transportation when combined with efforts to decarbonize the electricity sector, and they can play a role in the move towards electric vehicles for personal transportation [1-8].

Electric vehicles (EVs) in general are split into three categories: plug-in electric vehicles (PEV), hybrid electric vehicles (HEV) and fuel cell electric vehicles (FCEV). FCEVs use fuel cells to generate electricity using compressed hydrogen. HEVs are hybrid vehicles with an electric engine and a conventional engine, but the battery packs cannot be charged by plugging in. PEVs, on the other hand, are split into two categories: battery electric vehicles (BEVs) and PHEVs. BEVs utilize only an electric engine for propulsion and their only source of energy is their rechargeable battery packs; whereas PHEVs combine an electric engine with a conventional one, so they have rechargeable battery packs as well as fuel tanks. The unique position of PHEVs as a vehicle that can utilize two different energy sources makes the analysis of their fuel economy and environmental impact more complex [9].

There has been an ongoing debate about the role of plug-in hybrid electric vehicles in the move towards electrification of the transportation sector, particularly in comparison to battery electric vehicles. PHEVs can offer a few advantages over BEVs, including not having strict range limitations and not being entirely reliant on charging infrastructure, which can make them more appealing to a broader range of people. Regarding production costs, PHEVs have dual motors, and the cost of the extra powertrain can be substantial; on the other hand, BEVs have much larger battery packs which can similarly increase the production costs substantially [10]. When battery costs are high and range expectations are increasing, PHEVs would be at an advantage, yet the battery costs continue to decline [11-14]. Although BEVs have a better environmental impact in a single case comparison due to not using fuel and the possibility of relying on low carbon energy sources to charge their batteries, the larger battery sizes of BEVs also have a larger impact on energy production and material resources [15]. As battery costs continue to fall [11-14], BEVs can be produced at lower costs and with higher ranges, making them a more attractive option for a greater number of people.

PHEVs consistently perform worse in real-world usage than the test procedures indicate, with regards to fuel economy, CO_2 emissions and share of electrified kilometers [16]. However, throughout the work carried out in this thesis, it is shown that PHEVs can considerably contribute to the share of electrified kilometers in the transport sector. The debate regarding PHEVs' role in decarbonizing the transport sector usually revolves around whether they are inherently good or bad for the environment. Depending on the angle you look at PHEVs from, they are sometimes called the wolf in sheep's clothing in news articles [17] which highlight their conventional engine, and sometimes as the gateway drug into the world of electric vehicles [18] which highlight their electric engine. However, what is usually lacking in this debate is how we can maximize the environmental benefits of PHEVs that are currently on the roads and the ones that will be sold in the near future, since they will be around until 100% battery electric vehicle adoption. This can only be achieved through studying their real-world usage. The overall research question in this thesis is: **what is the role of PHEVs in electrifying personal transport?** The role here can interpreted as PHEVs' contribution to increased electrification and reduced use of fossil fuels. Furthermore, this thesis looks at what factors impact this contribution and how it differs among countries. All the data sets used for analysis in this thesis come from mostly private users, hence the focus is on personal transport. By showing how PHEVs are charged and driven, and what impacts their electrification and fuel consumption, this PhD thesis aims to contribute to the understanding of how we can maximize PHEVs' environmental benefits.

1.1. Scope

In this doctoral thesis, with the five papers appended, the role of PHEVs in electrifying personal transport is investigated. The process of electrification in the transport sector has a wide scope and ranges from the electricity mix that goes into the battery of the vehicles to the manufacturing of the vehicle and batteries, the driving and charging behavior, shifting transport modes, car-sharing and infrastructure developments (installment of charging points). Therefore, it is important to define the scope within which the role of plug-in hybrid electric vehicles is investigated. The role of PHEVs in electrifying personal transport in this doctoral thesis are investigated in the following contexts:

- **Charging behavior: Paper I** maps out the range of charging behavior with additional charging and no overnight charging frequencies and analyzes this behavior with respect to characterization of frequent chargers and charging days. **Paper II** analyzes the direct effect of PHEV charging on fuel consumption and tail pipe emissions.

- **Household context: Paper III** analyzes measures related to electric vehicle miles travelled in the household context. The household context is defined using three categories: (1) plug-in electric vehicle technology in the household (range of the vehicle and the frequency of charging associated with it), (2) household vehicle usage, (3) internal combustion engine vehicles (ICEVs) in the household.
- **Multiple countries**: This context refers to analysis that focuses on country comparisons or utilizes data from multiple countries. **Paper IV** analyzes how PHEV driving behavior differs in the share of electrified kilometers among countries and what is behind these differences. **Paper V** provides an analysis of PHEV electric driving and fuel consumption in Europe with comparison of two data sets from multiple countries, and also investigates the impact of vehicle properties.

Although the main focus of a paper can be defined under one of the three contexts above, there are overlapping themes in all papers. For instance, the share of electrified vehicle kilometers/miles (also known as the utility factor) is investigated in all papers. In order to assess the potential of PHEVs to reduce greenhouse gas emissions, several aspects of their usage are important to understand.

First, it is important to understand the charging behavior, for several reasons: **(1)** charging behavior and patterns can help understand the impact of charging on the electricity system, e.g., increased peak loads due to charging [19-22]. In addition, charging patterns are also of interest from an energy systems perspective, for example in helping integrate intermittent renewable energy sources [23-26]. **(2)** it adds to the understanding of the environmental performance of PHEVs —reducing CO_2 emissions and environmental pollutants— by giving an insight into how much driving is done on gasoline and electricity respectively [9, 27-31]. **(3)** charging behavior provides input on how charging infrastructure policies should be developed [32, 33]. **(4)** it adds to the understanding of the relationship between public charging infrastructure and users' charging behavior [34-36]. **(5)** it clarifies the relation between battery size and charging behavior and the relation between vehicle choice and driving needs [37-40]. There is a lack of empirical studies in the literature that analyze charging and driving behavior for large samples of PHEV users and **Paper I** fills this gap. Regarding the environmental performance of PHEVs, previous studies in the literature have analyzed well-to-wheel greenhouse gas emissions [41, 42], but do not systematically study the effect of charging behavior on fuel consumption and tail pipe emissions and **Paper II** fills this gap.

Traditionally, the analysis on the share of electrification of miles has been done on a per vehicle basis, however, the household context is also important to consider. For example, trips can be shifted between vehicles, increasing or decreasing the electrified miles in multi-car households. However, this has not been previously studied enough, partly due to the difficulty of collecting good empirical data at the household level. **Paper III** fills this gap by analyzing measures related to electric vehicle miles traveled in the household context.

In the literature, there are different estimates for the share of electrified vehicle kilometers of PHEVs depending on the make and model of the vehicle and where they are used. It is challenging to analyze and compare PHEV usage in different countries due to the difficulty of finding and combining multiple datasets together which have differences ranging from sample sizes to collection methods. Analyzing how the same PHEV is driven across different countries (with regards to its share of electrified kilometers) and what factors in those countries can cause differences is important to understand the varying role of PHEVs across the globe. This type of analysis, based on a large real-world dataset, furthermore, combined with additional data to analyze country level differences is currently missing in the literature and **Paper IV** fills this gap. **Paper V** complements the previous studies on electric driving and real-world fuel consumption of PHEVs in Europe by combining and comparing two different data sets. This leads to a more comprehensive understanding of real-world fuel consumption and how vehicle properties such as range and engine impact the share of electric driving.

1.2. Disposition of this thesis

The thesis consists of seven chapters that provide information on the research that has been carried out, followed by five appended papers. Chapter 2 provides a background on how the share of electrified vehicle kilometers and PHEV charging behavior have been approached in the literature. Chapter 3 gives a summary of the data and methods used in the appended papers. Chapter 4 presents the results from appended papers. Discussion of the results and conclusions are given in Chapter 5. My reflections on my research and doctoral journey are given in Chapter 6. Finally, key contributions and findings are presented in Chapter 7.

2. Background

This chapter gives a brief overview on how the share of electrified vehicle kilometers/miles travelled and PHEV charging behavior have been approached in the literature, and how these are related to each appended paper. These two topics are important in understanding how PHEVs are driven and charged.

2.1. Share of electrified vehicle kilometers travelled

Utility factor (UF), defined as the share of electrified vehicle miles/kilometers travelled (eVMT/eVKT) within total vehicle miles/kilometers travelled (VMT/VKT), is the most common metric to analyze the performance of PHEVs regarding their ability to provide tail-pipe emission-free travel. There are two main approaches to assessing UF in the literature based on the data used.

The first approach is to run simulations based on test-cycles or transportation surveys. In this approach, the UF is calculated under certain assumptions regarding the charging frequency, vehicle characteristics and driver characteristics. It is also common practice to follow the standardized methods from the Society of Automotive Engineers, SAE J2841 and SAE J1711, to calculate the UF [43, 44]. Elgowainy, et al. [45] used the U.S. National Household Transportation Survey (NHTS) to report on the UFs of PHEVs with an all-electric-range (AER) of 10, 20, 30, 40 and 60 miles. Axsen, et al. [46] used survey data from 877 Californian new vehicle buyers and estimated the UF of PHEVs with an AER of 20 and 40 miles under different emission scenarios. Tal, et al. [38] used a self-reported web map survey with a sample size of 800 Prius plug-ins and 600 Chevrolet Volts to study charging behavior. Moawad, et al. [47] used a test cycle—measured by the U.S. Environmental Protection Agency (EPA), in which they collected driving statistics from 100 drivers in Kansas City for the duration of a day—to estimate the decrease in the consumed fuel of PHEVs with a battery capacity of 4, 8, 12 and 16 kWh, compared with internal combustion engine vehicles (ICEVs). Björnsson, et al. [48] used GPS data logged for a representative sample of individual conventional vehicles in private use, to analyze how the utility factor is influenced by the choice of objective function when determining optimal battery sizes for PHEVs. Dauphin, et al. [49] simulate the use of PHEVs in real-world conditions and report on their UF, CO_2 emissions and fuel consumption depending on battery capacities and charging frequencies. Standardized methods that rely heavily on assumptions have been criticized for not accounting for complex scenarios. SAE J2841, for instance, is based on the assumptions that each vehicle starts the day fully charged, does not charge until after the last trip of the day and only charges once a day; it also assumes that PHEVs are driven in the same patterns as national average vehicles [50, 51].

Bradley and Quinn [50] investigated how different assumptions in these standards would result in different UF calculations, and they found that UF calculations were very sensitive to assumptions regarding charging behavior, vehicle age, and vehicle annual distance driven.

The second approach is to use empirical, real-world data to estimate the UF, which provides an insight into actual travel behavior patterns. Plötz, et al. [9] and Plötz, et al. [31] used publicly available real-world driving data from two online sources, voltstats.net and spritmonitor.de, to estimate the UFs for several PHEVs in the U.S., Canada and Germany. Ligterink, et al. [28] analyzed the fueling and charging data of plug-in vehicles, collected from lease companies in the Netherlands, and estimated the UF for the Dutch plug-in fleet. Davies and Kurani [29] analyzed the data from 25 converted Toyota Prius which had onboard loggers to record driving and charging data; they compared the observed UF with the simulated UF of a scenario that accounted for additional workplace charging and concluded that additional workplace charging can result in a relatively higher UF. Idaho National Laboratory, in their EV project, analyzed the driving and charging data of 21,600 vehicles in the U.S., obtained from several OEMs, and reported their estimated eVMT and VMT [52]. Nicholas, et al. [30] used a subset of the dataset we used in **Paper III**—which contained logger data placed on vehicles for a year—and reported on the UF of Toyota Prius, Ford Energi and Chevrolet Volt. Hao, et al. [53] studied the actual UF of seven Chinese cities using PHEV driving big data, concluding that PHEVs with an all-electric-range of over 50 miles would lead to better energy saving and emission reduction potential. Raghavan and Tal [54] and Raghavan and Tal [55] used multi-year longitudinal data from PHEVs in California and studied their UF. Plötz, et al. [56] analyzed the real-world utility factor, fuel consumption and tail-pipe emissions using a combination of data sets from China, Europe, and North America, and reported that PHEVs drive less on electricity and have higher fuel consumption compared to test cycles. Tal, et al. [57] analyzed vehicle usage and refueling behavior in California using logger data, surveys, and interviews; and they reported that real-world UF of PHEVs are lower than test cycle values and PHEVs with larger batteries achieve higher UFs. A similar conclusion regarding PHEV UF being lower than test cycle values was also presented by Plötz, et al. [16] using a combination of real-world data sets.

Between the two main approaches, using empirical, real-world data is rarer , due to the difficulty of data collection. In all papers appended in this thesis, the second approach (empirical, real-world data) is used which adds valuable input to the limited literature in the area. More specifically, **Paper III** makes an assessment of the UF at the household level, as the share of VMT within total household vehicle miles travelled, that includes all vehicles in the household and captures the overall household electrification of miles. **Paper IV** analyzes country level differences regarding the share of electrified vehicle kilometers; and **Paper V** solely focuses on electric driving of PHEVs in Europe and looks at how factors such as range and engine impact the share of electric driving.

2.2. PHEV charging behavior

Similar to the share of electrified vehicle kilometers travelled, there are two main approaches to assessing the charging behavior of PHEVs in the literature based on the data used.

The first approach uses a range of methods and data but no PHEV charging or driving data from the vehicle itself or the charging station. Data and methods used in this approach include household travel surveys, simulation and optimization models, online questionnaires, stated preference surveys or data from conventional vehicles applied to PHEVs or plug-in electric vehicles (PEVs) in general. Some studies focus solely on the impact of charging behavior on charging infrastructure. Dong and Lin [58] use a household travel survey in Austin, Texas, with recorded global positioning system (GPS) data for a single day, collected from 229 conventional vehicles. They analyze the impact of charger network coverage on PHEV energy consumption based on travel patterns. Xi, et al. [36] develop a simulation-optimization model to determine the locations of charging points for electric vehicles and apply their model on a dataset from central-Ohio region with generated trip data based on a typical workday. Bi, et al. [59] use an agent-based traffic simulation to analyze the impact of charging behavior on the performance of charging infrastructure in Singapore with the assumption that charging stations are placed at existing petrol stations and residential car parks. Pagani, et al. [60] use an agent-based simulation to analyze the impact of individual charging behavior on charging infrastructure in a mid-sized city in Switzerland. Chakraborty, et al. [61] and Chakraborty, et al. [62] analyze the demand drivers for charging infrastructure by modelling the charging behavior of 3,000 PEV drivers using survey data. Goebel and Plötz [63] compare machine learning methods and regression analysis to sample PHEV simulations using a full recharge overnight as assumption. They find machine learning methods to perform only slightly better than simulations.

Other studies within this group focus on charging patterns, environmental impacts, the share of electric driving, and battery requirements rather than infrastructure. Axsen, et al. [46] use survey data from 877 respondents in California and address the relationship between charging behavior and total greenhouse gas emissions. Tal, et al. [38] and Tal, et al. [39] use data from an online survey that includes extensive data on driving and charging behavior from more than 3,500 plug-in electric vehicle owners in California to analyze how charging behavior impacts electric vehicle miles travelled. They conclude that higher range PHEV and BEV users charge more often compared to lower range PHEV and BEV owners which further increases their share of electric driving. Björnsson and Karlsson [64] use GPS logged data for 30 days or longer from 432 conventional vehicles in Sweden to analyze how individual driving and charging behavior impact battery requirements for PHEVs. Philipsen, et al. [65] conducted qualitative interviews and a large-scale questionnaire with 1,021 respondents in Germany to identify conventional refueling behavior and charging behavior and then made a comparison between the two regarding conditions, frequencies and critical filling levels. They conclude that the perceived critical filling level is identical for fuel tanks and batteries, but in terms of behavioral patterns conventional vehicle users often run on empty and then refill tank completely while electric vehicle users charge in a timely manner. Tal, et al. [66] provide a snapshot of charging behavior of PEV users in California based on self-reported data. Chakraborty, et al. [67] analyze the 30-day charging behavior of 5,418 PHEV users in California and investigate why some PHEV users do not charge their vehicles. They find that several factors play a role in the decision making of plugging in or not, such as high home electricity prices, low electric driving range and low potential cost savings from charging. In addition, there are some studies that look at only BEV charging behavior, for example, Ashkrof, et al. [68] use data from a stated preference survey with 505 BEV drivers in the Netherlands to explore charging preferences and drivers' route choices for BEVs. Zhou, et al. [40] conduct an online stated preference survey with 132 respondents to study charging decision making of BEV users and then analyze the data using a latent class model. They apply their model to a case study in Beijing and conclude that to satisfy travel demand for 90% of drivers, a 354 km (220 US miles) battery range is needed for taxis, and a 482 km (300 US miles) battery range is needed for private vehicle owners.

The second approach in the literature uses empirical PHEV or PEV charging or driving data from the vehicle itself or the charging station. Among the studies that use data collected from charging stations, Gnann, et al. [32] analyze the charging behavior in Norway and Sweden by using empirical fast charging data from charging points. They conclude that if battery size and charging power keep increasing, the ratio of PEVs and fast chargers can be similar to conventional vehicles and refueling stations. Morrissey, et al. [33] analyze the charging behavior in Ireland and Northern Ireland by using data from 711 charging points with mixed fast and standard chargers, of which 43 are household charging points. They find that the majority of PEV users charge at home during peak demand times and incentivization may be necessary to encourage charging at other times. They also find that fast chargers have a much higher usage frequency compared to standard charging points.

Some of the studies within this second approach use data collected directly from the vehicles and overlap with the studies mentioned in the previous section regarding the utility factor. Ligterink, et al. [28] analyze the charging behavior of more than 10% of the Dutch plug-in fleet using the charging data from plug-in vehicles collected through lease companies in the Netherlands. Davies and Kurani [29] use data from 25 converted Toyota Prius with recorded driving and charging data and explore the effects of assumptions regarding PHEV charging and driving behavior on the estimated emission impacts of PHEVs. Nicholas, et al. [30] analyze the charging behavior of 72 PEV households in California with recorded driving and charging data from onboard loggers for a full year. Raghavan and Tal [54] and Raghavan and Tal [55] use multi-year longitudinal data from 153 PHEVs in California, ranging from 18 to 85 km (11 to 53 US miles) in all-electric-range and analyze their driving and charging patterns. They conclude that enhanced charging infrastructure can improve the observed UF of short-range PHEVs, and increasing the frequency of home charging can improve the observed UF of long-range PHEVs. There are also some studies focusing only on BEV charging. For example, Fieltsch, et al. [69] use recorded charging, driving and energy data from 160 commercial BEVs in Hamburg, Germany to analyze the charging behavior of BEVs in commercial transport. Their analysis focuses on temporal charging behavior and the initial and final state of charge. They conclude that longer charging events tend to occur after operating hours and that the BEVs in their dataset are predominantly fully charged since most charging events start at a high initial state of charge. Plötz, et al. [70] compare the actual mean real world UF as a function of all-electric range of 1,385 PHEV in Germany to the simulated mean UF of a large fleet of conventional vehicles. Using different scenarios for the share of days with charging, they conclude that the typical charging frequency of privately owned PHEV in Germany is about 75 % of the days [56, 70]. Tal, et al. [57] examines charging behavior in PEV households in California using data collected through placing monitors on household vehicles. Most recently, Li, et al. [71] analyze real-world charging behavior of almost 6,000 PHEVs in China and investigate the relationship between energy consumption efficiency and charging.

Existing studies on PHEV charging behavior are often based on conventional vehicles or have a limited PHEV sample with a short observation period. **Paper I and II** fill this gap with a large sample and long observation period for one PHEV model in North America; **Paper I** focuses more on the charging behavior itself and **Paper II** on how charging affects fuel consumption and tail-pipe emissions. The details regarding the data and methods used in all appended papers are provided in the next chapter (Chapter 3).

3. Data and methods

The relevant datasets that have been analyzed and the methods used are briefly summarized in this chapter. For more details on the data, variables and methods, please refer to the relevant appended paper. For any abbreviation not explained in text, refer to page x.

3.1 Overview of the data sets used in appended papers

The data set for **Paper I and II** contains user specific performance data of Chevrolet Volt (a PHEV) users from 2011 to 2020 with 4.3 million driving days and 10,488 users/vehicles from North America (United States and Canada). The data was retrieved from voltsats.net, an online database with automatically collected (from an additional device) real-world fuel consumption data from registered Chevrolet Volt users. Every user profile on the website contains cumulative daily data on the electric and gasoline mileage including daily fuel consumption on gallons of gasoline per day. The data was pre-processed, cleaned and cumulative mileage values were converted to daily driven km. Data cleaning comprised the exclusion of values with daily vehicle kilometers travelled (VKT) greater than 1,500 km and with higher electric VKT than total VKT per day.

After data cleaning, the average number of days observed per vehicle is 479 days with a median of 355, and maximum of 2,751 days; and average number of driving days per vehicle is 410 with a median of 303 and maximum of 2,500 days. Only users with at least 28 driving days were included in the analysis. Based on the available data, we calculated the following parameters: electric vehicle kilometers travelled (eVKT), gasoline vehicle kilometers travelled (gVKT) and total vehicle kilometers travelled (VKT). The average distance travelled was extrapolated to annual values. The individual observed UF per user is obtained by dividing all electric km by total km driven during the observation period. **Paper I** utilizes the entire data set, where as **Paper II** uses a subset of the data set with a smaller number of vehicles and driving days. This is due to the data used in **Paper II** being retrieved earlier than **Paper I** (**Paper II** is published before **Paper I**).

In **Paper III**, we use data from the Advanced Plug-in Electric Vehicle Travel and Charging Behavior Project which aims to provide an insight into how plug-in electric vehicles are used on a day to day basis within the household travel context, by placing data loggers in participant households for one year [30]. The project was initiated by the Electric Vehicle Research Center at University of California, Davis. Data was collected from summer 2015 to summer 2020, in California, U.S.A., from 287 households, by placing a monitor in all household vehicles driven more than

1,000 miles per year. Participating households were selected, in consultation with the California Air Resource Board, to fit an appropriate sampling of the population. Odometer readings were taken from cars that were driven less than 1,000 miles per year. Each household owned only one plug-in electric vehicle (either a PHEV or a BEV). In total, there were 5 PHEV models and 3 BEV models. Including the conventional vehicles in the households, the data set has 650 vehicles in total. Toyota Prius Plug-in & Prius Prime, Ford C-max Fusion/Energi, Chrysler Pacifica and Chevrolet Volt were the PHEV models, and Nissan Leaf, Chevrolet Bolt and Tesla Model S were the BEV models. The model years for the PEVs in the dataset ranged from 2012 to 2019. The dataset also included an extensive survey with the PEV owners prior to the placement of the monitors.

The raw data collected from the loggers and through the survey was cleaned by the Electric Vehicle Research Center. We used two main sets of data in our analysis: trip data and charging data. Trip data consisted of each single trip by the logged vehicle. The separating factor between trips was that the car remained at the same position idly with a speed of zero for at least 5 min. The data set provided information regarding the start time and duration of the trip, the total distance traveled, and fuel consumption during the trip. It also included the electric vehicle miles traveled (eVMT) and gasoline vehicle miles traveled (gVMT) for each single trip. Charging data consisted of each single charging event performed by the logged vehicle. It provided information regarding the start and end times of the charging event, charge levels (either level 1 or level 2) and start and end state of charge (SOC). From the datasets provided by the Electric Vehicle Research Center, we selected and computed variables that we labeled as factors relating to the household context, see **Paper III** for details. In **Paper I**, a subset of this data set was used that included only Chevrolet Volt vehicles, to validate and finetune the method in that paper.

In **Paper IV**, we use data from a single manufacturer with a worldwide operation. It contains 117,387 vehicles (of 9 different PHEV models) in 84 countries. For each vehicle, we have information on the make and model year, engine name and type, observation period and total vehicle kilometers travelled (VKT) on combustion and electric engine. Data was collected between 2018 and 2021. Model years also ranged from 2018 to 2021. The data is aggregated over the observation period, from the handover date to the customer to when the vehicle goes into the workshop for maintenance. The mean observation period for all the vehicles in the dataset is 573 days.

In **Paper V**, we use two primary data sets on real-world electric driving in Europe. One of the data sets is the subset of data we used in **Paper IV**, including only European countries. The other data set combines different online sources, company car data, and a PHEV user survey. It has been collected during the years 2021 and 2022 and contains 8,855 vehicles of 150+ PHEV models from 27 countries in Europe.

See **Table 1** for an overview of all the data sets and the appended papers that they are used in.

Table 1: Data sets used in appended papers

Data set	Paper I	Paper II	Paper III	Paper IV	Paper V
• 1 PHEV model • 10,488 vehicles • 2011 to 2020 • Daily data on electric and gasoline mileage • N. America (US and Canada)	X	X (subset)			
• 5 PHEV models, 3 BEV models • 287 households, 650 vehicles (including ICEV in households) • 2015 to 2020 • Trip and charging event based data • US (California)	X (subset)		X		
• 9 PHEV models • 117,387 vehicles • 2018 to 2021 • Aggregated electric and gasoline mileage data • 84 countries worldwide				X	X (subset)
• 150+ PHEV models • 8,855 vehicles • 2021 to 2022 • Combination of different sources (See [16]) • 27 countries in Europe					X

The data sets used in appended papers vary based on their sample sizes, observation periods and geographical distribution. Different types of data have advantages and disadvantages. A short observation period may be easier to obtain and thus facilitates a higher resolution or more information on individual users; however, the results can be difficult to generalize and apply to different circumstances due to limitations of spatial and geographical scopes. Longer observation periods are more cumbersome to collect and usually result in lower resolution due to higher data collection costs and can provide a better understanding of general trends. Empirical data collected directly from vehicles has the advantage of presenting real-world usage (e.g. compared to simulation models) [72-74], however installing monitors on vehicles comes at a cost, and thus there is usually a trade of between collecting short-period data with high resolution and small sample size, and collecting long-period data with low resolution and large sample size.

3.2 New method to identify charging events

In **Paper I and II,** the data did not provide us directly with the charging behavior of the users and thus this had to be computed. Departing from the common assumption in drive cycles and simulations that the PHEVs are charged once during a 24 hour cycle (referred to as overnight charging), we developed a method to identify how real-life data deviates from this assumption through additional charging events and nights with no charging. The frequency of additional charging is defined as the share of days with an additional charging event within the total number of driving days for a given user. Similarly, the frequency of no overnight charging is defined as the share of days with no overnight charging within the total number of driving days. A charging event here refers to the driver plugging in the vehicle to the grid and charging the battery.

First, we define calculated UF and observed UF for each day and user, as given in **Eq. 1** and **Eq. 2** respectively (AER stands for all-electric-range of the vehicle).

$$\mathrm{UF_{cal}} = \begin{cases} {AER}/{daily\ VKT}, & \text{if } daily\ VKT > AER \\ 1, & \text{otherwise} \end{cases} \tag{1}$$

$$\mathrm{UF_{obs}} = {daily\ eVKT}/{daily\ VKT} \tag{2}$$

The calculation assumes a full charge overnight implicitly. If the observed UF is much higher than the calculated UF, there must have been at least one additional charge during the day for that user. We use the assumptions given in **Eq. 3** and **Eq. 4** for the occurrence of additional charging or no overnight charging, for a user, for a given day.

$$\text{additional charging} = \begin{cases} \text{true}, & \text{if } \frac{UF_{obs}}{UF_{cal}} > X \\ \text{false}, & \text{otherwise} \end{cases} \tag{3}$$

$$\text{No overnight charging} = \begin{cases} \text{true}, & \text{if } \frac{UF_{obs}}{UF_{cal}} < Y \\ \text{false}, & \text{otherwise} \end{cases} \quad (4)$$

In order to estimate the two thresholds (X and Y) in **Eq. 3** and **Eq. 4**, we use a real-world charging data for the Chevrolet Volt. This is a subset of the data set used in **Paper III** that includes detailed charging and driving data on Chevrolet Volt. We only use this data for calibration and demonstration of our method.

Through varying X and Y in **Eq. 3** and **Eq. 4**, we estimate the occurrence of additional charging and no overnight charging. Then we compare these estimations with the real-world charging data of the same vehicles to see how well our model performs. We provide the receiver operating characteristic (ROC) curves for additional charging and no overnight charging, which illustrates the performance of our model when the threshold is varied. The ROC curve shows the true positive rate (TPR), known as the probability of detection or sensitivity, as a function of the false positive rate (FPR), i.e., the probability of false alarm. We also provide the balanced accuracy scores to evaluate the performance of the threshold levels. Balanced accuracy, the arithmetic mean of TPR and true negative rate (TNR), is one of the most common metrics used to evaluate how good a varied threshold is on a ROC curve. Based on graphical interpretation of the ROC curves (see Figure 1 and Figure 2 in **Paper I**) and a thorough sensitivity analysis, we pick a threshold of 1 for additional charging (X) and 0.5 for no overnight charging (Y).

Table 2: True positive rate (TPR), true negative rate (TNR) and accuracy of additional charging and no overnight charging occurrences when the threshold choices are 1 and 0.5 respectively **(Paper I)**

	True positive rate (TPR)	True negative rate (TNR)	Accuracy
Additional charging	44%	90%	80%
No overnight charging	23%	93%	76%

Note: False positive rate (FPR) is 1-TNR and false negative rate (FNR) is 1-TPR. The share of real positives within total cases is 20% for additional charging and 24% for no overnight charging.

With a threshold choice of 1 for additional charging, TPR is 44%, TNR is 90% and overall accuracy is 80% (see **Table 2**). This shows that our method is better at identifying days where additional charging did not happen (TNR) compared to the days where additional charging did happen (TPR). Given any random driving day, our method can identify that day as a day with additional charging or not with 80%

accuracy. On the other hand, with a threshold of 0.5 for no overnight charging, TPR is 23%, TNR is 93% and overall accuracy is 76%. Given any random driving day, our method can identify that day as a day with overnight charging or not with 76% accuracy.

Our method to detect additional charging and no overnight charging is rather conservative, e.g., if a vehicle drives less than the AER on a given day and still charges that day, this charging event will not be captured. Thus, some additional charging will be missed, however, this additional charging will not contribute to increased UF and thus the environmental performance of the PHEV.

With this method, we can calculate the frequency of additional charging and the frequency of no overnight charging for each user. In **Paper I** we use additional charging and no overnight charging frequencies and analyze charging behavior with respect to characterization of frequent chargers and charging days. In **Paper II**, we plot additional charging and no overnight charging frequencies against mean fuel consumption and utility factor; and analyze the impact of charging behavior on fuel consumption, tail pipe emissions and share of electrification of vehicle kilometers.

We use slightly different versions of this method in **Paper I** and **Paper II**. The version in **Paper II** was not calibrated using real-world charging data and thus the additional charging threshold was assumed to be 1.5. How this might have impacted our results is discussed in Chapter 4.1 where we present the results from **Paper I and II**.

3.3 Regression analysis

In **Paper II**, we use a multivariable regression analysis for a quantitative assessment of the effect of charging on fuel consumption. We distinguish between the frequencies of additional charging and the frequency of no overnight charging. Furthermore, we control for two additional variables with noteworthy impact on the UF and fuel consumption: the user's average daily VKT and the standard deviation (SD) of the daily VKT. The former indicates the typical daily driving distance while the latter also captures the variation in daily VKT where high SD is indicative of more frequent long-distance driving which additionally lowers the UF and increases fuel consumption at fixed mean daily VKT [27].

Our regression model in **Paper II** is the following:

$$FC = \beta_0 + \beta_1 \log(f_{\text{additional charging}}) + \beta_2 \log(f_{\text{no charging}}) + \beta_3 \text{Mean daily VKT} + \beta_4 \text{SD daily VKT} + \varepsilon \quad (5)$$

Where FC denotes fuel consumption in litres per 100 km, $f_{\text{additional charging}}$ is the frequency of additional charging (in %), $f_{\text{no charging}}$ is the frequency of no overnight charging (in %) and the last two variables denote the mean and standard deviation of daily VKT (both measured in km). We use the log of the charging frequencies as this reduces the likelihood of heteroscedasticity. See the Appendix in **Paper II** for the detailed discussion and robustness checks on heteroscedasticity and normality assumption in our model. The inclusion of the mean and SD of daily VKT reduces potential omitted variable bias.

In **Paper III**, we run regression analysis on the compiled data set in order to assess the electrification of vehicle miles travelled within the household context.

Generic regression model used in **Paper III** is given below in **Eq. 6**; we use the same independent variables for all: range (all-electric-range), frequency of charging (average number of charging events per day), frequency of long-distance trips (percentage of single trips (not daily) above 50 miles undertaken by the PEVs), frequency of overlaps (percentage of PEV trips that overlapped with any of the ICEV trips in the household), standard deviation (SD) of daily household vehicle miles travelled (VMT) and the MPG (miles per gallon) of the ICEV in the household.

$$Y_i = \beta_0 + \beta_1 Range + \beta_2 FreqCharging + \beta_3 FreqLongdistance + \beta_4 FreqOverlaps + \beta_5 SD\_dailyHHVMT + \beta_6 ICEVMpg + \varepsilon \tag{6}$$

$i = \{1, \ldots, 8\}$ where Y_1 = eVMT, Y_2 = VMT of the PEV, Y_3 = VMT of the household, Y_4 = Utility factor of the PHEV, Y_5 = Utility factor of the household, Y_6 = Fuel consumption of households, Y_7 = Fuel consumption of PHEV households, Y_8 = Fuel consumption of BEV households

We perform multiple linear regression analysis on electric vehicle miles travelled (eVMT), VMT of the PEV and VMT of the household, and logistic regression on the UF of the PHEV, and the UF of the household, since the utility factor was always between 0 and 1. Similarly, we perform a logistic regression on the fuel consumption of all households, because we observed a logarithmic relationship between fuel consumption and all-electric range when all PEVs were included. When we observed the relationship between fuel consumption and all-electric-range for PHEV households and BEV households separately, this logarithmic relationship disappeared. Therefore, to investigate further, we perform multiple linear regression analyses on the fuel consumption of PHEV and BEV households, separately.

In **Paper V**, we also use a regression model to analyze fuel consumption (FC) and electric driving share (EDS) (also known as utility factor). See **Eq. 7** and **Eq. 8**.

$$FC^{real} = exp(\beta_0 + \beta_1 Power/Mass + \beta_2 Range + \alpha\, Controls \quad) + \varepsilon \tag{7}$$

$$EDS = exp(\beta_0 + \beta_1 Power/Mass + \beta_2 Range + \alpha\, Controls \quad) + \varepsilon \tag{8}$$

Here, system power (Power) is in units of 100 kW and all-electric range (Range) in 10 km. The chosen dependence is physically meaningful: For Range→0, the fuel consumption approaches a finite value (i.e. the fuel consumption in charge-sustaining mode) and goes to zero for Range→∞. Likewise, the fuel consumption approaches zero for Power→0 and grows with increasing power (for positive β1). Furthermore, we added several control variables such as the model year, country and user group (private or company car) to account for additional effects. The linear regression is performed after taking logarithms by square root of sample size weighted least squares.

3.4 Hierarchical linear modeling

In **Paper IV**, the multi-country characteristic of the data set gives us the opportunity to make statistically significant comparisons between different countries and regions. The data set contains factors that can cause variation in the share of electrification among users in general, such as the model year, engine type, annual VKT and aggregate observation days. If these variables are skewed towards a certain direction in a given country, this might affect the share of electrification in that country. For example, a high daily and annual VKT can be indicative of more long-distance driving [75] and it is well established that long-distance driving results in lower fuel economy and lower share of electrification. In countries where the aggregate observation period is longer, user group might reflect a more saturated group of users resulting in more efficient driving. However, our dataset has limited information on the country level that can help explain differences between countries. Therefore, to figure out which country level factors are behind these differences, we enrich the dataset with the following data on country level: electricity and gasoline prices, charging infrastructure (number of public chargers per person, per area and per road network), share of company cars, share of detached housing and climate indicators (annual average temperature and precipitation). We levelized the electricity and gasoline prices based on purchasing power parities.

To analyze if any of the country level factors has an impact on the share of electrification between countries, we apply hierarchical linear modelling with utility factor (UF) as the dependent variable. The reason we use a hierarchical linear model is the assumption that country level factors impact the share of electrification at a different rate in each country. Normal linear models violate independence assumption (standard errors often too small and there are incorrect p-values); and they cannot distinguish between micro and macro levels. Predictor effects can differ under different contexts. A single level model would have error terms that would represent clustered data errors across levels, which would limit the effect of the key predictor. A hierarchical linear model, therefore, would fit better in understanding the differences between countries (macro levels), concerning individual users (micro level). See the following literature on hierarchical linear modeling for a better understanding of the method: [76-82]. The hierarchical linear model is given below:

$$UF_{ij} = \beta_{0j} + \beta_{1j} * VKT_{ij} + \varepsilon_{ij}$$

$$\beta_{0j} = \gamma_{00} + \gamma_{01}EG_j + \gamma_{02}CH_j + \gamma_{03}CO_j + \upsilon_{0j} \qquad (9)$$

$$\beta_{1j} = \gamma_{10}$$

where UF (utility factor, share of electrified vehicle kilometers), VKT (annual VKT), EG (electricity price to gasoline price ratio), CH (charging stations per 10,000 people), CO (share of company cars among newly sold PHEVs), i (vehicles) and j (countries)

In our modelling, we only use the six countries that are prevalent for all PHEV models in our selection, all of which are European countries (France, Germany, Netherlands, Norway, Sweden and United Kingdom). We use a smaller number of variables than the country level data we collected. We tested several hierarchical linear models for each PHEV model that differ in the number and type of the variables chosen. High number of parameters make the model too complex such that it creates issues of convergence and multicollinearity between country level factors, which we have observed in our testing that led us to limiting our country level variables to only three variables (electricity price to gasoline price ratio, charging stations per 10,000 people and share of company cars among newly sold PHEVs).

4. Results

This chapter presents the most important results from the appended papers under the titles of charging behavior, household context and multiple countries. For any abbreviation not explained in text, refer to page x.

4.1. Charging behavior

This subsection presents the results from Paper I and II. Paper I investigates the charging behavior of PHEVs and Paper II investigates how this behavior impacts fuel consumption and tail-pipe emissions.

In **Paper I**, we analyze the frequency of additional charging and no overnight charging for a PHEV model in North America (US and Canada) from a sample of 10,488 vehicles. The frequency of additional charging is defined as the share of days with an additional charging event within the total number of driving days for a given user. Similarly, the frequency of no overnight charging is defined as the share of days with no overnight charging within the total number of driving days. A charging event here refers to the driver plugging in the vehicle to the grid and charging the battery. Distributions of these charging frequencies are shown in **Figure 1** and **Figure 2**. We also analyze charging behavior for different days of the week and observed holidays. We use a two-sample t-test to check for any statistically significant difference between average charging frequencies on Monday to Thursday and Friday to Sunday.

Figure 1 and **Figure 2** show the normalized distributions of driving days with additional charging and no overnight charging frequency among all users, respectively. From **Figure 1**, we observe that the average share of days with additional charging is typically 20 – 26 % and most commonly less than 40 % of the days with a mean of 25.5 % and a median of 20.3 %.

The typical share of days without overnight charging, shown in **Figure 2**, is 3 – 7 % and almost always below 25% of the days with a mean of 6.6 % and a median of 3.3%. Accordingly, the observed vehicles are commonly charged overnight, and users avoid high shares of nights without charging. This implies that the PHEVs in this sample are, on average, almost daily charged.

Looking at different days of the week, we find a difference in both driving behavior and charging frequency between weekdays and weekends. **Table 3** provides a comparison of weekdays, weekends and observed holidays in terms of frequency of additional charging, no overnight charging and daily VKT.

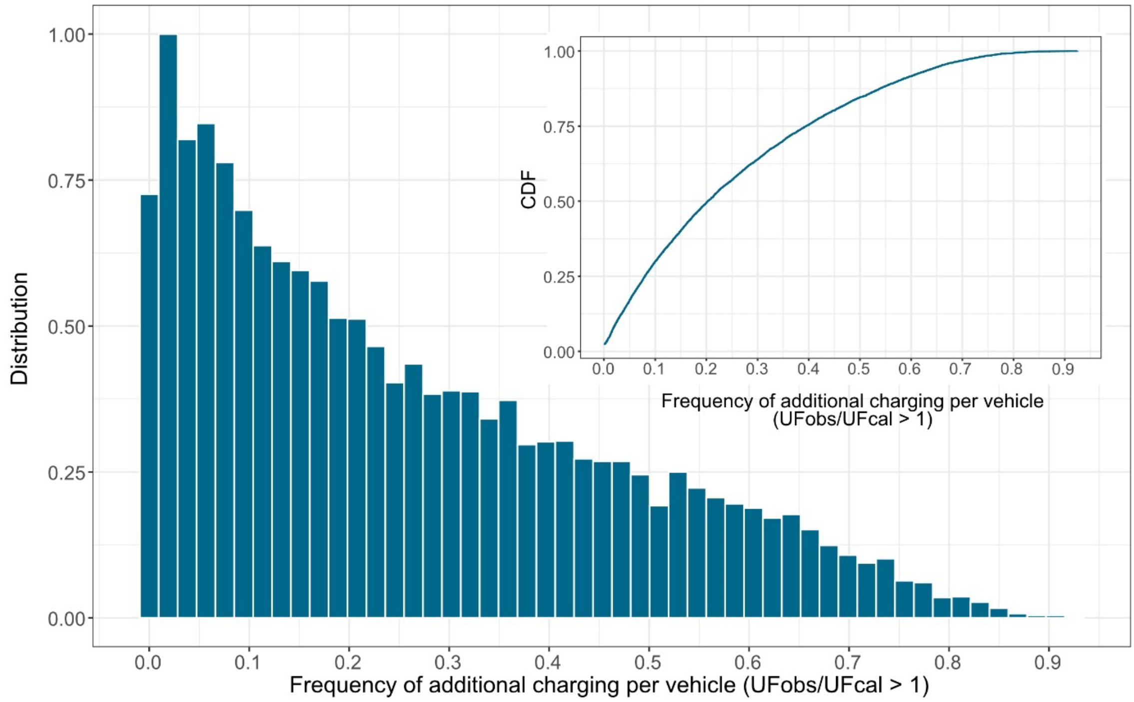

Figure 1: Distribution of additional charging frequency, normalized so maximum is 1. CDF given inset. **(Paper I)**

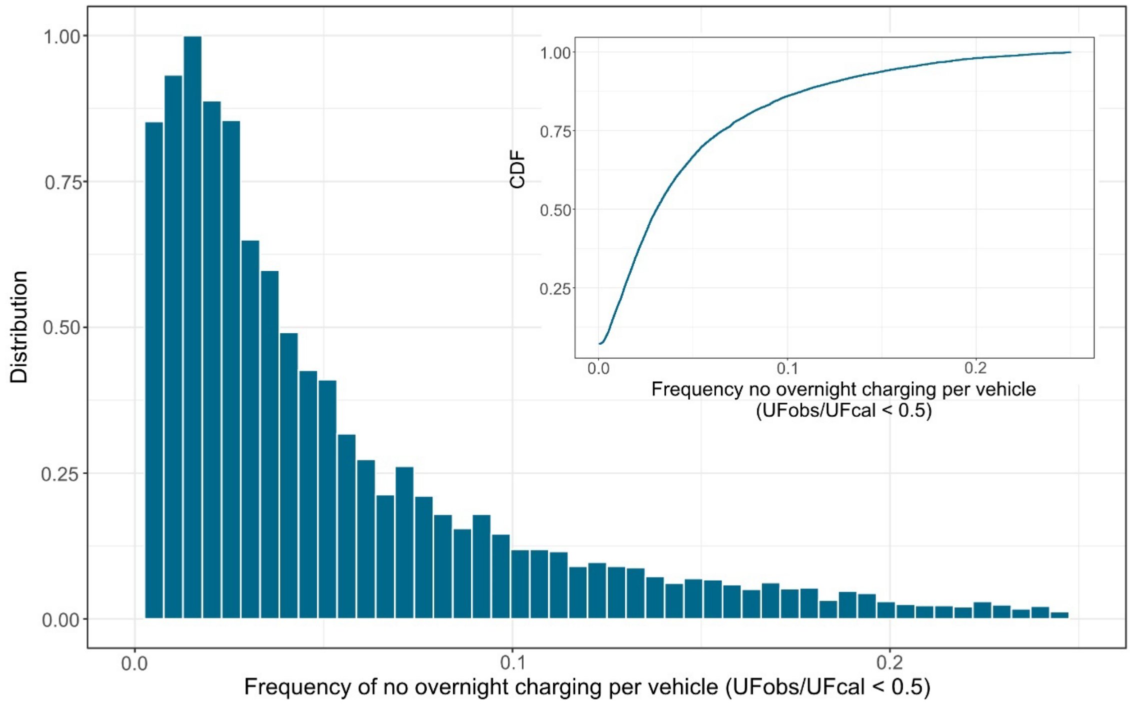

Figure 2: Distribution of frequency of no overnight charging, normalized so maximum is 1. CDF given inset. **(Paper I)**

Users charge additionally on average more frequently on Monday to Thursday with an average frequency of 28.5 %, while the average for Friday to Sunday is 20.9 %, meaning additional charging is more common on working days.

They also have nights without charging less frequently on the nights before weekends, with an average frequency of 8.0 % compared to 5.6 % on Monday to Thursday, meaning that not charging overnight is more common on weekends. A two-sample t-test shows that there is a statistically significant difference between Monday to Thursday and Friday to Saturday in charging frequencies both additionally and overnight. There is also a difference in daily driving distances. On average, the vehicles are driven less on weekends with Saturday having the lowest average VKT of 50.1 km.

Table 3: Means of frequency of additional charging, no overnight charging, and daily VKT of weekdays, weekends and observed holidays **(Paper I)**

	Mean frequency of additional charging		Mean frequency of no overnight charging		Mean daily VKT
All driving days (N=4,301,842)	**25.5%**		**6.6%**		**60.5**
Monday-Thursday	28.5%		5.6%		64.3
Friday-Sunday	20.9%		8.0%		56.8
Difference	*7.6%*	***	*2.5%*	***	*7.5*
Monday	27.5%		5.4%		62.2
Tuesday	29.0%		5.4%		63.8
Wednesday	28.9%		5.5%		64.6
Thursday	28.6%		6.0%		65.8
Friday	22.1%		8.4%		59.9
Saturday	17.6%		9.2%		50.1
Sunday	22.1%		6.8%		57.7
New Year’s Eve	9.8%		10.9%		39.6
New Year’s Day	15.1%		7.8%		48.8
Easter Sunday	21.9%		6.7%		60.7
Memorial Day	25.2%		5.6%		60.9
Independence Day	23.3%		6.9%		54.5
Labor Day	24.6%		5.5%		60.5
Thanksgiving	15.2%		11.2%		47.5
Christmas Eve	12.6%		12.6%		40.6
Christmas Day	12.7%		10.7%		45.8

Note: Observation period is from April 2011 to January 2020. Difference indicates the absolute difference between the means of two subgroups. Frequency of no overnight charging on a specific day reflects the night before, e.g. mean frequency of no overnight charging on Tuesday (5.4%) reflects the night connecting Monday to Tuesday.
Sign. Codes: ‘***’: $p < 0.001$; ‘**’: $p < 0.01$; ‘*’: $p < 0.05$

Given the large number of users and long average observation time, our sample allowed us to investigate specific days such as holidays. Generally, we observe that the vehicles are charged less during these days and that the driving distances are shorter (it's possible that longer driving distances occur on the days around the holidays). New Year's Eve sees the lowest frequency of additional charging, with only 9.8% of users charging on New Year's Eve on average, this is followed by Christmas Eve, Christmas Day, New Year's Day, and Thanksgiving. These five days also have the lowest mean daily VKT among holidays, ranging from 39.6 km on New Year's Eve to 48.8 km on New Year's Day, and the highest mean frequency of no overnight charging, ranging from 7.8% the night before New Year's Day, to 12.6% the night before Christmas Eve. On the other hand, Easter Sunday, Memorial Day, Independence Day, and Labor Day are comparable to a weekend with mean frequency of additional charging between 21.9% and 25.2%, and no overnight charging between 5.5% and 6.9%.

To better understand the difference in driving and charging behavior among users, we look more specifically at certain user groups. The studied groups are top 10% and bottom 90% of additional chargers — top referring to more frequent and bottom to less frequent —, top 10% and bottom 90% of no overnight chargers, intense vehicle users (users with more than 30,000 km annual VKT) and non-intense vehicle users. See **Paper I** for the reasoning behind these user groups. **Figure 3** summarizes the observed utility factor, daily VKT, frequency of additional charging and frequency of no overnight charging for all users and all subgroups (top 10 % and bottom 90% of additional chargers, top 10 % and bottom 90 % of no overnight chargers, intense vehicle users and non-intense vehicle users). The top 10% of additional chargers have a mean frequency of additional charging of 67.2%, whereas the bottom 90% is at 20.9%. There are on average 410 driving days recorded per user and the observed average UF for all users is 73.6 %.

We find that not charging overnight has a larger effect on the utility factor than more frequent additional charging. The change in UF from not charging overnight is typically larger than charging additionally. The top 10 % of no overnight chargers have an average UF of 43.5% compared to the average UF of 73.6 % for all users and the average UF of 77 % for the bottom 90 % of no overnight chargers. In comparison the top 10 % of additional chargers have a UF of 79.7 % compared to the average UF of 73.0 % for the bottom 90% of additional chargers. The top 10% of no overnight chargers seem to charge less in general since their average frequency of additional charging is also lower (13.2 %) compared to all users (25.5%).

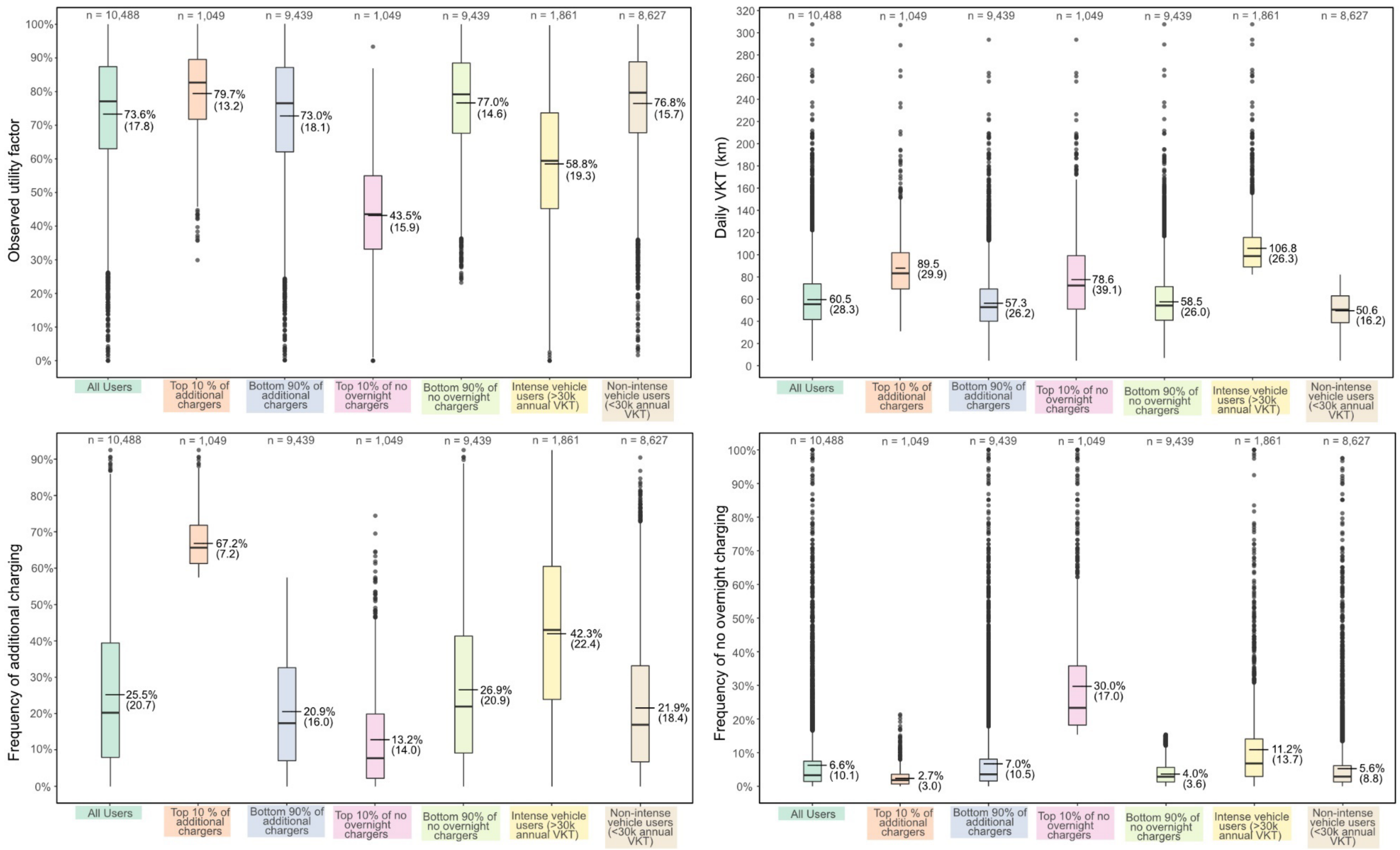

Figure 3: Distribution of observed utility factor (UF), daily VKT, frequency of additional charging and frequency of no overnight charging in different user groups. Means are indicated and the standard deviation is given in parentheses. **(Paper I)**

Intense vehicle users (users above 30,000 km annual VKT) have an average frequency of additional charging of 42.3% compared to average of the whole sample of 25.5% and 21.9% for the non-intensive users. However, their average UF is lower (58.8 % compared to 73.6 % for all users) meaning their increased additional charging behavior falls short of matching their increased total VKT. It should also be noted that they also have a higher frequency of no overnight charging.

Within the total 4.3 million driving days in our dataset, the share of days where the daily VKT is larger than the all-electric-range (AER) is 36%. This shows that more than one third of the time users drive beyond the AER, which makes the impact of long-distance driving worth looking into. **Table 4** shows the share of days with long-distance driving, i.e., days with daily VKT over 100 km or 200 km, within driving days and annual VKT among different user groups. We observe that daily VKT larger than 100 km happens on 19.7 % of the driving days for all users, but accounts for 41.3 % of the annual VKT. This indicates that long distance driving, although occurring only once in five days on average, accounts for close to half of the annual VKT. A threshold of 200 km for long distance driving highlights this impact even more and we observe that days with daily VKT larger than 200 km make up 4.3 % of the driving days but 15.9 % of the annual VKT on average. The vehicles in our sample appear to drive a lot, but please note the average annual driving distance in our sample is comparable to the US national average (22,113 km annual driving distance for our sample compared to 21,700 km US average) [83].

Table 4: Share of days with long-distance driving within driving days and annual VKT among different user groups **(Paper I)**

	Mean share of days where				N (users in the sample)
	Daily VKT > 100 km		Daily VKT > 200 km		
	Driving days	Annual VKT	Driving days	Annual VKT	
All users	19.7%	41.3%	4.3%	15.9%	10,488
Top 10% of additional chargers	41.8%	60.3%	6.7%	15.0%	1,049
Bottom 90% of additional chargers	17.3%	39.2%	4.0%	16.0%	9,439
Top 10% of no overnight chargers	31.4%	58.9%	9.5%	28.0%	1,049
Bottom 90% of no overnight chargers	18.4%	39.3%	3.7%	14.6%	9,439
Users above 30k annual VKT	48.3%	73.5%	12.3%	29.8%	1,861
Users below 30k annual VKT	13.6%	34.4%	2.5%	12.9%	8,627

In **Paper II**, we quantify the environmental effect of not charging a PHEV (same model and data set in **Paper I**) on some nights (no overnight charging) and the effect of charging a PHEV twice or more frequently per day (additional charging), with a focus on the tail-pipe emissions of a long-range PHEV. More specifically, we analyze the change in utility factor and fuel consumption.

We use the same definition for additional charging and no overnight charging as in **Paper I**, but with a slightly difference threshold for the occurrence of additional charging. In **Paper I**, the threshold for the occurrence of additional charging (ratio of observed utility factor to calculated utility factor) was taken as 1. This was done after rigorous fine-tuning using real-life charging data. At the time of writing **Paper II** (which is published before **Paper I**), this fine-tuning was not available and we assumed a threshold of 1.5 for the occurrence of additional charging. However, we had performed robustness checks for our results in **Paper II**, with different threshold choices and we observed that lowering the threshold for additional charging from 1.5 to 1.3 did not affect the output and significance of our results, only slightly changed the coefficient estimates. Therefore, if we had taken the threshold in **Paper II**, the same as **Paper I**, the results in **Paper II** would not change in interpretation.

In **Paper II**, we first investigate the effect of not charging overnight on average fuel consumption. We find that regularly charging overnight — low frequencies of no overnight charging — reduces the mean fuel consumption below one litre per 100 km, see **Figure 4**. Note that in **Figure 4** and **Figure 5**, small dots represent users grouped and rounded to percentage values and blue line shows local average. We observe that higher frequencies of no overnight charging increase the mean fuel consumption and a share of above 60% nights without charging can push up the mean fuel consumption above 5 litres per 100 km. This significant difference shows that regularly charging overnight has a substantial effect on mean fuel consumption. The correlation between low charging frequency and higher vehicle emissions has a clear technical cause: If the battery has been fully recharged before the trip, then the battery will be fully depleted after the electric range has been exceeded. In that situation the combustion engine is used for propulsion of the vehicle and the battery can only buffer some energy from regenerative breaking. If the battery is not fully or only partly recharged before driving, the engine is needed for propulsion earlier or exclusively. Thus, low charging leads to more frequent use of the combustion engine and thus higher emissions.

Given inset in **Figure 4**, we control for daily VKT and look at the isolated effect of no overnight charging. This is done by looking at the difference between observed mean fuel consumption and calculated mean fuel consumption, where the calculated mean fuel consumption refers to 1- UF_{cal} multiplied by the fuel consumption in charge sustaining mode. From the inset in **Figure 4**, we observe that regularly charging once overnight can result in a reduced observed mean fuel consumption of 1 litres per 100 km compared to a calculated mean fuel consumption, whereas not charging overnight 70% of the time can increase the observed mean fuel consumption by 3 litres per 100 km.

In **Figure 4**, we observe that mean fuel consumption tends to increase in a steeper slope below 10% frequency of no overnight charging. We observe a different trend from 10% frequency of no overnight charging to 20% where the slope is less steep, and another trend with even a less steep slope when the frequency of no overnight charging is above 20%. We have run a piecewise linear regression for these three different trends, and we find that the frequency of no overnight charging is statistically significant with a confidence level of 99.9% for all three trends. Here we provide the estimates and the standard error as added uncertainty (±): we find that fuel consumption and tail-pipe emissions increase by 1.85 ± 0.03 l/100 km or 42.7 ± 0.8 gCO_2/km tail-pipe emissions from 0% to 10% driving days without overnight charging (going from charging overnight every day to only 9 out of 10 driving days). Conversion of fuel consumption to tail-pipe emission was performed by using U.S. Environmental Protection Agency values [84]. Around the mean frequency of no overnight charging (4.7%), mean fuel consumption is close to 2 litres per 100 km. We find that fuel consumption and tail-pipe emissions increase by 0.94 ± 0.12 l/100 km or 21.6 ± 2.87 g tail-pipe CO_2 per km from 10% to 20% driving days without overnight charging. Above 20% driving days without overnight charging, fuel consumption and tail-pipe emissions increase by approximately 0.42 ± 0.05 l/100 km or 9.73 ± 1.25 g tail-pipe CO_2 per km every 10% driving days without overnight charging.

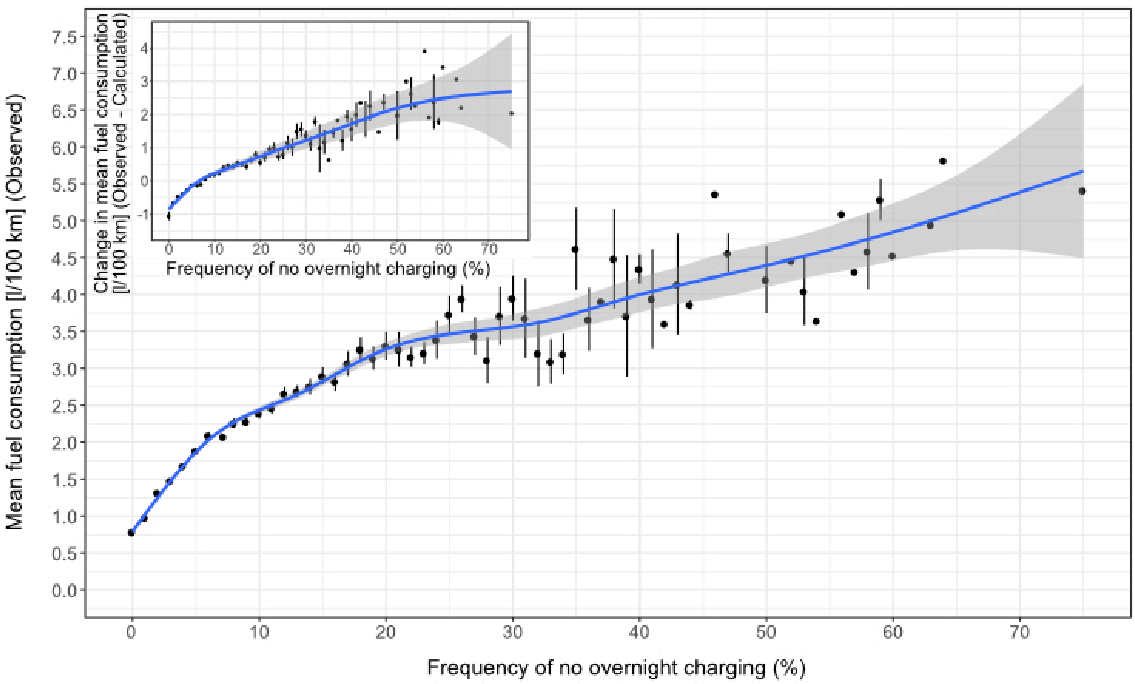

Figure 4: Mean fuel consumption vs frequency of no overnight charging, change in mean fuel consumption (observed-calculated) vs frequency of no overnight charging given inset **(Paper II)**

From **Figure 5**, we observe that the effect of an additional charging event is less substantial compared to overnight charging, yet higher shares of additional charging results in lower mean fuel consumption. In **Figure 5**, we observe that the mean fuel consumption is level around 1.6 l/100 km or 37 g tail-pipe CO_2 per km below 20% driving days with additional charging. A piecewise linear regression reveals that there is no statistically significant relationship between additional charging and fuel consumption when additional charging frequency is below 20%. Above 20% driving days with additional charging, regression analysis reveals a statistically significant relationship at the 0.1% level between additional charging and fuel consumption; and mean fuel consumption and tail pipe emissions decrease, on average by 0.08 ± 0.02 l/100 km or 1.86 ± 0.46 gCO_2/km tail-pipe CO_2 per km every 10% driving days with additional charging.

Given inset in **Figure 5**, if we control for daily VKT and look at the isolated effect of additional charging, we observe more clearly that an increase from 0% to 10% driving days with additional charging can result in a reduced observed mean fuel consumption of approximately 1 ¼ l/100 km or 29 g tail-pipe CO_2 per km. Above 10% driving days with additional charging, we find a reduced observed mean fuel consumption of approximately 0.3 l/100 km or 69 g tail-pipe CO_2 per km every 10% driving days with additional charging; e.g. 80% of driving days with additional charging can reduce observed mean fuel consumption by 3 l/100 km or 69 g tail-pipe CO_2 per km.

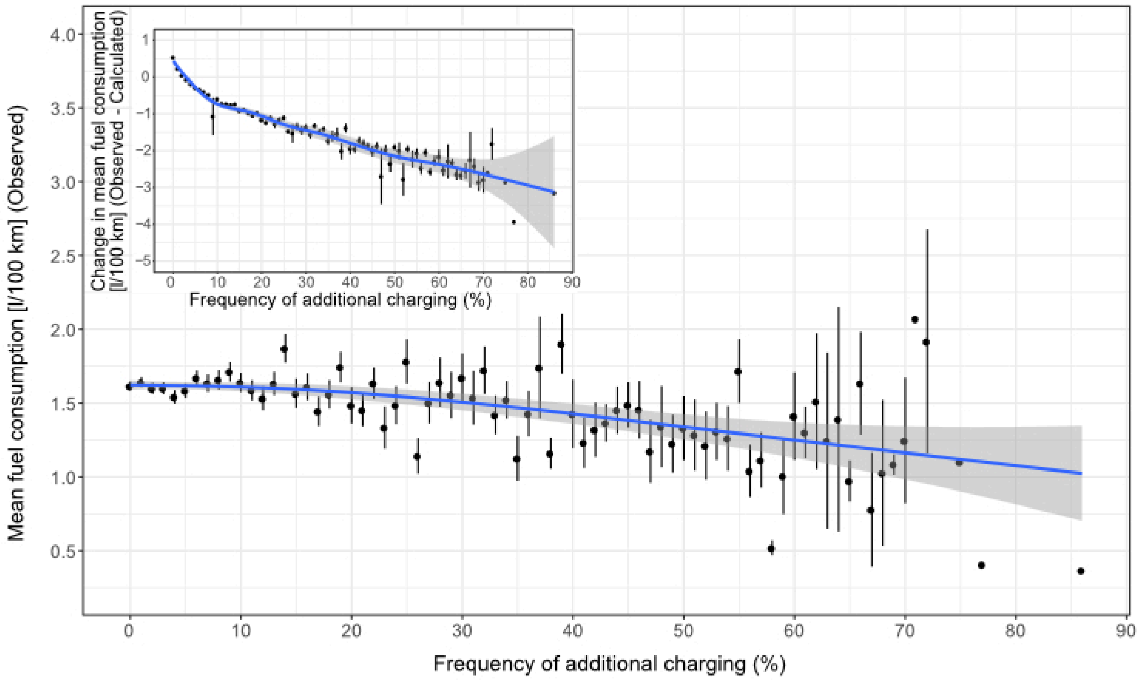

Figure 5: Mean fuel consumption (observed) vs frequency of additional charging, change in mean fuel consumption (observed-calculated) vs frequency of additional charging given inset **(Paper II)**

We use a multivariable regression analysis for a quantitative assessment of the effect of charging on fuel consumption. The results of the regression analysis are given in **Table 5**. The model itself and all variables are significant (mean daily VKT at 95% confidence level and all others at 99.9% level) and have the expected sign. The simple model explains about 67% of the variance in fuel consumption, which is acceptable for the low number of variables included. An increase in no overnight charging, i.e. a decrease in charging leads to higher fuel consumption. Likewise, an increase in additional charging reduces fuel consumption and increases the UF. A higher mean daily VKT leads to a higher fuel consumption as a smaller share of km is driven on electricity. Finally, a higher SD of daily VKT indicates more frequent long-distance driving and thus lower UF coupled to higher fuel consumption.

Table 5: Regression results for dependent variable fuel consumption. Shown are coefficient estimates with standard errors in parentheses. **(Paper II)**

Dependent variable	Fuel consumption (l/100 km)
Intercept	1.79*** (0.06)
(Log of) frequency of no overnight charging	0.42*** (0.01)
(Log of) frequency of additional charging	-0.05*** (0.01)
Mean daily VKT	0.0009* (0.0004)
SD of mean daily VKT	0.01*** (0.0003)
Sample Size N	6245
Multiple R-squared	0.669
Adjusted R-squared	0.669
F-statistic	3158 (p-value: < 0.0001)

Confidence levels: *** %99.9, **%99, *%95

We observe that both the log of frequency of no overnight charging and additional charging are statistically significant. For every relative 10% increase in the frequency of no overnight charging (e.g. from 10% to 11%), fuel consumption increases by 0.017 l/100 km (calculated by log(1.1)*0.42) and tail-pipe emissions increase by 0.40 gCO_2/km. For every relative doubling of the frequency of no overnight charging (e.g. from 10% to 20%), fuel consumption increases by 0.13 l/100 km (calculated by log(2)*0.42) and tail-pipe emissions increase by 2.92 gCO_2/km. On the other hand, for every relative 10% increase in the frequency of additional charging, (e.g. from 10% to 11%), fuel consumption decreases by 0.002 l/100 km and tail-pipe emissions decrease by 0.05 gCO_2/km. Similarly, for every relative doubling of the frequency of additional charging, fuel consumption decreases by 0.015 l/100 km and tail-pipe emissions by 0.35 gCO_2/km. For a concrete comparison, any relative doubling of the frequency of no overnight charging, for instance going from charging overnight 9 out of 10 nights (10%) to 8 out of 10 nights (20%) has almost ten times more impact on fuel consumption and tail-pipe emissions compared to a relative doubling in additional charging frequency, for instance going from additional charging 4 out of 10 driving days to 8 out of 10 driving days. The regression analysis further establishes in a statistically significant way that no overnight charging has more impact on fuel consumption and tail-pipe emissions compared to additional charging.

The most important findings from **Paper I** and **Paper II** regarding PHEV charging behavior can be summarized as follows:

- Users (of one long-range PHEV model) avoid high shares of nights without charging, meaning charging mostly occurs overnight. **(Paper I)**
- The change in utility factor from not charging overnight is typically larger than charging additionally, meaning overnight charging has more impact on increasing the share of electrified kilometers compared to additional charging. **(Paper I)**
- Long distance driving limits the effect of additional charging. **(Paper I)**
- Overnight charging has a more significant impact on reducing fuel consumption and tail-pipe emissions compared to additional charging. **(Paper II)**

4.2. Household context

This subsection presents the results from Paper III. Paper III investigates electrified vehicle kilometers/miles travelled and fuel consumption within the household context.

In **Paper III**, we assess the UF within the household context, and investigate how household factors impact electrification of vehicle miles traveled (eVMT) and fuel consumption, using an empirical data set. We used data from 650 vehicles which had onboard loggers that recorded driving and charging data for a year, distributed among 287 households where each household had a PEV.

The UF of a PHEV encapsulates the eVMT and VMT of that PHEV; similarly, the UF of a household encapsulates the eVMT of the PEV of that household and the VMT of that household. Therefore, in this paper, we use the following metrics regarding electrification of vehicle miles traveled: eVMT of the PEV, VMT of the PEV, VMT of the household, UF of the PHEV, and UF of the household. We define the household context using three categories: (1) PEV technology in the household, (2) household vehicle usage, and (3) ICEVs in the household. For each of these categories, we identify relevant factors and the corresponding variables in our data set. Then, we use descriptive statistics to explain how the most salient factors impact our metrics. This is followed by a regression analysis for each of our metrics where we investigate the statistical significance of the identified factors. In addition, we also analyze the household fuel consumption and perform a regression analysis on how these factors impact fuel consumption in: (1) all households, (2) PHEV households, and (3) BEV households. For our analysis, we focus mostly on two-car households—which is most common in our data set, with 64% of households being two-car households, and also the largest group of vehicle owners in California—for a more standard comparison between different PEV-type households.

Summary statistics for all two-car households are provided in **Table 6** (all households combined). Frequency of charging was, on average, higher for PHEVs compared with BEVs, ranging from 0.67 per day for Chevrolet Bolts, to 1.1 per day for Ford C-Max/Fusion. See the Appendix in **Paper III** for details of each PEV-type household. The frequency of long-distance trips, in general, was low for all PEVs, except Tesla Model S which went on long-distance trips, on average, almost three to six times more often than the other PEVs in our data set.

Table 6: Summary statistics for two-car households. **(Paper III)**

	Min.	**0.25-Quantile**	**Median**	**Mean**	**0.75-Quantile**	**Max.**
All households combined (N = 183)						
Annual household VMT (mi)	7341	16,535	21,200	22,426	27,485	56,521
Daily household VMT (mi)	20.11	45.30	58.08	61.44	75.30	154.85
Household utility factor (%)	0.59%	27.41%	42.99%	41.77%	54.70%	98.35%
PHEV utility factor (%) *	1.27%	31.35%	51.54%	50.15%	69.32%	98.95%
Household fuel consumption (gal/100 mi)	0.04	1.54	2.15	2.12	2.61	5.01
Household tailpipe emissions (gCO_2/km)	2.25	83.72	116.84	115.27	141.55	271.99
ICEV fuel economy (MPG)	11.17	19.52	23.93	26.26	30.85	52.83
PHEV fuel economy (MPG) *	36.64	57.78	86.25	156.80	133.75	4065.52
Frequency of charging (events per day)	0.01	0.61	0.80	0.87	1.13	2.73
Frequency of long-distance trips with PEV (%)	0.00%	0.24%	0.88%	2.53%	2.45%	37.97%
Frequency of overlaps (%)	0.00%	6.22%	10.68%	12.00%	16.61%	51.09%

Note: *Excluding BEV (Leaf, Bolt, Model S) households.

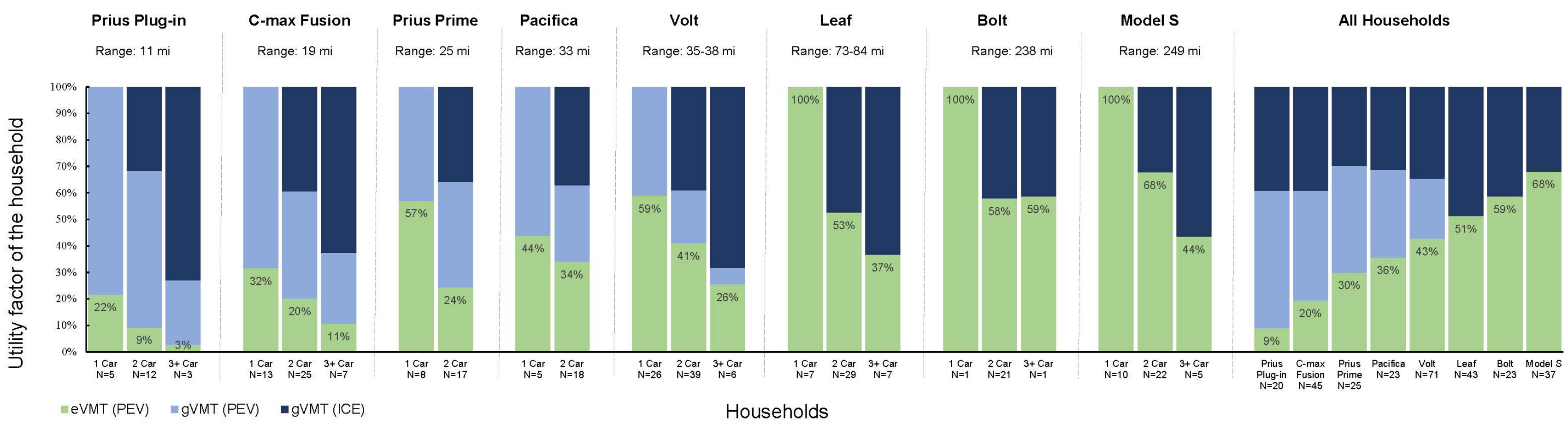

Figure 6: Utility factor of households, categorized by PEV-type and total number of cars in the household. (**Paper III**)

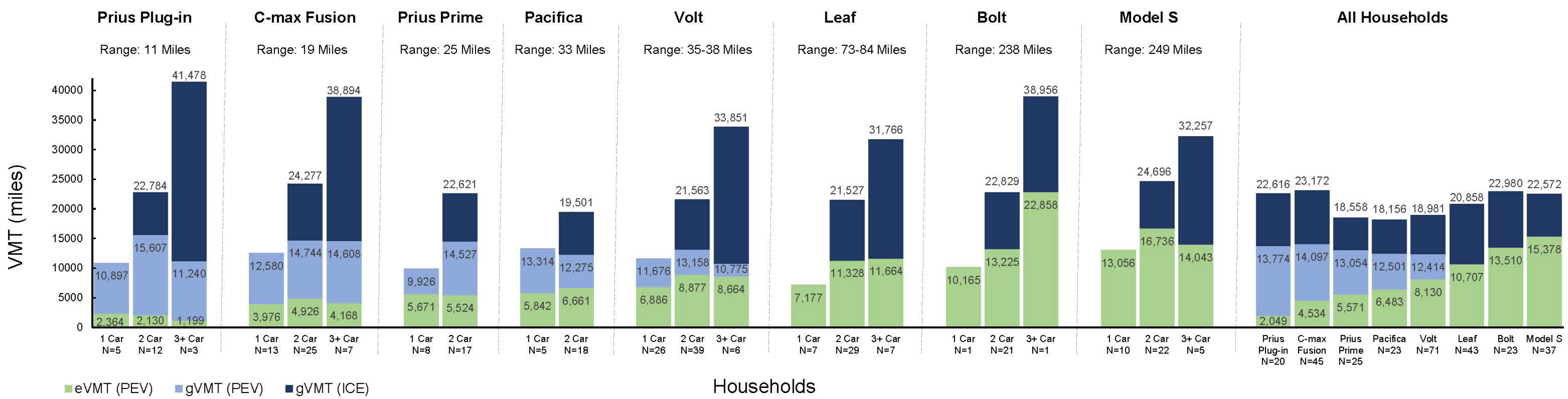

Figure 7: VMT of households, categorized by PEV-type and total number of cars in the household. (**Paper III**)

The utility factor of the household allows a comparison between households with a different number of cars, and between PHEV and BEV households. As seen in **Figure 6**, the utility factor of the households had a downward trend when the number of cars increased. In other words, households with more cars electrified a lower share of their total travel, which was expected since these households also drive more in total, as seen in **Figure 7**. Overall, we observed that there was a general increase in eVMT and UF with all-electric range.

Combining same-PEV households and observing their utility factor provided quite interesting results. When we scrutinized the UF of households (**Figure 6**), we observed that Chevrolet Volt, a PHEV with a range of 35–38 miles (56–61 km), electrified 43% of the total household miles; whereas Nissan Leaf, a BEV with a range of 73–84 miles (117–135 km), was at 51%; Chevrolet Bolt, a BEV with a range of 238 miles (383 km), was at 59%; and Tesla Model S, a BEV with a range of 249 miles (400 km), was at 68%. This finding shows that, in the context of the whole household, a PHEV such as the Chevrolet Volt, can electrify a similar share of household miles as a low range BEV (Leaf), and can electrify around 70% as many household miles as long range BEVs (Bolt and Model S).

The results of the regression analysis for eVMT, VMT of the PEV, VMT of the household, UF of the PHEV, and UF of the household, are given in **Table 7**. The results of the regression analysis on household fuel consumption are given in **Table 8**. Note that both regression analyses were performed only on two-car households.

Table 7: Regression results for how household factors impact vehicle miles and electrification in two-car households. **(Paper III)**

Dependent	eVMT (mi)	VMT of the PEV (mi)	VMT of the Household (mi)	UF of the PHEV (%)	UF of the Household (%)
Intercept	−3061.20 * (1440.65)	2125.20 (1476.15)	3518.39 . (2002.98)	−3.87 (8.28)	24.88 *** (4.77)
Range (mi)	43.58 *** (3.77)	3.18 (3.87)	1.92 (5.25)	1.82 *** (0.15)	0.17 *** (0.01)
Frequency of charging (events per day)	6023.18 *** (756.55)	5763.80 *** (775.19)	4964.41 *** (1051.85)	17.37 *** (3.13)	15.55 *** (2.51)
Frequency of long-distance trips (%)	307.55 *** (71.18)	519.61 *** (72.93)	274.30 ** (98.96)	−1.31 ** (0.46)	0.16 (0.24)
Frequency of overlaps (%)	28.24 (39.75)	117.28 ** (40.73)	329.89 *** (55.27)	−0.13 (0.19)	−0.43 ** (0.13)
Standard deviation of daily household VMT (mi)	25.26 (17.71)	79.63 *** (18.14)	197.93 *** (24.62)	−0.26 ** (0.09)	−0.20 *** (0.06)
ICEV fuel economy (MPG)	36.82 (32.56)	−8.90 (33.36)	6.31 (45.27)	0.13 (0.16)	0.11 (0.11)
N	183	183	183	111 [x]	183

Multiple R-squared	0.5919	0.5638	0.5517	-	-
Adjusted R-squared	0.5779	0.5487	0.5362	-	-
F-statistic	42.07	37.48	35.69	-	-

Confidence levels *** 99.9%, ** 99%, * 95%, .90%. Values represent estimates, standard error is given in parentheses. [x] Excluding BEV (Leaf, Bolt, Model S) households.

Our results in **Table 7** show that range was statistically very significant in electrification of miles, and higher ranges resulted in higher eVMT, UF of the PHEV, and UF of the household. This result confirmed the initial trend observed in the descriptive statistics section and was also in line with the findings of previous studies [27, 50, 51].

As seen in **Table 7**, frequency of charging was also statistically significant, showing up in all main metrics. This suggests that more frequent charging results in higher eVMT, UF of the PHEV and UF of the household. However, it should be noted that the frequency of charging was based on the number of charging events and not the length of these charging events; also, the charging level was not taken into account.

The frequency of long-distance trips was statistically significant for eVMT, VMT of the PEV, VMT of the household and UF of the PHEV. The results show that more frequent long-distance trips increased eVMT and VMT of PEV as expected but decreased the UF of the PHEV. This suggests that the decrease in the UF of the PHEV can be explained by the increase in gVMT of the PHEV, meaning a lower fuel economy as long-distance trips become more frequent. Plötz, et al. [27] also reached the same conclusion in their papers on the impact of daily and annual driving on fuel economy, where they concluded that the tendency for long-distance trips decreased the UF of a PHEV, and PHEV fuel economy.

As seen in **Table 7**, the frequency of overlaps was statistically significant for the VMT of the household and the UF of the household. As expected, more overlaps between PEVs and ICEVs resulted in higher ICEV usage which increased the gVMT and VMT of the household and, thus, lowered the UF of the household.

Table 8: Regression results for how household factors impact fuel consumption in two-car households. **(Paper III)**

Dependent	Household Fuel Consumption (gal/100 mi)					
	All Households		***PHEV Households***		***BEV Households***	
Intercept	3.704 (0.174)	***	3.889 (0.238)	***	3.745 (0.339)	***
Range (mi)	−0.004 (0.0004)	***	−0.018 (0.004)	***	−0.003 (0.001)	
Frequency of charging (events per day)	−0.509 (0.091)	***	−0.451 (0.090)	***	−0.753 (0.236)	

Frequency of long-distance trips (%)	−0.023 (0.009)	**	−0.020 (0.013)		−0.023 (0.012)	
Frequency of overlaps (%)	0.021 (0.005)	***	0.020 (0.005)	***	0.019 (0.009)	
Standard deviation of daily household VMT (mi)	0.009 (0.002)	***	0.011 (0.002)	***	0.007 (0.004)	
ICEV fuel economy (MPG)	−0.054 (0.0034)	***	−0.050 (0.005)	***	−0.054 (0.007)	***
N	183		111		72	
Multiple R-squared	-		0.6435		0.6153	
Adjusted R-squared	-		0.6229		0.5787	
F-statistic	-		31.28		16.8	

Confidence levels *** 99.9%, ** 99%, * 95%, .90%. Values represent estimates, standard error is given in parentheses.

In **Table 8**, we observe that the range and frequency of charging was significant in reducing household fuel consumption in PHEV households, but not in BEV households. **Table 8** also shows that for every 10-mile increase in range for PHEV households, household fuel consumption and household tailpipe emissions were reduced by 0.2 gal/100 mi and 17.5 gCO_2/mi (10.9 gCO_2/km), respectively. Conversion of fuel consumption to tailpipe emission was performed by using U.S. Environmental Protection Agency values [84].

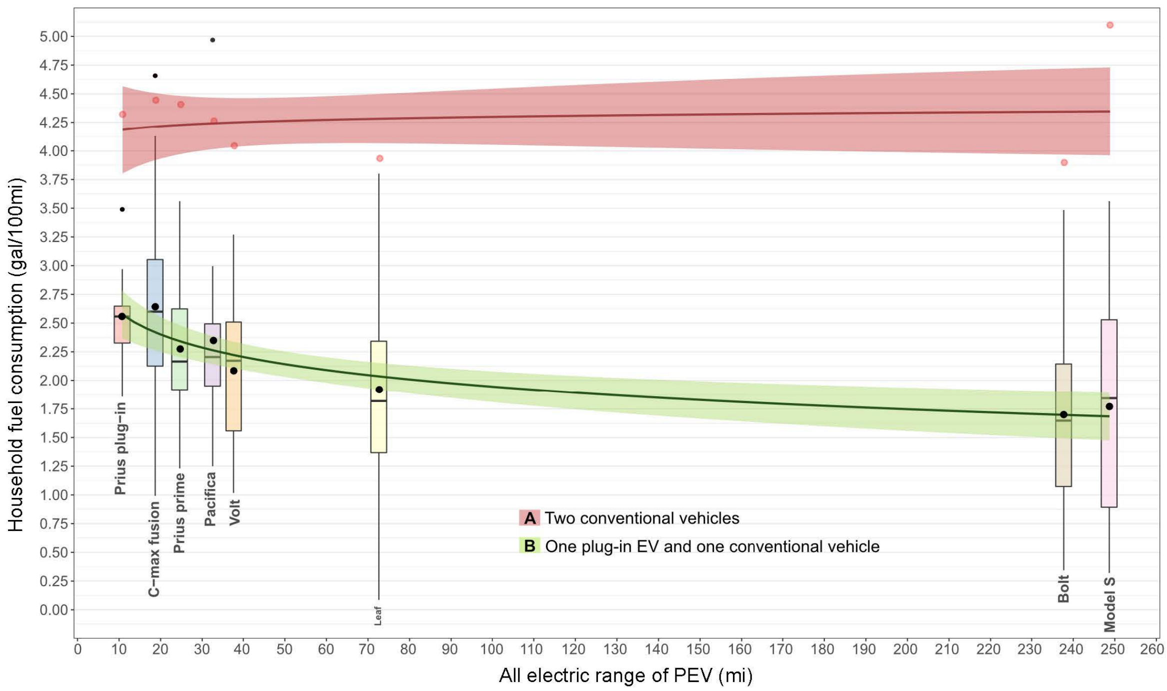

Figure 8: Household fuel consumption vs. range of PEV in two-car households. **(Paper III)**

In **Figure 8**, we show the household fuel consumption vs range for two-car households categorized by PEV-type, with a logistic regression curve (marked as B in the figure) and also box plots with the distribution of household fuel consumption. We observed only a small difference between long range BEV households and short-range BEV households. The decrease in fuel consumption was smaller in long range BEV households than what was intuitively expected, compared with short range BEV and long-range PHEV households. In two-car households with one PEV, BEVs did not reduce household fuel consumption as significantly, compared with long range PHEVs; and consequently, some long-range PHEVs reduced household fuel consumption to a similar degree with BEVs. **Figure 8** also shows a logistic regression curve (marked as A in the figure) for the household fuel consumption if the households had two of the same ICEV instead of one PEV and one ICEV. (We assumed a hypothetical scenario that the second ICEV would be the same as the one already owned, where in reality it could have a higher or lower MPG.) The difference between curve A and B visualizes how much fuel consumption is hypothetically saved through owning a PEV instead of an ICEV. It further shows the similar impact of owning a long-range PHEV in two-car households compared to BEV households.

The most important findings from **Paper III** regarding the use of PHEVs within the household context can be summarized as follows:

- Long range PHEVs with (like the Chevrolet Volt) can electrify as much share of kilometers as short range BEVs (like Nissan Leaf) and up to 70% as much as long range BEVs (like Chevrolet Bolt and Tesla Model S). **(Paper III)**
- In two-car households with one PEV, long range PHEVs can reduce household fuel consumption to a similar degree as with some BEVs. **(Paper III)**

4.3. Multiple countries

This subsection presents the results from Paper IV and V. Paper IV investigates how PHEVs are driven differently in different countries and what causes this difference. Paper V utilizes multi-country PHEV data with a focus on Europe and investigates if vehicle properties have an impact on fuel consumption and share of electrification and to what extent.

In **Paper IV**, we ask the following research question: how does PHEV driving behavior differ among countries in their share of electrified kilometers and what is behind these differences? This study focuses on how the same PHEV model is used in different countries; therefore, our analyses focus on country comparisons and not PHEV model comparisons. The research question is made up of two parts: (1) are there noticeable significant differences in how the same vehicle is used (with regards to its share of electrified kilometers) in different countries? (2) what factors within those countries can cause these differences? To answer the first part, we use descriptive and inductive statistical methods, and to answer the second part, first we enrich our data set with additional data on countries which can be factors causing differences such as electricity and gasoline prices, number of public charging stations, share of company cars, share of detached housing etc., and then we apply hierarchical linear modelling to analyze if those country level factors have any impact on the share of electric driving.

The PHEV sample in **Paper IV** contains over 110,000 vehicles of 9 PHEV models in 84 different countries. The sheer size of this dataset provides the opportunity to analyze how the same vehicle is used in different countries, with different electricity and gasoline prices, different charging infrastructure and different user compositions (such as private users vs company car users). In this study, we focus on 4 PHEV models across mainly 6 countries in Europe (France, Germany, Netherlands, Norway, Sweden and United Kingdom) and 10 countries overall worldwide (with the addition of Brazil, China, Israel and United States).

See **Table 9** for a summary of the PHEV models analyzed. Model 1 and 2 are both SUVs with Model 2 being larger in size. Model 3 is a European D-segment, compact executive car and Model 4 is a larger European E-segment, executive car. Model 3 has a battery size of 11.6 kWh and all other models have battery sizes ranging from 10.4 to 11.6 kWh depending on their model year.

Table 9: Selected PHEV models and countries for detailed analysis. **(Paper IV)**

Reference name	Vehicle features	Battery size (kWh)	Countries	N
Model 1	5 seat, compact luxury crossover SUV class	10.4 to 11.6	BR, CN, FR, DE, IL, NL, NO, SE, UK, US	34,408
Model 2	5+ seat, midsize luxury crossover SUV class	10.4 to 11.6	BR, CN, FR, DE, IL, NL, NO, SE, UK, US	22,060
Model 3	5 seat, compact executive car class, European D-segment	11.6	FR, DE, NL, NO, SE, UK	8,737
Model 4	5 seat, executive car class, European E-segment	10.4 to 11.6	FR, DE, NL, NO, SE, UK	7,825

Country abbreviations: BR (Brazil), CN (China), FR (France), DE (Germany), IL (Israel), NL (Netherlands), NO (Norway), SE (Sweden), UK (United Kingdom), US (United States). N: Total number of vehicles

For the descriptive part of our analysis, we focus on 10 countries: Brazil, China, France, Germany, Israel, Netherlands, Norway, Sweden, United Kingdom and United States. The mean utility factors for all PHEV models and countries, as well as the mean annual and daily VKT, and mean number of aggregated observation days are shown in **Table 10**. We observe a wide range of utility factors for the same models across the 10 countries. For PHEV Model 1 and 3, UFs range from 35% to 49%, whereas for PHEV Model 2 and 4, UFs range from 32% to 44%.

Table 10: Means of utility factor, annual VKT, daily VKT and number of aggregated observation days per country. **(Paper IV)**

	Mean utility factor (%)				Mean annual VKT (km)	Mean daily VKT (km)	Mean # of days[1]	N
	M1	*M2*	*M3*	*M4*	*All models combined*			
Brazil	42.09	38.14	-	-	13,238	36.34	422.44	2,118
China	45.30	39.60	-	-	17,630	48.40	517.85	4,120
France	36.56	31.60	36.05	34.36	19,147	52.57	590.71	7,448
Germany	37.47	33.98	37.47	34.35	19,473	53.46	516.84	7,535
Israel	48.41	40.06	-	-	18,794	51.60	610.29	1,402
Netherlands	39.35	32.05	37.07	33.43	22,279	61.16	560.39	3,196
Norway	49.49	44.27	48.52	44.72	17,431	47.85	687.41	17,829
Sweden	44.55	39.55	45.97	42.66	22,360	61.39	519.75	13,722
United Kingdom	38.13	36.59	35.34	34.13	17,848	48.99	616.16	7,317
United States	41.10	37.43	-	-	16,773	46.05	596.42	8,343
All Countries	43.04	37.54	43.86	41.98	18,837	51.72	586.62	73,030

Notes: [1]Mean number of aggregated observation days, N: Total number of vehicles

Figure 9 shows the UFs in selected countries for a 5 seat SUV PHEV with a 10.4 to 11.6 kWh battery (PHEV Model 1). We observe significant differences in UF among different countries. Norway has the highest UF (49%) with the lowest standard deviation, whereas countries like the UK, Germany and France are at the lower end of the scale with UFs of 38%, 37% and 36% respectively, 10% to 13% lower than Norway. United States has a slightly higher UF of 41% compared to the UK, Germany and France. Sweden finds itself somewhere in the middle with a UF of 44% and follows Norway in Europe. China and Israel have slightly higher UF than Sweden with 45% and 48% respectively.

In **Figure 9**, maximum and minimum WLTP (Worldwide Harmonized Light-Duty Vehicles Test Procedure for conventional and hybrid vehicles) values are also indicated. WLTP is the standard fuel economy and tail-pipe emissions test procedure for EU countries and is also accepted in other countries such as the United States, China, and Japan. In our study, we use the method in [16] as the basis for WLTP utility factor calculation for PHEVs. Minimum and maximum WLTP UF values are based on the minimum and maximum OEM all-electric-ranges among all model years of that vehicle. We observe that the mean UFs for PHEV Model 1 in all countries are 20% to 35% lower in all countries than the WLTP values, meaning that the WLTP overestimates the share of electrified kilometers by a large margin. In France, for instance, the mean UF is almost half of the expected WLTP values.

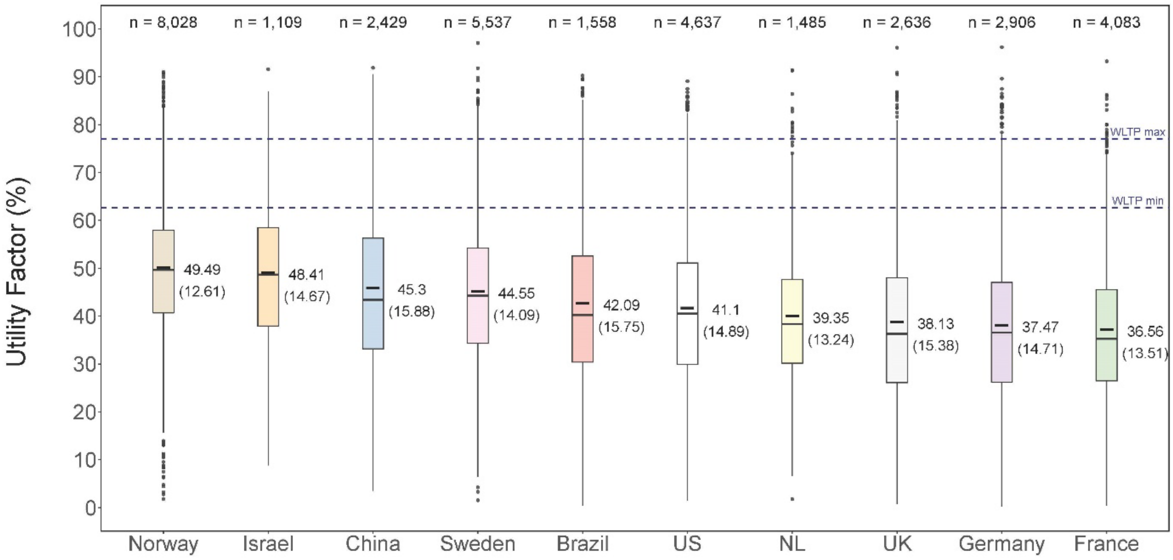

Figure 9: Utility factor in selected countries for a 5 seat SUV PHEV with 10.4 to 11.6 kWh battery. (PHEV Model 1) Means are indicated and the standard deviation is given in parentheses. Min-max WLTP values indicated based on OEM all-electric range. Country abbreviations: NL (Netherlands), UK (United Kingdom), US (United States). **(Paper IV)**

We performed two sample t-tests to detect statistically significant differences in means, and rank-sum tests to detect statistically significant differences in medians between the six European countries: France, Germany, Netherlands, Norway, Sweden and United Kingdom. We find that there is a statistically significant difference in almost each comparison, for both tests, with a few exceptions. The statistical tests overall further prove the significant differences between these countries that were descriptively visible.

We observe the same visible pattern in the rest of the PHEV models between Nordic countries and western European countries, where Nordic countries have 10% to 12% higher UF. Similarly, we repeated the two-sample t-tests and the rank-sum tests for the six countries for the rest of the PHEV models and again find significant differences in almost each comparison.

Results from the hierarchical linear modelling (4 PHEV models and 6 selected countries: France, Germany, Netherlands, Norway, Sweden and United Kingdom) are given in **Table 11** (here only PHEV model 1 is shown, see **Paper IV** for all models). We observe that the coefficient signs for all fixed effects are consistent across 4 PHEV models. Fixed effects of annual VKT and the share of company cars are statistically significant with a confidence level of 95% to 99.9% across all 4 PHEV models. Annual VKT is a level 1 variable, corresponding to the individual vehicle level, and a higher annual VKT is associated with a lower UF based on hierarchical linear modelling results; meaning that more driving leads to lower shares of electrified kilometers. More precisely, an increase of 1,000 km in annual VKT leads to a decrease of 0.42% to 0.52% in UF. The share of company cars among newly sold PHEVs is a level 2 variable, corresponding to the country level and it is positively associated with UF. We would like to note here that the interpretation of level 2 fixed effects require caution; meaning that the effect of the variable is for differences between countries and not for individual vehicles within the same country. In this regard, a higher share of company cars is associated with a higher UF, meaning that countries with a higher share of company cars is associated with a higher share of electrified kilometers. One percent increase in share of company cars is associated with 0.11% to 0.42% increase in UF across 4 PHEV models. This result is counterintuitive to the expected negative impact of company cars on electrification in the literature [16, 28]. This might indicate that policies regarding PHEVs at the workplace (such as incentivizing workplace charging) impact driving & charging behavior (and thus share of electrified kilometers) in a country. In addition, contrary to the expectations in the literature, with increased opportunities of workplace charging, company cars can lead to an increased share of electrified kilometers as seen in our dataset.

Table 11: Hierarchical linear modelling results for UF in 6 selected countries for PHEV Model 1. **(Paper IV)**

PHEV Model 1		Dependent: UF (%)		
	Fixed effects	Estimate	Std. Err.	Sig.
	Intercept	36.59	5.99	***
Level 1	Annual VKT (1,000 km)	-0.52	0.05	***
Level 2	Electricity price (€/kWh) to gasoline price (€/L) ratio (%)	-0.46	0.16	*
Level 2	Number of charging stations (all types) per 10,000 people	0.28	0.08	*
Level 2	Share of company cars (%)	0.29	0.06	**
	AIC	-30968.2		
	BIC	-30895.2		
	N= 24,675			
	Confidence levels: ***99.9%, **99%, *95%, .90%			

In **Table 11**, our results indicate that countries with a higher electricity price to gasoline price ratio are associated with a lower utility factor, with a confidence level of 95% to 99% for PHEV Model 1 (and also PHEV Model 4, see **Paper IV**). The electricity price to gasoline price ratio not being statistically significant for the other two PHEV models can be reflective of the vehicle and user characteristics. For instance, PHEV Model 2 is a larger and thus more expensive vehicle with the same battery size compared to PHEV Model 1; and this can reflect a user group which is less sensitive to changes in electricity and gasoline prices, therefore appearing statistically insignificant in our model. This is also in line with the observation of descriptive statistics (see **Paper IV** for details) where we observe a 5% drop in UF in all countries going from PHEV Model 1 to Model 2, which indicates that Model 2 vehicles are charged less and driven less on electricity on average. Regarding electricity and gasoline prices, hierarchical linear modeling suggests that for some PHEV models, countries with lower electricity prices compared to gasoline prices push users to electrify more. More precisely, assuming a fixed gasoline price, one percent decrease in electricity price can increase the share of electrified kilometers by 0.46% to 0.62%.

Our results also indicate that countries with a higher number of public charging stations per person are associated with a higher utility factor, with a confidence level of 95% to 99.9%, for PHEV Models 1, 2 and 4. This finding is in line with the intuition that more charging opportunities lead to more actual charging and thus a higher share of electrified kilometers. Our modelling suggests an increase of 0.13% to 0.45% in the share of electrified kilometers for an additional charging station per 10,000 people. It should be noted however that this is an average estimation taking into account all charging stations and the total population in a country, and should be interpreted as an overall estimate. The location of charging stations and their type based on sockets and charging speed requires a detailed study on their own, which was not the focus of this study.

In **Paper V**, we perform an empirical and quantitative analysis of real-world electric driving share (EDS) and fuel consumption and look at which vehicle properties impact EDS and fuel consumption of PHEVs to which extent. EDS is the same as the term UF that was used in previous papers. We combine two different data sets, with almost 100,000 vehicles in total, over 150 models in 41 countries. One of the data sets is partially the same one we used in **Paper IV** but covering only European countries. The combination of two data sets allows us to give a more comprehensive understanding of real-world fuel consumption and electric driving shares, and how factors such as range and engine impact the share of electric driving.

Data set 1 in **Paper V** contains a larger number of different vehicle makes and in general more variance within the control variables as well as more control variables such as user groups. Yet, the sample size of data set 1 is noteworthy smaller (8,855 vehicles) than in data set 2 and it covers mostly Germany. Data set 2, on the other hand, has a much larger sample (87,509 vehicles) and covers more countries from the same make which allows more accurate coverage of country specific differences.

Summary statistics of fuel consumption and electric driving share for both data sets are given in **Table 12**. It should be noted that the summary statistics reflect the overall fuel consumption and electric driving share for all vehicles in a user group, without distinguishing for ranges of the vehicles or other factors that can have an impact.

We observe that the mean fuel consumption is higher for company cars in data set 1, with 7.5 l/100 km, compared to the 4.4 l/100 km for private cars. For the mixed fleet in data set 2, the fuel consumption on average is 5.8 l/100 km. If the private and company cars in data set 2 are assumed to have the mean fuel consumption as estimated in data set 1, this would mean that the approximate share of company cars in data set 2 is around 55%. The share of company cars (among newly sold PHEVs) in western and northern European countries range from 57% to 69% [85]. This shows that the mixed fleet in data set 2 has a ratio of private to company cars that is close to expectations.

Table 12: Summary statistics of fuel consumption and electric driving share in both data sets. **(Paper V)**

			Min	**0.25 quantile**	**Median**	**Mean**	**0.75 quantile**	**Max**	**Std. dev.**	**N***
Fuel consumption (l/100 km)	Data set 1	Private cars	0.02	3.1	4.2	4.4	5.5	13.0	1.9	5,808
		Company cars	0.3	6.1	7.4	7.5	8.8	17.1	2.2	3,047
	Data set 2	Mixed fleet	0.1	4.6	5.7	5.8	7.1	11.5	1.7	87,509
Electric driving share (%)	Data set 1	Private cars	0.0%	34.3%	46.6%	46.3%	59.0%	99.7%	18.8%	5,808
		Company cars	0.0%	2.1%	9.7%	15.1%	22.0%	97.0%	16.9%	3,047
	Data set 2	Mixed fleet	0.0%	28.1%	39.2%	39.9%	50.5%	98.9%	15.5%	87,509

Note: *N refers to the total number of vehicles aggregated within subsamples.

The EDS for private cars in data set 1 is on average 46%, much higher compared to the 15% for company cars. This inversely mirrors the average fuel consumption from those user groups as expected, meaning that company cars have higher fuel consumption and lower EDS on average, and private cars have lower fuel consumption and higher EDS on average. On the other hand, for the mixed fleet in data set 2, the average EDS is 40% which is expectedly between the values observed separately for private and company cars.

The finding regarding company cars having higher fuel consumption and lower EDS in **Paper V** is different than the finding in **Paper IV** regarding a high share of company cars leading to a higher EDS (UF). First of all, the finding in **Paper IV** is not about individual users, instead it focuses on countries and the share of company cars in a given country, so they are slightly different comparisons. Secondly, the finding in **Paper V** comes from a much smaller data set which is dominated by German vehicles (80% of the total vehicles), which might explain the difference between the two results. German company cars can have lower EDS and higher fuel consumption compared to private cars, yet comparing different countries, a higher share of company cars can lead to higher EDS.

The CO_2 emissions target for newly sold passenger cars in the European Union for the period of 2020-24 is 95 gCO_2/km [86]. Based on the conversion values of the Environmental Protection Agency in the US [84], this corresponds to 4.1 l/100 km in fuel consumption. The average fuel consumption in both data sets (for both private and company cars) is above this value. For comparison, the average fuel consumption of 4.4 l/100 km for private cars in data set 1 corresponds to 102 gCO_2/km in tail-pipe emissions, for company cars this corresponds to 173 gCO_2/km and for the mixed fleet in data set 2 to 134 gCO_2/km; all of which are significantly above the target level of 95 gCO_2/km.

See **Paper V** for the regression results tables on fuel consumption and EDS. For both data sets and both regressions, all coefficients (range, system power/mass, model year, annual VKT, user group) are statistically significant with a confidence level of 99.9% and have the expected signs.

We find that a 10 km increase of WLTP (Worldwide Harmonized Light-Duty Vehicles Test Procedure, type-approval value) range leads on average to a 13% decrease (11-15% with 95% confidence interval) in fuel consumption in data set 1 compared to a 17% decrease (16.6-17.3% with 95% confidence interval) in data set 2. The similarity in estimated coefficients and the level of significance for two data sets (which are starkly different than each other in sample size and model variance) shows that the effect of range on fuel consumption is consistent across PHEV models and countries in Europe.

We also find that every kW increase in system power for 100 kg of vehicle mass leads on average to a 7.4% increase (6.2-8.6% with 95% confidence interval) in fuel consumption in data set 1 compared to a 8.6% increase (8.3-8.9% with 95% confidence interval) in data set 2. This shows that PHEVs with higher system power on average lead to higher fuel consumption across model variants and countries.

We observe that a higher WLTP range is associated with a higher EDS in both data sets. A 10 km increase in WLTP range leads on average to 3-4% increase in EDS in data set 1, and 1-2% increase in data set 2. The effect of range in data set 1 is almost three times that of data set 2. This difference can be due to the higher number of model variants and thus higher variation in ranges in data set 1, whereas the range variation is quite limited in data set 2.

We also observe that a higher system power per mass is associated with a lower EDS in both data sets. Every kW increase in system power for 100 kg of vehicle mass leads on average to 0.8-1.8% decrease in EDS in data set 1, and 0.2-0.5% decrease in data set 2. Similarly, the effect is larger in data set 1, which can be again due to the limited model variation in data set 2.

The most important findings from **Paper IV and V** regarding the use of PHEVs in multiple countries and how vehicle properties impact fuel consumption and EDS using a multi-country data set can be summarized as follows:

- PHEVs have poor environmental performance compared to type approval standards. **(Paper IV and V)**
- Nordic countries have higher shares of electrification compared to Western European countries **(Paper IV)**
- Higher electricity price to gasoline price ratio leads to lower UF. **(Paper IV)**
- Higher percentage of company cars can lead to higher UF in Europe, yet in some countries (e.g. Germany) individual company car users can have the opposite behavior. **(Paper IV and V)**
- Apart from range, system power per vehicle mass also has a significant impact on fuel consumption and EDS. Higher system power per vehicle mass results in higher fuel consumption and lower EDS. **(Paper V)**

5. Discussion and conclusions

This chapter presents a discussion of the results and limitations from all appended papers. This is followed by the conclusions and policy implications. Finally, future research areas are presented. For any abbreviation not explained in text, refer to page x.

5.1. Discussion of results and limitations

In **Paper I**, we find that long-distance driving has a noteworthy impact on annual mileage. The impact of long-distance driving can be a limiting factor for the effect of additional charging, given even frequent chargers with long-ranged PHEV can hardly achieve more than 90% electric driving. This is complemented with our finding in **Paper III** from a different data set, where we observe that a higher frequency of long-distance trips leads to a lower UF, which was also previously reported in literature [27]. We took into account the significant impact of long-distance driving in **Paper II, IV and V** as well. In the regression analysis we performed in those papers, daily or annual VKT (which are reflective of long-distance driving) was included as a factor impacting fuel consumption and UF.

Both **Paper I** and **Paper II** focus on PHEV charging behavior. **Paper I** focuses on what this charging behavior is and **Paper II** complements it by looking into how this charging behavior impacts the environmental performance of PHEVs. Both of these papers also contributed to the development of the method we used in detecting the occurrence of additional and no overnight charging events. The first version of the method was used in **Paper II** (which was published earlier) and then it was fine-tuned using partially the data from **Paper III** and then applied in **Paper I.**

One aspect of charging behavior that was not investigated in **Paper I and II** is how charging behavior could relate to electric vehicle integration into transmission grids. PHEVs in general have much smaller battery packs than BEVs, therefore less impact on power systems. A long-range PHEV like Chevrolet Volt has a 18.4 kWh battery (85 km or 50 miles range), whereas a long-range BEV like Tesla Model S has a 100 kWh battery (up to 647 km or 402 miles range) which is around five times larger in battery size and eight times larger in range. However, this does not exclude PHEVs from having an impact on power systems and their charging behavior can be modeled as part of the vehicle fleet. For instance, a study by Lauvergne, et al. [87] models both BEVs and PHEVs in the vehicle fleet and looks at how they interact with the electricity system prospectively in 2040.

In **Paper II**, one of the possible future extensions to the study was identified as looking at how vehicle properties can impact fuel consumption. This idea finally came into realization in **Paper V** where we looked at how vehicle properties impact fuel consumption and electric driving share.

It was previously reported in the literature that a longer all-electric-range is associated with a higher utility factor for PHEVs [27, 51, 88]. We also observe this in **Paper V**. However, **Paper III** finds this also holds true for the share of electrification within the household context, considering all vehicles. This is in line with the findings of Jia and Chen [89] where they find that higher range and home charging capabilities increase the eVMT of PHEV households. Furthermore, our results show that, within the household context, a PHEV like the Chevrolet Volt with half the range of a BEV like the Nissan Leaf can electrify a similar share of miles or 70% as much as long range BEVs like the Chevrolet Bolt and Tesla Model S. Our results indicate that a long-range PHEV has the potential to electrify a high share of miles within the household context.

Both **Paper IV** and **Paper V** utilize multi-country data in their analysis, but the analysis in **Paper IV** focuses on the country level, whereas in **Paper V** it is on the individual user level. This led to an interesting finding in both papers. In **Paper IV**, we find that a higher share of company cars in a country is associated with a higher UF. However, in **Paper V**, we find that company cars have higher fuel consumption and lower UF compared to private cars. The finding in **Paper V** comes from only one of the two data sets used in the paper and has a small sample size compared the sample size used in the regression analysis in **Paper IV** (8,855 vehicles vs 57,047 vehicles), and the data set in **Paper V** is dominated by German users (80% of all vehicles). A dominating behavior in a single country can explain the difference in results between **Paper IV and V**, and moreover both findings can exist without contradictions: higher percentage of company cars can lead to higher UF in some European countries, yet in some countries (e.g. Germany) individual company car users can have the opposite behavior. Users in Germany have already much lower UF (10-12%) in general compared to for example Norway and Sweden as shown in **Paper IV**. In addition, this can further indicate the reason why some countries can have high shares of company cars and have high UF while others don't might have to do with the policies regarding PHEVs in those countries. For instance, increased opportunities and incentives for workplace charging can have a positive impact on the share of electrified kilometers [90]. Complementing incentives for workplace charging, how fueling expenses are covered for company cars is another important aspect. A recent study by De Wilde, et al. [91] shows that having access to an unlimited fuel card (company pays for the fuel) leads to low incentive to charge the PHEV. Policies incentivizing workplace charging —while taking into account company policies regarding fueling expenses— or increasing the number of workplace chargers can explain the positive relationship we see in **Paper IV** between the share of company cars in countries and the share of electrified kilometers.

The limitations in all papers can be categorized into two types: limitations regarding the dataset and limitations regarding the method. Regarding the dataset, for **Paper I and II**, the data is rich when it comes to number of users and observation time, but sparse in additional information about the users; also, it only covers one PHEV model. Other factors can impact charging behavior such as access to workplace charging, dwelling type and commute distance [90]. In addition, the data was collected on a voluntary basis, thus there is a risk of self-selection bias in the data for consumers who are particularly concerned about fuel economy. It can be assumed that mainly those PHEV users who are sensitive to their fuel economy register on these platforms. Furthermore, all users can be considered as early adopters, especially those from the first years of data collection. It is not sure that the early majority users will have the same behavior. However, the average annual VKT of our sample in **Paper I and II** is close to the US average, indicating not too strong deviation from other vehicles with respect to total distance travelled. In **Paper III**, on the other hand, the sample size is limited to 287 households. The data in **Paper III** is regionally bound to California, and the households included could be considered early adopters, with higher education levels and income. Of the households in this dataset, 76% had an annual income of over USD 100,000 compared with the USD 78,672 median income in California in 2020 [92]. Based on the household survey in **Paper III**, 86% of the adults had at least a college degree or higher. We recognize that this might have created a bias towards more conscious driving and charging behavior. Our results might have differed slightly if a larger and geographically more diverse population sample had been used. Yet, the strong suit of the data in **Paper III** is that it was collected for the length of a year and includes all vehicles in the household, which is unique.

The data sets used in **Paper IV and V** also suffer from lack of additional information on users. The aggregated nature of the data set in **Paper IV**, for example, prevents detailed analysis of for instance, seasonal variations in utility factor, changes in individual behavior over time and differences within large countries such as the US, China and Brazil. However, the limitations caused by aggregation and lack of detailed information on users would only have a considerable impact if the analyses were focused on individual users (low level); whereas in **Paper IV** we focus on country comparisons (high level), thus minimizing these limitations through the strength of the sample size.

The data set in **Paper I and II** are regionally bound to Canada and US, and the data set in **Paper III** to California in the US, which means all data sets used in **Paper I, II and III** come from North America with a high availability of home charging in garages [93]; therefore our results are not directly transferrable to other parts of the world with less home charging like China or Japan. The users in all datasets are almost all private users, therefore our results are also not directly transferrable to company cars or fleet vehicles. On the other hand, the data sets in **Paper IV and V** are much more diverse in terms of geographical boundaries. The data in **Paper IV** is worldwide, yet we focus on European countries in our analysis. Similarly, **Paper V** also focuses on Europe. In addition to focusing on Europe, the data in **Paper IV and V** cover a very large number of countries (41 countries). In **Paper IV**, this provided the opportunity to do a higher level analysis that focuses on country differences, rather than individual behavior.

Regarding limitations of the methods; the method for identifying additional and no overnight charging events in **Paper I and II** implicitly assumes a full charge once a day. Yet, in practice some users might not fully charge the battery to 100% or have a partial charge one day and second full charge, e.g., for free at work, the following day. Our method is not able to detect such cases. However, as PHEV batteries are charged within a few hours and vehicles are typically standing many hours at the most common locations such as home or work, the share of these cases is likely limited. Furthermore, our results from these papers are on a more aggregated level about the overall share of no charging and additional charging that this uncertainty in the method will not qualitatively affect our conclusions. Our method might also wrongly assign certain charging events, for instance if the daily VKT is very small and the vehicle on that day is used on electric mode only; however, these cases account for less than 1% of the dataset and do not impact our overall results. Thus, despite its limitations, the method in **Paper I and II** is far easier to use for large samples than comprehensive technical in-vehicle measurement or surveys.

In **Paper V**, we use a specific method (see **Paper V** for the explanation of the method) to derive real-world electric driving share in data set 1, and real-world fuel consumption in data set 2. This derivation comes with its own assumptions. We assume that the EDS is the share of pure electric driving, meaning the internal combustion engine (ICE) is switched off. In WLTP type-approval calculations, this corresponds to the share of charge depleting (CD) mode driving share. For some PHEVs, CD mode corresponds to ICE switched off, however in others, the PHEV can make use of their ICE under certain conditions depending on e.g., the load and operation temperatures [94, 95]. In cases where the PHEV makes use of its ICE, the estimated electric driving share will be higher, however in that case the CD mode range will also be higher. In data set 2, we have access to both pure electric driving (ICE switched off) and CD mode driving (ICE switched off + ICE idle where the PHEV can make use of the ICE). We calculated EDS both as share of pure electric driving and as share of CD mode driving. We find that the EDS as share of pure electric driving is on average 1% lower than EDS as share of CD mode driving. We also find that this difference does not result in any difference in our regression analysis, except for slight changes to coefficient estimates (at the hundredth digit). Furthermore, our assumptions regarding the calculation of fuel consumption in charge sustaining mode, were validated in Plötz, et al. [16] and shows only minor deviations in recalculation to WLTP type-approval values. Therefore, overall, we consider the method to derive real-world EDS and real-world fuel consumption in **Paper V** to be sufficiently accurate.

5.2. Conclusions and policy implications

Through the work carried on in appended papers, this doctoral thesis aimed to answer the question "**What is the role of PHEVs in electrifying personal transport?**". There is no simple answer to this question. Our results show that PHEVs have poor environmental performance across the globe compared to set standards: lower share of electrified kilometers compared to type approval values and higher fuel consumption than e.g. European Union targets. However, on the other hand, our results also show that long-range PHEVs can electrify a similar share of kilometers as short-range BEVs or can reach up to 70% as much electrification as some long range BEVs within the household context. A long-range PHEV like the Chevrolet Volt can have on average, across different user groups, a UF of 70%. Our results also show that charging overnight at home can substantially increase the UF of PHEVs. Lower electricity price to gasoline price ratio in countries also lead to an increase in UF of PHEVs. The transition to 100% BEV adoption has not happened yet and there are millions of PHEVs on the roads today and more to come in the near future. In conclusion, PHEVs can considerably contribute to the share of electrified kilometers in the transport sector and play an important role in decarbonizing it if the debate regarding PHEVs is focused on maximizing their environmental benefits until a time when 100% BEV adoption is within reach.

Policy implications regarding charging behavior from **Paper I and II** can be summarized as follows:

- The possibility to charge overnight has a bigger effect than additional charging during the day, thus, to support the advantages of PHEVs, policies should prioritize easy access to home charging, e.g., through support for installation of charging in multi-dwelling buildings, above public and workplace charging infrastructure.
- Charging frequency can further be increased through pushing for performance-based policies that credit the OEM based on road performance of their vehicles and thus pushing for more involvement from OEMs in charging behavior, which could result in OEMs taking active roles in making it easier to charge and install or subsidize chargers.

Policy implications regarding the household context from **Paper III** can be summarized as follows:

- PHEVs with a range of at least 35 miles (56 km) have the potential to electrify a similar share of total household miles as some short range BEVs, or can reach up to 70% as much electrification as some long range BEVs and thus, can play an important role in decarbonizing the transport sector.

Policy implications from **Paper IV and V** that utilize data from multiple countries can be summarized as follows:

- Purchase or tax incentives for PHEVs should be based on monitoring of real-world fuel consumption and electric driving due to the poor environmental performance of PHEVs compared to type-approval values.
- The share of electrified kilometers of PHEVs can be maximized through following the examples of Nordic countries.
- Apart from range, other factors such as system power of the vehicle should also be considered by policy makers in decision making.

5.3. Future research

Future studies could collect larger samples of PHEV users to study empirical charging behavior in different PHEV populations and user groups. This would complement **Paper IV** where the country comparisons are focused on differences in the share of electrified kilometers, and not charging behavior. Analyzing how the same vehicle is charged differently in different countries would provide an insight on how country characteristics and PHEV policies impact charging.

Paper III looks into how PHEVs are used within the household context with one PHEV or BEV in the household. However, the transition to future households with multiple PHEVs and BEVs is needed in order gradually increase electrification and then eventually reach 100% electrification in the household. Therefore, future studies could focus on how households with multiple PHEVs or BEVs charge and drive, and e.g. how households with multiple BEVs can be integrated into the grid (addressing peak demand and irregularity of renewable energy sources).

In **Paper IV**, we investigate the factors that can be behind the differences in the share of electrified kilometers between countries. The factors we focus on are quantitative such as electricity and gasoline prices, share of company cars, etc. In a future study, this can be complemented through a comparative policy analysis of selected countries regarding PHEV positions and incentives, and how these policies can impact the share of electrified kilometers in those countries.

6. Reflections

This chapter provides my reflections on my research and doctoral journey.

The world of electric vehicles is moving fast, and it certainly has changed a lot in the past six years since I started doing my PhD. When I first started working with PHEVs back in 2017, the market penetration in Europe was in PHEV's favor compared to BEVs: 160,000 PHEVs sold compared to 140,000 BEVs [96]. In the US, it was slightly in BEVs' favor with 100,000 new BEVs compared to 90,000 new PHEVs [96]. Starting in 2018, BEVs quickly caught up and surpassed PHEVs in terms of number of new passenger cars sold in Europe and have stayed on top ever since. The gap between new PHEVs sold compared to new BEVs sold has increased dramatically in the US since then, with BEVs being sold three times as much in 2021 (470,000 BEVs to 160,000 PHEVs) [96]. However, this has not been the case in Europe. In Europe, yes, BEVs are being sold more every year compared to PHEVs and are expected to be sold increasingly more in the coming years, but PHEVs have not fallen out of grace as they did in the US. For comparison, in 2021, there were 1.2. million BEVs sold in Europe, compared to 1.1 million PHEVs [96]. The sheer number of electric vehicles (BEVs + PHEVs) sold went from 300,000 to 2.3 million in Europe and from 190,000 to 630,000 in the US. This also shows that the adoption of electric vehicles today is happening at a much higher rate in Europe compared to the US. This difference between Europe and the US also shapes the view of institutions and researchers who are based there. From my personal observations through conferences and conversations with colleagues, there was a shift towards giving less space to PHEVs in research in the US over the last five years, whereas in Europe, interest in PHEVs stayed at a steady level during the same period.

My personal opinion is that in order to reach 100% electrification in personal road transportation, we will have to switch to an all BEV market eventually at a certain point in the future. The switch from PHEVs to BEVs has to happen. Any researcher who is in favor of 100% electrification would end up in the same conclusion. However, no one can deny the large share of PHEVs in electric vehicle sales today. PHEV sale numbers are expected to stay over 1 million units and reach close to 2 million by 2027 in Europe [96]. This goes to show that in the short term until 2030, they are still going to take a significant share of the electric vehicle sales in Europe. While in the US, they are sold much less than BEVs, the sheer number of PHEVs sold is still significant. I am not a researcher working on how to reach to an all BEV market, nor am I a policy maker that can decide on whether to ban sale of PHEVs in the near future, however I am interested in how PHEVs that are currently in the fleet are driven and most importantly how we can make the most out of them in terms of environmental benefits such as higher share of electrified kilometers and reduced fuel consumption and tail-pipe emissions.

This PhD thesis serves exactly to that interest of how PHEVs are driven and what is their role in electrifying personal transport. The role here can be interpreted as their contribution to increased electrification and reduced use of fossil fuels, what factors impact this contribution and how does this differ among countries. **Paper I and II** looks specifically at how PHEVs are charged and how this charging behavior impacts the share of electrified kilometers, fuel consumption and tail-pipe emissions. **Paper III** investigates the use of PHEVs within the household context, what factors impact their share of electrified kilometers and how their environmental benefits compare to that of BEVs in a household. **Paper IV** uses multi-country data and looks at what differences there are in the share of electrified kilometers of PHEVs among different countries and what can cause these differences. **Paper V** similarly uses multi-country data to report on the share of electrified kilometers and fuel consumption of PHEVs, and what vehicle properties impact those. The debate regarding PHEVs mostly focuses on whether they are inherently good or bad; what is lacking in this debate is how we can maximize the environmental benefits of PHEVs that are currently on the roads. By showing how PHEVs are charged and driven, and what impacts their electrification and fuel consumption, this PhD thesis shines a light on this lacking part of the debate.

It is one thing to place your research in reference to the wider literature and what knowledge gaps it fills; however, it is another thing to place yourself as to where you fit as a researcher. A lot of emphasis was put on self-improvement throughout the courses I took during my PhD. One of the concepts that stuck with me from those courses is the four idealized roles for scientists/researchers by Pielke [97]: pure scientist, issue advocate, science arbiter and honest broker. Briefly explaining the concepts; a scientist whose work is characterized by values consensus and low uncertainty can be a pure scientist if they are not connected to policy or decision making, and can be a science arbiter if they are. A scientist whose work is not characterized by values consensus and low uncertainty on the other hand can be an issue advocate if their aim is to reduce the scope of decision making, and can be an honest broker if they don't aim to reduce the scope. I don't have any influence over explicit considerations of policy and politics at the moment; however, in the long-term, assuming I get more experience in my current area of research, I would like to see myself as an honest broker, interacting directly with stakeholders and expanding the scope of choices without being an advocate for a certain side. Unlike researchers who are working in fields where there isn't much relevance to policy or debate about the nature of their work (mostly natural sciences), in the field of sustainable electromobility, almost every angle of research can be debated and connected to policy. This creates a situation where there is no black and white, but there are fifty shades of gray both in regard to the topics of research one can conduct and to the position one can place themselves in. With that in mind, I think my self-positioning as an honest broker is also a reflection of the field itself in the way that it is fast-changing and evolving, with many stakeholders involved, thus a researcher would also feel the need to adopt to this environment by expanding their scope.

I have given a considerable amount of thought to what the purpose of a doctoral study is. Did my PhD make me an expert in data analysis, modelling or statistics? No, it did not. All of these areas are quite wide and they are categorized into much smaller topics depending on what you want to investigate. What kind of data analysis? What kind of modelling? What kind of statistical tools? I learned most of the methods and software I used through the courses I took and spent long nights implementing them for my research. Although, at this point, I am quite knowledgeable with the methods I use in this thesis and good at analyzing the data related to PHEVs, being an expert at data analysis, modelling or statistics (or a certain sub-topic of those) was not my goal, and neither can I claim to be an expert on those. The tools I used for my research are not the topic of my PhD.

Then what is the purpose of doing a PhD? I have found or rather understood the answer to this question only in the final stages of my PhD when I had more freedom to choose a direction for my research. There is a lot of difference between the researcher who I was six years ago and the researcher I am now. My research focuses mostly on analyzing data and the data I used during my PhD were mostly predetermined and out of my control. I wasn't involved in data collection, nor did I have the freedom to pick from different sets of data. Thus, in a way, the scope of my research was limited. However, I accept that most researchers will never get their perfect data, it is a limitation most people cannot avoid due to the circumstances of their funding. Yet, in my PhD we had the freedom to ask the research question ourselves based on the data we have and move the research into that direction, which is the process of conceptualization. In the earlier stages of my PhD, I was involved in conceptualization through improving the research questions that were put forward by my supervisors and colleagues I worked with. For example, in **Paper I and II**, the idea of looking into two types of charging behavior (no overnight charging and additional charging) was first put forward by my co-authors. I was, of course involved in all stages of this conceptualization, for example it was my idea to fine-tune and improve the method we use in **Paper I and II** through testing on real-world data; however, the original research idea did not belong to me. Through the later stages of my PhD, I was encouraged and expected to take a much more independent role in coming up with original research questions. For example, in **Paper IV**, the conceptualization of the study, from the research question to the additional data collection and to the methods used, all originated from me. I realize now that this transition towards an increased role in conceptualization happened gradually over the years, through writing papers and getting rejected from journals and re-submitting, and through going to conferences and networking and talking to colleagues from different parts of the world. Therefore, I think the purpose of a doctoral degree is exactly this: to learn how to conduct research independently, in addition to getting extensive knowledge in a tiny area within your research field. As I heard from some colleagues before, it is like a driving license. This also comes with the realization that improving your skills when it comes to the methods of your research is a continuous and never-ending process.

Working with electric vehicles or broadly in the field of sustainable electromobility gives me a certain kind of excitement. Maybe it is because it is developing so fast, and I can observe the changes firsthand myself. Or maybe it is because I feel like my contributions can have practical implications. Given the opportunity, I would like to stay in this field, whether as a researcher in academia or at a research institute or working in industry. I am aware that it is not always possible to find positions neither in academia nor in industry that fit into exactly what you want to work on, yet if I had the choice, there are two areas that draw my attention (not related to each other): one is the incorporation of AI systems into PHEVs and BEVs and what it would mean in terms of environmental benefits. This is a very broad area ranging from different levels of automated driving to smart charging technologies. The second is electric vehicle adoption in developing countries. While working on PHEVs, it was not difficult to notice that the number of countries that you can do detailed analysis on are limited. This creates a situation where we don't know much (or anything) about how users drive and charge (or how they would, given the opportunity) in developing countries, and most of the world's population falls under this category. However, I am aware that this would come with great challenges regarding data collection and access.

It was a long PhD journey, also an extended one due to the pandemic, and looking back at those six years I appreciate everything I have gained from this journey. Not only have I gained immeasurable experience at being a researcher and developing into an independent one, but I have also learnt a lot when it comes to working in a positive work environment and more importantly separating my work from the rest of my life. The culture at our division at Chalmers, and more generally in Sweden, focuses a lot on the well-being of the self and this can only be done through taking time off with a clear separation from work. Growing up in Turkey, I had a very different view of how work and workplace looked like. It meant working long hours and spending very little time for yourself and taking few vacations. This is not a good recipe for personal well-being, it creates exhaustion and does the opposite of creating an environment where ideas flourish. In my first year in Sweden, I remember getting an email from the head of our division. It was a reminder to take our vacation days, and this kept happening throughout my time here. In seminars, appraisal talks and progress meetings, the issue of overworking was commonly brought up. They wanted to make sure that I was not overworking, that I was not under too much stress I cannot handle and that I was spending enough time away from work. This had come to me as a shock in the beginning, but after living six years in Sweden and being exposed to the working culture here I cannot imagine a different working environment. Sweden is repeatedly rated in the top ten happiest countries in the world, and I think the emphasis on personal well-being and the clear work-life balance is one of the reasons.

I appreciate all parts of this doctoral journey and I am thankful for the experience, skills and insights I have gained, and the people I have met and worked with.

7. Key contributions and findings

Key contributions and findings of this doctoral thesis are summarized below.

1. A new method to identify charging events and analyze PHEV charging behavior for large samples that only have driving data.

2. The possibility to charge overnight has a bigger effect than additional charging during the day on increasing the share of electrified kilometers of PHEVs and reducing their fuel consumption and tail pipe emissions. Therefore, it is important to ensure adequate access and incentives for users to plug-in every night to make sure PHEVs can contribute to a reduction of CO_2 emissions; and policies for PHEVs should prioritize easy access to overnight charging above public and workplace infrastructure to achieve high shares of electrification.

3. PHEVs with a range of at least 35 miles (56 km) have the potential to electrify a similar share of total household miles as some short range BEVs or can reach up to 70% as much electrification as some long range BEVs and, thus, can play an important role in decarbonizing the transport sector.

4. PHEVs have poor environmental performance across the globe compared to set standards: lower share of electrified kilometers compared to type approval values and higher fuel consumption than e.g. European Union targets. Purchase or tax incentives for PHEVs can be coupled to real-world fuel consumption and electric driving to incentivize users to charge and electrify more.

5. Countries with a higher electricity price to gasoline price ratio are associated with lower shares of electrified kilometers, for some PHEV models. This implies that policies incentivizing charging through cheap electricity or disincentivizing fuel use though high gasoline prices should take into account the interaction effects between the two prices.

6. Countries like Norway and Sweden have significantly higher shares of electrified kilometers compared to some western European countries (France, Germany, Netherlands and UK). The share of electrified kilometers of PHEVs can be maximized through following the examples of Norway and Sweden.

7. Apart from range, system power per vehicle mass also has a significant impact on fuel consumption and share of electrified kilometers, where a higher system power per vehicle mass results in higher fuel consumption and lower share of electrified kilometers.

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