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Electric vehicles and driving behavior: evidence from Swedish register and GPS data

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ABSTRACT

We examine whether electric vehicle (EV) users differ from internal combustion engine vehicle (ICEV) users in real-world driving behavior, and whether observed patterns arise from trip frequency, trip length, or car and user characteristics. Using evidence from Sweden—a mature EV market—we use register data on annual vehicle kilometers traveled (VKT) alongside multi-month GPS travel diaries capturing daily mobility patterns. Register-based estimates indicate that battery electric vehicles (BEVs) have 13–17 % higher annual VKT than comparable ICEVs. Plug-in hybrid electric vehicles (PHEVs) also exhibit higher annual VKT, although the differences are smaller and more sensitive to controls for car characteristics. GPS data show similar patterns: BEV users drive longer daily distances but do not make more trips, whereas the corresponding estimates for PHEVs are generally statistically insignificant. Overall, the higher VKT among EVs may reflect selection into EV adoption or behavioral responses consistent with lower perceived marginal driving costs.

1. Introduction

As the electrification of the car fleet accelerates, understanding how electric vehicles (EVs)—battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs)—affect real-world driving demand becomes increasingly important. Lower operating costs per kilometer may induce rebound effects, as documented in the broader fuel-price elasticity literature (Gillingham et al., 2016; Small & Van Dender, 2007), potentially contributing to higher congestion, road wear, and infrastructure demand. At the same time, range limitations, charging requirements, and charging habits can constrain travel flexibility. The net effect on realized driving is therefore theoretically ambiguous: EVs may both enable and constrain car use (e.g., Jakobsson et al., 2022).

In this paper, we examine how EV adoption relates to actual car use by comparing annual and daily driving patterns of BEVs, PHEVs, and ICEVs across both single- and multi-car households, focusing on private car use. The study is conducted in Sweden, a relatively mature market where EVs accounted for nearly 60% of new passenger car registrations and approximately 11% of the total passenger car fleet in 2023 (Power Circle, 2026). EV adoption in Sweden has expanded rapidly in recent years, with electric passenger cars increasing from about 100,000 in 2019 to over 850,000 in 2026 (Power Circle, 2026; Transport Analysis, 2024). This expansion has been supported by extensive charging infrastructure, reaching around 60 000 charging points across 9 000 charging stations in

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2026 (Power Circle, 2026), government support for charging infrastructure expansion (Swedish Energy Agency 2026), widespread home charging opportunities including subsidies for the installation of home charging points (Swedish Energy Agency 2026), and policy incentives favoring EV ownership, including tax benefits and purchase subsidies (European Commission, 2026; Swedish Environmental Protection Agency, 2026). This setting allows us to examine travel behavior under more mature technological and market conditions rather than during the early adoption phase of EV diffusion.

Several mechanisms may generate rebound effects among EV users. First, a direct rebound effect may arise because lower marginal costs per kilometer for EVs reduce the perceived cost of driving (Linn, 2016; Small & Van Dender, 2007; Sorrell, 2009; Sorrell et al., 2009), potentially increasing VKT either through longer or more frequent trips. Second, indirect rebound effects may occur if fuel cost savings free up disposable income that may be spent on other consumption, including additional travel (Gillingham et al., 2016; Sorrell, 2009). Third, environmental moral licensing may play a role: EV users may perceive their driving as more environmentally friendly, reducing psychological barriers to additional travel (Andersson et al., 2019; Kosmidis et al., 2023; Ojeda-Diaz et al., 2025).

At the same time, several mechanisms can reduce EV mileage. Range limitations, especially for early-generation BEVs, can constrain long-distance travel (Davis, 2019, 2023; Langbroek et al., 2017). Charging requirements may reduce driving flexibility by requiring longer stops and more planning, particularly for users without access to home charging. Infrastructure availability affects route and destination choices, and EV users may avoid destinations with limited public charging or adjust their travel timing to accommodate charging opportunities (Malabanan et al., 2026). Some studies also suggest that EV drivers adopt more energy-efficient driving styles or limit discretionary trips to preserve battery health (Wang et al., 2020). Taken together, these mechanisms suggest that the overall effect of EV adoption on realized driving behavior is theoretically ambiguous and ultimately an empirical question.

A recent review by Zhang et al. (2026) concludes that evidence on EV-related changes in VKT remains mixed and context-dependent, with results varying across datasets, household structures, stages of EV diffusion, and national contexts. Some studies report higher (unconditional) average mileage among EV users than ICEV users (Bauer, 2018; Zhang et al., 2025). Using one-day travel diaries from Greater Stockholm, Langbroek et al. (2017) find that EVs make more trips and account for a larger share of total distance traveled. Wangsness et al. (2020) show that EV adoption in Norway likely increases congestion and reduces public transport use. EV adoption has also been linked to increased household car ownership (Bauer, 2018; Davis, 2023), potentially expanding overall car availability and total household vehicle kilometers traveled (VKT). Additionally, EVs are disproportionately represented among company and fringe benefit cars (Trafikanalys, 2024; Zhang et al., 2025), a car category shown to be associated with increased car ownership and higher VKT (Börjesson & Roberts, 2023; Gutiérrez-i-Puigarnau & van Ommeren, 2011; Shiftan et al., 2012). Evidence from two-car households adds further nuance. Karlsson (2020), using detailed GPS data from Gothenburg, shows that EVs are disproportionately used for everyday travel and short local trips, while ICEVs are preferred for long-distance travel. Other studies find little difference, or even lower mileage, among EVs, particularly for early-generation BEVs with limited range (Chakraborty et al., 2022; Davis, 2019; Feng et al., 2024; Habla et al., 2021).

Recently published studies underscore the importance of household context for variations in car use across powertrains. For example, Zhang et al. (2025), analyzing single-car households in the Netherlands in 2018–2020, document higher unconditional daily VKT among BEV and PHEV users. However, once socioeconomic and car characteristics (including company car and leasing status) are accounted for, they find that EV users do not drive more than comparable ICEV users—and BEVs even show lower non-commuting VKT. Using the 2017 National Household Travel Survey (NHTS), Chowdhury et al. (2024) show that in multi-car households in the U.S., EVs often serve as secondary cars, with usage varying systematically by income, fleet composition, and commuting needs. Feng et al. (2024), also based on the 2017 NHTS, find that BEV-only households drove fewer annual miles, primarily because they undertook fewer long-distance trips. Davis (2019), using the same data, shows that PHEVs are also driven less than ICEVs, suggesting that factors other than range limitations may shape observed differences. Overall, differences across studies often appear more related to ownership status, household fleet composition, and sociodemographic factors than to powertrain type per se (Hasan & Simsekoglu, 2020; Nickkar et al., 2020).

Importantly, several of these findings reflect travel conditions characterized by shorter battery ranges and less developed charging infrastructure. EV technology has improved substantially in recent years, with battery ranges now exceeding average daily trip distances (European Commission, 2025a; Plötz & Sprei, 2021), raising the question of whether earlier findings generalize to contemporary market conditions. This raises the possibility that behavioral patterns identified in earlier EV studies may not generalize to current EV markets characterized by longer ranges, denser charging infrastructure, and broader adoption beyond early adopters.

A related challenge in interpreting this literature concerns data limitations. Much of the evidence relies on self-reported mileage or one- or two-day travel diaries, which make it difficult to distinguish persistent differences in driving behavior from short-term variation. Self-reported annual VKT is also prone to measurement error. While register-based studies using odometer readings provide more reliable measures of annual driving, they remain scarce, in part because EVs represented only a small share of the fleet until recently. Moreover, existing studies often cannot disentangle whether EV–ICEV differences arise from differences in trip frequency or trip length or shifts in the timing and purpose of travel, nor how such patterns vary across household fleet compositions. Distinguishing between these margins is essential for identifying potential rebound mechanisms and assessing system-level implications for congestion, charging demand, and network load. Existing evidence therefore remains limited regarding how EV adoption relates to realized driving behavior in mature EV markets, how these patterns differ across household fleet compositions, and whether observed differences primarily reflect trip frequency, trip length, or within-household car allocation mechanisms.

We address these gaps through an empirical design that draws on two complementary data sources: Swedish register data with multi-day GPS travel diaries. The register data provide odometer-based annual VKT measures across powertrains and household structures, while the GPS data capture realized daily driving behavior, including trip frequency, trip length, timing, and trip purpose. Together, these data allow us to distinguish between intensive and extensive margins of driving—that is, between how much cars are

driven conditional on use (e.g., trip length or distance) and the decision of whether to use a car on a given day—and to assess how observed patterns vary across household fleet compositions. To minimize confounding from company and benefit cars, we restrict the analysis to privately owned or leased cars and to trips classified as private (including commuting but excluding business travel).

The remainder of the paper is organized as follows. Section 2 describes the data sources and sampling. Section 3 presents the empirical framework, including key variables used in the main analysis. Section 4 reports descriptive statistics, while Section 5 presents the main results from register-based and GPS-based analyses. Section 6 discusses the findings, and Section 7 concludes.

2. Data

2.1. Register-Based Data and Sample

The register-based data come from administrative databases provided by Statistics Sweden. These registers cover the full population of registered passenger cars in Sweden and contain detailed technical information for each car, including powertrain type, registered owner type (privately- or company-owned), annual VKT, make, model, model year, and leasing status, among other attributes. The data on registered passenger cars are linked to administrative individual records through encrypted personal identifiers. This linkage allows us to connect each car to its registered user and to incorporate information on age, gender, education, income, household composition, number of cars in the household, and place of residence of the registered user. Because the registers cover multiple years, we can also observe when the registered user acquired the car and compute historical (lagged) VKT based on previous cars registered to the same individual.

Because detailed and reliable information on leasing contracts by powertrain type is not available—and because company-leased cars (including company and fringe benefit cars) often reflect employer-provided mobility rather than private travel needs—we restrict the analysis to privately owned cars.[1] This restriction ensures that annual VKT reflects private use rather than company-related travel patterns, and avoids potential biases related to benefit-car taxation, corporate leasing policies, and other institutional factors that may differentially affect mileage across powertrains.

We restrict our analysis of annual VKT to the year 2023. The sample includes cars of model year 2019 or newer that were acquired by their current registered user between 2019 and 2022, and for which annual VKT in 2023 is based on odometer readings collected at a vehicle inspection. Observations where annual VKT is imputed using model-based estimates—typically applied to newer cars that have not yet undergone a vehicle inspection—are excluded. These restrictions serve several purposes. First, annual VKT is observed from odometer readings collected at vehicle inspections, which typically take place for the first time when a car is about three years old (with exceptions). Second, restricting the sample to post-2018 model years increases the representation of newer-generation EVs, which is important given the substantially shorter driving ranges of earlier EV models, and improves comparability across powertrain types. Although information on battery range and luggage capacity is not available, restricting the sample to newer model years reduces heterogeneity associated with early-generation EVs, which typically had substantially shorter driving ranges and different car characteristics than contemporary EVs. Third, applying a common acquisition-year window across powertrain types ensures a similar usage duration since acquisition and reduces confounding from car age and potential new-car effects. As a result, the sample primarily consists of cars that are approximately three years old in 2023.

Some users may have owned their car for less than three years, as long as the car became subject to inspection in 2023. Conversely, we exclude recently acquired cars that had not yet undergone inspection, thereby filtering out individuals who frequently replace their cars. We also exclude users who acquired more than one car during the observation period to ensure that each observation corresponds to a unique user–car pair. This avoids dependence between observations and ensures that the estimated differences in VKT across powertrains are not confounded by individuals with atypical ownership patterns, such as faster car turnover or a disproportionate share of premium cars. The final sample used in the main analysis includes 6,865 BEVs, 14,172 PHEVs, and 70,462 ICEVs.

It is important to note that the registered user is not necessarily the primary driver of the car within the household. However, individuals within the same household share key contextual characteristics, such as residential location, partnership status, and number of children. In contrast, variables like income, age, education, and employment are individual-specific and thus serve as informative, though imperfect, proxies for household-level travel needs, socio-demographic conditions, and broader residential context. Linking cars to individual-level data also enables us to assess the extent to which differences in VKT across powertrains may reflect compositional differences in who acquires which type of car. Because annual VKT is measured at the car level, the register-based analysis captures total realized car use, regardless of which household member drives the car.

2.2. GPS-Based Travel Data and Sample

The GPS-based data were collected in 2023–2024 using the smartphone application TravelVu, which records respondents' movements using GPS positioning and generates suggested daily travel diaries that users validate manually. Unlike the register data, which measure annual use of a specific car, the GPS data capture individual travel behavior and driving activity. Consequently, GPS-based VKT measures reflect the distance driven by the respondent rather than total use of a particular car. The analysis includes only observations that were validated by respondents and classified as private travel.

[1] We further restrict the sample to cars registered to users in households with at most five passenger cars, to exclude atypical multi-car households and potential commercial use.

The TravelVu platform also provided background information and follow-up survey responses on topics such as charging behavior, access to charging, and car use. Collecting GPS-based travel diaries provides rich and highly detailed data on real-world driving behavior at a relatively low cost, particularly compared with traditional multi-day travel surveys (Bauer, 2018). While an ideal research design would involve a randomized experiment assigning different powertrains to individuals, such an approach was infeasible in practice.

To recruit participants, we drew a random sample from the Swedish Transport Agency's vehicle register. The sampling frame included all individuals in Sweden who acquired a BEV, PHEV, or ICEV passenger car—either new or used, through purchase or private leasing—in 2021–2023, hereafter referred to as BEV/PHEV/ICEV users. This restriction ensures broadly comparable post-acquisition usage conditions and reduces heterogeneity associated with car depreciation, reliability concerns, or changing driving habits over the car life cycle. Consequently, the GPS sample contains somewhat newer cars on average than the register sample, which should be kept in mind when comparing results across the two data sources.

The sample was stratified by powertrain, with one-third of invitations sent to recent users of BEVs, one-third to PHEVs, and one-third to ICEVs. To ensure geographic diversity, invitations were sent to individuals residing in seven counties: Stockholm, Västra Götaland, Skåne, Halland, Jönköping, Östergötland, and Uppsala. These counties include Sweden's largest metropolitan areas and the majority of the national population, providing broad coverage of typical driving environments, although northern and sparsely populated counties are not represented.

A total of 40,002 invitations were distributed, followed by a reminder. The share of individuals who accepted the invitation by installing the TravelVu app was approximately 7.4%, comparable to other voluntary app-based mobility studies. Participants contributed data for periods of up to six months, between October 2023 and April 2024.

After data collection, we imposed additional restrictions to ensure data quality and comparability with the register sample. We retain only individuals who validated at least seven travel days (including days with zero travel), covering at least one weekend day, who reported having a valid driver's license and access to a car during the data collection period, and who had no missing values on key explanatory variables used in the main analysis. The final GPS sample consists of 762 individuals: 410 BEV users, 243 PHEV users, and 109 ICEV users.[2] After further restricting the sample to private trips (including commuting to work but excluding business travel), these individuals contributed 80,271 validated travel days and 338,735 logged trips.[3] Because participants were observed for periods of up to six months rather than over a full calendar year, the GPS data may not fully capture seasonal variation in driving behavior, particularly infrequent long-distance trips.

A trip is defined as a continuous movement between two distinct activity locations (e.g., home, work, shops). In TravelVu, an activity location is recorded when the respondent remains in the same location for about 2 minutes, excluding stops that are typical of traffic behavior (e.g., stopping at a traffic light).

The GPS-based data cover all trips recorded on validated travel days, along with detailed background information on the respondents. At the trip level, the data include start and end times and dates, trip distance, trip purpose, and travel mode. These variables allow us to analyze daily VKT, vehicle trip frequency (VTF), trip-length distributions, and temporal patterns such as rush-hour and weekend driving. The background information collected in the TravelVu platform includes information on the powertrain of the most recently acquired car, the number of cars (owned or leased) of different powertrains in the household, and sociodemographic variables such as age, gender, education, household income, employment status, household structure, dwelling type, and residential area. For a subsample, we also observe car characteristics, such as make, model, and model year, for both the most recently acquired car and the car it replaced. Because participation is voluntary, the GPS sample may not be fully representative of all recent car adopters. We therefore describe and compare key observable car and user characteristics between the GPS sample and the register-based sample in Section 4, including sociodemographic characteristics, residential location, car age, and car class.

3. Empirical framework

3.1. Register-Based Analysis of Annual VKT

The objective of the register-based analysis is to quantify differences in annual VKT across BEVs, PHEVs, and ICEVs while controlling for observable characteristics of the registered user, household context, and car characteristics. We estimate a sequence of specifications that progressively expand the set of controls and assess robustness to alternative ways of accounting for car characteristics. The baseline specification includes a limited set of key controls directly related to car use, while the subsequent specifications add a broader set of individual- and household-level characteristics. We begin with a baseline specification:

$$y_i = \beta_0 + \boldsymbol{\beta_{PT}}\boldsymbol{PT_i} + \boldsymbol{\beta_Z}\boldsymbol{Z_i} + \beta_F F_i + \boldsymbol{\beta_E}\boldsymbol{E_i} + \boldsymbol{\beta_G}\boldsymbol{G_i} + \boldsymbol{\beta_R}\boldsymbol{R_i} + \boldsymbol{\beta_M}\boldsymbol{M_i} + u_i \quad (1)$$

Here y_i denotes annual VKT and $\boldsymbol{PT_i}$ is a vector of powertrain dummies, consisting of a BEV dummy and a PHEV dummy, with ICEV as

[2] Relative to the number of invitations sent, this corresponds to approximately 2% of invited individuals after applying the participation and data-quality restrictions described above. While this participation rate is relatively low, the final sample nevertheless contains a large number of validated travel days and trips, enabling detailed analyses of realized driving behavior across powertrains.

[3] After restricting the sample to private trips, 13 individuals contribute six validated travel days, of whom one individual does not include a validated weekend day. These individuals are retained in the analysis given the overall sample size and because all estimations are weighted by the number of validated travel days per individual.

the reference category, of car i. $\boldsymbol{Z_i}$ is a vector of car-related characteristics of the registered user of car i, including number of cars in the household, prior car user (equal to 1 if the registered user owned a car 1–3 years prior to the new car acquisition), prior EV owner (equal to 1 if the registered user owned at least one EV 1–3 years prior to the new car acquisition), and lagged annual VKT of previously owned cars (averaged per year). Lagged annual VKT enters the model only through an interaction with the lagged car-user indicator. F_i is a dummy equal to 1 if the registered user is female. $\boldsymbol{E_i}$ includes an employment dummy equal to 1 if the registered user is employed and the Euclidean commuting distance, which enters the model only through an interaction with being employed. $\boldsymbol{G_i}$ is a vector of residential location dummies (city/urban area as the reference group, suburban area/small town, and rural area). $\boldsymbol{R_i}$ denotes a vector of county dummies and $\boldsymbol{M_i}$ denotes a vector of model-year dummies. u_i is the error term.

We next extend the baseline specification by including additional individual-level characteristics and controls for car class:

$$y_i = \beta_0 + \boldsymbol{\beta_{PT}PT_i} + \boldsymbol{\beta_Z Z_i} + \beta_F F_i + \boldsymbol{\beta_X X_i} + \boldsymbol{\beta_E E_i} + \boldsymbol{\beta_G G_i} + \boldsymbol{\beta_{PT^*G}}(\boldsymbol{PT^*G})_i + \boldsymbol{\beta_C C_i} + \boldsymbol{\beta_R R_i} + \boldsymbol{\beta_M M_i} + u_i \quad (2)$$

where $\boldsymbol{X_i}$ is a vector of characteristics of the registered user of car i, including age, age squared, partner status (single), the presence of children in the household, dwelling type (detached house) educational level, and income level (quartiles).[4] $\boldsymbol{C_i}$ denotes dummies for passenger car class following the European standard classification (segments A–F, J, S, and M; European Commission, 2025) and is included to account for systematic differences in car class across powertrains.[5] The European standard classification is used primarily to facilitate comparability with the GPS-based analysis, where detailed physical car characteristics are not consistently available. However, European car-class assignments do not always uniquely reflect physical car size, and some cars may plausibly fit into more than one class. Consequently, car-class classifications involve a degree of judgment and may not fully capture variation in car dimensions across powertrains.

To assess the robustness of the results to alternative ways of characterizing cars, we estimate two additional specifications. First, we replace the European car-class dummies with body-type indicators (e.g., sedan, hatchback, and wagon). Body type provides a relatively transparent characterization of car design and intended use while avoiding some of the ambiguity associated with European car-class classifications. Nevertheless, body-type categories remain broad. For example, SUV and crossover cars may be classified into different body-type categories depending on their size and design, while multi-purpose vehicle categories are typically less finely differentiated than the corresponding European car-class categories. We therefore also estimate a specification based on continuous measures of car dimensions. However, because body type arguably captures car functionality and intended use more directly than either European car-class categories or physical dimensions alone, we regard the specification including body-type dummies as our preferred specification.

To analyze whether differences in annual VKT vary systematically across geographic contexts, we include interactions between geographic area and powertrain. All specifications are estimated using ordinary least squares (OLS) with robust standard errors.

As an alternative modelling approach, we also estimate differences in outcomes using propensity score matching (PSM). BEV and PHEV users are matched separately to observably similar ICEV users based on pre-adoption individual and household characteristics, including age, gender, household composition, education, income quartiles, housing type, employment status, geography, and household car holdings, as well as characteristics of the current car, including model year, acquisition year, and body type. A small number of observations with missing pre-adoption covariate information were excluded prior to estimation. Propensity scores are estimated using logit models, and matching is conducted using one-to-one nearest-neighbor matching. Standard errors for the treatment-effect estimates are computed using the Abadie–Imbens analytic variance estimator. Squared and interaction terms are excluded from the propensity score model to avoid overfitting. This approach allows us to compare annual VKT across powertrain types within more balanced samples and to assess the sensitivity of the results to alternative modelling approaches. As matching relies on observables, it should be interpreted as a robustness check rather than a source of stronger causal identification.

3.2. GPS-Based Analysis of Daily Car Use

The data used for analyzing daily car use are based on high-resolution GPS measurements, which exhibit substantial day-to-day variation as well as many zero-car travel days. Standard OLS models are therefore unsuitable for two reasons. First, daily VKT is a continuous outcome with many actual zeros, generating a mass point at zero. Second, daily VTF is an integer-valued count outcome with overdispersion. To address these features, we rely on two-part models for daily VKT and hurdle models for daily VTF (Mullahy, 1998). These models separately capture the extensive margin (whether any car travel occurs) and the intensive margin (car travel conditional on car use), thereby providing a richer description of daily mobility patterns.

The first stage models the probability that individual s uses a car on day d, defined as recording either positive daily VKT (in the two-part model) or at least one car trip (in the hurdle model):

[4] Employment status, commuting distance, education, income, residential area, and dwelling type are measured in 2022, as corresponding data for 2023 are not yet available and are therefore used as proxies for 2023.

[5] Car class is based on a combination of car body type, car length, and model names. For cars lacking detailed model information, size class is determined using manufacturer and car length. Non-passenger cars, such as light commercial vehicles and motorhomes, are excluded from the analysis.

$$P(y_{sd} > 0) = \text{logit}^{-1}(\alpha_0 + \boldsymbol{\alpha_{PT}PT_s} + \alpha_F F_s + \boldsymbol{\alpha_X X_s} + \boldsymbol{\alpha_G G_s} + T_d) \quad (3)$$

where y_{sd} is daily VKT or VTF. Daily VKT is defined as the total distance an individual s on day d, regardless of which car was used. This provides a consistent measure of overall mobility and avoids attributing differences in travel behavior to within-household car choice rather than to underlying travel demand.[6] VTF is defined as the number of car trips on a given day. PT_s denotes a vector of powertrain dummies (BEV and PHEV) for the most recently acquired car by individual s. F_s is a dummy equal to 1 if individual s is female. $\boldsymbol{X_s}$ is a vector with individual and household characteristics, including a dummy equal to 1 if the household has a second car, whether the household has at least one leased car, age, presence of children in the household, partner status (single), dwelling type (detached house or apartment), educational level, employment status, and household income level. $\boldsymbol{G_s}$ is a vector of residential-location dummies (city/urban area (reference group), suburban area/small town, rural area). $\boldsymbol{X_s}$ also includes innovation-stage dummies (five categories; see Appendix for innovation-stage definition and category distribution), capturing the individual's technology adoption stage. T_d includes dummies for weekend/holiday and month.

Conditional on car use, the second stage models the intensity of car use. In the two-part model for daily VKT, the second stage is specified as a linear model estimated on days with positive VKT:

$$E(y_{sd}|y_{sd} > 0) = \delta_0 + \boldsymbol{\delta_{PT}PT_s} + \delta_F F_s + \boldsymbol{\delta_X X_s} + \boldsymbol{\delta_G G_s} + T_d \quad (4)$$

In the hurdle model for daily VTF, the second stage is specified as a zero-truncated negative binomial model, capturing the number of trips conditional on at least one car trip:

$$\ln(\mu_{sd}) = \delta_0 + \boldsymbol{\delta_{PT}PT_s} + \delta_F F_s + \boldsymbol{\delta_X X_s} + \boldsymbol{\delta_G G_s} + T_d, y_{sd} > 0 \quad (5)$$

where μ_{sd} denotes the conditional mean parameter of the negative binomial distribution.

To examine whether differences in daily car use vary systematically across individual observable characteristics, we also estimate Equations (3)–(5) excluding the vector X_s for comparison. In all two-part and hurdle specifications, we apply weights that account for differences in the number of validated days per individual and for differences in powertrain-group sample sizes. Since multiple days are observed per individual, standard errors are clustered at the individual level to account for within-person correlation over time.

Equations (3)–(5) are estimated for the full sample (see Section 2.2) as well as for a subsample restricted to individuals living in households that only have cars of one powertrain type, henceforth referred to as 'single-powertrain households'. By focusing on individuals in single-powertrain households, we isolate the part of driving behavior that can be attributed to powertrain. Since these users do not have access to cars with different powertrains within the household, differences in daily car use are less likely to arise from choosing which type of car to drive for a given trip.

In further analysis, we also include indicators for the car class (C_s) of the most recently acquired car and the previously owned car in Equations (3)–(5). The idea of the latter is that individuals who previously owned the same type of car tend to share similar underlying travel needs and preferences; in this respect, they are comparable except for the choice they later made between adopting an EV or an ICEV. By conditioning on past car class, we therefore reduce selection bias stemming from underlying differences in driving patterns and isolate variation more closely attributable to the powertrain of the newly acquired car.

To provide a broader picture of how EV adoption affects driving behavior, we additionally estimate models for several other dimensions of daily car use: average trip length, the probability of making long-distance trips (trip length > 100km), and the probability of making rush-hour trips (6:00–09:00 and 15:00–18:00 during weekdays). These specifications are estimated at the trip level. Differences in average trip length across powertrains are estimated using pooled OLS, whereas the probabilities of long-distance trips and rush-hour trips are estimated using logit models. All trip-level models are estimated for individuals in single-powertrain households only, to ensure that car use is correctly attributed to the car's powertrain.

In a secondary analysis, we estimate car choice within two-car households with mixed powertrains (EV + ICEV) using logit models, where the dependent variable equals one if the EV is chosen for a given trip. Depending on the specification, the explanatory variables include the logarithm of trip length, an indicator for non-commuting trips, whether the EV is the most recently acquired car, a rush-hour indicator, a indicator for long trips (>=100km), and the vectors $\boldsymbol{X_s}$ and $\boldsymbol{G_s}$.

4. Descriptive Statistics

Tables 1 and 2 summarize descriptive statistics for the register-based and the GPS-based samples, respectively. Starting with the register-based sample, several clear patterns emerge. First, BEVs display the highest mean annual VKT (17,085 km), followed by PHEVs (16,082 km), while ICEVs are driven substantially less (13,797 km). Fig. 1 shows the distribution of annual VKT by powertrain, excluding observations at or above the 99th percentile. While the distributions overlap substantially, BEVs and PHEVs generally exhibit higher annual VKT levels than ICEVs. A similar ordering appears for lagged VKT among individuals who previously owned a car, suggesting that differences in current driving may reflect pre-existing differences in mobility patterns (Table 1).

BEV registered users are more likely to live in multi-car households (on average 1.60 cars, compared with 1.48 for PHEVs and 1.41 for ICEVs) and to have previously owned an EV. Moreover, BEVs are slightly newer (mean age 3.16 years, compared with 3.47 for

[6] In a sensitivity analysis, we re-estimated Equations (3)–(5) using powertrain-specific daily VKT for BEV, PHEV, and ICEV acquirers, respectively (not shown). The resulting estimates were similar in direction but smaller in magnitude.

Table 1
Descriptive statistics Register Data.

Powertrain	***BEV***		***PHEV***		***ICEV***	
	mean	sd	mean	sd	mean	sd
	(1)	(2)	(3)	(4)	(5)	(6)
VKT	17,085	8,189	16,082	6,400	13,797	7,000
Lagged VKT	17,126	8,917	16,360	7,403	14,977	7,694
Prior car owner (share)	0.82		0.85		0.84	
Prior EV owner (share)	0.13		0.05		0.01	
No. of cars in the household	1.60	0.64	1.48	0.60	1.41	0.59
1-car households (share)	0.48		0.58		0.65	
2-car households (share)	0.44		0.36		0.30	
Car age (based on model year)	3.16	0.56	3.11	0.56	3.47	0.57
Car curb weight (kg)	1,850	311	1,908	251	1,535	277
Car length (cm)	440	33	461	20	443	31
Car width (cm)	181	7	185	5	181	6
Car class A: Mini (share)	0.04		0.00		0.03	
Car class B: Small (share)	0.16		0.00		0.12	
Car class C: Compact (share)	0.30		0.26		0.22	
Car class D: Mid-size (share)	0.25		0.17		0.14	
Car class E: Executive (share)	0.04		0.19		0.13	
Car class F: Luxury (share)	0.04		0.07		0.05	
Car class J: SUV (share)	0.17		0.31		0.30	
Car class M: MPV (share)	0.00		0.00		0.01	
Car class S: Sports (share)	0.00		0.00		0.00	
Car body type: sedan	0.27		0.04		0.03	
Car body type: hatchback	0.25		0.07		0.23	
Car body type: wagon/smaller SUV	0.33		0.81		0.58	
Car body type: coupé	0.00		0.00		0.00	
Car body type: convertible	0.00		0.00		0.01	
Car body type: mpv/larger SUV	0.16		0.07		0.16	
City/urban area (share)	0.69		0.77		0.76	
Suburban area/small town (share)	0.12		0.10		0.11	
Rural area (share)	0.19		0.13		0.14	
Detached house (share)	0.77		0.75		0.60	
Cooperative housing (share)	0.15		0.17		0.22	
Apartment (share)	0.04		0.05		0.14	
Other (share)	0.04		0.03		0.03	
Commuting distance	34	82	27	72	25	68
Employed (share)	0.72		0.65		0.61	
Female (share)	0.30		0.28		0.39	
Age	54	14	56	14	57	15
Single (share)	0.24		0.21		0.37	
Children in the household (share)	0.42		0.37		0.25	
Primary education (share)	0.04		0.07		0.12	
Secondary education (share)	0.48		0.54		0.60	
Tertiary education (share)	0.48		0.40		0.28	
Income quartile 1 (share)	0.03		0.03		0.06	
Income quartile 2 (share)	0.08		0.10		0.19	
Income quartile 3 (share)	0.20		0.24		0.31	
Income quartile 4 (share)	0.69		0.63		0.44	
Sample size	*6,865*		*14,172*		*70,462*	

Table 1 reports descriptive statistics for the register-based sample. Columns 1, 3, and 5 present means, while columns 2, 4, and 6 report standard deviations. All statistics refer to the most recently acquired privately owned car and its owner as observed in 2022/2023. The lagged VKT measure captures the individual's average annual VKT during the 1–3 years prior to car acquisition, based on register data for 2016–2022. Mean lagged VKT is calculated only for individuals who had a registered car during the relevant 1–3-year period, and mean commuting distance is calculated only for individuals who are employed.

ICEVs) and relatively more concentrated in compact and mid-size car classes (segments C and D). In terms of body type, BEVs are more frequently represented among sedans, hatchbacks, and wagons. PHEVs are strongly represented in executive and SUV segments (E and J) and are overwhelmingly concentrated in the wagon category. ICEVs are more evenly distributed across both car classes and body types. EVs are also heavier on average than ICEVs.

Geographically, BEV and PHEV registered users are somewhat more urban than ICEV registered users, and BEV registered users in particular have the highest share of detached houses (77%). BEV and PHEV registered users also tend to have higher income and higher levels of tertiary education. ICEV registered users are more likely to be female, single, and living in apartments, and they exhibit lower commuting distances and employment rates.

Overall, the register data indicate that BEV and PHEV users differ from ICEV owners in both car fleet characteristics and socio-demographic profiles of the registered users.

Table 2
Descriptive statistics GPS Data.

Powertrain	***BEV***		***PHEV***		***ICEV***	
	mean	sd	mean	sd	mean	sd
	(1)	(2)	(3)	(4)	(5)	(6)
Logged travel days	105.09	69.22	102.00	71.54	113.72	72.59
Daily VKT	54.09	30.20	45.76	26.83	48.48	28.24
Powertrain-specific daily VKT based on the most recently acquired car	46.70	28.53	37.31	24.22	42.50	27.25
Daily VKT – commuting trips	10.46	12.72	6.81	8.65	8.12	16.12
Daily VKT – non-commuting trips	43.32	25.86	38.76	22.85	38.17	20.54
Trip frequency per day – all modes	5.96	2.06	5.52	1.91	5.80	1.92
Daily VTF	2.77	1.48	2.64	1.41	2.80	1.62
Daily VTF – short trips (max 5 km)	0.88	0.80	0.96	0.88	0.90	0.80
No. of cars in the household	1.43	0.50	1.34	0.47	1.42	0.50
Leasing at least one car (share)	0.45		0.44		0.40	
1-car households (share)	0.57		0.66		0.58	
2-car households – same powertrain (share)	0.15		0.08		0.27	
2-car households – mixed powertrain (share)	0.28		0.26		0.16	
Car age (based on model year)	0.83	0.79	0.96	0.78	2.04	3.26
Car class A: Mini (share)	0.01		0.00		0.07	
Car class B: Small (share)	0.12		0.03		0.31	
Car class C: Compact (share)	0.47		0.61		0.46	
Car class D: Mid-size (share)	0.34		0.28		0.09	
Car class E: Executive (share)	0.04		0.06		0.02	
Car class F: Luxury (share)	0.00		0.00		0.01	
Car class J: SUV (share)	0.02		0.01		0.02	
Car class M: MPV (share)	0.01		0.01		0.01	
Car class S: Sports (share)	–		–		–	
Distance to nearest public charging point (km)	2.09	3.07	1.56	2.05	1.92	2.76
Commuting distance	26.58	42.54	28.12	48.07	21.92	24.95
City/urban area (share)	0.74		0.77		0.73	
Suburban area/small town (share)	0.10		0.14		0.12	
Rural area (share)	0.17		0.10		0.16	
Detached house (share)	0.73		0.72		0.61	
Apartment	0.27		0.28		0.39	
Female (share)	0.20		0.20		0.42	
Age	56.21	13.27	59.46	13.05	57.48	13.00
Single (share)	0.16		0.17		0.22	
Children in the household (share)	0.38		0.32		0.22	
Less than tertiary schooling (share)	0.26		0.25		0.35	
University up to 3 years (share)	0.21		0.26		0.23	
University more than 3 years (share)	0.53		0.50		0.42	
Household income < 20 000 SEK (share)	0.01		0.00		0.02	
Household income 20 000 – 40 000 SEK (share)	0.08		0.07		0.11	
Household income 40 001 – 70 000 SEK (share)	0.27		0.35		0.50	
Household income 70 001 –100 000 SEK (share)	0.32		0.35		0.26	
Household income 100 001 – 150 000 SEK (share)	0.27		0.17		0.10	
Household income > 150 000 SEK (share)	0.05		0.06		0.02	
Employed (share)	0.66		0.57		0.66	
Student (share)	0.01		0.00		0.00	
Unemployed/not working (share)	0.01		0.01		0.01	
Retired (share)	0.31		0.40		0.31	
Sample size	*410*		*243*		*109*	
Number of logged days	*43,088*		*24,787*		*12,396*	
Number of logged trips	*186,408*		*97,889*		*54,438*	

Table 2 reports descriptive statistics for the GPS-based sample. Columns 1, 3, and 5 present means, while columns 2, 4, and 6 report standard deviations. For variables originally measured at the trip or daily level, statistics are based on individual-level averages. Daily VKT by commuting and non-commuting trips, as well as commuting distance, is computed only for employed individuals. Car class information is available only for a subsample of the respondents.

Turning to the GPS-based data and daily car use, differences across powertrains are smaller than in the register-based sample. BEV users record slightly higher total daily VKT (54 km) than ICEV users (48 km), and across all three groups about 85% of average daily VKT is attributed to powertrain-specific car travel associated with the most recently acquired car.

Figs. 2 and 3 show that the distributions of individual average daily VKT and VTF overlap substantially across powertrains, although BEV users exhibit somewhat higher upper-tail daily VKT values. Decomposing daily VKT into commuting and non-commuting travel among employed individuals reveals that BEV users drive more for both purposes. Average daily commuting VKT amounts to 10.5 km for BEV users, compared with 8.1 km for ICEV users and 6.8 km for PHEV users, while non-commuting travel constitutes the dominant share of daily driving. At the same time, the overall level of daily driving in the GPS sample is relatively high: a simple scaling of average daily VKT corresponds to annual driving distances on the order of 17,000 to nearly 20,000 km. This

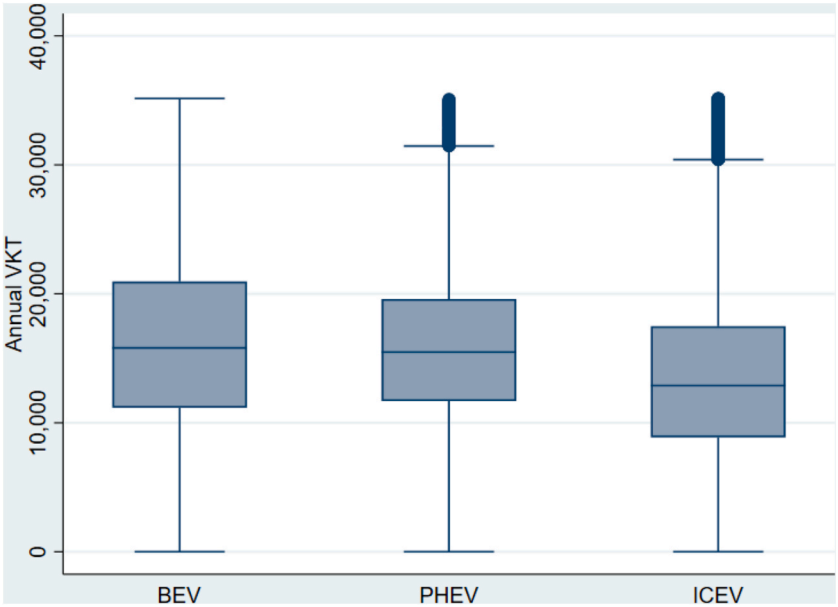

Fig. 1. Distribution of annual VKT by powertrain (register data).

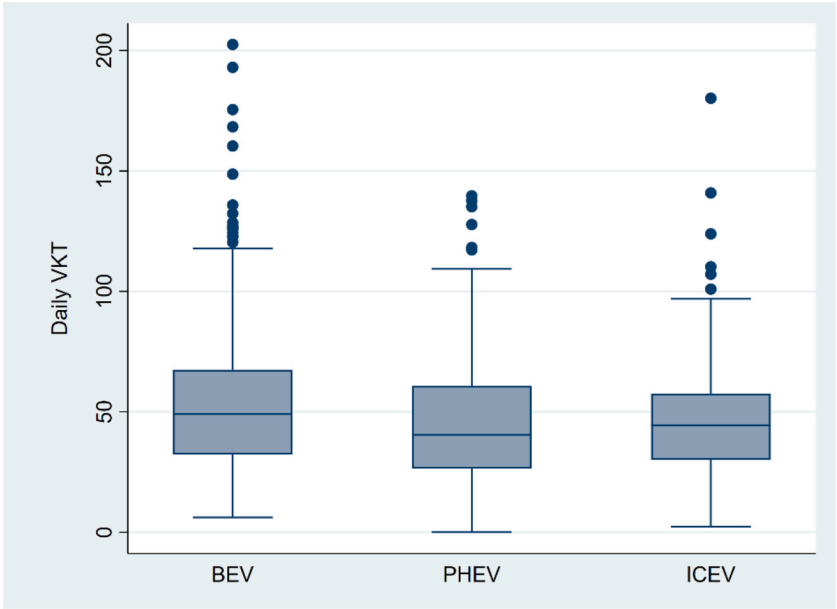

Fig. 2. Distribution of individual average daily VKT by powertrain (GPS data).

suggests that the GPS sample may represent a group of comparatively high-intensity car users, even though cross-powertrain differences in daily use are more modest than in the register-based data.

Daily VTF is highly similar across powertrains—around 2.7–2.8 car trips per day—and total daily mobility across all modes (roughly six trips per day) does not vary meaningfully across users of different powertrains.

EVs in the GPS sample are substantially newer than in the register data (mean car age below one year for both BEVs and PHEVs), and car-class distributions differ accordingly: all three powertrain groups are primarily concentrated in the small, compact, and mid-size car classes. Sociodemographic patterns largely mirror those in Table 1—BEV and PHEV users have higher levels of education, higher incomes, and are more likely to live in detached houses, whereas ICEV users are more likely to live in apartments and have lower incomes. Female representation is also lower among BEV and PHEV users (around 20%) than among ICEV users (42%).

In contrast to BEV users, PHEV users record lower daily VKT (46 km) than ICEV users. On average, PHEV users are also older than

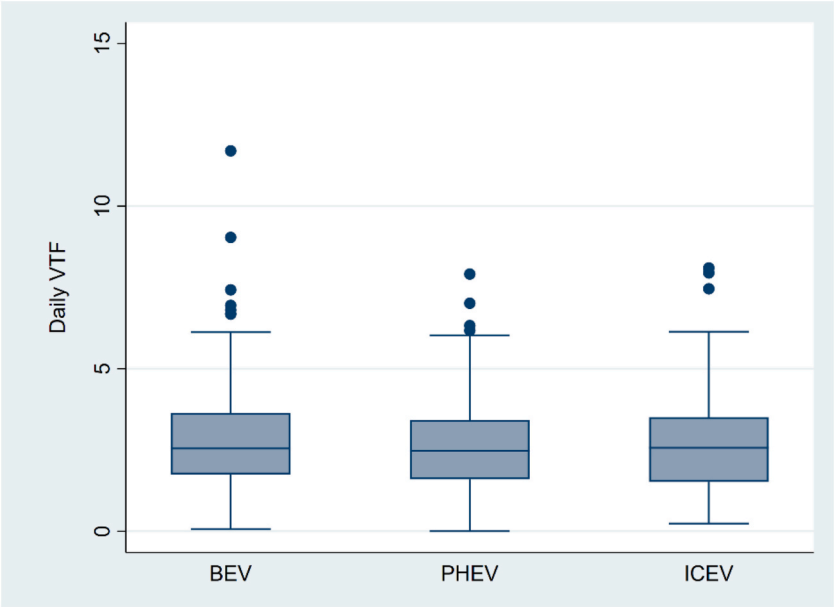

Fig. 3. Distribution of individual average daily VTF by powertrain (GPS data).

both BEV and ICEV users, and older than PHEV users in the register-based sample. This is reflected in the higher share of retirees among PHEV users (around 40%), compared with roughly 30% among BEV and ICEV users. The higher age and retirement share among PHEV users may help explain their lower unconditional daily VKT levels, as older individuals and retirees typically have different mobility needs and fewer obligatory trips.

Comparing Tables 1 and 2, the GPS-based sample broadly resembles the register-based sample in terms of age composition, household structure, residential location, and housing type. However, cars in the GPS sample are substantially newer and somewhat more concentrated in compact and mid-size car classes, while participants tend to have slightly higher levels of education and income. These differences likely reflect both the recruitment criteria and the voluntary nature of participation and may contribute to the smaller observed differences in daily car use across powertrains. Finally, neither sample is intended to be representative of the full population of car owners or car users, as the analysis focuses on relatively new cars and on a subset of powertrains.

5. Results

5.1. Results from Register-Based Analysis of Annual VKT

Table 3 reports OLS and PSM estimates of the differences in annual VKT between privately owned BEVs, PHEVs, and ICEVs in 2023. PSM diagnostics tests (covariate balance before and after matching and propensity score distributions) are reported in Appendix Tables A.1–A.2 and Figs. A.1–A.2. Across specifications, BEVs and PHEVs are consistently driven more than comparable ICEVs, whereas the results for PHEVs are smaller and more sensitive to model specification.

In the baseline specification (column 1), BEVs are driven approximately 2,210 km more per year than ICEVs, while PHEVs are driven around 1,704 km more. Lagged VKT is positive (0.323) and statistically significant, indicating persistence in driving behavior over time. However, the estimated coefficient is substantially smaller than the BEV–ICEV difference, suggesting that pre-existing differences in mobility demand cannot fully explain the observed gap. Adding individual, household and geographic controls (column 2) reduces the estimated differences in annual VKT to 1,793 km for BEVs and 1,486 for PHEVs, indicating that part of the unconditional differences reflects systematic variation in observable characteristics across powertrain groups.

Including European standard car-class dummies (column 3) increases the estimated BEV–ICEV difference to 2,286 km, while the PHEV–ICEV difference declines to 1,151 km. The increase in the BEV estimate after controlling for car class suggests that differences in car-segment composition mask part of the association between BEV ownership and annual VKT. Conditional on belonging to the same car class, BEVs are driven substantially farther than comparable ICEVs. For PHEVs, by contrast, the estimated difference decreases after controlling for car class, indicating that part of the higher annual VKT among PHEVs reflects their concentration in car segments that are typically driven longer distances.

Replacing the baseline specification with body-type indicators, our preferred specification (column 4), leaves the estimated BEV–ICEV difference virtually unchanged (1,746 km versus 1,793 km in column 2) but reduces the estimated PHEV–ICEV difference to 1,094 km. This suggests that differences in body type account for a larger share of the observed PHEV–ICEV differences than of the corresponding BEV–ICEV differences.

Finally, controlling flexibly for continuous measures of car length and width (column 5) results in estimated differences of 2,084 km

Table 3
OLS and Propensity Score Matching Estimates of Annual VKT using Register Data.

	OLS base specification	OLS extended specification	OLS extended specification	OLS extended specification	OLS extended specification	PSM BEV	PSM PHEV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
BEV	2,209.948***	1,792.766***	2,285.918***	1,745.961***	2,083.755***	2,403.743***	
	(97.870)	(114.390)	(111.746)	(114.203)	(111.661)	(172.757)	
PHEV	1,703.934***	1,486.298***	1,151.131***	1,093.575***	796.123***		548.748***
	(58.346)	(65.728)	(65.593)	(65.957)	(65.916)		(96.972)
Number of cars in the household	203.634***	−51.378	30.824	30.745	–22.588		
	(38.209)	(38.986)	(38.042)	(38.438)	(38.027)		
Prior car owner	−4,694.227***	−3,750.906***	−3,573.851***	−3,637.008***	−3,529.603***		
	(84.902)	(86.138)	(83.659)	(84.733)	(83.549)		
Lagged VKT*prior car owner	0.323***	0.294***	0.274***	0.283***	0.271***		
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)		
Prior plug-in car ownership	159.942	18.107	47.821	113.526	−64.535		
	(179.338)	(178.095)	(172.437)	(174.285)	(172.957)		
Car length					−7.773		
					(27.878)		
Car length^2					0.059*		
					(0.031)		
Car width					644.707***		
					(201.328)		
Car width^2					−1.701***		
					(0.550)		
Female	−844.581***	−749.388***	−246.348***	−569.487***	−146.003***		
	(44.955)	(46.638)	(46.466)	(46.453)	(46.465)		
Age		93.142***	100.419***	98.835***	97.196***		
		(11.045)	(10.828)	(10.941)	(10.820)		
Age^2		−1.711***	−1.682***	−1.729***	−1.623***		
		(0.098)	(0.096)	(0.097)	(0.096)		
Single		−557.100***	−216.027***	−358.598***	−208.949***		
		(50.539)	(49.973)	(50.200)	(49.949)		
Children		−448.987***	−536.487***	−492.242***	−606.502***		
		(65.163)	(63.644)	(64.289)	(63.636)		
Detached house		236.345***	3.687	127.996***	−28.917		
		(49.313)	(48.606)	(48.923)	(48.580)		
Secondary education		35.529	66.116	54.539	57.946		
		(70.617)	(69.507)	(69.953)	(69.579)		
Tertiary education		155.724*	174.903**	166.259**	162.347**		
		(79.793)	(78.383)	(78.901)	(78.469)		
Income Q2		268.101***	310.017***	272.999***	349.407***		
		(98.926)	(96.770)	(97.985)	(96.701)		
Income Q3		921.412***	777.292***	823.652***	817.245***		
		(101.133)	(98.870)	(100.053)	(98.801)		
Income Q4		1,602.689***	1,224.764***	1,415.424***	1,171.725***		
		(102.967)	(100.840)	(101.963)	(100.837)		
Suburban area/small town	1,242.051***	1,352.464***	1,372.810***	1,380.999***	1,388.018***		
	(71.518)	(79.125)	(77.233)	(77.730)	(77.210)		
Rural area	2,033.969***	2,205.121***	2,152.775***	2,181.045***	2,171.302***		
	(66.332)	(75.591)	(73.890)	(74.569)	(73.755)		

(*continued on next page*)

Table 3 (*continued*)

	OLS base specification	OLS extended specification	OLS extended specification	OLS extended specification	OLS extended specification	PSM BEV	PSM PHEV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Suburban area/small town*BEV		−197.664	−60.360	−174.236	−2.567		
		(291.599)	(283.693)	(287.100)	(283.279)		
Suburban area/small town*PHEV		−248.184	−221.453	−254.367	−189.674		
		(185.025)	(183.590)	(184.235)	(182.744)		
Rural area*BEV		95.218	537.225**	358.900	644.074***		
		(249.954)	(243.342)	(246.845)	(244.331)		
Rural area*PHEV		−596.327***	−444.020***	−526.562***	−457.575***		
		(167.192)	(165.337)	(166.332)	(165.281)		
Employed	2,001.229***	−314.470***	−121.616*	−226.932***	−93.847		
	(45.626)	(63.409)	(62.133)	(62.567)	(62.060)		
Employed*commuting distance	5.783***	5.505***	5.340***	5.428***	5.303***		
	(0.457)	(0.453)	(0.439)	(0.442)	(0.443)		
Constant	11,904.373***	12,756.724***	8,283.982***	13,309.475***	−57,036.335***		
	(92.364)	(316.301)	(333.850)	(329.604)	(13,499.213)		
Car class (EU standard) dummies	No	No	Yes	No	No		
Car body type dummies	No	No	No	Yes	No		
Number of observations	*91,499*	*91,499*	*91,499*	*91,499*	*91,499*	*13,634*	*28, 164*

Table 3 reports OLS and propensity score matching (PSM) estimates of annual vehicle kilometers traveled (VKT) in 2023 based on register data. Specification 1 includes the baseline covariates. Specification 2 adds extended individual and household controls. Specification 3 adds European standard car-class dummies. Specification 4 instead includes body-type dummies. Specification 5 includes continuous measures of car length and width, including quadratic terms. Specifications 6 and 7 report PSM estimates based on matched comparisons of observationally similar BEV/PHEV and ICEV users. The BEV matching sample consists of 6,817 treated and 6,817 matched control observations, while the PHEV matching sample consists of 14,082 treated and 14,082 matched control observations. All specifications include county and vehicle model-year dummies. Robust standard errors are reported in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

and 796 km, respectively. Taken together, these results suggest that differences in car characteristics explain part of the observed annual VKT differences, particularly for PHEVs, but do not eliminate the substantial difference between BEVs and ICEVs.

The interaction terms with residential location indicate that the relationship between powertrain and annual VKT varies across

Table 4
Average Marginal Effects from Two-Part Model of Daily VKT.

	Specification 1		**Specification 2**		**Specification 3**		**Specification 4**	
	All	Single powertrain	All	Single powertrain	All	Single powertrain	All	Single powertrain
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
BEV	4.069*	5.819**	3.456	4.823**	1.666	3.739	1.762	3.803
	(2.445)	(2.552)	(2.352)	(2.435)	(2.893)	(3.501)	(2.939)	(3.548)
PHEV	−1.329	−0.434	−0.604	0.037	0.382	3.237	0.516	3.043
	(2.565)	(2.729)	(2.475)	(2.670)	(3.032)	(3.779)	(3.041)	(3.823)
Second car	11.766***	13.426***	10.209***	11.752***	7.028***	11.090***	7.417***	10.871***
	(2.162)	(3.323)	(2.036)	(3.171)	(2.371)	(3.742)	(2.304)	(3.558)
Second car BEV	7.809**		6.332*		6.489		6.297	
	(3.685)		(3.408)		(4.189)		(4.378)	
Second car PHEV	12.245***		10.594**		14.603***		12.899**	
	(4.515)		(4.350)		(5.260)		(5.276)	
Leasing	−2.742	−2.928	−4.602***	−4.556**	−3.537	−3.678	−3.649	−4.214
	(1.699)	(1.934)	(1.675)	(1.926)	(2.294)	(2.888)	(2.366)	(2.971)
Female	−5.398**	−4.399*	−8.585***	−7.858***	−9.578***	−7.651**	−9.715***	−6.828**
	(2.136)	(2.458)	(2.063)	(2.395)	(2.810)	(3.416)	(2.863)	(3.270)
Age			1.071*	0.736	1.097*	0.610	1.180*	0.824
			(0.591)	(0.616)	(0.648)	(0.726)	(0.678)	(0.764)
Age^2			−0.014**	−0.010	−0.013**	−0.007	−0.014**	−0.009
			(0.006)	(0.006)	(0.006)	(0.007)	(0.006)	(0.007)
Children			−6.996***	−8.355***	−4.371	−6.936*	−4.403	−7.025**
			(2.382)	(2.683)	(2.962)	(3.565)	(2.995)	(3.502)
Single			3.890	3.368	4.352	4.759	4.466	5.014
			(2.493)	(2.497)	(3.248)	(3.312)	(3.185)	(3.289)
Apartment			−2.491	−3.503	−1.342	−2.975	−1.026	−2.600
			(2.363)	(2.469)	(3.191)	(3.359)	(3.141)	(3.248)
University up to 3 yrs			−3.422	−3.370	−2.503	−2.561	−2.720	−3.036
			(2.372)	(2.625)	(2.904)	(3.207)	(2.919)	(3.153)
University more than 3 yrs			−2.023	−0.099	−4.095	−1.183	−3.803	−1.586
			(2.256)	(2.544)	(2.684)	(3.059)	(2.607)	(2.944)
Employed/working			1.035	3.425	4.318	7.841	3.989	6.847
			(3.731)	(4.159)	(4.054)	(5.149)	(4.017)	(5.032)
Income 20 000 – 40 000 SEK			−3.646	−5.134	−15.781	−15.569	−16.301	−16.462
			(5.549)	(6.615)	(11.241)	(11.773)	(10.386)	(10.752)
Income 40 001 – 70 000 SEK			4.359	2.867	−8.577	−8.601	−8.803	−9.274
			(5.438)	(6.606)	(11.122)	(11.623)	(10.229)	(10.595)
Income 70 001 –100 000 SEK			4.012	2.401	−7.236	−6.112	−7.572	−6.641
			(5.966)	(7.284)	(11.394)	(12.036)	(10.485)	(10.990)
Income 100 001 – 150 000 SEK			6.257	4.410	−5.268	−6.472	−5.026	−6.245
			(6.155)	(7.462)	(11.611)	(12.335)	(10.733)	(11.358)
Income > 150 000 SEK			6.957	6.518	1.156	0.812	0.851	0.312
			(7.634)	(9.461)	(12.847)	(13.932)	(12.199)	(13.239)
Suburban area/small town	6.802**	6.703*	6.641**	6.557*	6.831*	10.194**	7.886**	10.606**
	(2.755)	(3.549)	(2.700)	(3.505)	(3.507)	(4.821)	(3.622)	(4.852)
Rural area	9.051***	7.021*	10.164***	7.611**	15.339***	14.347***	15.459***	14.056***
	(2.971)	(3.729)	(3.077)	(3.760)	(3.987)	(4.816)	(3.868)	(4.441)
Weekend	4.413***	5.944***	4.021***	5.388***	2.353	3.058	2.351	3.030
	(1.376)	(1.448)	(1.374)	(1.457)	(1.884)	(2.077)	(1.882)	(2.060)
Innovation stage dummies	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	*80,271*	*57,743*	*80,271*	*57,743*	*51,350*	*36,520*	*51,350*	*36,520*

Table 4 reports average marginal effects from a two-part model of daily vehicle kilometers traveled (VKT), estimated using GPS data. Specification 1 includes only the base covariates and Specification 2 adds extended controls. Specification 3 additionally includes dummies for the car class (European standard) of the most recently acquired car, while Specification 4 further adds dummies for the car class of the previously owned car. All specifications are weighted by the number of validated travel days and powertrain group size and include month dummies. Standard errors are clustered at the individual level. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

geographic contexts. For BEVs, the estimated difference relative to ICEVs tends to be larger in rural areas, although the magnitude and statistical significance vary across specifications. By contrast, the rural interaction term for PHEVs is consistently negative and statistically significant, indicating that the PHEV–ICEV difference is substantially smaller outside urban areas.

As an alternative modelling approach, we use propensity score matching (PSM) to compare annual driving distances across samples with improved covariate balance (Table 3, columns 6–7). The matching procedure substantially improved covariate balance, with post-matching standardized differences generally below 0.10 for the included covariates (Appendix Tables A.1–A.2). The estimated propensity score distributions indicate adequate common support between treated and control groups (Appendix Figs. A.1–A.2). The matched estimates indicate that BEV users drive approximately 2,404 km more per year than observationally similar ICEV users. For PHEVs, the estimated difference is smaller but remains positive and statistically significant at approximately 549 km per year.

Table 5
Hurdle Model Results of Daily VTF.

	All		**Single Powertrain**	
	Zero Hurdle	Count Hurdle	Zero Hurdle	Count Hurdle
	(1)	(2)	(3)	(4)
BEV	−0.023	−0.064	−0.020	−0.090*
	(0.091)	(0.040)	(0.112)	(0.052)
PHEV	−0.034	−0.033	0.014	−0.041
	(0.083)	(0.037)	(0.098)	(0.045)
Second car	0.464***	−0.020	0.539***	−0.067*
	(0.073)	(0.026)	(0.106)	(0.036)
Second car BEV	0.185	0.040		
	(0.126)	(0.044)		
Second car PHEV	0.266**	0.045		
	(0.132)	(0.065)		
Leasing	−0.075	−0.025	−0.110	−0.040
	(0.064)	(0.025)	(0.080)	(0.032)
Female	−0.106	−0.077**	−0.046	−0.061*
	(0.078)	(0.032)	(0.092)	(0.036)
Age	−0.040*	0.010	−0.056**	0.016**
	(0.022)	(0.007)	(0.024)	(0.008)
Age^2	0.000	−0.000*	0.000**	−0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
Children	0.016	0.053	0.007	0.046
	(0.093)	(0.035)	(0.107)	(0.040)
Single	0.297***	0.064	0.306***	0.050
	(0.114)	(0.053)	(0.116)	(0.052)
Apartment	−0.472***	−0.114***	−0.518***	−0.119***
	(0.079)	(0.032)	(0.086)	(0.035)
University up to 3 yrs	−0.006	0.041	0.060	0.048
	(0.087)	(0.035)	(0.105)	(0.045)
University more than 3 yrs	−0.167**	−0.003	−0.101	0.016
	(0.077)	(0.032)	(0.092)	(0.040)
Employed/working	0.255**	−0.066	0.262**	−0.043
	(0.111)	(0.054)	(0.130)	(0.063)
Income 20 000 – 40 000 SEK	0.171	−0.060	0.102	−0.044
	(0.188)	(0.120)	(0.216)	(0.124)
Income 40 001 – 70 000 SEK	0.363*	−0.003	0.324	0.009
	(0.190)	(0.123)	(0.222)	(0.130)
Income 70 001 –100 000 SEK	0.255	−0.016	0.150	−0.028
	(0.208)	(0.130)	(0.249)	(0.141)
Income 100 001 – 150 000 SEK	0.074	0.020	−0.034	0.058
	(0.222)	(0.135)	(0.267)	(0.147)
Income > 150 000 SEK	−0.002	−0.028	−0.003	0.022
	(0.240)	(0.155)	(0.295)	(0.179)
Suburban area/small town	−0.102	0.059	−0.194	0.027
	(0.103)	(0.051)	(0.136)	(0.071)
Rural area	−0.025	0.008	−0.108	−0.011
	(0.101)	(0.040)	(0.131)	(0.053)
Weekend	−0.130***	−0.078***	−0.068	−0.091***
	(0.042)	(0.017)	(0.048)	(0.020)
Constant	1.204*	1.490***	1.100	1.278***
	(0.670)	(0.239)	(0.723)	(0.245)
Innovation stage dummies	Yes	Yes	Yes	Yes
Number of observations	*80,271*	*41,911*	*57,743*	*28,473*

Table 5 reports the results from hurdle models estimating daily vehicle trip frequency (VTF). The zero-hurdle component is a logit model predicting the probability of making any car trip, and the count-hurdle component is a negative binomial model predicting the number of trips conditional on making at least one. All specifications are weighted by the number of validated travel days and powertrain group size and includes month dummies. Standard errors are clustered at the individual level. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Overall, the register-based analysis shows that both BEVs and PHEVs are driven farther on an annual basis than comparable ICEVs, although the differences are consistently larger for BEVs. Estimated BEV–ICEV differences range from roughly 1,750 to 2,400 km per year across specifications, while corresponding PHEV–ICEV differences range from about 550 to 1,700 km. Controlling for individual,

Table 6
Estimated Average Marginal Effects Across Powertrains for Different Dimensions of Car Use.

Outcome variable	*trip length*	*long distance trip*	*rush hour trip*	*daily VKT*	*daily VKT*
Estimation model	pooled OLS	logit	logit	two-part model	two-part model
	(1)	(2)	(3)	(4)	(5)
BEV	2.180**	0.006	0.043**	5.764**	2.903
	(0.925)	(0.004)	(0.021)	(2.642)	(2.859)
PHEV	1.340	0.008**	0.036	0.516	−3.111
	(0.980)	(0.003)	(0.024)	(2.866)	(3.044)
Second car	2.815**	0.008*	0.051**	11.136***	11.720***
	(1.287)	(0.004)	(0.022)	(3.143)	(3.170)
Leasing	−0.767	−0.000	0.015	−4.567**	−4.567**
	(0.726)	(0.003)	(0.017)	(1.919)	(1.928)
Female	−2.646***	−0.013***	0.033	−7.247***	−7.835***
	(0.936)	(0.004)	(0.022)	(2.376)	(2.395)
Age	0.347	0.002**	0.008	0.703	0.729
	(0.243)	(0.001)	(0.007)	(0.635)	(0.616)
Age^2	−0.004	−0.000**	−0.000	−0.009	−0.010
	(0.003)	(0.000)	(0.000)	(0.006)	(0.006)
Children	−5.145***	−0.013***	0.039	−8.379***	−8.439***
	(1.072)	(0.004)	(0.024)	(2.663)	(2.687)
Single	−1.005	−0.001	0.038	3.171	3.308
	(0.898)	(0.003)	(0.025)	(2.492)	(2.500)
Apartment	2.912***	0.012***	−0.010	−3.437	−3.525
	(1.067)	(0.004)	(0.021)	(2.436)	(2.468)
University up to 3 yrs	−1.895*	−0.009**	−0.000	−2.999	−3.358
	(0.999)	(0.004)	(0.024)	(2.610)	(2.626)
University more than 3 yrs	0.805	−0.000	0.006	0.203	−0.069
	(1.017)	(0.003)	(0.022)	(2.541)	(2.544)
Employed/working	0.097	−0.006	0.168***	3.548	3.374
	(1.847)	(0.006)	(0.026)	(4.206)	(4.160)
Income 20 000 – 40 000 SEK	−1.785	−0.003	0.062	−4.093	−5.160
	(3.014)	(0.010)	(0.047)	(6.762)	(6.623)
Income 40 001 – 70 000 SEK	−0.524	−0.001	0.066	4.253	2.834
	(2.929)	(0.009)	(0.046)	(6.797)	(6.614)
Income 70 001 –100 000 SEK	0.575	0.005	0.059	3.430	2.357
	(3.138)	(0.010)	(0.049)	(7.373)	(7.288)
Income 100 001 – 150 000 SEK	0.949	0.007	0.016	5.425	4.370
	(3.182)	(0.010)	(0.054)	(7.585)	(7.468)
Income > 150 000 SEK	2.133	0.012	0.014	7.565	6.528
	(3.461)	(0.011)	(0.063)	(9.537)	(9.479)
Suburban area/small town	3.819**	0.010**	−0.014	2.324	6.507*
	(1.517)	(0.005)	(0.024)	(6.543)	(3.504)
Rural area	4.164***	0.009	0.018	14.469**	7.602**
	(1.598)	(0.007)	(0.025)	(7.338)	(3.765)
Suburban area/small town*BEV				5.025	
				(8.047)	
Suburban area/small town*PHEV				7.821	
				(8.778)	
Rural area*BEV				−9.956	
				(7.619)	
Rural area*PHEV				−12.453	
				(8.621)	
Weekend	4.197***	0.009***		5.354***	−0.608
	(0.587)	(0.002)		(1.455)	(3.245)
Weekend*BEV					6.648*
					(3.641)
Weekend*PHEV					10.698***
					(3.978)
Innovation stage dummies	Yes	Yes	Yes	Yes	Yes
Month dummies	Yes	Yes	Yes	Yes	Yes
Number of observations	*134,918*	*134,918*	*97,255*	*57,743*	*57,743*

Table 6 reports estimated coefficients for different dimensions of daily car use, comparing driving behavior across powertrains for individuals in single powertrain households (GPS data). All models are weighted by the number of validated travel days and powertrain group size. Standard errors are clustered at the individual level. Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

household, and car characteristics attenuates the estimated gaps but does not eliminate them, suggesting that observable differences explain only part of the higher annual VKT among EV users.

5.2. Results from GPS-Based Analysis of Daily VKT and VTF

Table 4 reports average marginal effects from two-part model estimations of daily VKT using the GPS data (first- and second-stage estimates are reported in Appendix Tables A.3–A.4). These results should be interpreted with some caution given the relatively small number of ICEV users in the GPS sample.

Consistent with the register-based results at the car level (Section 5.1), BEV users tend to travel more kilometers per day by car than ICEV users, although the magnitude and statistical significance of this gap depend on the model specification. In the baseline specification (Specification 1), BEV users travel 4.1 km more by car per day than comparable ICEV users, a difference that increases to 5.8 km among single-powertrain households. For comparability, a simple scaling of this daily difference implies an annual VKT gap of roughly 1,500–2,100 km which lies within the range of BEV–ICEV differences observed in the register-based analysis (approximately 1,750 km in our preferred specification). Thus, the GPS-based estimates are broadly consistent in magnitude with the register results, although not directly comparable.

Once extended sociodemographic controls and car class are added (Specifications 2–4), the BEV–ICEV daily VKT gap becomes smaller and loses statistical significance in the full sample. In the single-powertrain sample, the gap decreases only modestly and remains statistically significant in Specification (2). When controls for both the car class of the most recently acquired car and the car class of the previously owned car are included (Specifications 3–4), the estimated BEV–ICEV gap in daily VKT diminishes further and becomes statistically insignificant. This pattern suggests that differences in car class and pre-existing travel needs and preferences account for part of the observed VKT gap. It should, however, be noted that the loss of statistical significance in the extended models may also partly reflect the smaller sample sizes and lower within-individual variation in the GPS data. As a robustness check, we re-estimated Specifications 1–2 using the smaller sample available for Specifications 3–4. The BEV estimates remained very similar (1.753 and 1.729, respectively), suggesting that the reduction in the estimated BEV–ICEV gap is not driven by the change in estimation sample.

Additional insights emerge from the decomposition of the two-part model (Appendix Tables A.3–A.4). The first-stage logit results show no statistically significant differences in the likelihood of making any car trip across powertrain types in any specification. This indicates that BEV and PHEV users are neither more nor less likely than ICEV users to record a positive-travel day. Accordingly, the differences reported in Table 4 primarily reflect variation on the intensive margin rather than the extensive margin. The second-stage linear models confirm this pattern. Conditional on using the car on a given day, BEV users tend to drive longer distances per day, with estimated BEV–ICEV gaps ranging from 4.5 to 8.6 km depending on specification—all statistically significant among single-powertrain households.

The results for PHEVs are less pronounced. In the baseline specification, the estimated PHEV–ICEV gap in daily VKT is small and negative, consistent with the unconditional mean differences. Across all specifications, however, the PHEV–ICEV estimates are statistically insignificant. This aligns with the register-based matching results, which also provide no robust evidence that PHEVs are driven more than comparable ICEVs once observable differences are accounted for.

Part of the unconditional PHEV–ICEV difference in the GPS data may reflect compositional factors. PHEV users in the GPS sample are, on average, older than both BEV and ICEV users and include a substantially higher share of retirees (around 40%, compared with roughly 30% in the other groups). Since retirees typically have fewer mandatory trips and lower overall mobility needs, demographic composition likely contributes to the negative unconditional PHEV–ICEV difference.

Table 5 presents the results from hurdle models of daily VTF, separating the probability of making any car trip (the zero hurdle) from the number of trips conditional on car use (the count hurdle). As in the first stage of the two-part model for daily VKT, there are no statistically significant differences in the probability of car use between EV and ICEV users (Table 5, columns 1 and 3). However, conditional on car use, BEV users make fewer trips, although the point estimates are small and only statistically significant at the 10% level in the single-powertrain sample (columns 2 and 4). A similar pattern emerges for the estimated difference between PHEV and ICEV users, although all point estimates are statistically insignificant.

Taken together, the VTF results suggest that EV users do not make more trips per day than ICEV users. Combined with the findings for daily VKT, this implies that the BEV–ICEV gap in VKT stems primarily from trip length rather than trip frequency. This reinforces the interpretation that behavioral adjustments associated with EV adoption relate more to how far people travel on days they use a car, rather than how often they travel.

5.3. Results from GPS-Based Analysis of Car Use Across Powertrains and Household Car-Fleet Composition

Table 6 presents the estimated average marginal effects of different dimensions of car use across powertrains: average trip length, the likelihood of making long-distance trips, and the likelihood of driving during peak hours (columns 1–3).

Across these outcomes, BEV users in single-powertrain households exhibit a pattern consistent with more intensive car use. First, BEV users record significantly longer average trip lengths (2.2 km) than comparable ICEV users, consistent with the intensive-margin results in Section 5.2. BEV users are also slightly more likely to undertake long-distance trips and to drive during rush hours. Although these differences are modest in absolute terms, particularly for long-distance trips where the estimates are less precisely estimated, the overall pattern points toward somewhat more distance-intensive travel behavior among BEV users. As a robustness check, Appendix Table A.5 reports estimates using the logarithm of trip length. The estimated BEV coefficient remains positive but becomes

smaller and less precisely estimated, suggesting that BEV–ICEV differences are somewhat more pronounced for longer trips than for shorter trips.

For PHEV users, the estimated differences relative to ICEV users are smaller and less robust. PHEV users take somewhat longer trips on average (1.3 km), though this estimate is not statistically significant. They are, however, marginally more likely to undertake long-distance trips, but the effect size remains small. Overall, the PHEV–ICEV differences in trip characteristics are weaker and less consistent than the corresponding BEV–ICEV differences.

Extending the daily VKT specification to include interactions between powertrain and residential location (column 4) reveals no statistically significant spatial heterogeneity in the BEV–ICEV gap. By contrast, interacting powertrain with weekend/holiday indicators shows that a substantial share of the EV–ICEV difference in daily VKT is concentrated on weekends. The difference between BEV and ICEV is approximately 6.6 km during weekends, and the corresponding weekend effect is even larger for PHEV users (10.7

Table 7
Average Marginal Effects from Logit Model Estimation of the Probability of Choosing the EV in Multi-car Households with Mixed Powertrains.

	Specification 1	**Specification 2**	**Specification 3**	**Specification 4**
	(1)	(2)	(3)	(4)
Trip length	−0.005	−0.007	−0.007	−0.003
	(0.006)	(0.005)	(0.005)	(0.006)
Non-commuting trip	0.087***	0.037**	0.041**	0.040**
	(0.028)	(0.018)	(0.018)	(0.018)
Rush hour			0.024*	
			(0.013)	
Long Trip				−0.079**
				(0.031)
Leasing	−0.047	−0.041	−0.040	−0.042
	(0.036)	(0.033)	(0.033)	(0.033)
Newest car is an EV	0.097*	0.090	0.089	0.089
	(0.055)	(0.059)	(0.059)	(0.059)
PHEV + ICEV household	−0.058	−0.052	−0.052	−0.052
	(0.044)	(0.042)	(0.042)	(0.042)
Female	−0.035	0.012	0.012	0.012
	(0.046)	(0.042)	(0.042)	(0.042)
Age		−0.004	−0.005	−0.004
		(0.011)	(0.011)	(0.011)
Age^2		0.000	0.000	0.000
		(0.000)	(0.000)	(0.000)
Children		−0.097	−0.097	−0.096
		(0.059)	(0.060)	(0.060)
Single		−0.072	−0.070	−0.071
		(0.086)	(0.087)	(0.086)
Apartment		−0.019	−0.019	−0.019
		(0.067)	(0.067)	(0.067)
University up to 3 yrs		−0.051	−0.052	−0.052
		(0.045)	(0.046)	(0.045)
University more than 3 yrs		−0.043	−0.044	−0.044
		(0.044)	(0.044)	(0.044)
Employed/working		−0.168**	−0.170**	−0.168**
		(0.072)	(0.072)	(0.072)
Income 20 000 – 40 000 SEK		−0.086	−0.092	−0.084
		(0.081)	(0.080)	(0.081)
Income 40 001 – 70 000 SEK		−0.015	−0.021	−0.015
		(0.062)	(0.062)	(0.062)
Income 70 001 –100 000 SEK		−0.024	−0.031	−0.022
		(0.071)	(0.071)	(0.071)
Income 100 001 – 150 000 SEK		0.024	0.019	0.027
		(0.049)	(0.049)	(0.049)
Income > 150 000 SEK		−0.075	−0.080	−0.072
		(0.068)	(0.068)	(0.068)
Suburban area/small town	−0.155***	−0.154***	−0.155***	−0.155***
	(0.054)	(0.054)	(0.053)	(0.053)
Rural area	0.020	0.017	0.017	0.015
	(0.045)	(0.046)	(0.046)	(0.046)
Weekend	−0.015	0.005	0.016	0.006
	(0.014)	(0.013)	(0.014)	(0.013)
Innovation stage dummies	Yes	Yes	Yes	Yes
Month dummies	Yes	Yes	Yes	Yes
Number of observations	*57,758*	*57,758*	*57,758*	*57,758*

Table 7 reports the average marginal effects from logit model estimation of EV choice in multi-car households with mixed powertrains (GPS data). Standard errors are clustered at the individual level. Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

km). This suggests that EV-related differences in driving behavior are more pronounced during discretionary travel periods.

Overall, the results in Table 6 reinforce the conclusion that BEV–ICEV differences operate primarily through trip length and timing rather than through higher trip frequency. BEV users in single-powertrain households tend to undertake longer trips and exhibit somewhat higher weekend driving intensity, whereas PHEV users show weaker and less consistent deviations from ICEV users.

Table 7 presents the average marginal effects from logit models of EV choice in multi-car households with mixed powertrains (either BEV+ICEV or PHEV+ICEV). Overall, the results show that EVs are more likely to be chosen for non-commuting trips and less likely to be chosen for long trips (≥100 km). While the coefficient on trip length is negative across all specifications, it is not statistically significant, indicating no clear linear association between trip distance (in kilometers) and EV use. However, when a dummy for long trip is included, EVs are significantly less likely to be selected for such trips.

Trip purpose appears to play an important role. EVs are more likely to be used for non-commuting trips across all specifications and during rush-hour periods (Specification 3). In contrast, the probability of choosing the EV is significantly lower for employed individuals and in suburban and small-town areas across all specifications. We find no systematic differences in the probability of choosing the EV between BEV+ICEV and PHEV+ICEV households.

Taken together, the comparison between single-powertrain and mixed-powertrain households highlights the importance of household car-fleet composition. In single-powertrain households, BEV users exhibit longer trips relative to ICEV users. In mixed-powertrain households, however, longer trips are disproportionately allocated to ICEVs, while EVs are more commonly used for non-commuting travel. This pattern suggests that part of the BEV–ICEV difference in single-powertrain households reflects underlying travel demand, whereas in mixed households, households actively sort trips by car capability. Additional analyses separating commuting and non-commuting travel in single-powertrain households do not reveal statistically significant differences in the VKT gap by trip purpose (results not shown), further underscoring that within-household allocation plays a central role in mixed fleets.

6. Discussion

We examine whether EV adoption is associated with differences in real-world driving demand. This paper contributes to the literature in three ways. First, by using population-wide register data at the car level alongside high-resolution GPS data at the individual level, we are able to compare annual VKT differences across powertrains with detailed patterns of daily travel behavior. Second, we provide evidence from a relatively mature EV market under contemporary technological conditions, reducing concerns that results reflect early-generation constraints. Third, by distinguishing between intensive and extensive margins of car travel—i.e., trip length and frequency conditional on car use, and the decision of whether to use a car on a given day—and between single- and mixed-powertrain households, we clarify the mechanisms through which electrification interacts with travel demand. The register data offer population-level external validity, while the GPS data allow us to identify whether differences reflect trip frequency, trip length, or timing.

Across specifications, the results show that BEVs are driven substantially farther annually than comparable ICEVs. In our preferred specification, which controls for car body type, BEVs are driven approximately 1,750 km (~13 %) more per year than comparable ICEVs, while the corresponding difference for PHEVs is approximately 1,100 km (~8%). The gap persists after conditioning on detailed sociodemographic characteristics, residential area, and car characteristics—including alternative controls for car class and physical size—and after matching on observables. These findings differ from much of the earlier literature, which often reported lower VKT among BEVs than among comparable ICEVs (see Zhang et al. (2026) for a recent review). One possible explanation is that many previous studies were conducted during earlier stages of EV diffusion, when vehicle range was more limited, charging infrastructure less developed, and EV adopters more selective. Our results also contrast with Zhang et al. (2025), who find no significant differences in VKT between BEVs and comparable ICEVs once observable characteristics are accounted for. Unlike Zhang et al., our estimates are not confounded by leasing or company-car use: the register sample includes only privately owned cars, while the GPS sample includes privately owned or leased cars and excludes business travel, thereby minimizing institutional influences on observed VKT.

For PHEVs, the register-based gap relative to ICEVs is smaller than for BEVs and more sensitive to the inclusion of car characteristics. While unconditional annual VKT is substantially higher for PHEVs than for ICEVs, the estimated difference declines when sociodemographic and car characteristics are included. Nevertheless, the estimated PHEV–ICEV difference remains positive across specifications, including the matched comparison. This suggests that compositional factors explain part of the observed difference, but may not account for it entirely. The pattern is consistent with PHEVs occupying an intermediate position in terms of operating costs and usage incentives.

The GPS-based results reinforce the register findings but clarify the underlying behavioral margins. BEV users drive longer distances per day, yet they do not make more trips per day than ICEV users. Once car class (including both the current and previously owned car) and user characteristics are included, the daily VKT gap becomes statistically insignificant in the full sample, indicating that selection into EV adoption accounts for part of the observed difference. However, in single-powertrain households, BEV users continue to exhibit longer average trip lengths, indicating that observable selection does not fully account for the pattern.

These findings have direct implications for the rebound-effect hypothesis. A pure direct rebound effect—operating through lower marginal cost per kilometer—would predict increased trip frequency. Consistent with Zhang et al. (2025), we find no evidence that EV users make more trips per day than comparable ICEV users. Instead, differences arise because EV users travel longer distances on days when they use the car. This pattern is consistent with an intensive-margin rebound mechanism. However, because the analyses do not identify causal effects of EV adoption, the observed differences may also reflect self-selection into adoption by individuals with higher underlying travel demand.

Moreover, the stronger and more persistent annual VKT gap for BEVs—compared with the weaker and specification-sensitive

results for PHEVs—aligns with theoretical expectations. The high share of detached housing in Sweden highly supports BEV charging at home (Mandev & Sprei, 2024), where electricity costs per kilometer are typically substantially lower than fuel costs for conventional cars. Under such conditions, BEVs combine lower marginal operating costs with stronger environmental signaling, potentially amplifying both direct rebound and moral-licensing mechanisms. However, the cost advantage is smaller for trips requiring fast charging, where charging prices may approach or even exceed the fuel costs of efficient ICEVs or PHEVs. PHEVs, by contrast, retain fuel-based marginal costs for a substantial share of driving and therefore provide weaker incentives for distance expansion.

Evidence from mixed-powertrain households further clarifies the mechanism. When households have access to both EVs and ICEVs, EVs are less likely to be used for distinctly long trips, while being more frequently chosen for non-commuting travel. For BEVs, this pattern may reflect charging considerations, range constraints, or the relatively high cost and inconvenience of fast charging during long-distance travel. For PHEVs, the hybrid drivetrain reduces many of these constraints, making them more flexible for long-distance use while still allowing lower operating costs during shorter trips driven in electric mode. More generally, the within-household allocation pattern suggests that car choice across trips continues to be shaped by differences in operating characteristics and travel suitability across powertrains. Household fleet composition therefore fundamentally conditions how powertrain differences manifest in observed travel behavior. Consequently, aggregate VKT differences across powertrains may partly reflect within-household allocation mechanisms rather than changes in total mobility demand. Ignoring household fleet composition may therefore lead to misleading conclusions regarding the relationship between electrification and travel demand.

Taken together, the results indicate that EV adoption in Sweden—a context characterized by relatively advanced electrification and charging infrastructure—is associated with higher VKT, particularly for BEVs. This difference appears partly driven by compositional factors and primarily manifests through longer trips rather than increased trip frequency. The findings therefore qualify simple rebound narratives: electrification may be associated with increased distance traveled, but the mechanism is more nuanced than a straightforward expansion of mobility demand. At the same time, a residual difference in VKT remains even after extensive controls and matching on observables. This remaining gap may reflect unobserved heterogeneity in travel demand—where high-mileage drivers are more likely to adopt BEVs—or behavioral adjustments following adoption. Disentangling these mechanisms requires longitudinal data and stronger causal identification strategies.

Several limitations remain. The register analysis is cross-sectional in annual VKT and does not observe individuals before and after powertrain transitions. The GPS data provide behavioral detail but are based on a voluntary sample and do not allow causal identification of post-adoption changes. Average daily VKT in the GPS sample is relatively high compared with population averages, suggesting that participants may represent more active drivers than the broader population. The GPS data may therefore be particularly informative regarding behavioral margins and travel patterns rather than population-average levels of car use. In addition, cars in the GPS sample are somewhat newer on average than those in the register sample, reflecting differences in the sampling windows across the two data sources. Consequently, some differences between the two analyses may reflect car-age-related factors, such as novelty effects, perceived reliability, or range confidence, rather than powertrain differences alone. In addition, the analysis excludes company and fringe-benefit cars, which account for a substantial share of new-car registrations in Sweden. The results should therefore primarily be interpreted as applying to privately owned or privately leased cars. Finally, the relatively small number of ICEV users in the GPS sample limits statistical power, particularly for detecting moderate differences in outcomes such as trip frequency. Future research using longitudinal designs that follow individuals across powertrain transitions would allow stronger identification of behavioral responses and clearer separation of selection from rebound effects.

7. Conclusions

This study examines whether EV adoption is associated with differences in real-world driving behavior in a mature electrification context. Using population-wide register data alongside high-resolution GPS travel diaries, we show that BEVs are driven farther annually than comparable ICEVs, even after extensive controls for user characteristics, residential context, and car characteristics. In our preferred specification, the BEV–ICEV gap corresponds to 13% higher annual VKT. Differences between PHEVs and ICEVs are consistently smaller but remain positive after controlling for observable user, household, and car characteristics.

The GPS-based analysis shows that differences in driving behavior between BEV and ICEV users operate primarily through trip length rather than trip frequency. BEV users do not make more trips per day than ICEV users; instead, they tend to drive farther on days when they use the car. This pattern qualifies simple rebound interpretations: lower marginal driving costs do not appear to generate additional trips, but may be associated with modest increases in distance traveled.

Our findings contribute to a growing literature suggesting that EV travel behavior may vary substantially across countries and stages of market development. Previous studies, many of which were conducted during earlier stages of EV adoption, have generally found that EVs, particularly BEVs, exhibit lower VKT than comparable ICEVs. In contrast, we find the opposite pattern in Sweden, a mature EV market with widespread charging access and high EV penetration. This suggests that travel behavior associated with EV ownership may evolve as markets mature and technological constraints become less important. Understanding these contextual differences remains an important task for future research.

Our results cannot fully disentangle whether the higher VKT observed among BEV users reflects selection—where individuals with higher underlying travel demand are more likely to adopt BEVs—or behavioral responses following adoption. While descriptive evidence suggests that pre-existing differences in mobility play a role, the persistence of a gap after extensive controls leaves open the possibility of rebound-type adjustments along the intensive margin. The results therefore document robust associations rather than causal effects of EV adoption on driving demand. Distinguishing between these mechanisms requires longitudinal data tracking the same individuals before and after powertrain transitions while observing both car ownership and realized travel behavior. Such data

would allow researchers to distinguish more clearly between self-selection into EV adoption and behavioral responses following adoption, as well as to examine how these mechanisms vary across household fleet compositions and travel context.

CRediT authorship contribution statement

Elisabeth Lång: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Emeli Adell:** Writing – review & editing, Writing – original draft, Validation, Supervision, Software, Resources, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Lena Winslott Hiselius:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization.

Declaration of competing interest

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

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Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

Statement: During the preparation of this work the author(s) used ChatGPT in order to improve language and readability of the manuscript. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the published article.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.trd.2026.105695.

Data availability

The authors do not have permission to share data.

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