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The impact of electric vehicle adoption on travel mode choices*

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Abstract

Electric vehicles (EVs) eliminate tailpipe emissions, but their lower marginal costs may stimulate additional car travel and a shift away from active and public transport. We examine how EV adoption affects travel behavior using trip-level data and administrative microdata on households and passenger cars in the Netherlands. To mitigate endogeneity concerns, we employ a quasi-experimental design comparing trips of EV users with those of car users who adopted an EV relatively soon after the survey, i.e. not-yet-adopters. EV adoption substantially increases car kilometers, but the size of the effect varies across space and over time. Car use rises especially on weekends and among urban households. We find no evidence for reduced cycling, walking, or public transport use, although estimates for public transport are imprecise due to low baseline usage. The additional car use by EVs may amplify accident, infrastructure, and congestion costs, underscoring the need for targeted policy action.

Keywords: Electric vehicles, mode substitution, household behavior, rebound effect
JEL codes: D12, R41, O18, Q55, L91

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1 Introduction

The transition from internal combustion engine vehicles (ICEVs) to battery electric vehicles (hereafter EVs) is widely expected to deliver substantial reductions in greenhouse gas emissions and air pollution, and is viewed as a key pillar of sustainable mobility. Road transport produces roughly 12% of global greenhouse gas emissions and remains one of the few sectors where emissions show no clear decline (IEA, 2025). In the European Union, passenger cars alone account for about 15% (EEA, 2025). Cars are also a major source of outdoor air pollution, which contributes to an estimated 4.2 million premature deaths annually (WHO, 2025). EVs eliminate tailpipe emissions and, when paired with a decarbonizing power sector, can substantially reduce road transport's environmental impact.

However, the electrification of the vehicle fleet addresses only part of the negative externalities of car use. Other negative externalities, predominantly traffic congestion, accidents, non-exhaust emissions, and infrastructure tear and wear depend on how much, when, and where people drive, regardless of fuel type.[1] Policy discussions on sustainable mobility are often structured along the "avoid–shift–improve" hierarchy (Creutzig et al., 2018), emphasizing trip reduction, shifts of trips to public and active transport, and improvements of vehicle energy efficiency. Current policy primarily targets the "improve" pillar, most notably through price incentives for EV adoption, and fuel economy and CO_2-emissions standards for cars.[2] While this reduces emissions, it does little to alleviate social costs from congestion, accidents, or infrastructure tear and wear—in fact, policies directed to energy efficiency improvements may even lead to an increase of these costs (Brockway et al., 2021; Hediger, 2023; Huwe and Gessner, 2020; Jochem et al., 2016). The cost of driving an additional kilometer in an EV is smaller than driving it in an ICEV and hence may induce a *rebound effect*, possibly exacerbated by the perception of EVs as environmentally benign (Chan and Gillingham, 2015; Gillingham et al., 2016; Sorrell and Dimitropoulos, 2008)[3]. Furthermore, EVs may displace public or active transport (*substitution effect*).

Gaining insights into substitution effects is crucial, as the social costs of extra driving depend on uninternalized costs and benefits of activities forgone for more driving time

[1] In the Netherlands, the external costs of passenger car traffic were estimated to be €28.7 billion in 2018 (Schroten et al., 2022), with traffic accidents (€10 bn), congestion (€8.1 bn), and infrastructure (€6.8 bn) being the largest components. The environmental and climate damages associated with CO_2 and air emissions, and noise, were estimated at €1.2 bn, €0.8, and €0.7 bn respectively.

[2] For example via EV purchase and lease subsidies, tax credits and exemptions, targeted incentives in company car taxation, and financial support for the roll-out of charging infrastructure. In the EU and elsewhere, instruments to promote EV adoption are combined with disincentives for ICEV purchase and use, including fuel excise duties, tightened emissions standards for car manufacturers, and the upcoming EU's new emissions trading system (ETS-2) which will cover CO_2 emissions from road transport.

[3] EVs are roughly three times as energy efficient as ICEVs, and cheaper to operate (Antweiler, 2025; NRDC, 2024).

(Borenstein, 2015). Active travel, such as cycling or walking, provides substantial health benefits, so shifts to car use entail relevant increases in external costs (van den Bijgaart et al., 2024; Woodcock et al., 2009). Shifts from public transport to EVs can reduce network efficiency and weaken returns on public transport investment. Previous studies show that substitution effects can be significant: Chitnis and Sorrell (2015) and Green and Østli (2025) find sizable substitution from public transport and active travel to car use due to fuel-efficiency gains and EV adoption respectively, while the removal of congestion pricing in Milan reduced cycling by 5–8% as car use became cheaper (Cornago et al., 2023).

In this paper, we examine whether EV adoption increases car travel and reduces cycling, walking, or public transport use. Using trip-level data from a comprehensive 2023 Dutch national travel survey linked with administrative data on personal, household, and vehicle characteristics, as well as car registrations from 2023–2025, we estimate the effects of EV adoption on travel distances and trip counts by mode. To mitigate confounding from unobserved factors, EV adopters—respondents with an EV at the time of the survey—are compared with "not-yet-adopters", i.e. ICEV users at the survey date who go on to adopt an EV shortly after the survey. Rich microdata allow us to control for numerous determinants of mode choice and distance traveled. The Dutch context is interesting and different from that studied in other papers. Mode choice is diverse, distances are short, and infrastructure is generally of high quality, contrasting to, e.g., the US, where car dependency is high, and the coverage of cycling and public transport infrastructure is less wide.

We find that EV adoption substantially increases car kilometers, with effects varying strongly across space and over time. The identified 31% average increase in car kilometers is not accompanied by a significant rise in the number of car trips, suggesting that EV users tend to make longer trips or connected trips rather than to travel more frequently. Additional driving primarily occurs when in-vehicle time costs are lower—for non-commuting trips and on weekends—and where car dependency is low, i.e. in densely populated areas with well-developed infrastructure for other modes. No evidence is found that EV adoption displaces cycling or walking. Although we find no significant reduction in public transport use, estimates for public transport are imprecise due to limited usage among both EV adopters and not-yet-adopters in our sample. While EVs drastically reduce emissions per kilometer, additional car travel increases social costs related to congestion, accidents and infrastructure development.[4]

[4]The effects of EV adoption on mode choice may also raise questions around equity, as they may disproportionately affect low-income households. Although equity is beyond this paper's scope, studies like West (2004) and—for the Netherlands—Cellissen et al. (2025), Dalla Longa et al. (2024), van Meerkerk et al. (2024), and van Ruijven and Loumeau (2025) highlight the regressive nature of current mobility trends, while Linn (2022) shows that equity and efficiency can align under progressive, income-based EV subsidies.

This paper makes three key contributions to the very thin literature studying the effects of EV adoption on car use and mode choice. Its first contribution lies with its identification approach – our study is the first exploiting variation in the timing of EV adoption to identify its effect on mode choice. By comparing the travel behavior of EV adopters with that of not-yet-adopters, we can better disentangle the effect of EV adoption from the effects of unobserved factors that would pose a threat to our identification, including individual concerns about the environment and climate change, and established travel patterns benefiting the use of EVs (e.g., shorter rides). In the only previous empirical attempt (Green and Østli, 2025), the authors use a selection on observables approach, which is less effective at ruling out these differences between EV and ICEV users.

The second contribution of this paper is that it pertains to a later stage of EV adoption than previous studies. Zhang et al. (2025) and Green and Østli (2025) use data until 2019/2020, while earlier studies (e.g., Huwe and Gessner, 2020; Langbroek et al., 2017)—which focus only on the relationship between EV adoption and car usage, and make use of empirical approaches not aiming to establish causality—use data until 2017. Between 2020 and 2023 (the year of our travel survey) the number of EV models in the Netherlands has more than quadrupled (from 29 to 131) and the average driving range of EVs has substantially increased (RVO and Revnext, 2025). The number of private EVs in the Netherlands grew from 9,100 in 2019 to 110,700 in 2023, roughly doubling each year (Statistics Netherlands, 2023). These developments show that our study considers a period with a much more attractive range of EVs and EV characteristics than previous studies, which can influence mode choice effects of EV adoption.

Third, this is the first study analyzing the heterogeneity of the effects of EV adoption on mode choice across space and trip purposes, and over time. Gaining insight into the spatial and temporal heterogeneity of these effects is important, as they ultimately co-determine the external costs of EV use—especially those related to traffic congestion. This insight also helps in the design of effective policies to internalize those costs.

Our study also relates to the broad literature on the direct rebound effect in road transport. The direct rebound effect reflects the difference between the observed energy savings from efficiency improvements and those emerging from standard engineering calculations, due to additional car use. The literature uses two main measures to estimate the rebound effect: (i) the elasticity of vehicle kilometers traveled (VKT) with respect to energy efficiency; and (ii) the elasticity of VKT with respect to energy costs per kilometer (Sorrell and Dimitropoulos, 2008). While the literature on the rebound effect in road transport is vast (see Dimitropoulos et al., 2018), it offers no insight into the size of the rebound effect when energy efficiency increases are as large as those implied from the transition to EVs.

The effect of EV adoption on car use estimated in this paper results from behavior changes that can be induced by multiple factors, including the lower energy costs of operating an EV, but also the perception that driving in an EV is environmentally benign. The identified effect also captures the influence of factors that limit extra car use, such as the shorter driving range of EVs compared to ICEVs and their relatively long charging times. Therefore, using estimates of the effect of EV adoption on car use to infer a rebound effect estimate is far from straightforward and requires additional strong assumptions. If one assumes the entire 31% effect stems from the tripling of energy efficiency when switching from an ICEV to an EV, the inferred estimate of the direct rebound effect would be around 15%. This estimate falls well in the range of the literature on the elasticity of VKT with respect to energy efficiency (Dimitropoulos et al., 2018).[5]

The rest of the paper is organized as follows: Section 2 describes the trip-level data and empirical approach. Results are discussed in Section 3. Section 4 concludes and discusses policy implications.

2 Data and empirical approach

2.1 Data

Our main dataset is the 2023 Dutch National Travel Survey (*Onderweg in Nederland*, ODiN), which contains representative cross-sectional data on about 64,500 respondents and 212,000 trips. The ODiN survey asks randomly selected respondents to report their complete travel diary for a randomly assigned day. This random assignment, also applying between household members, ensures an unbiased estimate of how much the average adult travels and eliminates the risk that the survey would disproportionately capture travel behavior of specific households or household members. Respondents are asked for detailed trip-level information, including trip purpose, origin and destination, departure and arrival times, travel distance, and transport mode(s). National travel survey data have been used in previous studies (Davis, 2019; Green and Østli, 2025; Huwe and Gessner, 2020; Zhang et al., 2025) and also serve as a basis for government statistics on travel mode developments and projections (see e.g., KiM, 2025).

Using these data, we construct our outcome variables of interest: total distance traveled and trip frequency by mode. A trip may consist of multiple legs (or segments), for each of

[5] EV marginal costs can strongly vary across households, depending on where and when they charge and on whether they own rooftop solar panels. As we lack information on charging costs for our sample, we refrain from making back-of-the-envelope calculations to provide an inferred estimate of the elasticity of VKT with respect to energy costs per kilometer.

which a different mode may have been used. For each trip leg, the distance traveled (in km) and the mode used are recorded. In our main analysis, we assign the total distance of a trip to the mode used to cover the largest share of that distance. For example, if the respondent cycled for 4 km to reach the nearest train station, then took the train for 30 km, and then walked for another 1 km to arrive at their final destination, we consider this a train trip of 35 km. In a robustness analysis, we alternatively treat legs of serial trips as individual trips and find similar results.

The 2023 wave of the ODiN survey is the most recent available. It is also the first wave of the survey allowing us to do an empirical analysis on adopters of battery electric vehicles (EVs) for two reasons. First, it contains a large enough sample of users of (privately held) EVs. The number of private EVs in the Netherlands grew from 9,100 in 2019 to 110,700 in 2023. In 2023, EVs accounted for 4% of the passenger car fleet (Statistics Netherlands, 2023). Second, 2023 is the first post-COVID year without mobility restrictions, which implies that it better represents Dutch mobility patterns than the years directly preceding it.

The survey includes detailed information on household vehicle holdings, covering the first and second youngest own passenger cars and the youngest lease or company car. Given that most Dutch households own less than two cars (Witte et al., 2022),[6] the survey provides comprehensive coverage of households' car portfolios. We classify vehicles as battery electric (BEV), plug-in hybrid (PHEV), or internal combustion engine (ICEV). We focus the analysis on BEV—labeled as EV henceforth—and compare these with ICEVs, including hybrids (HEVs). Respondents are defined as EV adopters if at least one EV is registered in their name, and as non-adopters if only ICEVs are registered at the time of the survey. The group of non-adopters can be further decomposed into ICEV users that later gain access to an EV (not-yet-adopters) and those that did not (ICEV only users).[7]

We restrict the sample to employed adults with at least one car registered in their name, who made at least one domestic trip and no international trips on the day of the survey.[8] We focus on private cars, as company cars are associated with distinct usage patterns and their users often do not pay fuel or electricity costs themselves.[9] Focusing on respondents with cars registered in their name ensures that our sample only includes respondents with direct access to at least one car, so that traveling by car is indeed in their choice set.

[6]About 21% of Dutch households have two cars, 47% one car, and 26% no car (Witte et al., 2022).

[7]PHEVs are excluded from the baseline analysis, as they differ substantially from EVs in driving costs and energy usage. Importantly, the share of electric driving of PHEVs tends to be low: real-world CO_2 emissions exceed test-cycle emissions estimates by a factor of 2 to 5 (see e.g. Gessner et al., 2025).

[8]16% of respondents did not travel on the reporting day; 1% made only international trips.

[9]About one third of EVs in the Netherlands in 2023 was private, the other two thirds were company cars (Statistics Netherlands, 2023)).

2.2 Empirical approach

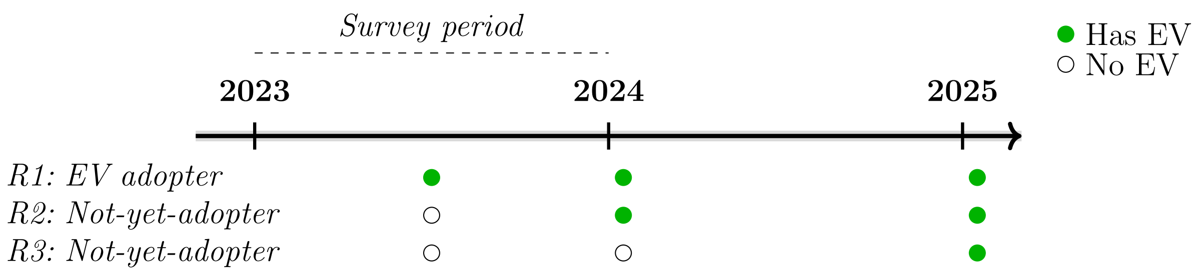
Identifying the effect of EV adoption on mode choice is complicated by non-random EV adoption. To mitigate selection bias, we construct a control group of respondents that is as similar as possible to EV adopters. We link the 2023 ODiN data to administrative vehicle registrations for 2024–2025. Tracking vehicle registrations post-survey allows us to distinguish between: (i) respondents with an EV in their household on the survey date (EV adopters); (ii) respondents who only have ICEVs on the survey date but whose household adopts an EV during the remainder of 2023 or in 2024 (not-yet-adopters); and (iii) respondents in households with only ICEVs throughout this period.

Our analysis compares the travel behavior of EV adopters with that of not-yet-adopters. Figure 1 illustrates these two groups and Table 1 provides an overview. We postulate that not-yet-adopters serve as a natural comparison group, sharing similar latent characteristics related to vehicle and travel preferences with EV adopters. Identification assumes that preferences for mode choices remain stable within the short time window around EV adoption, and that—conditional on observed individual, household and trip characteristics—EV adopters and not-yet-adopters would have exhibited similar travel behavior in the absence of EV adoption. Using not-yet-treated individuals as a control group mirrors the logic of staggered adoption designs, as it exploits the idea that future adopters are comparable to current adopters in both observed and unobserved characteristics. For recent similar applications in environmental economics, see for instance De Silva and Taylor (2024) and Ovaere and Vergouwen (2025).

Previous studies investigating how the travel behavior of EV users differs from that of ICEV users refer to earlier stages of EV adoption and are mostly not concerned with establishing causality (see, e.g., Figenbaum and Nordbakke, 2019; Langbroek et al., 2017; Zhang et al., 2025). A few studies address selection bias using matching-on-observables approaches, yet these tend to yield mixed and specification-sensitive results (Green and Østli, 2025; Huwe and Gessner, 2020). We argue that our identification strategy—leveraging not-yet-adopters as a counterfactual—offers a key methodological advancement. Because future EV adopters are already observable in the cross-section, our comparison group more closely resembles current adopters in both observed and unobserved characteristics, alleviating concerns that commonly undermine matching-based designs.

As a robustness check, we broaden the pool of contemporaneous and future EV users by adding ICEV users who are similar to EV adopters on observed characteristics using a propensity score matching (PSM) approach (see Appendix). These ICEV users can serve as a valid control group insofar as unobserved individual heterogeneity does not simultaneously affect EV adoption and mobility behavior. Since this unconfoundedness assumption may be too strong in our setting (Caliendo and Kopeinig, 2008), we treat the PSM results as a robustness exercise rather than as part of our baseline identification strategy.

Figure 1: Timing of EV adoption for adopters and not-yet-adopters



Note: The figure illustrates how EV_i, t_i is coded in Eq. 1. For each respondent, we record the household's EV adoption status at the individual survey date in 2023. Respondent 1 is an EV adopter, i.e., $EV_1, t_1 = 1$. Respondents 2 and 3 are not-yet-adopters, i.e. ICEV users at the survey date that adopt an EV shortly after, as indicated by registration records for 1/1/2024 and 1/1/2025.

Table 1: Sample overview

Group:	Respondents	Share (%)
EV adopters*	500	3.64
ICEV users		
Not-yet-adopters*	376	2.74
ICEV only users	12,871	93.63
Total observations	13,747	100.00

Note: The baseline sample includes employed EV adopters and not-yet-adopters with a car registered in their name (indicated with an asterisk). These account for about 47% of all EV adopters and not-yet-adopters in the full survey. The remaining respondents mainly consist of pensioners and employed individuals without a privately registered car, who are excluded from the baseline analysis. EV adopters' households have at least one private EV at the time of the survey.

We combine the survey and vehicle registration data with microdata at the household and individual level, to additionally control for observed determinants of travel mode choice on the survey date. This includes socio-demographic characteristics (such as including income, household composition and house type), mode accessibility (such as distance to driveways and train stations, as well as charging station density), household vehicle fleet characteristics, travel reimbursement, and past car use (in 2019). We also collect information about contextual factors of potential influence on the date of the survey response, including day of week, public or school holidays, and weather conditions.

We estimate EV adoption effects on mobility behavior using a Poisson pseudo-maximum likelihood (PPML) model. PPML allows for consistent estimation of models with multiplicative functional form and handles heteroskedasticity robustly. It is well-suited for both count and continuous outcomes with many zeros, as is the case in our data (Santos Silva and Winkelmann, 2024). Our model is estimated separately for each mobility mode m, and for each of our two main outcome variables: the *distance traveled* and the *number of trips*.

$$\mathbb{E}[Mobility_{i,m,t_i} \mid EV_{i,t_i}, X_{i,t_i}] = \exp\left(\alpha_m + \beta_m EV_{i,t_i} + \gamma_m X'_{i,t_i}\right) \tag{1}$$

where $Mobility_{i,m,t_i}$ denotes either the total distance traveled or the number of trips made by individual i using mode m on the individual-specific trip registration date t_i. The intercept α_m is a mode-specific constant, β_m is the coefficient of interest and γ_m is the vector of coefficients of the covariates used in our model. The semi-elasticity of mobility by mode m with respect to EV adoption (in percent) in this model is given by $(\exp(\beta_m) - 1) \times 100\%$. We expect β_m to be positive for car travel due to the reduction of marginal costs induced by EVs, and negative for active travel modes and public transport, if EV users shift trips from other modes to cars.

The vector X'_{i,t_i} includes individual and contextual determinants of mode choice, which are listed and defined in Table A.1. Included are employer reimbursements, as main marginal cost driver. Travel choices further vary by day-specific characteristics such as workday, weekend, holidays, and weather conditions (e.g., rain and temperature). Accessibility by travel modes is proxied for by distance to the nearest train station and highway. We also control for urbanization, metropolitan area, and Randstad province (the population- and employment-dense provinces), as geography influences mode attractiveness (Cao et al., 2010). EV use depends on charging infrastructure (Pan et al., 2024), which is proxied by charging station density in the municipality of the household's residence, and by dwelling type. The latter strongly determines the potential for home charging, and thus the marginal costs of driving. Charging station density is computed by dividing the number of charging points per municipality, as provided by the Netherlands Enterprise Agency (RVO), by the municipality's surface area. Individual mode preferences (Vij et al., 2013) are further captured through past car use, number of cars, car age and weight (comfort/fuel efficiency proxies), and recent car acquisition. E-bikes and speedpedelecs expand modal options, including for commutes, especially in a context of dense cycling infrastructure (Hendrich et al., 2025; Yin et al., 2024). Income affects affordability, and together with age and education may influence job type and preferences. We additionally control for gender, which may shape travel choices, although evidence on its importance is mixed and appears to be moderated by the presence of children (Borghorst et al., 2024; Exley et al., 2025; Le Barbanchon et al., 2021). Household size and young children are included as they drive mobility needs, restrict mode choice options, and influence commute distance (Borghorst et al., 2024; Le Barbanchon et al., 2021). In a robustness check, we verify that results hold when only trip-day controls are included, omitting other respondent characteristics—given that the sample is already restricted to EV adopters and not-yet-EV adopters, who are arguably comparable in both observed and unobserved characteristics.

3 Results

3.1 Descriptive analysis

Descriptive statistics for a series of observable characteristics for EV adopters, not-yet-adopters, and ICEV-only users who do not adopt an EV during the study period 2023–2025, are presented in Table 2. Not-yet-adopters are similar to EV adopters in several characteristics, including income and household size, while ICEV users differ from both groups in those aspects. Past household car use appears to be a relevant control for EV–ICEV differences, with EV adopter households driving more in 2019. Note that when considering only the usage of the car(s) registered in the respondent's name in 2019, instead of the usage of the cars registered in the names of all household members, VKT are highly similar across the three groups (roughly 10,000 km/yr). Respondents' own pre-EV-adoption[10] driving intensity is thus comparable to that of ICEV users. We use household-level past car use in the baseline regressions, to align with our other household-level car-ownership measures and to take into account how past car ownership and use by all household members might influence respondents' current travel behavior. Baseline results are almost identical when using the individual-level instead of the household-level measure of VKT in 2019.

Key factors likely correlated with EV adoption—and potentially travel mode choice include age, income and past car use: EV adopters tend to be slightly older, have higher incomes, and are the most intensive car users considering historical total car use. Other individual or trip characteristics that correlate with EV adoption may also shape travel behavior; to isolate the effects of EV adoption, we control for those in our econometric analyses.

[10]Only a small fraction (8%) of EV adopters in the ODiN 2023 survey already had an EV in 2019; results are very similar when excluding them, ensuring that past car use reflects pre-adoption behavior.

Interestingly, EV households have about 0.4 more private cars than not-yet-adopters and 0.7 more than ICEV-only users, suggesting that the EV often comes in addition to existing vehicles. They also have a significantly lower share of hybrid and diesel cars, indicating that EVs partly replace other energy-efficient cars, in line with prior econometric evidence (Xing et al., 2021).

Table 2: Summary statistics of control variables by group

	(1) EV adopters (N=491)		(2) Not-yet-EV (N=372)		(3) ICEV only (N=12871)		Mean differences		
Variable	Mean	SD	Mean	SD	Mean	SD	(1)-(2)	(1)-(3)	(2)-(3)
Trip cost reimbursement									
Reimbursement (binary)									
—per KM	0.34	0.48	0.37	0.48	0.33	0.47	−0.02	0.01	0.04
—fuel costs	n/a	n/a	n/a	n/a	0.02	0.12	n/a	n/a	n/a
—public transport	0.04	0.20	0.04	0.20	0.05	0.22	0.00	−0.01	−0.01
—parking costs	0.05	0.22	0.04	0.20	0.03	0.17	0.01	0.02*	0.01
—vehicle (binary)	0.06	0.24	0.06	0.24	0.05	0.22	0.00	0.01	0.01
Socio-demographics									
Age	48.11	10.58	45.84	10.85	45.53	12.00	2.27***	2.58***	0.31
Gender: female = 1	0.36	0.48	0.40	0.49	0.41	0.49	−0.04	−0.05**	−0.01
Higher education (binary)	0.70	0.46	0.64	0.48	0.55	0.50	0.06*	0.16***	0.09***
Employment (categorical)									
—12-30h	0.16	0.36	0.18	0.38	0.21	0.40	−0.02	−0.05***	−0.03
—>30h	0.84	0.36	0.83	0.38	0.79	0.40	0.02	0.05***	0.03
Income (percentile)	84.01	15.43	82.18	17.34	70.00	22.38	1.82	14.01***	12.18***
Household size (categorical)									
—1 person	0.05	0.22	0.08	0.26	0.17	0.38	−0.03	−0.12***	−0.10***
—2 persons	0.32	0.47	0.34	0.47	0.32	0.47	−0.02	0.00	0.02
—3 persons	0.23	0.42	0.19	0.39	0.19	0.40	0.04	0.04**	0.00
—4 persons	0.28	0.45	0.30	0.46	0.23	0.42	−0.03	0.04**	0.07***
—5+ persons	0.12	0.33	0.09	0.29	0.08	0.27	0.03	0.04***	0.01
Young children (binary)	0.33	0.47	0.31	0.46	0.27	0.45	0.02	0.06**	0.03
Dwelling type and location									
Dwelling type (categorical)									
—(semi-)detached/corner	0.58	0.50	0.51	0.50	0.41	0.49	0.06*	0.17***	0.11***
—row	0.34	0.47	0.37	0.48	0.39	0.49	−0.03	−0.05**	−0.02
—apartment	0.09	0.28	0.12	0.32	0.21	0.40	−0.03	−0.12***	−0.09***
Urbanization (categorical)									
—Low	0.26	0.44	0.24	0.43	0.27	0.44	0.02	−0.01	−0.03
—Medium	0.22	0.41	0.18	0.39	0.18	0.39	0.04	0.03*	0.00
—High	0.52	0.50	0.58	0.50	0.55	0.50	−0.06	−0.03	0.03
Randstad province (binary)	0.61	0.49	0.65	0.48	0.56	0.50	−0.04	0.05**	0.09***
Metropolitan area (categorical)									
—Amsterdam	0.19	0.39	0.20	0.40	0.18	0.39	−0.01	0.01	0.02

Continuation of Table 2									
—The Hague/Rotterdam	0.26	0.44	0.29	0.45	0.23	0.42	−0.03	0.02	0.05**
—Utrecht	0.16	0.37	0.17	0.37	0.14	0.35	−0.01	0.02	0.03
Charger density (N/KM^2)	15.46	19.02	16.64	19.29	14.51	17.91	−1.18	0.96	2.13**
Distance to driveway (KM)	1.68	0.86	1.78	0.88	1.76	1.15	−0.10*	−0.08**	0.02
Distance to train station (KM)	5.11	5.27	5.90	6.41	5.27	5.68	−0.80*	−0.16	0.64*
Vehicle characteristics and past car use									
Past car use (hh VKT, 2019)	12731	9688	11367	8512	11265	9214	1364**	1465***	101
Past car use (resp. VKT, 2019)	10175	10996	9787	9077	10139	10010	388	36	−352
Cars: total	2.37	1.09	2.00	0.84	1.69	0.81	0.38***	0.68***	0.30***
Cars (categorical)									
—1 car	0.18	0.39	0.28	0.45	0.47	0.50	−0.10***	−0.29***	−0.19***
—2 cars	0.44	0.50	0.50	0.50	0.41	0.49	−0.05	0.03	0.08***
—3+ cars	0.38	0.49	0.22	0.42	0.12	0.33	0.15***	0.25***	0.10***
Company lease cars (categorical)									
—1 car	0.36	0.48	0.28	0.45	0.15	0.36	0.08**	0.21***	0.13***
—2+ cars	0.10	0.30	0.03	0.16	0.01	0.12	0.07***	0.09***	0.01
Car age (years)	3.61	2.16	9.09	4.87	10.72	5.43	−5.48***	−7.11***	−1.63***
Diesel/HEV (binary)	0.09	0.29	0.25	0.43	0.19	0.39	−0.16***	−0.10***	0.06**
E-bike (binary)	0.51	0.50	0.48	0.50	0.40	0.49	0.03	0.11***	0.08***
Trip day characteristics									
Day of week (categorical)									
—Monday	0.13	0.34	0.18	0.39	0.14	0.35	−0.05*	−0.01	0.04**
—Tuesday	0.15	0.35	0.16	0.36	0.14	0.35	−0.01	0.00	0.01
—Wednesday	0.15	0.35	0.12	0.32	0.14	0.35	0.03	0.01	−0.02
—Thursday	0.13	0.34	0.13	0.33	0.15	0.36	0.01	−0.02	−0.02
—Friday	0.16	0.36	0.15	0.36	0.15	0.36	0.00	0.01	0.00
—Saturday	0.12	0.33	0.13	0.34	0.14	0.35	−0.01	−0.02	−0.01
—Sunday	0.16	0.37	0.13	0.34	0.13	0.34	0.03	0.03*	0.00
Holiday (binary)	n/a	n/a	n/a	n/a	0.02	0.15	n/a	n/a	n/a
Commuting day (binary)	0.42	0.49	0.47	0.50	0.47	0.50	−0.06	−0.06***	0.00
Temperature (°C)	8.74	5.57	7.53	5.93	8.33	5.61	1.21***	0.42	−0.80**
Precipitation (MM)	4.06	7.10	4.17	9.15	3.84	6.73	−0.11	0.22	0.33

The summary statistics in Table 3 show that EV adopters travel longer distances by car than not-yet-adopters (27%), while not-yet-adopters drive similar distances to always-ICEV users. EV adopters also make more car trips than ICEV users, although that difference is modest.

Both trip distances and frequencies are very low for train or BTM. Indicatively, both the average distance traveled and the average number of trips is higher for active modes than for public transport across our groups of car users. This is an interesting finding in itself, as it indicates that few people in our sample use public transport. However, it also indicates a limited statistical power for subsequent analyses involving public transport.

Table 3: Summary statistics of outcome variables by group

	(1) EV adopters (N=491)		(2) Not-yet-EV (N=372)		(3) ICEV only (N=12871)		Mean differences		
Variable	Mean	SD	Mean	SD	Mean	SD	(1)-(2)	(1)-(3)	(2)-(3)
Trip distance (KMs)									
Car	49.62	61.95	38.92	49.96	40.08	55.65	10.70***	9.54***	−1.16
Train	n/a	n/a	2.49	17.30	2.80	20.31	n/a	n/a	−0.30
BTM	n/a	n/a	0.32	2.77	0.42	4.31	n/a	n/a	−0.10
PT (Train+BTM)	3.80	26.86	2.82	17.48	3.22	20.77	0.98	0.58	−0.40
Bike	2.69	7.39	2.95	8.55	2.70	6.94	−0.27	−0.02	0.25
Foot	1.33	2.78	1.32	2.60	1.22	2.63	0.01	0.11	0.10
Active (Bike+Foot)	4.01	7.92	4.27	8.92	3.92	7.36	−0.26	0.09	0.35
Total (Car+PT+Active)	57.43	63.76	46.01	49.94	47.22	56.46	11.42***	10.21***	−1.21
Trip frequency (count)									
Car	2.36	1.98	2.16	1.80	2.13	1.84	0.20	0.23**	0.03
Train	n/a	n/a	0.05	0.32	0.05	0.31	n/a	n/a	0.00
BTM	n/a	n/a	0.04	0.28	0.03	0.23	n/a	n/a	0.01
PT (Train+BTM)	0.06	0.35	0.09	0.42	0.08	0.39	−0.03	−0.02	0.01
Bike	0.60	1.17	0.67	1.28	0.68	1.31	−0.07	−0.08	−0.01
Foot	0.60	1.01	0.66	1.07	0.62	1.11	−0.06	−0.02	0.04
Active (Bike+Foot)	1.20	1.61	1.33	1.70	1.29	1.70	−0.13	−0.09	0.04
Total (Car+PT+Active)	3.62	2.13	3.58	1.92	3.50	2.01	0.04	0.12	0.08

Summary statistics of kilometers traveled by car by trip purpose and time are shown in Table 4. We observe that the average distance traveled for commuting purposes by EV adopters and not-yet-adopters is very similar, and that the difference in the distance traveled during peak hours between the two groups is small and statistically insignificant. On the other hand, EV adopters make significantly more car kilometers for non-commuting purposes (47% more) and during off-peak times (41% more).

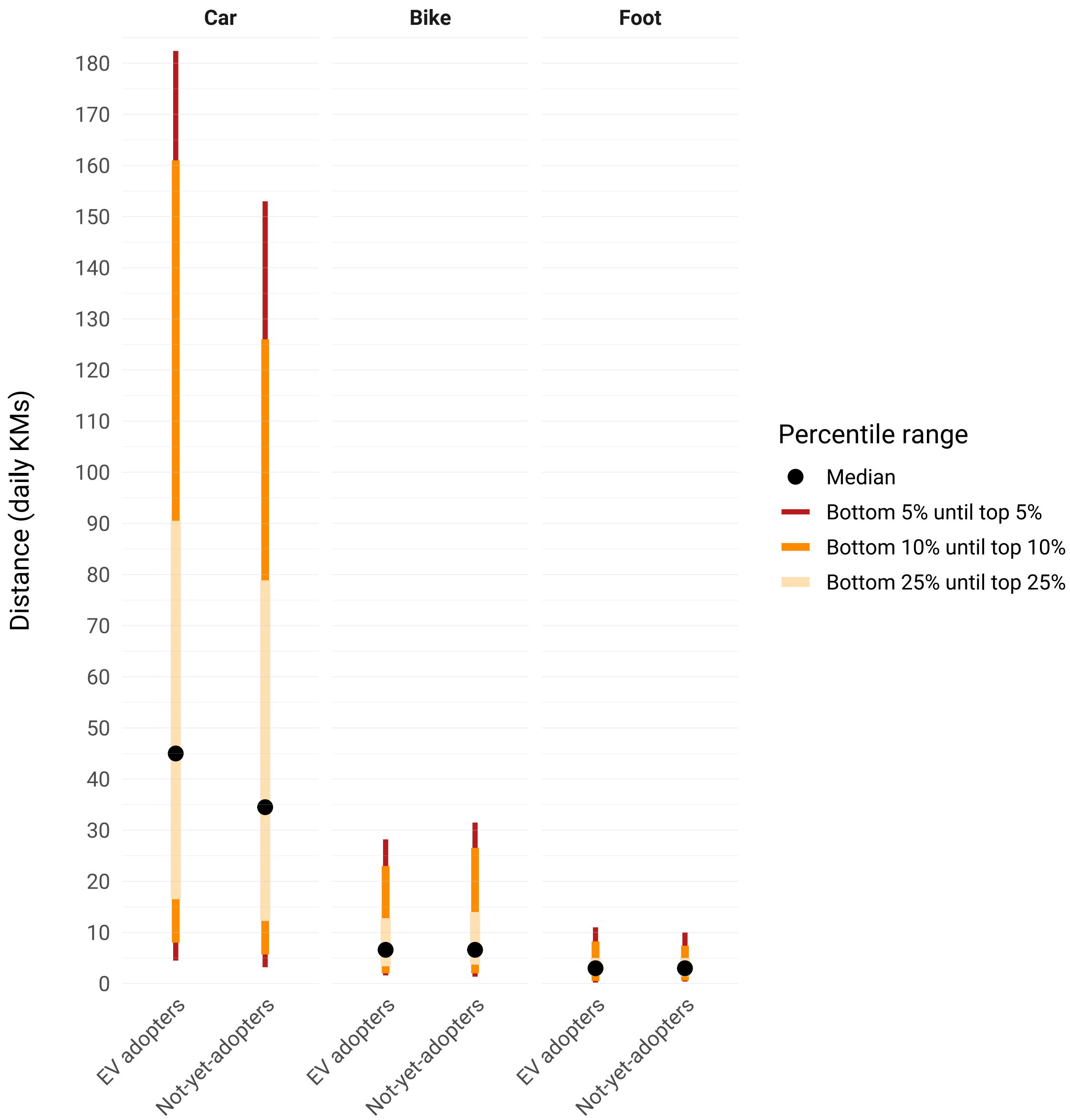
Table 4: Summary statistics of car kilometers by trip purpose and time

	(1) EV adopters		(2) Not-yet-EV		Mean difference
Variable	Mean	SD	Mean	SD	(1)–(2)
Commuting	14.57	34.68	14.60	32.69	−0.03
Non-commuting	30.31	54.18	20.61	38.54	9.70***
Peak hours	17.42	35.28	15.83	31.32	1.59
Off-peak hours	27.46	48.86	19.38	37.97	8.08***

Additional insights into differences in mode choice between EV adopters and not-yet-adopters are provided in Figure 2. The figure shows the distribution of trip distances by travel mode, conditional on that mode being used on the survey date. Car use is higher among EV adopters than not-yet-adopters (median 45 km vs. 35 km), and EV adopters undertake more long-distance trips: the 25% longest car trips exceed 91 km for EV adopters compared with 79 km for not-yet-adopters; for the 5% longest car trips, this is about 182 km and 153 km respectively. Conversely, EV adopters make fewer short car trips: the 25% shortest trips are below 16.5 km for EV adopters vs. 12.3 km for not-yet-adopters; while the 5% shortest car trips are 4.5 km and 3.2 km respectively. For active modes (cycling and walking), EV adopters and not-yet-adopters travel similar distances for typical trips, although EV adopters make slightly fewer longer-distance bike trips (75th–90th percentiles).

Finally, Figure 2 also highlights the considerable heterogeneity in mode use for given trip lengths. While cars are generally used for long-distance trips (median 39.7 km) and active modes for short trips (median for cycling is 6.6 km; for walking 3 km), car trip distances are highly dispersed. Interestingly, 5% of car trips are shorter than 4 km (see the part below the p5-p95 line), 10% shorter than 7 km (part below the p10-p90 line), and 25% below 15 km (part below the p25-p75 line). These short distances overlap considerably with trip distances made by active modes. This suggests a potential to reduce car use for certain short-distance trips and/or to rely on active modes for some of these trips.

Figure 2: Travel distances by mode



Note: Percentile distribution of travel distances by mode, conditional on the mode being used as the main mode for one or more trips on the survey date. Percentiles are omitted for public transport to comply with disclosure rules and protect privacy.

3.2 Econometric results

Table 5 presents the estimates obtained from our baseline model (Eq. 1) and Figure 3 visualizes the results as percentage changes, to facilitate interpretation. We find that EV adoption significantly affects travel behavior, primarily through an increase in car use. EV adopters drive on average about 31% more kilometers than not-yet-adopters. In contrast, the number of car trips increases less strongly and is not statistically significant, suggesting that existing trips become longer or combined rather than that additional trips are made. This is also observed descriptively in Figure 2, which shows that EV adopters use their cars for short distances less than not-yet-adopters.

We find no evidence that EV adoption displaces cycling or walking. While the estimated effects of EV adoption on active travel modes are negative (see Table 5), they are not statistically significant.

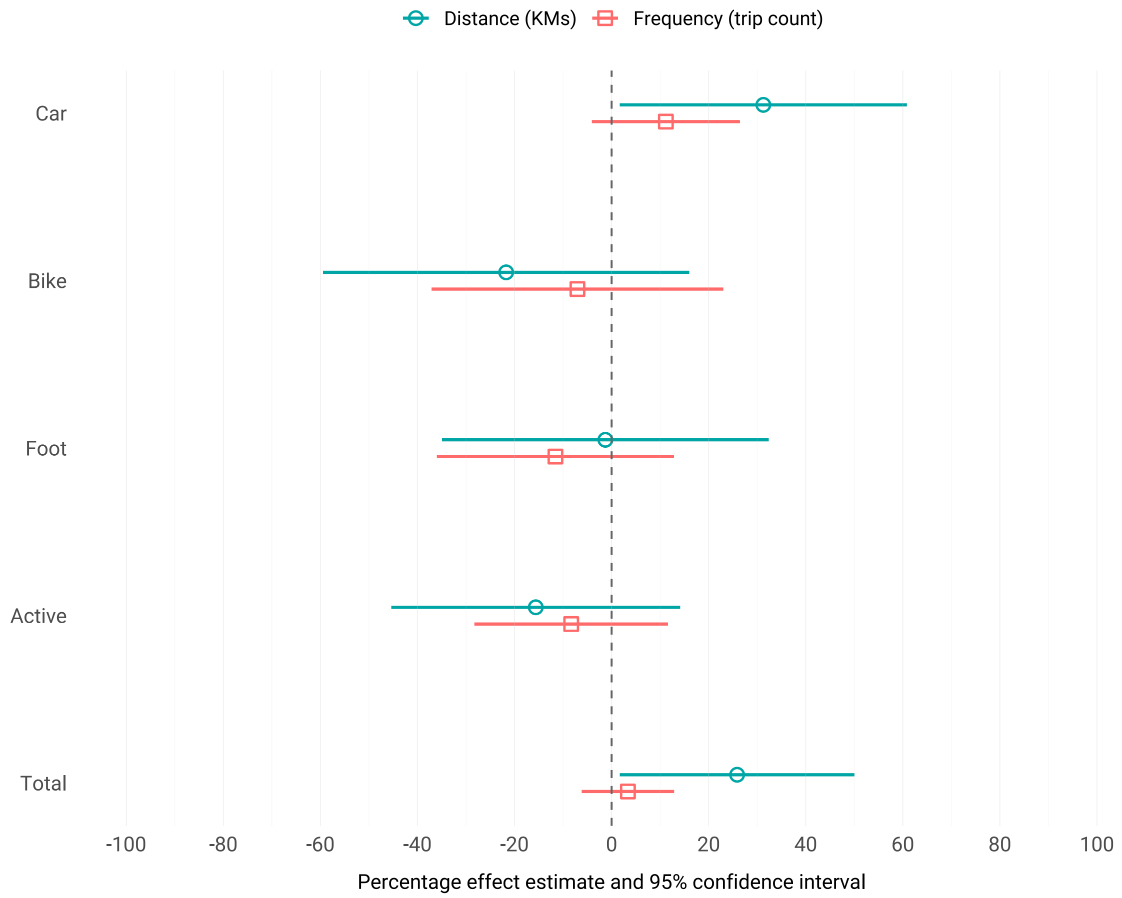
For public transport, the large uncertainty surrounding our estimates makes it hard to draw any conclusions, and thus we do not show these results in Figure 3. As the base use frequency for public transport is low in our survey data (see Table 3), future research would be needed to obtain more precise effect estimates, preferably using larger-scale public transport trip data.

Table 5: Baseline results: EV adoption and travel mode choices

Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Outcome:	Car	Train	PT	Bike	Foot	Active	Total
Panel A: Distance traveled (km) by mode							
EV adoption	0.272^{**}	0.466	0.367	-0.245	-0.013	-0.170	0.230^{**}
	(0.115)	(0.562)	(0.509)	(0.246)	(0.174)	(0.180)	(0.098)
N	863	679	796	863	863	863	863
Pseudo-R^2	0.108	0.701	0.695	0.113	0.111	0.096	0.110
Panel B: Trip frequency (count) by mode							
EV adoption	0.106	0.130	-0.154	-0.073	-0.123	-0.087	0.033
	(0.070)	(0.573)	(0.458)	(0.165)	(0.141)	(0.111)	(0.047)
N	863	679	795	863	863	863	863
Pseudo-R^2	0.041	0.471	0.410	0.087	0.071	0.069	0.027

PPML estimates of the effect of EV adoption on distance traveled by mode (Panel A) and trip frequency by mode (Panel B) (Eq. 1). *Active* sums bike and foot; *Total* sums car, active, and public transport (PT). Full PPML estimates, including those for control variables, are shown in Tables B.1 and B.2. All models are estimated on the baseline sample of EV adopters and not-yet-adopters (Table 1), and include controls for observed determinants. Variable definitions and data sources are listed in Table A.1. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure 3: EV adoption and travel mode choices



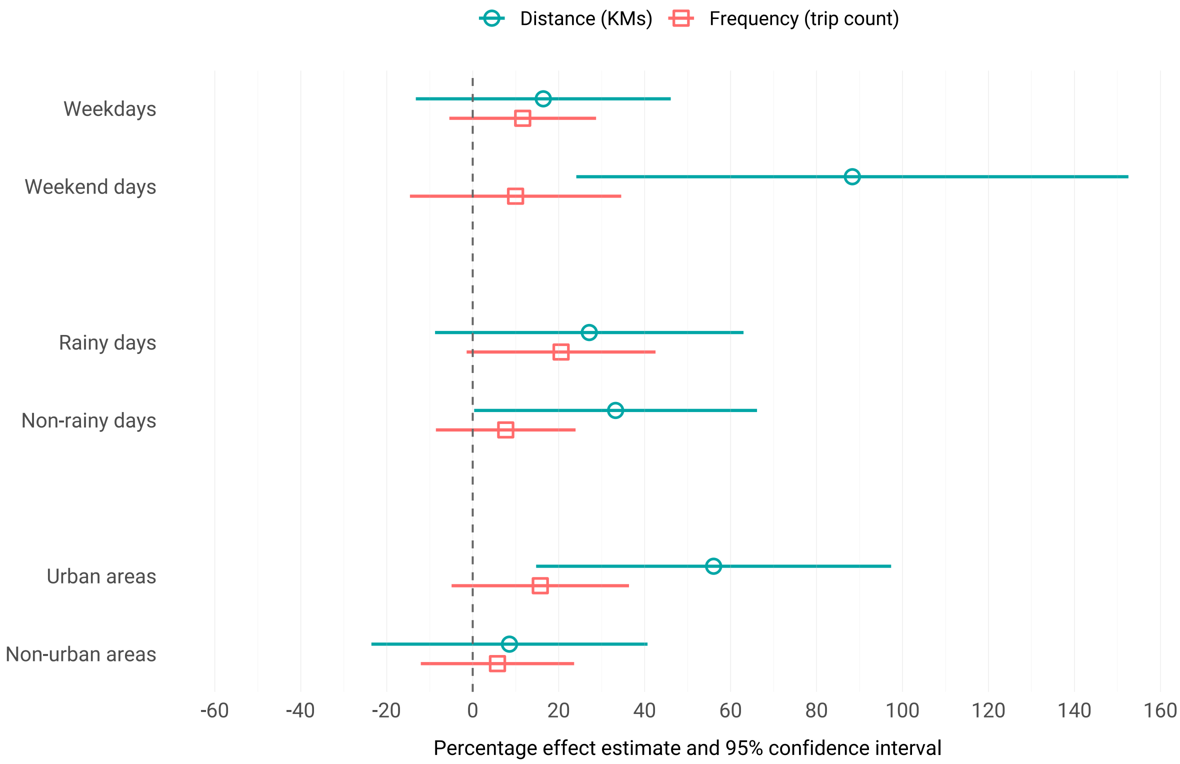
Note: Effect estimates of EV adoption on trip distance and frequency by mode (Eq. 1). *Active* sums bike and foot; *Total* sums car, active, and public transport—the latter omitted due to low survey use and wide intervals. The point estimates and 95% robust confidence intervals shown are expressed in percentage terms using $\Delta Y = (e^{\hat{\beta}} - 1) \times 100$ and Delta-method approximation. PPML results are in Table 5. All models are estimated on the baseline sample of EV adopters and not-yet-adopters (Table 1), and include controls for observed determinants. Variable definitions and data sources are listed in Table A.1.

We further find that the effect of EV adoption on car use is strongly context-dependent. Figure 4 shows that the effect of EV adoption on car kilometers is very large on weekends and much smaller and statistically insignificant on weekdays. The difference between weekends and weekdays is noticeable and statistically significant (see Appendix Tables B.3 and B.4 for full results). In Figure 5, we further examine effects on car kilometers by trip purpose and time. We find that EV adoption significantly affects non-commuting trips and off-peak hour trips. The impact on commuting trips and peak-hour trips is not significantly different from zero, despite the generally wide confidence intervals. These results suggest that additional car use induced by EV adoption is most pronounced outside commuting and peak-hour periods, highlighting that discretionary trips—rather than regular work commutes—drive most of the observed changes. This aligns with Ton et al. (2020), who report that most individuals have a stable, unimodal commuting choice set, primarily determined by employer reimbursement, car ownership, and urban density. Note, however, that although our data do not detect a statistically significant effect on weekday and commuting travel, caution is warranted for commuting distances: even small increases in peak-hour car use can lead to substantially more congestion, as traffic delays rise sharply with traffic volumes during peak hours (Hilbers et al., 2020).

We also find that the increase in car kilometers is more pronounced for households living in urban areas than for those living outside of them. An explanation for this may be that non-urban areas have higher baseline car dependence and more limited access to public transport (Bastiaanssen and Breedijk, 2024; Martensen and Arendsen, 2024) than urban ones. The lack of an effect among non-urban households likely reflects a "saturation effect": they already use the car as much as necessary, leaving little room for discretionary travel to respond to lower marginal costs. By contrast, urban households have a higher elasticity, particularly for discretionary trips, which drives the larger observed effect. This pattern suggests a higher price elasticity of car use among households living in urban areas and a lower one among residents of non-urban ones.

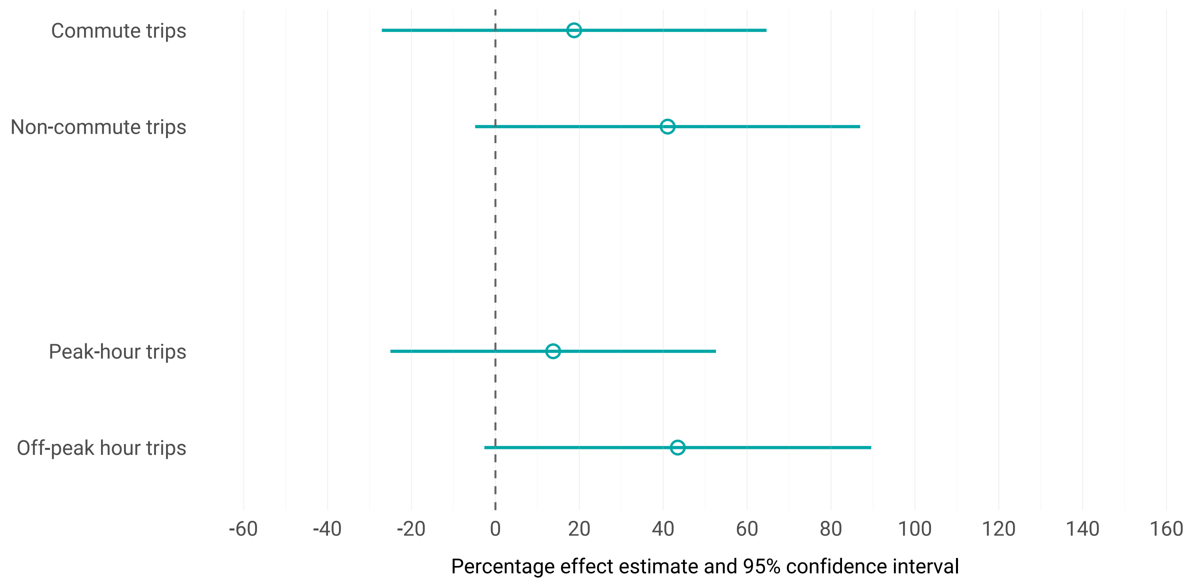
Other day-specific characteristics, such as weather conditions appear to have minimal impact: on rainy days, both EV and ICEV users generally prefer the car over cycling, suggesting that convenience and comfort outweigh cost considerations.

Figure 4: EV adoption and car travel by day and location type



Note: Effect estimates of EV adoption on car trip distance and frequency for heterogeneity groups: Weekdays (1 if the survey date is a weekday (Monday–Friday), 0 if Saturday or Sunday), Rainy days (1 if daily precipitation exceeds 5 mm, 0 otherwise), and Urban areas (1 if the respondent's dwelling is located in an area with a strong or very strong urbanization index, 0 if the index is medium or low). The point estimates and 95% robust confidence intervals shown are expressed in percentage terms using $\Delta Y = (e^{\hat{\beta}} - 1) \times 100$ and Delta-method approximation. PPML estimates, included in Tables B.3 and B.4, are significant at the 5% level for distance on weekend days, non-rainy days, and urban areas, and for trip frequency on rainy days; in these tables we also assess statistical significance of effect differences between groups. All models are estimated on the baseline sample of EV adopters and not-yet-adopters (Table 1), and include controls for observed determinants. Variable definitions and data sources are listed in Table A.1.

Figure 5: EV adoption and car travel by trip purpose and time



Note: Effect estimates of EV adoption on car trip distance for commuting and non-commuting trips and peak-hour trips (weekdays, departure time between 6:30–9:00 or 16:00–18:30) and off-peak hour trips. The point estimates and 95% robust confidence intervals are expressed in percentage terms using $\Delta Y = (e^{\hat{\beta}} - 1) \times 100$ and Delta-method approximation. PPML estimates, included in Table B.5, are significant at the 5% level for non-commuting and off-peak trips. All models are estimated on the baseline sample of EV adopters and not-yet-adopters (Table 1), and include controls for observed determinants. Variable definitions and data sources are listed in Table A.1.

3.3 Robustness

As a first robustness check, we treat each leg of multi-part trips as a separate observation rather than assigning the total distance to the mode covering the largest share. In the baseline analysis, serial or connected trips are treated as one (combined) trip, with the mode assigned based on the longest-distance segment. While treating each leg as a separate observation may better capture distances and counts per individual mode, it does not account for common dependencies in travel behavior—such as active-mode segments preceding or following a train trip—potentially overstating trips for certain modes. Given the high correlation between both trip definitions, we obtain near-identical results when defining trips based on individual legs (Table B.6).

Next, we examine sample composition. We expand the sample to all workers, including respondents for whom we cannot verify actual EV access (Table B.7). Respondents are defined as EV adopters if at least one EV is registered in their name, and as non-adopters if only ICEVs are registered at the survey time. As expected, the estimated effects are less precisely identified in this broader sample, possibly reflecting greater uncertainty about vehicle access. Nonetheless, the overall pattern remains consistent with the baseline analysis, with EV adoption associated with increased car distance and total travel, and only modest changes in active mode use and trip counts, indicating robustness to sample composition. In Table B.8 we further examine single- and multiple-car households. We find no significant difference in the EV adoption effect between these household types. While single-car households might be expected to exhibit a more direct response to EV adoption, consistent with Green and Østli (2025), our data do not show a statistically meaningful difference.

We further examine the sensitivity of our results to model specification. First, we estimate models including only day-level control variables (Table B.9), omitting respondent background characteristics. Given that the sample is restricted to EV adopters and not-yet-EV adopters—who are largely comparable in observed and unobserved traits—our estimates remain largely unchanged, indicating a limited influence of controls specification. Second, we exclude early adopters, defined as respondents who already had an EV in 2019 (8% of EV adopters; Table B.10). Results remain consistent, confirming that past car use—which captures pre-adoption differences between contemporaneous EV users and ICEV users—adequately controls for baseline driving behavior and that not-yet-adopters provide a valid counterfactual for EV adoption.

We experimented with alternative estimation methods, including OLS, negative binomial, and a Seemingly Unrelated Regression (SUR) approach in which the equations for different modes are estimated jointly, resulting in a slight efficiency improvement (Table B.11). These alternative methods yield results that are highly consistent with our preferred PPML specification, though their interpretation differs: for OLS and SUR models, the effects are to be interpreted as absolute changes in kilometers or trip counts. The SUR model delivers only a marginal gain in efficiency relative to OLS, indicating limited cross-equation correlation. This demonstrates that interdependencies between travel modes—which is already partly mitigated in the construction of the dataset by treating linked multi-modal sequences as single trips——do not materially affect our results. Overall, PPML remains our preferred estimator because of its robustness to heteroskedasticity, natural handling of zero outcomes, and straightforward percentage interpretation.

Our identification strategy of comparing EV adopters with not-yet-adopters strongly helps mitigate selection bias, but also restricts our sample. We therefore ran an analysis using a broader sample of all ICEV users—i.e., including never-EV-adopters—using propensity score matching (PSM) to construct the EV adopter counterfactual group based on observed characteristics. Following recommended practice (Caliendo and Kopeinig, 2008), we estimate each household's probability of adopting an EV using observed characteristics, match EV adopters to near-neighbor ICEV households, and compute the Average Treatment Effect on the Treated (ATT). Results (Table B.12) align with our baseline estimates, but are somewhat weaker and less precisely identified. This suggests that potential unobserved heterogeneity between EV adopters and ICEV users may be both conceptually and empirically important to account for—which our identification strategy using not-yet-adopters does.

Taken together, these robustness checks provide confidence that our core conclusions are not sensitive to sample and methodological specifications.

4 Conclusions and policy implications

Electric vehicles (EVs) are cheaper and greener to drive than internal combustion engine vehicles (ICEVs), which may induce their users to drive more and shift away from more sustainable transport modes. We combine detailed travel survey data with vehicle registration data and individual microdata from the Netherlands to estimate how private EV adoption influences revealed travel patterns. To address the endogeneity of EV adoption, we use a quasi-experimental design with future EV adopters as a control group.

Our results indicate that EV adoption leads to a significant increase in passenger car kilometers, which amounts to about 31% on average. The number of car trips increases less strongly and not significantly, suggesting that the increase in car use mainly results from adopters making longer or combined trips rather than traveling more frequently.

The effects of EV adoption on car use are time- and location-dependent. Additional EV kilometers mainly take place during weekends and off-peak. For commuting purposes and peak-hour travel, we find no evidence of significant changes due to EV adoption. The effect of EV adoption on car use is larger among residents of urban areas and smaller and insignificant among those living in less urbanized and rural areas, where baseline car dependence is already high.

We find no consistent evidence for substitution effects away from public transport or active modes, although estimates for public transport are particularly imprecise. Descriptively, EV adopters have largely similar cycling and walking behavior to not-yet-adopters, except that EV adopters make fewer of the longest active-mode trips. While substitution away from other modes cannot be ruled out, our analysis suggests that any such effects are unlikely to be strongly negative and tend to be concentrated among longer trips.

Our findings have several implications for transport and climate policy. While electrification of the car fleet remains essential for reducing emissions from road transport, EVs stimulate additional car use and associated externalities, including traffic congestion and accidents, and infrastructure wear and tear. Integrated policy design should therefore not only focus on vehicle decarbonization, but also encourage modal shift towards travel modes with lower external costs (Schroten et al., 2022), and reduced travel demand ("avoid"), aligning private incentives more closely with social costs (Börjesson et al., 2023; Verrips and Hilbers, 2020). The extra kilometers driven by EVs suggest that policies stimulating EV adoption—such as purchase subsidies and tax exemptions—need to be complemented with measures that limit the increase in external costs of car use, such as road pricing.

The context-dependent effect we observe further underscores that policy design should carefully reflect *where* and *when* additional vehicle kilometers occur, as other authors have conceptually argued for (Rapson and Muehlegger, 2023), for example through charges varying over time and space. Our findings suggest that extra kilometers by EVs most strongly occur during weekends and outside peak hours, when congestion-related external costs tend to be smaller.

In addition, the limited evidence we find for mode substitution suggests that shifting travelers out of cars will likely require policies that improve the price attractiveness, availability, and infrastructure of these alternative modes (Bastiaanssen and Breedijk, 2024; Dai et al., 2020). Broader strategies to reduce travel demand, such as denser spatial planning that improves accessibility and stimulates cycling and walking (Bastiaanssen and Breedijk, 2024; Hendrich et al., 2025; Verrips and Hilbers, 2020), can also play an important role, although these lie beyond the scope of our analysis.

Despite their richness and timeliness, the data used in our analysis come with some limitations. The cross-sectional nature of the data restricts our ability to study longer-run effects and—in the case of public transport—does not allow precise mode choice effect estimation. Moreover, our quasi-experimental identification using not-yet-adopters minimizes selection bias due to unobserved differences between EV and ICEV users, but this comes at the cost of a more limited generalizability of our results. Still, our sample may be largely representative of new EV adopter cohorts in the short- to medium-term. Future research could build on our work using panel data and more detailed mode-specific datasets, especially when such datasets for public transport become available. Such extensions would allow precise longer-term estimates of the effects of EV adoption on mode choice and of effect heterogeneity across household types.

Additional materials

Additional materials associated with this article are included in Online Appendix B.

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A Appendix

Table A.1: Variable definitions and data sources

Variable	Definition	Source
Outcome variables		
Distance traveled	Set of linear variables for each mode, measuring hectometers traveled on the reporting date by the specified mode	ODiN
Number of trips	Set of count variables for each mode, measuring number of trips on the reporting date by the specified mode	ODiN
Independent variable of interest		
EV adoption	Binary variable equal to 1 if at least one EV is registered to a household member at the reporting date, and 0 for ICEV users adopting an EV by January 1 next year or the year after	ODiN, RDW
Control variables for mobility behavior		
Employer reimbursements	Set of binary variables equaling 1 if the respondent receives reimbursement for commuting in the specified form: mileage, fuel costs, public transport, employer car, mobility budget, parking costs	ODiN
Employment status	Categorical variable reflecting what type of work the respondent has (categorical: unemployed, employed 12–30 hours, employed >30 hours, self-employed)	ODiN
Commute day	Binary variable equaling 1 if the individual commuted on the reporting date, and 0 otherwise	ODiN
Weekday	Binary variable equaling 1 if the reporting date is a weekday, and 0 otherwise	ODiN
Holiday	Binary variable equaling 1 if the respondent has a holiday on the reporting date, and 0 otherwise	ODiN
School vacation day	Binary variable equaling 1 if the reporting date falls in a school vacation day, and 0 otherwise	ODiN
Precipitation	Daily average mm precipitation in the province's largest city on the reporting date	KNMI
Temperature	Minimum temperature in degrees Celcius in the province's largest city on reporting date	KNMI
Distance to train	Road distance of center point of the household's home address' PC4 to the closest-by train station	CBS
Distance to autoroute	Road distance of center point of the household's home address' PC4 to the closest-by thoroughfare	CBS
Urbanization	Index reflecting the level of urbanization (5 categories: not urban to very strongly urban) at the location of the respondent's dwelling	ODiN
Randstad province	Binary variable equaling 1 if the home is located in North-Holland, South-Holland, Utrecht, or Flevoland	ODiN
Metropolitan area	Set of binary variables equaling 1 if the home is located in the specified major metropolitan area: The Hague/Rotterdam, Amsterdam, or Utrecht	ODiN
Charger density	Number of EV charging stations in municipality scaled by municipality surface area, one year before the respondent's survey date	RVO, CBS
House type	Type of house occupied by the household (categorical: apartment, attached house, or (semi-)detached house)	CBS, Kadaster

Continuation of Table A.1

Past car use	Vehicle kilometers traveled (VKT) by private cars in the household in 2019 (Eq. 1); Table 2 also shows summary statistics of VKT only of cars registered in the respondent's name in 2019 ('resp. VKT, 2019')	CBS, RDW
Car count	Number of cars registered in the name of somebody in the household	ODiN
Company car count	Number of lease cars registered in the name of somebody in the household	ODiN
Car age	Age of the youngest car in the household	ODiN
Diesel or HEV	Binary variable equaling 1 if there is at least one diesel or hybrid-electric car registered in the name of someone in the household	ODiN
E-bike	Binary variable equaling 1 if the household has an electric bicycle (regular or speedpedelec), and 0 otherwise	ODiN
Income	Standardized income (percentile)	CBS
Age	Age of the respondent	ODiN
Education	Binary variable equaling 1 if highest level of education completed is higher education or university, and 0 otherwise	ODiN
Gender: female	Binary variable equaling 1 if female, and 0 if male	ODiN
Household size	Number of adults and children in the household (categorical: 1, 2, 3, 4, 5+)	ODiN
Young children	Binary variable equaling 1 if there are one or more children of < 12 years old in the household, and 0 otherwise	ODiN

B Online Appendix

Contents

Table B.1: Full baseline results: EV adoption and distance traveled by mode

Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Outcome:	Car	Train	PT	Bike	Foot	Active	Total
EV adoption	0.272**	0.466	0.367	-0.245	-0.013	-0.170	0.230**
	(0.115)	(0.562)	(0.509)	(0.246)	(0.174)	(0.180)	(0.098)
Age	0.005	0.040	0.037	0.023**	0.008	0.019**	0.005
	(0.004)	(0.034)	(0.028)	(0.010)	(0.008)	(0.007)	(0.003)
Gender: female	-0.114	1.625*	1.362*	-0.024	0.222*	0.062	-0.058
	(0.096)	(0.872)	(0.744)	(0.197)	(0.134)	(0.138)	(0.082)
Education: higher	0.156*	1.157	0.898	0.054	0.597***	0.207	0.185**
	(0.089)	(0.929)	(0.774)	(0.213)	(0.155)	(0.163)	(0.078)
Employment: full-time	0.008	0.407	0.380	-0.174	-0.081	-0.137	0.021
	(0.133)	(0.724)	(0.658)	(0.223)	(0.191)	(0.165)	(0.116)
Income	0.006**	0.033**	0.030**	0.006	0.009*	0.007	0.006**
	(0.003)	(0.017)	(0.014)	(0.006)	(0.005)	(0.004)	(0.003)
Household size	-0.029	-0.530*	-0.575*	0.214**	0.024	0.143**	-0.027
	(0.051)	(0.306)	(0.297)	(0.097)	(0.074)	(0.072)	(0.044)
Young children	0.070	0.127	0.302	-0.338	-0.204	-0.269*	0.035
	(0.122)	(0.965)	(0.845)	(0.213)	(0.205)	(0.162)	(0.106)
Housetype:	0.038	-0.115	-0.206	-0.374*	-0.034	-0.281*	0.008
(semi-)detached/corner	(0.097)	(0.917)	(0.769)	(0.198)	(0.150)	(0.144)	(0.084)
Housetype:	0.393**	-1.762***	-1.706***	0.137	0.164	0.143	0.299**
apartment	(0.160)	(0.647)	(0.551)	(0.364)	(0.290)	(0.270)	(0.142)
Past car use (log km's)	0.008	-0.044	-0.039	0.003	-0.001	0.002	0.001
	(0.012)	(0.064)	(0.056)	(0.022)	(0.021)	(0.016)	(0.010)
Cars	0.124	-0.400	-0.458	-0.053	-0.076	-0.051	0.069
	(0.078)	(0.490)	(0.426)	(0.186)	(0.141)	(0.134)	(0.069)
Company cars	-0.116	0.280	0.295	-0.054	-0.002	-0.036	-0.095
	(0.082)	(0.424)	(0.403)	(0.213)	(0.134)	(0.151)	(0.072)
Car age	-0.001	0.052	0.051	-0.032	0.001	-0.019	-0.006
	(0.013)	(0.059)	(0.048)	(0.030)	(0.021)	(0.020)	(0.011)
Diesel or hybrid	0.186	0.685	0.644	0.251	-0.005	0.166	0.217**
	(0.119)	(0.709)	(0.645)	(0.260)	(0.176)	(0.191)	(0.105)
E-bike	-0.137	0.043	0.063	0.474**	0.032	0.336**	-0.094
	(0.086)	(0.383)	(0.342)	(0.216)	(0.138)	(0.144)	(0.075)
Reimbursement:	0.125	-1.230**	-1.151**	-0.189	0.037	-0.116	0.078
per KM	(0.090)	(0.577)	(0.487)	(0.199)	(0.140)	(0.139)	(0.082)
Reimbursement:	0.104	0.123	0.293	0.226	0.109		
fuel costs	(0.272)	(0.646)	(0.413)	(0.494)	(0.222)		
Reimbursement:	-1.349***	3.688***	3.554***	-0.526	0.439	-0.134	0.345*
public transport	(0.435)	(0.960)	(0.734)	(0.449)	(0.319)	(0.277)	(0.183)
Reimbursement:	0.213	0.176	0.183	-0.042	-0.511	-0.194	0.127
parking costs	(0.151)	(0.743)	(0.642)	(0.632)	(0.418)	(0.467)	(0.128)
Reimbursement:	0.322**	-19.500***	-0.490	0.276	-0.228	0.286**	
vehicle	(0.153)	(0.925)	(0.586)	(0.355)	(0.359)	(0.138)	
Day: Monday	-0.219	1.525	1.832	-0.054	0.355	0.107	-0.194
	(0.187)	(1.736)	(1.257)	(0.357)	(0.218)	(0.254)	(0.156)
Day: Tuesday	-0.057	2.333*	2.584**	-0.505	0.157	-0.263	-0.035
	(0.174)	(1.353)	(1.214)	(0.347)	(0.240)	(0.245)	(0.147)
Day: Wednesday	-0.033	1.069	1.638	-0.366	0.115	-0.187	-0.042
	(0.184)	(1.390)	(1.195)	(0.382)	(0.244)	(0.266)	(0.161)
Day: Thursday	-0.063	2.918**	3.153***	-0.428	0.272	-0.163	0.027
	(0.184)	(1.313)	(1.194)	(0.384)	(0.287)	(0.269)	(0.154)

Continuation of Table B.1							
Day: Friday	-0.029	1.870	2.248*	-0.419	0.073	-0.229	-0.020
	(0.180)	(1.828)	(1.305)	(0.337)	(0.234)	(0.244)	(0.159)
Day: Saturday	0.083	0.860	-0.436	-0.337	-0.401	0.023	
	(0.174)	(1.470)	(0.389)	(0.222)	(0.272)	(0.153)	
Holiday	0.194	-1.271	-0.342	-0.867*	0.182		
	(0.307)	(0.994)	(0.582)	(0.480)	(0.268)		
Commuting trips	0.382***	2.007***	1.712***	0.064	-1.032***	-0.271**	0.417***
	(0.102)	(0.573)	(0.421)	(0.189)	(0.170)	(0.137)	(0.089)
Urbanization:	0.002	-2.154	-1.678	0.145	0.051	0.147	-0.016
Moderately	(0.123)	(1.433)	(1.022)	(0.317)	(0.221)	(0.222)	(0.108)
Urbanization:	-0.084	0.207	0.142	-0.068	0.358*	0.091	0.004
Strongly/very strongly	(0.138)	(0.709)	(0.677)	(0.271)	(0.194)	(0.194)	(0.119)
Randstad province	-0.001	1.020*	0.694	0.447	-0.056	0.302	0.025
	(0.132)	(0.539)	(0.457)	(0.314)	(0.219)	(0.234)	(0.111)
Metropolitan area:	-0.050	-0.709	-0.646	-0.326	-0.137	-0.297	-0.110
Amsterdam	(0.134)	(0.720)	(0.687)	(0.294)	(0.240)	(0.224)	(0.114)
Metropolitan area:	-0.103	-0.739	-0.329	-0.505*	0.129	-0.327	-0.132
The Hague/Rotterdam	(0.128)	(1.055)	(0.786)	(0.268)	(0.219)	(0.202)	(0.109)
Charging station density	-0.003	-0.041***	-0.030**	0.003	-0.005	0.000	-0.005*
	(0.004)	(0.014)	(0.012)	(0.007)	(0.005)	(0.005)	(0.003)
Distance to driveway	0.031	0.311	0.215	0.044	-0.061	0.015	0.025
	(0.052)	(0.233)	(0.200)	(0.101)	(0.084)	(0.073)	(0.042)
Distance to train station	0.004	-0.087	-0.069	-0.000	0.022*	0.008	0.003
	(0.007)	(0.082)	(0.070)	(0.015)	(0.012)	(0.010)	(0.006)
Temperature	-0.005	-0.065	-0.052	0.022	0.002	0.016	-0.003
	(0.007)	(0.047)	(0.038)	(0.017)	(0.011)	(0.012)	(0.006)
Precipitation	0.009	-0.094**	-0.073**	-0.032	-0.015	-0.025*	0.005
	(0.005)	(0.042)	(0.036)	(0.022)	(0.009)	(0.013)	(0.005)
N	863	679	796	863	863	863	863
Pseudo-R^2	0.108	0.701	0.695	0.113	0.111	0.096	0.110

PPML estimates of the effect of EV adoption and covariates on distance traveled by mode (Eq. 1). *Active* sums bike and foot; *Total* sums car, active, and public transport (PT). All models are estimated on the baseline sample EV adopters and not-yet-adopters (Table 1), and control for observed determinants. Variable definitions and data sources are listed in Table A.1. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.2: Full baseline results: EV adoption and trip count by mode

Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Outcome:	Car	Train	PT	Bike	Foot	Active	Total
EV adoption	0.106	0.130	-0.154	-0.073	-0.123	-0.087	0.033
	(0.070)	(0.573)	(0.458)	(0.165)	(0.141)	(0.111)	(0.047)
Age	-0.003	0.038	0.021	0.005	0.003	0.004	-0.001
	(0.003)	(0.033)	(0.017)	(0.007)	(0.006)	(0.005)	(0.002)
Gender: female	0.040	0.881	0.621*	0.015	0.014	0.016	0.039
	(0.065)	(0.629)	(0.362)	(0.152)	(0.119)	(0.096)	(0.043)
Education: high	-0.066	1.598	0.394	0.179	0.356***	0.252**	0.048
	(0.060)	(1.016)	(0.459)	(0.150)	(0.132)	(0.102)	(0.044)
Employment: full-time	-0.015	0.161	0.371	-0.450***	-0.110	-0.291**	-0.116**
	(0.090)	(0.704)	(0.624)	(0.163)	(0.151)	(0.115)	(0.058)
Income (pct)	-0.002	0.030*	0.033***	0.001	0.007	0.004	0.001
	(0.002)	(0.017)	(0.012)	(0.005)	(0.004)	(0.004)	(0.001)
Household size	0.027	-0.527*	-0.694**	0.083	0.007	0.041	0.026
	(0.031)	(0.287)	(0.284)	(0.081)	(0.065)	(0.054)	(0.021)
Young children	0.046	0.535	0.932	0.290*	-0.141	0.092	0.067
	(0.075)	(0.870)	(0.702)	(0.176)	(0.164)	(0.122)	(0.052)
House type:	-0.064	-0.229	-0.479	-0.047	0.182	0.056	-0.030
(semi-)detached/corner	(0.063)	(0.812)	(0.487)	(0.138)	(0.125)	(0.095)	(0.042)
House type:	0.017	-1.947***	-1.168**	-0.125	0.108	-0.023	0.002
apartment	(0.113)	(0.745)	(0.496)	(0.263)	(0.219)	(0.177)	(0.077)
Past car use (log KMs)	-0.004	-0.091	-0.062	0.022	0.007	0.014	0.001
	(0.008)	(0.079)	(0.054)	(0.019)	(0.016)	(0.012)	(0.006)
Cars	0.153***	-0.083	-0.329	-0.297**	-0.166	-0.225***	0.015
	(0.052)	(0.549)	(0.354)	(0.121)	(0.105)	(0.083)	(0.036)
Company lease cars	-0.007	-0.162	-0.098	0.100	0.146	0.124	0.037
	(0.055)	(0.448)	(0.395)	(0.137)	(0.118)	(0.093)	(0.037)
Car age	0.005	0.025	0.021	0.003	-0.005	0.001	0.004
	(0.008)	(0.057)	(0.048)	(0.016)	(0.015)	(0.011)	(0.006)
Diesel or hybrid car	-0.061	0.418	0.690	0.279	0.078	0.186	0.034
	(0.072)	(0.691)	(0.589)	(0.180)	(0.153)	(0.117)	(0.049)
E-bike	0.007	0.060	0.026	0.122	0.026	0.080	0.030
	(0.060)	(0.398)	(0.311)	(0.134)	(0.111)	(0.087)	(0.040)
Reimbursement:	0.133**	-1.293**	-0.989**	-0.047	0.141	0.036	0.087**
per KM	(0.060)	(0.652)	(0.438)	(0.138)	(0.116)	(0.092)	(0.041)
Reimbursement:	0.259			-0.166	0.535	0.225	0.227
fuel	(0.217)			(0.617)	(0.341)	(0.325)	(0.164)
Reimbursement:	-0.719**	2.836***	2.655***	-0.049	0.613***	0.318	0.055
public transport	(0.284)	(0.696)	(0.418)	(0.367)	(0.218)	(0.199)	(0.081)
Reimbursement:	0.135	-0.177	0.823	-0.316	-0.565*	-0.435*	-0.028
parking	(0.119)	(0.722)	(0.751)	(0.371)	(0.309)	(0.261)	(0.084)
Reimbursement:	0.213*			-0.764*	-0.042	-0.342	0.038
vehicle	(0.119)			(0.435)	(0.244)	(0.218)	(0.085)
Day: Monday	0.080	-0.352	1.319	0.649***	0.481***	0.537***	0.255***
	(0.113)	(1.442)	(1.114)	(0.250)	(0.183)	(0.156)	(0.072)
Day: Tuesday	0.188*	0.186	2.212*	0.339	0.153	0.225	0.236***
	(0.112)	(1.164)	(1.175)	(0.268)	(0.210)	(0.163)	(0.077)
Day: Wednesday	0.044	-1.229	1.616	0.828***	0.169	0.486***	0.215***
	(0.107)	(1.212)	(1.313)	(0.251)	(0.207)	(0.165)	(0.078)
Day: Thursday	0.056	0.766	2.773**	0.536**	0.402*	0.450***	0.247***
	(0.110)	(1.214)	(1.179)	(0.264)	(0.222)	(0.164)	(0.076)

Continuation of Table B.2

Day: Friday	0.192*	-0.361	2.076*	0.806***	0.202	0.491***	0.317***
	(0.099)	(1.530)	(1.216)	(0.253)	(0.198)	(0.155)	(0.069)
Day: Saturday	0.427***		2.544*	0.599**	0.100	0.336**	0.411***
	(0.102)		(1.357)	(0.269)	(0.191)	(0.156)	(0.073)
Holiday	0.161			-0.760	-0.718	-0.756*	-0.119
	(0.228)			(1.000)	(0.491)	(0.415)	(0.116)
Commuting trips	0.143**	1.893***	0.994***	-0.115	-0.838***	-0.460***	-0.050
	(0.066)	(0.521)	(0.336)	(0.143)	(0.137)	(0.102)	(0.043)
Urbanization:	0.001	-1.658	-0.700	0.132	0.112	0.137	0.034
Moderate	(0.080)	(1.016)	(0.556)	(0.196)	(0.181)	(0.135)	(0.057)
Urbanization:	0.027	0.128	-0.126	-0.072	0.234	0.091	0.047
Strongly/very strongly	(0.086)	(0.743)	(0.586)	(0.191)	(0.175)	(0.134)	(0.061)
Randstad province	0.064	1.116**	0.394	0.259	0.041	0.170	0.112*
	(0.088)	(0.475)	(0.522)	(0.184)	(0.180)	(0.134)	(0.059)
Metropolitan area:	-0.088	-0.077	-0.196	-0.299	-0.245	-0.289**	-0.170***
Amsterdam	(0.090)	(0.715)	(0.645)	(0.200)	(0.196)	(0.147)	(0.064)
Metropolitan area:	0.063	-0.187	0.819	-0.384*	-0.038	-0.230*	-0.038
The Hague/Rotterdam	(0.094)	(0.841)	(0.509)	(0.207)	(0.176)	(0.137)	(0.060)
Charging station density	-0.005**	-0.029**	-0.005	0.005	-0.001	0.002	-0.002
	(0.002)	(0.013)	(0.012)	(0.004)	(0.004)	(0.003)	(0.001)
Distance to driveway	0.028	0.115	-0.027	-0.022	-0.049	-0.033	0.004
	(0.032)	(0.231)	(0.160)	(0.073)	(0.059)	(0.048)	(0.022)
Distance to train station	-0.005	-0.035	-0.040	-0.021	0.012	-0.003	-0.004
	(0.005)	(0.053)	(0.039)	(0.022)	(0.010)	(0.009)	(0.003)
Temperature	-0.007	-0.026	-0.003	0.027**	-0.002	0.011	0.000
	(0.005)	(0.048)	(0.031)	(0.012)	(0.009)	(0.008)	(0.003)
Precipitation	0.001	-0.075*	-0.006	-0.038***	-0.007	-0.019***	-0.006***
	(0.003)	(0.043)	(0.021)	(0.011)	(0.007)	(0.006)	(0.002)
N	863	679	795	863	863	863	863
Pseudo-R^2	0.041	0.471	0.410	0.087	0.071	0.069	0.027

PPML estimates of the effect of EV adoption and covariates on the trip count by mode (Eq. 1). *Active* sums bike and foot; *Total* sums car, active, and public transport (PT). All models are estimated on the baseline sample EV adopters and not-yet-adopters (Table 1), and control for observed determinants. Variable definitions and data sources are listed in Table A.1. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.3: Results on distance traveled by mode, by day and location type

Model:	(1)	(2)	(3)	(4)	(5)	(6)
Outcome:	Car	PT	Bike	Foot	Active	Total
Weekdays vs weekend days						
EV x Weekday	0.152	-0.161	0.089	-0.085	0.147	0.110
	(0.130)	(0.236)	(0.201)	(0.175)	(0.110)	(0.078)
EV x Weekend	0.633***	-0.427	-0.248	-0.358	0.489***	0.095
	(0.174)	(0.479)	(0.251)	(0.340)	(0.152)	(0.114)
N	863	795	863	863	863	863
Pseudo-R^2	0.115	0.114	0.113	0.097	0.114	0.041
Signif. coeff. difference	**	-	-	-	**	-
Rainy vs non-rainy days						
EV x Rainy day	0.240*	-0.595	-0.170	-0.461*	0.155	0.187**
	(0.144)	(0.379)	(0.270)	(0.275)	(0.125)	(0.093)
EV x Non-rainy day	0.287**	-0.153	0.036	-0.089	0.263**	0.074
	(0.126)	(0.239)	(0.183)	(0.175)	(0.107)	(0.077)
N	863	795	863	863	863	863
Pseudo-R^2	0.109	0.116	0.112	0.098	0.111	0.041
Signif. coeff. difference	-	-	-	*	-	-
Urban vs non-urban areas						
EV x Urban	0.445***	-0.274	0.197	-0.106	0.348***	0.146
	(0.135)	(0.322)	(0.206)	(0.232)	(0.114)	(0.091)
EV x Non-urban	0.082	-0.209	-0.313	-0.250	0.091	0.056
	(0.151)	(0.279)	(0.229)	(0.212)	(0.131)	(0.086)
N	863	795	863	863	863	863
Pseudo-R^2	0.113	0.113	0.115	0.096	0.113	0.041
Signif. coeff. difference	**	-	*	-	*	-

PPML estimates of the interaction effect of EV adoption and the following heterogeneity group dummies on distance traveled by mode (Eq. 1): Weekday (survey date is a Monday–Friday), Weekend (Saturday or Sunday), Rainy day (daily precipitation exceeds 5 mm), Non-rainy day (precipitation less or equal to 5 mm), Urban (respondent's dwelling located in an area with a strong or very strong urbanization index), and Non-urban (urbanization index is medium or low). *Active* sums bike and foot; *Total* sums car, active, and public transport (PT). All models are estimated on the baseline sample of EV adopters and not-yet-adopters (Table 1), and include all observed determinants. *Signif. coeff. difference* reports the significance of the difference of the EV adoption effect between heterogeneity groups, based on a single-interaction term model. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.4: Results on trip frequency by mode, by day and location type

Model:	(1)	(2)	(3)	(4)	(5)	(6)
Outcome:	Car	PT	Bike	Foot	Active	Total
Weekdays vs weekend days						
EV x Weekday	0.110	-0.117	-0.160	-0.129	0.017	0.017
	(0.078)	(0.180)	(0.161)	(0.125)	(0.051)	(0.051)
EV x Weekend	0.095	0.062	-0.035	0.025	0.074	0.074
	(0.114)	(0.289)	(0.214)	(0.173)	(0.080)	(0.080)
N	863	795	863	863	863	863
Pseudo-R^2	0.041	0.088	0.071	0.070	0.027	0.027
Signif. coeff. difference	-	-	-	-	-	-
Rainy vs non-rainy days						
EV x Rainy day	0.187**	-0.071	-0.197	-0.154	0.064	0.064
	(0.093)	(0.250)	(0.227)	(0.172)	(0.068)	(0.068)
EV x Non-rainy day	0.074	-0.074	-0.097	-0.068	0.022	0.022
	(0.077)	(0.174)	(0.146)	(0.117)	(0.051)	(0.051)
N	863	795	863	863	863	863
Pseudo-R^2	0.041	0.087	0.071	0.069	0.027	0.027
Signif. coeff. difference	-	-	-	-	-	-
Urban vs non-urban areas						
EV x Urban	0.146	-0.102	-0.135	-0.110	0.037	0.037
	(0.091)	(0.198)	(0.172)	(0.133)	(0.059)	(0.059)
EV x Non-urban	0.056	-0.035	-0.105	-0.056	0.028	0.028
	(0.086)	(0.219)	(0.186)	(0.149)	(0.061)	(0.061)
N	863	795	863	863	863	863
Pseudo-R^2	0.041	0.087	0.071	0.069	0.027	0.027
Signif. coeff. difference	-	-	-	-	-	-

PPML estimates of the interaction effect of EV adoption and the following heterogeneity group dummies on trip counts by mode (Eq. 1): Weekday (survey date is a Monday–Friday), Weekend (Saturday or Sunday), Rainy day (daily precipitation exceeds 5 mm), Non-rainy day (precipitation less or equal to 5 mm), Urban (respondent's dwelling located in an area with a strong or very strong urbanization index), and Non-urban (urbanization index is medium or low). *Active* sums bike and foot; *Total* sums car, active, and public transport (PT). All models are estimated on the baseline sample of EV adopters and not-yet-adopters (Table 1), and include all observed determinants. The heterogeneity groups are defined in Table A.1. *Signif. coeff. difference* reports the significance of the difference of the EV adoption effect between heterogeneity groups, based on a single-interaction term model. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.5: Effect of EV adoption on car kilometers by trip purpose and time

Model:	(1)	(2)	(3)	(4)
Outcome:	Commute	Non-commute	Peak-hour	Off-peak hour
EV adoption	0.172	0.344^{**}	0.129	0.361^{**}
	(0.197)	(0.166)	(0.174)	(0.164)
N	567	826	591	826
Pseudo-R^2	0.096	0.129	0.137	0.128

PPML estimates of the effect of EV adoption on car kilometers traveled, for commuting and non-commuting trips as well as peak-hour trips (trips on weekdays with departure time between 6:30–9:00 or 16:00–18:30) and off-peak hour trips. All models are estimated on the baseline sample of EV adopters and not-yet-adopters (Table 1) and control for observed determinants. Variable definitions and data sources are listed in Table A.1. Robust standard errors are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.6: Individual trips (serial trip movements treated as separate trips)

Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Outcome:	Car	Train	PT	Bike	Foot	Active	Total
Panel A: Distance (KMs) by mode							
EV adoption	0.268^{**}	0.589	0.458	-0.205	-0.006	-0.141	0.230^{**}
	(0.115)	(0.585)	(0.519)	(0.237)	(0.163)	(0.172)	(0.098)
N	863	679	844	863	863	863	863
Pseudo-R^2	0.108	0.687	0.682	0.124	0.120	0.109	0.110
Panel B: Trip frequency (count) by mode							
EV adoption	0.098	0.152	-0.151	-0.086	-0.078	-0.072	0.031
	(0.070)	(0.555)	(0.433)	(0.162)	(0.138)	(0.108)	(0.047)
N	863	679	844	863	863	863	863
Pseudo-R^2	0.038	0.459	0.422	0.091	0.082	0.079	0.035

PPML estimates of the effect of EV adoption on distance traveled by mode (Panel A) and trip count by mode (Panel B) (Eq. 1). *Active* sums bike and foot; *Total* sums car, active, and public transport (PT). All models are estimated on the baseline sample EV adopters and not-yet-adopters (Table 1), and control for observed determinants. Variable definitions and data sources are listed in Table A.1. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.7: Sample: all workers, including those without car on own name

Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Outcome:	Car	Train	PT	Bike	Foot	Active	Total
Panel A: Distance (KMs) by mode							
EV adoption	0.168*	0.769*	0.647*	0.036	0.061	0.058	0.176**
	(0.089)	(0.405)	(0.359)	(0.211)	(0.132)	(0.147)	(0.077)
N	1,312	1,203	1,203	1,312	1,312	1,312	1,312
Pseudo-R^2	0.102	0.435	0.426	0.104	0.088	0.086	0.094
Panel B: Trip frequency (count) by mode							
EV adoption	0.023	0.400	-0.056	0.204*	-0.152	0.038	0.031
	(0.057)	(0.395)	(0.313)	(0.135)	(0.116)	(0.087)	(0.038)
N	1,312	1,203	1,203	1,312	1,312	1,312	1,312
Pseudo-R^2	0.037	0.335	0.276	0.094	0.065	0.070	0.020

PPML estimates of the effect of EV adoption on distance traveled by mode (Panel A) and trip count by mode (Panel B) (Eq. 1). *Active* sums bike and foot; *Total* sums car, active, and public transport (PT). All models are estimated on the baseline sample EV adopters and not-yet-adopters (Table 1), and control for observed determinants. Variable definitions and data sources are listed in Table A.1. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.8: Sample: single vs multiple car households

Model:	(1)	(2)	(3)	(4)	(5)	(6)
Outcome:	Car	PT	Bike	Walk	Active	Total
Panel A: Distance (KMs) by mode						
EV x Single-car	0.312*	0.084	-0.244	0.237	-0.071	0.268*
	(0.162)	(0.688)	(0.266)	(0.223)	(0.193)	(0.139)
EV x Multiple-car	0.256**	0.601	-0.245	-0.157	-0.217	0.214**
	(0.120)	(0.530)	(0.306)	(0.199)	(0.224)	(0.101)
N	863	796	863	863	863	863
Pseudo-R^2	0.109	0.696	0.113	0.115	0.096	0.110
Signif. coeff. difference	-	-	-	-	-	-
Panel B: Trip frequency (count) by mode						
EV x Single-car	0.021	-0.326	0.099	-0.105	0.011	0.011
	(0.104)	(0.553)	(0.216)	(0.185)	(0.145)	(0.066)
EV x Multiple-car	0.142*	-0.014	-0.186	-0.135	-0.152	0.044
	(0.074)	(0.546)	(0.191)	(0.158)	(0.127)	(0.051)
N	863	795	863	863	863	863
Pseudo-R^2	0.042	0.411	0.089	0.071	0.070	0.027
Signif. coeff. difference	-	-	-	-	-	-

PPML estimates of the interaction effect of EV adoption and household car ownership type on trip distance (Panel A) and trip frequency (Panel B) by mode. *Active* sums bike and foot; *Total* sums car, active, and public transport (PT). Single-car households have one privately owned or private lease car, while multiple-car households have multiple private cars. *Signif. coeff. difference* reports the significance of the difference of the EV adoption effect between single- and multiple-car households, based on a single-interaction term model. Robust standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.9: Model specification: Small set of controls (only survey-day characteristics)

Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Outcome:	Car	Train	PT	Bike	Foot	Active	Total
Panel A: Distance (KMs) by mode							
EV adoption	0.254***	0.480	0.388	-0.092	-0.038	-0.074	0.236***
	(0.086)	(0.478)	(0.445)	(0.197)	(0.136)	(0.141)	(0.074)
N	863	728	855	863	863	863	863
Pseudo-R^2	0.033	0.190	0.206	0.015	0.061	0.017	0.050
Panel B: Trip frequency (count) by mode							
EV adoption	0.101*	0.068	-0.268	-0.120	-0.118	-0.120	0.016
	(0.056)	(0.438)	(0.345)	(0.132)	(0.110)	(0.088)	(0.038)
N	863	728	855	863	863	863	863
Pseudo-R^2	0.013	0.116	0.085	0.017	0.042	0.028	0.011

PPML estimates of the effect of EV adoption and covariates on distance traveled by mode (Panel A) and trip count by mode (Panel B) (Eq. 1). *Active* sums bike and foot; *Total* sums car, active, and public transport (PT). All models include only day-level control variables. Estimated on the baseline sample of EV adopters and not-yet-adopters (Table 1). Variable definitions and data sources are listed in Table A.1. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.10: Model specification: Exclude early-adopters

Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Outcome:	Car	Train	PT	Bike	Foot	Active	Total
Panel A: Distance (KMs) by mode							
EV adoption	0.326***	0.664	0.551	-0.226	-0.057	-0.176	0.280***
	(0.119)	(0.710)	(0.592)	(0.252)	(0.175)	(0.183)	(0.102)
N	825	620	761	825	825	825	825
Pseudo-R^2	0.112	0.723	0.713	0.121	0.125	0.098	0.114
Panel B: Trip frequency (count) by mode							
EV adoption	0.124*	-0.127	-0.146	-0.089	-0.097	-0.082	0.048
	(0.072)	(0.488)	(0.502)	(0.172)	(0.146)	(0.114)	(0.049)
N	825	620	761	825	825	825	825
Pseudo-R^2	0.042	0.491	0.417	0.096	0.074	0.072	0.030

PPML estimates of the effect of EV adoption on distance (Panel A) and trip frequency (Panel B) (Eq. 1), excluding early adopters, which are contemporaneous EV adopters that had an EV in 2019 (8% of EV adopters). *Active* sums bike and foot; *Total* sums car, active, and public transport (PT). All models are estimated on the remaining baseline sample of EV adopters and not-yet-adopters (Table 1), and control for observed determinants. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.11: Alternative estimation methods

Panel A: Distance (KMs) by mode

Estimation: OLS

Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Outcome:	Car	Train	PT	Bike	Foot	Active	Total
EV adoption	11.753**	0.739	0.829	-0.714	0.002	-0.713	11.869**
	(4.970)	(1.480)	(1.482)	(0.797)	(0.233)	(0.825)	(4.999)
N	863	863	863	863	863	863	863
Adj. R^2	0.054	0.223	0.243	0.011	0.047	0.021	0.059

Estimation: SUR

Model:	(1)	(2)	(3)	(4)	(5)
Outcome:	Car	Train	BTM	Bike	Foot
EV adoption	11.753**	0.739	0.090	-0.714	0.002
	(4.853)	(1.445)	(0.113)	(0.778)	(0.228)
N	863	863	863	863	863
R^2	0.097	0.259	0.114	0.056	0.090

Panel B: Trip frequency (count) by mode

Estimation: OLS

Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Outcome:	Car	Train	PT	Bike	Foot	Active	Total
EV adoption	0.245	-0.010	-0.018	-0.037	-0.076	-0.113	0.113
	(0.164)	(0.023)	(0.029)	(0.106)	(0.092)	(0.143)	(0.175)
N	863	863	863	863	863	863	863
Adj. R^2	0.058	0.173	0.231	0.049	0.051	0.070	0.053

Estimation: SUR

Model:	(1)	(2)	(3)	(4)	(5)
Outcome:	Car	Train	BTM	Bike	Foot
EV adoption	0.245	-0.010	-0.009	-0.037	-0.076
	(0.160)	(0.022)	(0.019)	(0.104)	(0.089)
N	863	863	863	863	863
R^2	0.100	0.211	0.121	0.092	0.094

Estimation: Negative binomial

Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Outcome:	Car	Train	PT	Bike	Foot	Active	Total
EV adoption	0.097	0.349	-0.399	-0.132	-0.080	-0.101	0.033
	(0.070)	(0.540)	(0.404)	(0.183)	(0.144)	(0.115)	(0.047)
N	863	863	863	863	863	863	863
Pseudo-R^2	0.027	0.368	0.276	0.034	0.043	0.034	0.025

Estimates of the effect of EV adoption on distance (Panel A) and trip frequency (Panel B) using OLS, SUR, or a negative binomial model. *Active* sums bike and foot; *Total* sums car, active, and public transport (PT). All models follow Eq. (1) and are estimated on the baseline sample of EV adopters and not-yet-adopters (Table 1), and control for observed determinants. Variable definitions and data sources are listed in Table A.1. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.12: Using matched ICEV users as control

Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Outcome:	Car	Train	PT	Bike	Foot	Active	Total
Panel A: Distance (KMs) by mode							
EV adoption	0.153*	0.886*	0.100	-0.017	0.030	-0.001	0.141**
	(0.079)	(0.472)	(0.368)	(0.165)	(0.138)	(0.120)	(0.069)
N	980	686	907	980	980	980	980
Pseudo-R^2	0.116	0.748	0.683	0.161	0.081	0.134	0.110
Panel B: Trip frequency (count) by mode							
EV adoption	0.050	0.283	-0.419	-0.066	0.063	0.000	0.024
	(0.049)	(0.448)	(0.347)	(0.120)	(0.109)	(0.081)	(0.034)
N	980	687	907	980	980	980	980
Pseudo-R^2	0.040	0.485	0.384	0.110	0.055	0.069	0.025

PPML estimates of the effect of EV adoption on distance traveled (Panel A) and trip frequency (Panel B) by mode, using PSM-matched ICEV users as a control group. *Active* sums bike and foot; *Total* sums car, active, and public transport (PT). All models follow Eq. (1) and control for observed determinants; matching is done on the set of observable excluding trip-specific ones. Variable definitions and data sources are listed in Table A.1. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.