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Ownership of battery electric vehicles is uneven in Norwegian households

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Davood Qorbani[1] ✉, Hubert P. L. M. Korzilius[2] & Stein-Erik Fleten[1] ✉

The transition to a zero-emission passenger vehicle fleet has become imperative because of the growing concerns about climate change. Here, we investigate the trends and socioeconomic determinants influencing emitting and battery electric vehicle ownership using longitudinal data of Norwegian households with any vehicle ownership record from 2005 to 2022, accounting for over 2.7 million unique households. Intriguingly, battery electric vehicle ownership has been concentrated on the wealthiest of those owners. Moreover, almost one in ten households once owned battery electric vehicles discontinued ownership by 2022. Our population-level panel data analysis indicates that larger household size, having children, and working away from the residence municipality are positively linked to owning emitting vehicles, while demonstrating the opposite effect regarding battery electric vehicle ownership. Higher income also appears to drive vehicle ownership positively, irrespective of fuel type.

In 2020, Norway became the first country experiencing the share of newly sold passenger battery electric vehicles (BEVs) surpassed the 50% mark[1]—a milestone in the green transition of passenger vehicle fleet[2,3] — cementing Norway's position as a global leader in the adoption of sustainable transportation solutions (BEVs share of sales hit a new record of 79.8% in 2022). This shift towards electric vehicles has considerable implications for reducing greenhouse gas (GHG) emissions from road transport, a major contributor to global emissions and climate change. In 2021, road transport share from energy-related CO_2 emissions was nearly 5.86 Gt CO_2, accounting for 16.1% globally[4,5], and in Norway was 8.70 million tons CO_2 equivalents, accounting for 20.6% nationally[6,7] (see Supplementary Note 1).

Norway has taken a dynamic approach and has stimulated ownership of various vehicle powertrains. Favor of policies shifted initially to diesel against gasoline (petrol) in 2006 and then to electric/green vehicles in 2011. In 2017, a decision was made to implement a sale ban on both diesel and gasoline vehicles from 2025[8,9]. There have been various favorable policies for BEV ownership from the outset (see Fig. 1 and Supplementary Note 2). The observed development in Norway's passenger vehicle fleet has been mainly attributed to implemented policies[1] (see Fig. 2). While the nation has appeared as a global example in transitioning towards battery electric vehicles in many studies, except for a few[10,11], a critical understanding of the underlying socioeconomic factors driving this transition remained relatively unexplored. Unraveling potential nuances in the evolution of passenger vehicle choices within Norwegian households and delving into the socioeconomic determinants influencing vehicle adoption from a population-level perspective contributes to our understanding of the intricate interplay between household dynamics and the evolution of the green transportation landscape.

Several research streams on personal vehicle fleet transition can be identified in the literature. Some studies are concerned with the transition enablers and accelerators, such as financial incentives for car purchases, tax ownership benefits, or infrastructure construction subsidies, across countries or within a country[12,13]. Other studies use quantitative methods like econometrics and simulation to project the fleet's future. Such studies have emphasized that the existing emitting fleet, the durability of newly sold cars, and the time that such vehicles remain in the on-road fleet are among the hampering factors in front of a smooth fleet turnover[3,14–17]. The focal point of these studies is that a business-as-usual scenario will not lead the way in reaching climate goals, and the existing emitting fleet should be phased out. Another group of studies delves into lifestyle or socioeconomic factors of household vehicle adoption. Most of these studies opt for interview, survey, or questionnaire data, and a few rely on longitudinal data from a subset of the entire population. These streams of research, either implicitly or explicitly, mention barriers faced by the transition. Interview[18,19] or questionnaire-based studies[20–26] mainly rely on the stated preferences of respondents, often using small sample sizes. Frequently, these studies analyze the sample's socioeconomic and demographic characteristics and propose policy recommendations that may not capture the diversity of the larger population.

[1]Norwegian University of Science and Technology (NTNU), Trondheim, Norway. [2]Institute for Management Research, Radboud University, Nijmegen, the Netherlands. ✉e-mail: Davood.Qorbani@gmail.com; Stein-Erik.Fleten@ntnu.no

Policy	Category	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
VAT exemption (a)	registration	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✗
Threshold VAT — a subsidy scheme (a)	registration	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	➡ SOON	➡ SOON	✓
Exemption from / deduction of new car registration fee (b)	registration	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Annual motor vehicle tax Exemption (c)	ownership	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✗	✗	✗	✗	✗	✗
Road traffic insurance tax deduction (c)	ownership	.	.	.	.	.	.	.	.	.	.	.	.	➡ SOON	✓	✓	✓	✓	✓	✓
Access to bus lanes (kollektivfelt) (d)	ownership	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✗	✗	✗	✗	✗	✗	✗
Access to bus lanes (kollektivfelt) — conditional (d)	ownership	.	.	.	.	.	.	.	.	.	.	.	➡ SOON	✓	✓	✓	✓	✓	✓	✓
Road tolls exemption (e)	ownership	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✗	✗	✗	✗	✗
Road tolls deduction (e)	ownership	.	.	.	.	.	.	.	.	.	.	.	.	.	➡ SOON	✓	✓	✓	✓	✓
Free parking in public (municipal) spaces (f)	ownership	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✗	✗	✗	✗	✗	✗
Free ferries (g)	ownership	.	.	.	➡ SOON	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✗	✗	✗	✗	✗
Ferry price deduction (g)	ownership	.	.	.	.	.	.	.	.	.	.	.	➡ SOON	➡ SOON	➡ SOON	✓	✓	✓	✓	✓
Oslo EVSE procurement installation (h)	infrastructure	.	.	➡ SOON	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✗	✗	✗	✗	✗	✗
All new cars sold by 2025 should be zero-emission (j)	ownership	.	.	.	.	.	.	.	.	.	.	.	.	➡ SOON	➡ SOON	➡ SOON	➡ SOON	➡ SOON	➡ SOON	➡ SOON
Zero emission zone in Oslo (k)	ownership	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	➡ SOON

Notations: ➡ SOON Pending (decided and waiting to be implemented); ✓ In force; ✗ Discontinued.

Fig. 1 | Notable electric vehicle (EV) supporting policies in Norway since 2005. Policy data are obtained from various sources[1,9,70–83]. NOK to Euro conversions are based on yearly exchange rates retrieved from the Central Bank of Norway (Norges Bank), with the yearly 2023 rates assumed for 2025. Euro values are rounded. **a** The value-added tax (VAT) exemption for electric cars has been abolished since the beginning of 2023 and replaced by a subsidy scheme, in which a VAT exemption up to a purchase price of NOK 500,000 (€43,780) is supported. As a result, only the most expensive electric cars will increase in price. **b** Exemption from paying a registration fee for new cars, first started as a pilot in 1991, then established permanently in 1995. EVs weighing less than 1540 kg do not have to pay this fee. Larger EVs receive a deduction. **c** The low rate for electric cars was introduced in 2005. EVs (and hydrogen cars) paid the lowest possible annual car fee, NOK 450 (€56). Årsavgift (Annual motor vehicle tax) was abolished and replaced by Trafikkforsikringsavgift (Road traffic insurance tax) in 2018. Annual fees increased to NOK 2150 (€212) in 2021 and then to NOK 3000 (€297) in 2022. Since 2023, EVs and fuel cell motor vehicles pay at the same rate as corresponding non-electric motor vehicles under 7500 kg, but at a lower price than diesel without factory-fitted particle filters. **d** Since 2005, electric and hydrogen-powered vehicles can drive in public transport lanes where the signs indicate this. Rules were revised in 2016, allowing local authorities to limit such access to EVs that carry at least one passenger in addition to the driver. These changes were introduced after receiving complaints from public transport users regarding congestion and schedule delays. A bittering fine awaits those EV drivers using public lanes without accompanying passenger(s). **e** EVs had an exemption from paying road tolls on projects where the Government had partnered since 1997. A new fiscal decision was made in 2018 regarding EV road tolls: daily NOK 30 in 2019, NOK 45 in 2020, and NOK 71 in 2025 (€3 in 2019, €4 in 2020, and €6 in 2025) for electric cars driving from Bærum to Oslo. Zero-emission vehicles receive a discount of between 50 and 100% based on various factors, depending on the car size and specific project. **f** Free public parking for EVs in certain public parking areas from 1993 and extended to count for all public parking spaces from 1999. This benefit was abolished in many municipalities in 2017. **g** From 2009 to 2018, EVs were exempted from paying ferry tickets for ferries that are a part of the national roads. Since 2019, EVs should not pay more than 50% of the nominal car fee on ferries. Local alternatives might occur for specific areas. **h** Two million euros were invested in installing 400 charging points between 2008 and 2011, 200 charging points yearly from 2013, 1200 charging points by the end of 2016, and 200 new charging points in 2017. **j** The Norwegian Parliament set a national goal in 2017 that all new passenger cars and light vans sold should be zero-emission (electric or hydrogen) by 2025. **k** The Oslo City Environment Agency recommended setting up a zero-emission zone in Oslo from 2025 at the earliest. The proposal recommends that the people living in that zone be exempted from the ban for the first five years. The municipality has decided that emissions must be cut by 95% by 2030, compared to 2009 levels.

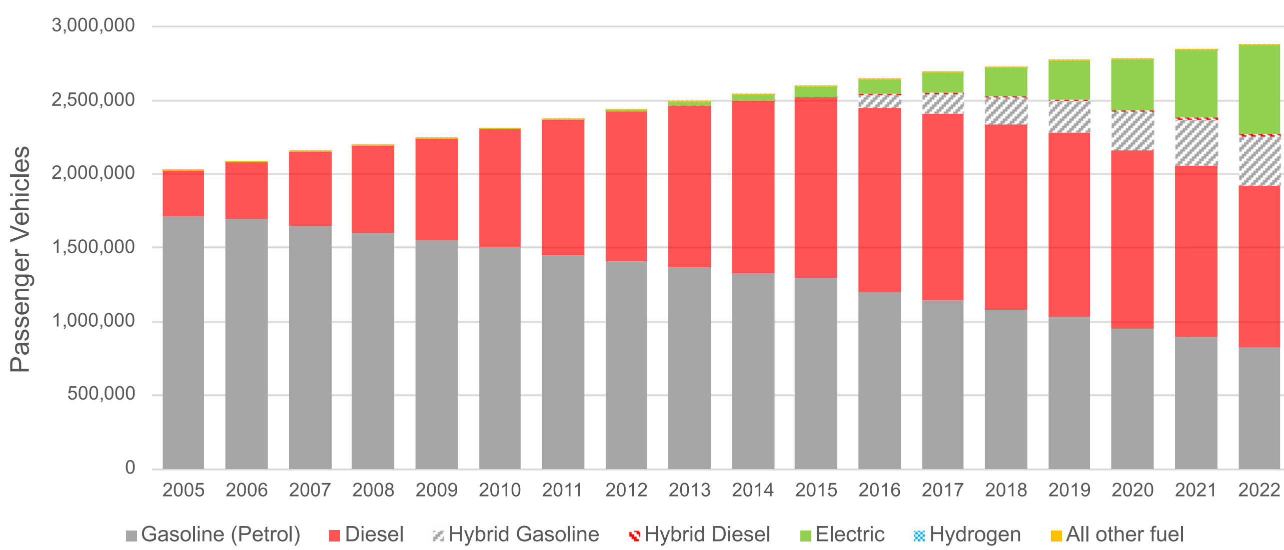

Fig. 2 | Fleet of passenger vehicles in Norway by fuel type from 2005 to 2022. Own creation based on a custom-written code on microdata.no. From 2005 to 2022, the stock of passenger vehicles in Norway increased by 41.7%. This fleet also evolved by fuel types in this period. For example, on the one hand, the stock of gasoline cars decreased continuously. On the other hand, the stock of diesel vehicles increased until 2017 but decreased afterward. Additionally, since 2012, electric and hybrid vehicles have become increasingly common on Norwegian roads. Note 1: The stock of electric vehicle (BEV) fleet in Norway increased from 1245 vehicles in 2005 to 599,167 vehicles in 2022. Note 2: The number of households with at least one electric vehicle (BEV) was less than 1000 in 2005 and around 436,000 in 2022.

While such studies are valuable for gaining initial insights, their main limitation lies in the potential for results to vary if the sample composition changes. An overview of the related literature follows (see also Additional information).

Household size and children

The number of children in a household was found to be positively associated with the likelihood of purchasing a BEV among North American vehicle owners[22]. Canadian households with more members tend to express a higher latent demand (i.e., demand for a product or service that would arise if certain conditions were met) for regular BEV or fully automated plug-in electric vehicle (PEV) and BEV[27]. Similarly, early BEV and PEV adopters in Germany were likely to be in suburban areas with larger household sizes, reported as affluent and high social status[28]. In line with this trend, research also shows that mobility needs drive PEV and BEV adoption in China. Notably, many of those adopters have children[25,29].

Having a larger household and a higher number of children are found to be positively related to electric vehicle (EV) adoption in Nordic countries[30–32]. Households with children, particularly those living in detached houses or with access to a secondary home in Norway, are more likely to own multiple cars, including BEVs. Furthermore, households with kids (under 18 years old) and those living in large cities are more likely to hold BEVs[10]. It is argued that people with young children, especially those under six years old who cannot go home alone, may derive greater benefits from BEV incentives in Norway. Couples with children are largely overrepresented among BEV owners, indicating that younger people and those with children are less negative towards BEV incentives[33]. These findings collectively suggest that the presence of children and household size are important demographics for PEV and BEV ownership and a positive disposition toward BEV incentives. Although not directly mentioning household size or having children, some of the following studies support the finding that households with more vehicles, or those owning a hybrid vehicle, tend to view BEVs more positively.

Multicar ownership

Due to exclusive reliance on electricity, BEVs are generally more distinctive and riskier than other vehicles, such as PEVs or internal combustion engine vehicles (also known as ICEVs)[34]. The resulting implication found across the studies is that these vehicles are often a second vehicle for households. For example, it is reported that households with more vehicles and those already owning a hybrid vehicle view electric vehicles more positively in large U.S. cities (Carley et al., 2013). Similarly, suburban households with multiple vehicles and children have higher mileage in Canada, making them more economically suited for BEV purchases[35]. In Beijing, most BEVs serve as supplementary vehicles, while plug-in hybrid electric vehicles (also known as PHEVs) are households' primary vehicles[29]. Additionally, the number of electric bicycles in a Chinese household is positively associated with the likelihood of purchasing a plug-in hybrid electric vehicle. Further, previous ownership of one's motorized vehicle favors the intention to re-purchase the same type of vehicle[26]. This finding suggests that households with more alternative vehicles may be more open to adopting BEVs. Studies in Norway and Sweden found that BEVs are less burdensome to adopt in multicar households as they can serve as the second car for shorter trips, complementing conventional long-range cars or PEVs[10,21,31,36]. Excluding travel to other countries, BEVs are more commonly used for various household purposes than conventional vehicles in Denmark and Sweden. This pattern held whether the BEV was the sole car in the household or if there was an additional car present[37]. BEV households, particularly one-car households, are more likely to keep their old car when purchasing a BEV, indicating that BEVs often supplement rather than replace the existing vehicle fleet[10]. Previous experiences with EVs are positively related to their potential adoption in Nordic countries. Nonetheless, one observation stands out: people with more vehicles show less interest in adopting EVs[30].

Economic resources (Income and Wealth)

Car ownership is identified to be strongly related to economic resources. GDP per capita, a proxy for income level, is found to be positively correlated with EV adoption using data from 28 countries[38]. It is argued that BEV owners, often with higher socioeconomic status, can better afford the higher upfront costs of purchasing such vehicles[10,25,26,30,35]. Such demographic characteristics are further reflected in the vehicle choices of households with higher travel demand, as they tend to opt for longer-range BEVs, which are generally more expensive[34,39,40]. North American high-end BEV adopters are found to be more affluent and have different perceptions of their vehicles. These adopters are more likely to continue with BEV ownership in subsequent purchases[22]. Meanwhile, a negative significant effect on the rate of PEV sales is reported in California among single parents with kids and those households with multiple adults and kids. The result is attributed to a correlation with low income and, consequently, a lower likelihood of buying new vehicles[34].

Similar results are reported in Nordic countries. For example, a study found strong interconnections between socioeconomic factors such as income level and the adoption rate of hybrid electric vehicles within households in the examined regions of Finland[32]. Another study—focusing on the geographical patterns of BEV adoption in Norway—found that the household income of BEV owners was significantly higher than that of hybrid electric vehicle owners, suggesting that BEVs might be more concentrated in wealthier areas[11]. A higher income is associated with a higher probability of owning a BEV or a plug-in hybrid electric vehicle in Norway. The effect of wealth on multicar BEV ownership was also positive but weaker than for income[10]. In Sweden, where high-income earners are more likely to own their house, many EV owners live in single-family freestanding houses that facilitate home charging[24].

Having a foreign-born member

The influence of having a foreign-born member in the household on vehicle ownership is mixed. The U.S. census data indicate that households with foreign-born members have slightly higher median equity in motor vehicles[41]. Related to this data, however, a lower rate of new BEV sales is reported where there is a higher share of African-American households, and a lower rate of new PEV sales is reported where there is a higher share of Asian households[34]. On the contrary, immigrants or children of immigrants in Norway are less likely to own a car and are also underrepresented in multicar households. However, the pattern varies when it comes to BEV ownership. Remarkably, there is a high share of immigrant-born among BEV owners or multiple car owners, where at least one of them is BEV[10].

Education

Education emerges as a positive predictor of BEV adoption across various studies. For example, education level significantly correlates with BEV market share but not PEV in the United States[42]. A high percentage of university education among early BEV adopters in North America and long-term commitment to BEV technology is reported[22]. Similarly, many PEV users in China hold college and university degrees[29]. Further, individuals with higher education levels tend to have a greater awareness of EVs. These people are more likely to adopt them due to their affordability and environmental awareness[25], significantly influencing Chinese consumers' BEV purchasing intent[43]. A comparable trend has been observed in Nordic countries. For example, a strong connection between educational attainment and the adoption of hybrid electric vehicles is found within households in Finland[32]. Similarly, EV owners typically have higher education levels than non-EV owners in Sweden[24]. Educational attainment is also a strong predictor of BEV ownership in Norway, where households with higher education levels are more likely to own BEVs[10].

Urban settlement

The effect of urban or residential places on the ownership, purchasing, or adoption of BEVs is not to be underestimated. A clustering pattern is observed in California regarding BEV and PEV adoption. Notably, it is found that economically disadvantaged communities and regions with lower income levels typically face financial constraints when it comes to acquiring new vehicles[34]. A similar pattern can be inferred from the findings in Canada, where educated households with higher income and living in areas with a medium level of urbanization (suburbs) are more likely to become suitable targets for BEV purchases[35]. It is also argued that BEV adoption in Norway has a clustering pattern. Notably, people living in urban areas with more public charging stations, higher incomes, and more travel demand are more likely to adopt BEVs[10,11]. Related to this thread, residential area influences EV ownership, indicating a neighborhood effect on EV adoption. For instance, EV adoption in Sweden has primarily occurred within metropolitan regions and, to a lesser degree, in specific hotspots outside these areas. These hotspots correspond to tourist regions that might encounter EVs, particularly through visiting Norwegian tourists[24]. Nonetheless, an investigation centered on Nordic countries found no notable disparities in EV adoption interest between rural and urban areas, questioning the perception of EVs solely as urban cars[30].

Proximity of work and residence places

Studies suggest that commuting patterns, including work-residence proximity and commuting distance, affect PEV and BEV adoption. Individuals with longer commutes are less likely to adopt BEVs due to range anxiety, whereas those with shorter commutes or working close to home are more inclined toward BEVs in Nordic countries[30]. Distance to work matters for Swedes to adopt BEV, although it is not the sole or most important factor in the adoption[24]. Similarly, people with an average travel distance of 15–100 km to work in Norway are more likely to own BEVs than internal combustion engine vehicles. When the work commutes get larger than 100 km, it becomes less likely to own a BEV, presumably because of range limitations. Furthermore, a strong association between BEV ownership and work-related commuting privileges, such as tolls, is documented[10].

Some studies do not explicitly mention the effect of work-residence proximity on BEV adoption. However, the emphasis on commuting patterns and the availability of workplace charging suggests that work-related travel impacts BEV ownership decisions. For instance, perceived attributes of BEVs, such as driving range and charging infrastructure, are found to be important indicators of BEV adoption likelihood among Swedes[36] and continuing with BEV ownership among North Americans[22]. Related to work commute, workplace charging and commute-related factors are influential in BEV adoption, indicating that access to charging infrastructure at work can encourage individuals to purchase PEVs and BEVs in California[34,44]. Additionally, travel demand and charging infrastructure availability influence California PEV buyers' decision choice to switch to BEV. Households with high travel demand tend to choose longer-range BEVs[39].

As this overview of socioeconomic factors on vehicle adoption indicates, these findings may vary depending on the specific context and demographic characteristics of the studied households. Even in a BEV front-runner country such as Norway, most passenger vehicles on the road are still polluting (see Fig. 2 on the fleet of passenger vehicles in Norway). Encouraging and guiding owners within this category to adopt cleaner alternatives could lead to a substantial reduction in emissions from the passenger vehicle fleet. Thus, gaining insight into the main drivers and consequences of changes in this sector offers value for the decarbonization of society. Nonetheless, limited research focuses on the rich socioeconomic factors that contribute to the transition and choice of households over an extended period using population-level data for various reasons, such as lack of data or not having access to data.

Dynamics and changes within households probably have influenced the adoption of green vehicles. In this regard, it is vital to investigate Norway's story as a role model and the underlying explanatory factors that interacted with the implemented policies and the observed changes over time. This is the motivation for this research. We aim to investigate the actual practices of Norwegian households regarding vehicle adoption—accounting for socioeconomic variables related to households. The surfaced explanatory factors can be leveraged to design more efficient policies targeting specific household categories. To achieve the goal of this study, we seek to answer these research questions:

- How has the choice of passenger vehicles evolved in Norwegian households from 2005 to 2022?

- What socioeconomic factors explain the choice of passenger vehicle adoption in Norwegian households?

We leverage the longitudinal data of over 2.4 million unique Norwegian households with any record of vehicle ownership in the mentioned period. We find an uneven distribution of BEV ownership concentrating on the wealthiest. However, we also find one in ten instances of BEV discontinuance in Norway, contradicting a sustainable adoption of BEVs and signaling a potential delay in achieving a zero-emission passenger vehicle fleet. Our population-level panel data analysis indicates that lower income, having children, and working away from the residence municipality are significantly linked to emitting vehicle ownership, while demonstrating the opposite effect for BEV ownership. Household size and household education level are also found to influence both emitting vehicle and BEV ownership positively. Finally, urban residence seems to negatively influence emitting vehicles, although it lacks statistical significance concerning ownership of battery electric vehicles.

Results and discussion

Descriptive analysis: socioeconomics of gray and green vehicle ownership

We analyze two mutually exclusive groups among those households that registered as residents and owned at least one private passenger vehicle in Norway in any year from 2005 to 2022: Those households who owned only gray vehicles (i.e., emitting), and those who owned at least one green vehicle (i.e., BEV) in any year in this period—not necessarily in all years (see Methods section for a description of gray and green vehicle categories). We call these two groups of households the gray and the green adopter populations, respectively.

We begin by examining the pattern of green (BEV) ownership in the green adopter population. Figure 3 presents a Sankey diagram of changes in the number of green vehicles per household for the green adopter population. One observation is a growing tendency among these households to own more than one green vehicle (BEV)—see Supplementary Note 3 and ref. 45. The other observation is that almost 10.9% of once green-vehicle-owners abandoned those vehicles by the end of this period, i.e., they had zero electric vehicles in 2022 (We note that the discontinuance we find does not factor in the leasing of BEVs into account, where leased vehicles are registered to the leasing company, not to a person or a household—see Data procedure). This finding corroborates previous questionnaire-based studies. For example, BEV discontinuance was recorded for 18% of BEV owners in California[20]. Another study found that one-tenth opt for a PEV as a replacement, and roughly one-fourth choose a conventional vehicle as a substitute for their BEV[39]. This value is even reported higher in China, where around 44% of respondents in Beijing indicated they would not consider repurchasing BEVs without a free license plate incentive[29].

Comparing economic factors between the two adopter populations reveals significant differences in variables such as income after tax, taxable gross wealth, and debt at the household level, as depicted in Fig. 4 (blank years on all figures from this point onward indicates unreported data from the data provider. See Supplementary Table 1 on reported data.) The households of the green adopter population have relatively higher levels of income and wealth and are in higher debt on average than those of the gray adopter population. Furthermore, the mean values of these economic indicators are greater than the median for both groups, indicating a right-skewed distribution of all these factors. The interpretation is that significant income, wealth, and debt are disproportionately concentrated in the wealthiest households of both gray and green populations.

Differences between the gray and the green adopter populations also appear to be present in other socioeconomic characteristics. For example, by looking at the highest education level in households of both population segments in Fig. 5, an increasing trend in favor of university education is visible. However, the green adopter population seems more educated than the gray adopter population. In any given year, the proportion of university education has been approximately 22 to 26 percentage points higher in the green adopter population than in the gray counterpart.

An important factor in vehicle ownership is household size. We observe a gradual decrease in the mean size of households in both population segments, from approximately 2.4 to 2.1 persons per household for the gray population and from 3.0 to 2.8 persons per household for the green population, from 2005 to 2022 (see Fig. 6). Another notable aspect of households regarding passenger vehicle ownership is the household combination regarding children and their age. Over the period, there is an increasing trend

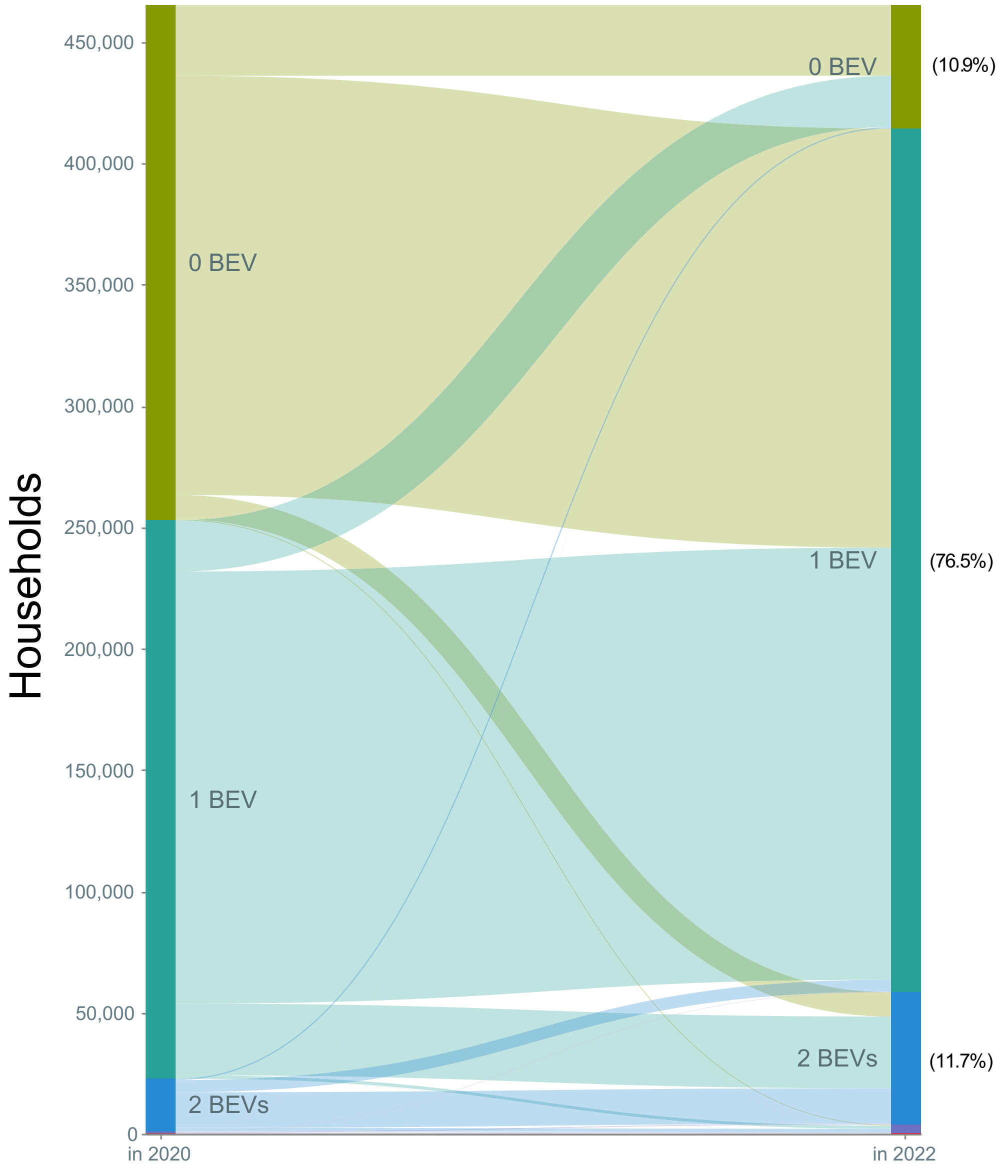

Fig. 3 | Green (BEV) ownership development in Norway from 2020 to 2022—Sankey diagram of the number of green vehicles per household in the green adopter population. Own creation using microdata.no. Find the link for the online interactive graph in the section Data availability. Note 1: This Sankey diagram illustrates the dynamic flow of the green vehicles (BEVs) owned per household in the green adopter population. The width of the streams corresponds to the flow rate. The pillar shows the development from 2020 to 2022 regarding the relative number of households having had 0, 1, 2, or more green vehicles (BEVs)—The percentages inside parentheses indicate those relative numbers for 2022 and are manually added to this figure from the interactive diagram. The height of the pillar (the outer y-axis value) shows the number of households in the green adopter population in 2020. The left side of the pillar indicates the start year, 2020, and its right side marks the last year, 2022. As a limitation, note that this pillar only shows the green ownership development in the households registered as residents by the beginning year of the pillar; i.e., this pillar does not capture any newly registered households after 2020. Note 2: Read the numbers on the inner edge of the Sankey diagram, depicted with split darker colors, as follows: share of households owning m green vehicle(s) in the year 2020 → share of households owning n green vehicle(s) in the year 2022, where m and n = 0, 1, 2, or more green vehicles (BEVs).

in the proportion of households with no child among both gray and green adopter segments. This proportion started at 57% in 2005 and reached 68% in 2022 for the gray adopter population, and started at 38% in 2005 and reached 45% in 2022 for their green counterpart. Nonetheless, we find that more of the green adopter population enjoyed having small and older children in the household compared to their gray counterparts (see Fig. 7).

In terms of household diversity, it appears to be a trend from 2005 to 2022, indicating an increase in the number of households with an immigrant background in Norway. Related to our study, our measures suggest that the green adopter population comprised approximately four percentage points more immigrant background households than the gray population in any given year (see Fig. 8).

We observe opposite trends regarding work-residence proximity among gray and green adopter population segments (see Supplementary Fig. 1). About 28% of the gray adopter population had a workplace away from the residence municipality in 2022, four percentage points lower than in 2005. On the contrary, this share was 49% for the green adopter population in 2022, two percentage points higher than in 2005. Overall, a higher percentage of green adopter households had a workplace away from the residence municipality than the gray adopter households, roughly 20 percentage points higher in 2022. The latter observation makes more sense when we investigate the vehicle ownership data. The median number of vehicles, irrespective of fuel type, was 2 for the green adopter population and only 1 for the gray adopter population in 2022. The gap still holds if we

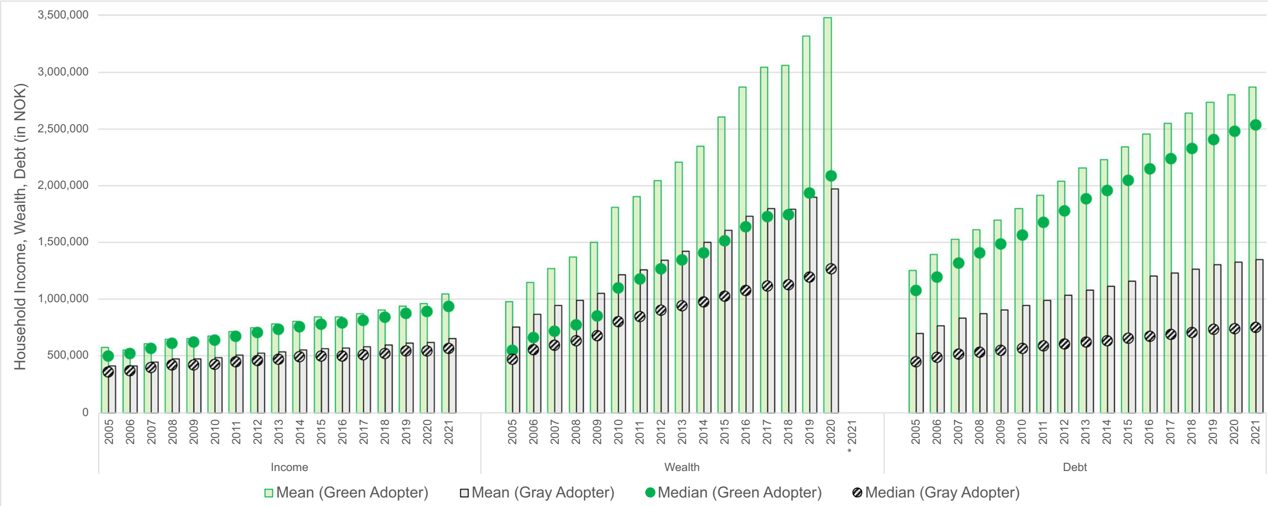

Fig. 4 | Household economic indicators: a gray vs. green adopter population comparison from 2005 to 2021. A comparison of household income after tax, taxable gross wealth, and debt indicates the green adopter population has been financially more privileged than the gray adopter population (*Note that wealth data for 2021 is unavailable).

further zoom into the data—conditioned to have at least one household member working away from the residence municipality and at least one vehicle in the household: The median number of all fuel vehicles was 2 for the green adopter population and 1 for the gray adopter population, in 2022. These observations indicate the prevalence of multi-vehicle ownership among the green adopter population.

Finally, we find a slow but steady trend toward dwelling in urban areas in both population segments—from roughly 75% to 80% for the gray and 83% to 87% for the green adopter population between 2005 and 2022. Further, the proportion of urban dwellers in the green adopter population has been relatively higher (up to almost eight percentage points) than that of Norway's gray adopter population in this period (see Supplementary Fig. 2).

Panel data analysis: factors related to households' gray and green vehicle ownership

We leverage the longitudinal population-level data of this study to conduct a panel data analysis. We account for potential endogeneity, as discussed in the Methods section. Following a Hausman test, we opt for fixed-effect models for both gray and green vehicle ownership as dependent variables. Table 1 presents the results, covering 2005–2021 (except for 2010, since urban data for this year is not reported—see also Supplementary Table 1 on reported data). The independent variables are household size, predicted household income after tax (instrumented by a dummy variable of household immigration background), highest education in the household, having children, working outside the residence municipality, and living in urban areas.

As the results in Table 1 indicate, p-values are near zero for all variables, implying a statistically significant association of the independent factors with both green and gray vehicle ownership. Comparing the relative strength of the independent variables (t values) reveals that living in non-urban areas, household size, and work-residence proximity are the top contributors to gray ownership. Meanwhile, household income, size, and work-residence proximity contribute most to green ownership.

Comparing gray and green vehicle ownership by the association sign shows that higher income is the driver of emitting vehicle and BEV ownership. Larger household size, having children, and working away from the residence municipality are positively associated with owning emitting vehicles, while demonstrating the opposite effect for BEV ownership. Simply put, higher income, no children in the household, and working within the residence municipality positively influence BEV ownership. These differences suggest that households with children or those who have to drive to other municipalities for work are less likely to adopt green cars, as they may face different challenges. One explanation is that families with children need big cars; bigger BEVs become too expensive for this group[40]. BEV battery capacities and limited charging infrastructure outside cities potentially explain these results.

Previous survey-based studies found BEV owners are more likely to have higher education[18,20–24]. Our study finds a close to zero association between the highest level of household education and green ownership. Intriguingly, we find a positive link between the highest level of education in the household and emitting vehicle ownership. Finally, urban residence seems to influence gray ownership negatively, but negligibly regarding green ownership. The results could be attributed to higher public transport availability in those areas and are in line with the zero-growth in passenger vehicle traffic policy in Norway[8]. Furthermore, it corroborates a Nordic-focused study that found no notable disparities in EV adoption interest between rural and urban areas[30].

Conclusions

This study presents a comprehensive analysis of household choices regarding passenger vehicles, specifically focusing on BEV adoption in Norway. By examining the evolution of these choices from 2005 to 2022 and using nationwide panel data, this research offers population-level long-term insights into the socioeconomic factors influencing BEV ownership. An intriguing aspect of our findings is that battery electric vehicle ownership has been concentrated on the wealthiest of those household vehicle owners. We also find that a significant proportion of households (one in ten) who once owned BEVs discontinued ownership by 2022 (Fig. 3). These observations signal potential challenges in front of private vehicle transition, underscoring the need for a deeper understanding of the factors influencing long-term ownership and sustained BEV adoption that directly contribute to emissions from the private transport sector.

This study has several aspects that distinguish it from previous research. First, this research covers a more extended period and a much larger dataset than in many previous studies, allowing for an extensive analysis of the evolution of private vehicle choices in more than 2.7 million Norwegian households over 18 years. This long-time span provides a broad understanding of the trends and changes in passenger vehicle adoption. Second, we employ a longitudinal analysis using panel data, which allows for examining individual households over multiple time points. This method provides more robust insights into the associations between socioeconomic factors and BEV ownership, capturing the dynamics and changes within households over time, by examining the specific influences of household composition and household dynamics in vehicle choice. It adds to the understanding of the socioeconomic factors shaping BEV adoption and is a worthwhile contribution to the literature, particularly given the specific

	Education	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022 *
Gray Adopter	School	34%	34%	33%	33%	32%	32%	31%	31%	30%	29%	29%	28%	28%	27%	27%	26%	26%	25%
	Vocational	32%	31%	31%	32%	32%	31%	31%	31%	31%	32%	32%	32%	31%	31%	32%	32%	32%	32%
	University	34%	34%	35%	35%	35%	36%	36%	37%	37%	38%	39%	39%	40%	40%	40%	41%	41%	41%
Green Adopter	School	12%	11%	11%	11%	10%	10%	10%	10%	9%	9%	8%	8%	8%	8%	8%	7%	7%	7%
	Vocational	32%	31%	31%	31%	30%	30%	29%	28%	28%	28%	27%	27%	26%	26%	26%	25%	25%	25%
	University	56%	57%	58%	58%	59%	60%	61%	62%	62%	63%	64%	65%	65%	66%	66%	67%	67%	67%

Fig. 5 | The highest education in the household: comparing the gray and green adopter populations from 2005 to 2022. The values (percentages) indicate the highest education in the household within each population segment each year. The length of horizontal bars corresponds with the percentages. Categories of education depicted here are as follows: School education: Primary, lower secondary, and upper secondary education; Vocational education: Professional and higher professional degree; University education: Bachelor, master, and PhD. No school and missing data on education are not depicted in this figure (*Note that partially available education data for 2022 is assumed to be valid for the whole year).

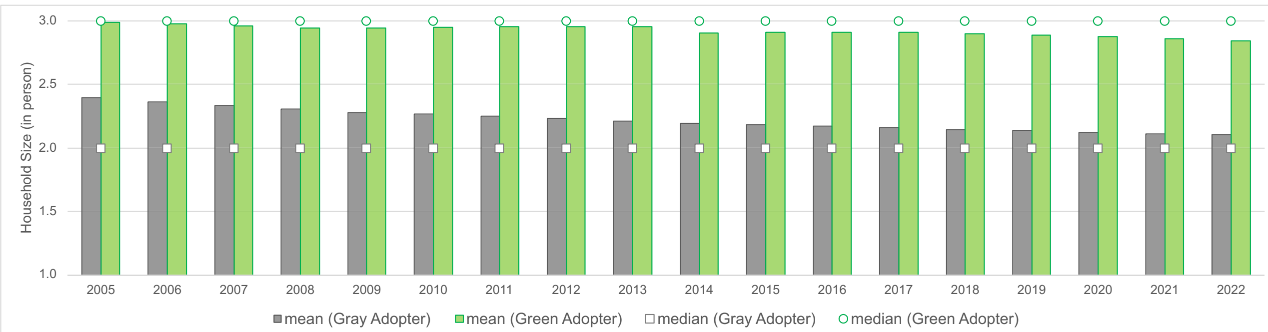

Fig. 6 | Household size: comparing the gray and green adopter populations from 2005 to 2022. A gradual decrease in the mean size of households in both gray and green adopter populations is observed, from approximately 2.4 to 2.1 persons per household for the gray population and from 3.0 to 2.8 persons per household for the green population. The median size of households in both segments remained stable in this period.

	Children	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Gray Adopter	no child	57%	58%	59%	60%	61%	61%	62%	62%	62%	64%	65%	65%	66%	66%	67%	67%	68%	68%
	small child	13%	12%	12%	12%	12%	11%	11%	11%	11%	11%	11%	10%	10%	10%	10%	10%	9%	9%
	older child	18%	18%	18%	18%	17%	17%	16%	16%	16%	15%	15%	15%	14%	14%	14%	14%	14%	14%
	adult child	11%	11%	10%	10%	10%	10%	10%	10%	10%	8%	8%	8%	8%	8%	8%	8%	8%	8%
Green Adopter	no child	38%	38%	39%	39%	39%	39%	39%	39%	39%	42%	42%	42%	42%	43%	43%	44%	44%	45%
	small child	29%	28%	28%	27%	27%	26%	26%	26%	25%	24%	24%	23%	22%	22%	21%	20%	19%	18%
	older child	25%	26%	26%	26%	26%	26%	26%	26%	26%	26%	26%	26%	26%	26%	27%	27%	27%	27%
	adult child	8%	8%	8%	8%	8%	8%	9%	9%	9%	7%	8%	8%	9%	9%	9%	10%	10%	10%

Fig. 7 | Household type by children: comparing the gray and green adopter populations from 2005 to 2022. Household type by age range of children is as follows: with small children (youngest child 0–5 years), with older children (youngest child 6–17 years), and with adult children (youngest child 18 years and over). Missing data is not depicted in this figure.

Immigrant Background?	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Gray Adopter	14%	14%	15%	16%	17%	18%	18%	19%	20%	21%	21%	22%	22%	23%	23%	24%	24%	24%
Green Adopter	18%	19%	19%	20%	21%	21%	22%	23%	23%	24%	25%	25%	26%	26%	26%	27%	27%	27%

Fig. 8 | Household immigrant background: comparing the gray (top) and green (bottom) adopter populations from 2005 to 2022. The higher values (toward blue color) indicate a higher percentage of households with immigrant background, while lower values (toward red color) indicate a higher percentage of all-Norwegian households over the years.

context of Norway's electric vehicle supportive scheme over this period. Third, this study explicitly focuses on the gray-to-green transition within Norway's private passenger vehicle fleet. By investigating the socioeconomic and demographic characteristics associated with both emitting vehicle and BEV ownership during this transition period, this research offers a side-by-side comparison of the factors driving the adoption of greener vehicles and the dynamics of Norway's sustainable transportation shift.

It is also important to acknowledge the limitations of this study. First, while the study provides insights into the factors influencing BEV adoption in Norway, a Nordic country, generalizing these findings to other countries, regions, or periods with different contexts, policies, cultural norms, or socioeconomic conditions needs a pinch of salt. Second, this study tries to capture a common denominator of all socioeconomic variables applicable nationally regarding emitting vehicle and BEV ownership. However, this approach may hinder incorporating some factors, including regional differences (such as the attitude of residents toward new technology or the dynamics of the social network of the adopters). Nonetheless, we have captured the essential elements of those differences by incorporating

Table 1 | Panel data analysis: households with any record of car ownership from 2005 to 2021

	R^2 within:		0.10				(a)	
	R^2 between:		0.10					
	R^2 overall:		0.12					
	Corr(u_i, Xb):		−0.11					
	Sigma u:		0.60					
	Sigma e:		0.54					
	Rho:		0.56					
	Number of observations:		23863878					
	Number of groups:		2187457					
	Observations per group	min:	1					
		average:	10.91					
		max:	16					
	F(6,20250528):		420630.98					
	Prob > F:		0					
→	owned vehicle gray per household	Coef.	Std. error	t	$P>\|t\|$	[95% Confidence Interval]		
	household size	0.15	0.00	97.76	0.00	0.15	0.16	
	household income (in natural log) PREDICTED	0.07	0.01	11.88	0.00	0.06	0.08	
	household highest education	0.11	0.00	93.64	0.00	0.11	0.11	
	have children (dummy)	0.06	0.00	59.80	0.00	0.06	0.06	
	different work residence place (dummy)	0.12	0.00	95.11	0.00	0.12	0.13	
	live in urban (dummy)	−0.09	0.00	−110.34	0.00	−0.09	−0.09	
	Constant	−0.61	0.07	−8.63	0.00	−0.74	−0.47	

	R^2 within:		0.03				(b)	
	R^2 between:		−0.20					
	R^2 overall:		−0.03					
	Corr(u_i, Xb):		−0.41					
	Sigma u:		0.28					
	Sigma e:		0.41					
	Rho:		0.32					
	Number of observations:		6330859					
	Number of groups:		504178					
	Observations per group	min:	1					
		average:	12.56					
		max:	16					
	F(6,3935694):		26463.47					
	Prob > F:		0					
→	owned vehicle green per household	Coef.	Std. error	t	$P>\|t\|$	[95% Confidence Interval]		
	household size	−0.05	0.00	−45.48	0.00	−0.05	−0.05	
	household income (in natural log) PREDICTED	0.44	0.01	77.52	0.00	0.43	0.46	
	household highest education	−0.01	0.00	−5.12	0.00	−0.01	0.00	
	have children (dummy)	−0.02	0.00	−23.12	0.00	−0.02	−0.02	
	different work residence place (dummy)	−0.04	0.00	−37.83	0.00	−0.04	−0.04	
	live in urban (dummy)	−0.01	0.00	−12.99	0.00	−0.02	−0.01	
	Constant	−5.52	0.07	−83.22	0.00	−5.65	−5.39	

These tables present the result of panel data analysis for gray vehicle ownership in the gray adopter population (a) vs. green vehicle ownership in the green adopter population (b). The dependent variables—the number of vehicles—are marked with arrows. All values are statistically significant ($p < 0.05$). Explanations of indicators in the panel data results are as follows. See Methods and refs. [52,67].

- R^2 within: The proportion of variance the model accounts for within the panel units.
- R^2 between: The proportion of variance that the model accounts for between separate panel units.
- R^2 overall: It measures the fit of the model, ignoring any included effects (The R^2 overall is a weighted average of the two above.)
- Corr(u_i, Xb): It measures the correlation between the within-entity errors u_i and the regressors in the model.
- Sigma u: standard deviation (SD) of residuals within groups u_i.
- Sigma e: standard deviation (SD) of residuals (overall error term) e_{it}.
- Rho: fraction of variance due to u_i.

influencing factors such as living in urban vs. rural areas and working outside the residence municipality. Third, by its nature, this study does not include any qualitative and survey-based data collection or analysis. Such data can provide additional insights into the reasons behind household choices and the impact of policy incentives beyond what can be captured in quantitative data alone. Finally, the study focuses primarily on the influence of household demographics on BEV ownership. It does not include other potential factors, such as the availability of charging infrastructure or the range of available BEV models, that could influence household choices.

This research suggests several avenues for future exploration. One future direction to advance this study is using open-source fast charging data[46] by regions in Norway and investigating to what extent the BEV adoption and socioeconomic factors interplayed over the years. Furthermore, more than 10% discontinuance of BEV ownership in Norway is disconcerting. It is vital to investigate the underlying factors that convinced a considerable proportion of households to discontinue BEV ownership in an EV-friendly country such as Norway. Another future direction is redirecting the attention to underprivileged households who have not owned vehicles and consequently have not been subject to various generous tax relief and support schemes targeting vehicle owners. This area of research has received less attention; however, it has the potential to provide a better understanding of the reality for policymakers. Besides, the unbalanced distribution of BEV ownership among wealthier households poses questions to policymakers and stakeholders involved in sustainable transport initiatives to review past decisions to ensure a more equitable transition and promote a sustainable path for electric vehicle adoption.

Methods

Research design: specifications of the research problem

The research questions of this study have several characteristics. First, individual and household heterogeneity needs to be controlled over time to discover contributing variables to changes in private vehicle ownership while avoiding the risk of establishing biased results. Second, more informative data and variability (variation in the data that signals unnoticed relation) are needed to answer such questions. One consequence is producing more reliable parameter estimates. Third, these questions also enable investigating households' transient or steady state regarding various socioeconomic variables such as income, education, and presence and age of children. These are among the characteristics that make panel data analysis a competent method to employ and answer the main research question of this study. We benefit from panel data, also known as longitudinal data[47–49]. This data type allows observing the same entity, such as households, over several periods and following their developments.

The statistical unit of analysis for this research is household. The main reason is that the decision regarding vehicle choices is often affected by household needs and how the household decides. In simple words, the vehicle user is the whole household, although vehicle owners are individuals who pay for it. Different definitions and compositions of households affect the inferred socioeconomic status and income of households[50]. We use the formal dwelling (residential) definition of households according to Statistics Norway (SSB)—see Supplementary Table 1.

Any households registered as residents from and after 2005 until 2022 are included in the analysis of the gray and green adopter populations if they meet the criteria mentioned. Households are dropped only in years they were not considered registered residents. We use Norwegian households, indicating households within the borders of Norway, regardless of the nationality or migration status of the individuals residing in those households. It encompasses households including Norwegian citizens, migrants, or individuals without Norwegian citizenship.

Data and data treatment

The population of this research is all households who resided in Norway and were registered as residents as of January 1st from 2005 to 2022, with at least one privately owned passenger vehicle in any year (not necessarily in all years). To find these households in the database, we start by omitting all households without any record of vehicle ownership in the mentioned period—reported as of December 31 each year. Then, we are left with a population that comprises every household in Norway that has owned a passenger vehicle at least once during this period—conditioned to the report date. That accounts for around 2,752,600 unique households over 18 years with the above criterion. Note that there might be years when these households have owned no vehicle. By including households that have owned vehicles at different points within the selected timeframe, we can compare and analyze the factors influencing vehicle ownership over the years, allowing us to investigate the transition from emitting vehicles to greener alternatives. Among these households, any household without a record of BEV ownership, i.e., those who owned only emitting vehicles, are called gray adopters in this study. Those with at least one record of BEV ownership in this period are called green adopters, even if they have owned gray vehicles. Such categories align with previous studies, finding that gray vehicle owners are more likely to keep their emitting vehicle even after buying BEVs[10,20]. These two groups are mutually exclusive (around 2,241,000 gray adopter households, and 511,000 green adopter households over 18 years).

Of course, a household is a dynamic entity: households are formed and dissolved, and the population increases. Given the criteria mentioned, and dynamics in households, that accounts for around 1,631,000 adopter households in 2005 and 2,083,000 adopter households in 2022 (see Supplementary Note 4. A detailed description of the households' profiles used in this study can be found in Supplementary Table 1). Our data can be considered as unbalanced panel data, which occurs for various reasons: temporary unit non-response, where some participants do not engage at all time points (e.g., when people are out of the country in some years); panel attrition, when participants drop out at specific points (e.g., the contact person passes away, or the household emigrates); and late entry, when new participants join the panel at later periods (e.g., the survivors form a new household; people leave their current household and form a new household; the arrival of immigrants)[51]. Despite its apparent flaws, this data type is more representative of the ongoing reality in society. It avoids myopic focus on a set of respondents with an uninterrupted record of data, which may lead to selection bias as a cause of endogeneity (Endogeneity is further discussed in the following sections).

The data source for this research is Statistics Norway (SSB), accessible through the microdata.no platform. The analysis is also conducted on this platform, and all charts (except for the Sankey diagram) are our own creation in Microsoft Excel—using data manually collected from the analysis results on the platform (see Supplementary Note 6). The Sankey diagram is made on microdata.no and exported to the Vega graph editor (https://vega.github.io/editor/). Data is treated following the platform confidentiality obligations and restrictions[52].

Data procedure: measures derived from data

Variables for this study are initially shortlisted from 474 available variables on microdata.no based on their relevance to the socioeconomic status of individual persons and privately owned vehicles and longitudinal availability. The shortlisted variables for the panel data regression analysis are controlled for correlation and multicollinearity. Regarding multicollinearity, we analyze the variance inflation factor (VIF) and tolerance (1/VIF) values (see Supplementary Table 2). The most common recommendation is that VIF values higher than 10[53,54], and a tolerance of less than 0.20 are alarming[55]. The variables used for this study are measured and operationalized as follows.

Household size. This variable indicates the number of persons registered under the same unique household identification number. Household size is calculated by counting the people with the same household identification number in our analysis.

Household background. Immigration background is an aggregated dummy variable. In this study, people who were not born in Norway with two Norwegian-born parents, or those foreign-born with two Norwegian-born parents are marked as having immigrant backgrounds. Any household that comprises at least one person with an immigrant background is given a dummy value of 1—See notes in Supplementary Table 1 for more details. This variable is used as an instrument in this study.

Household income, wealth, debt. Individual persons' income after tax, wealth, and debt is aggregated into household levels by the unique household identification number. This number is the identification number of the contact person in the household and indicates persons who live in the same household. In the case of zero or negative income after tax for the household, often related to family businesses that suffered losses within a specific year, such values are set to 1 in our regression analysis (this is done to avoid ending up with null values, and unwanted dropping of those households from the analysis by the microdata.no platform in the next transformation step). Then, aggregated values are transformed into natural log values.

Education (the highest in the household). The highest education level that any person has achieved or holds within a year is called from the database (see the structure of the Norwegian education system[56]). Then, the highest education in the household is found by the unique household identification number.

Household type by children. To examine the influence of children in vehicle adoption, we aggregate 24 categories of households defined by SSB: For the descriptive analysis, we present an overview of households without children, households with small children (youngest child 0–5 years), with older children (youngest child 6–17 years), and with adult children (youngest child 18 years and over). These four categories are mutually exclusive. In the panel regression analysis, we introduce a dummy for those households with children, which are assigned a value of 1. Not having children is the reference. See notes in Supplementary Table 1 for more details.

Urban vs. non-urban settlement. We account for urban vs. non-urban settlement of the households. Consistent with the practice of connecting persons using a household ID, we make a simplistic assumption that all household members live at the same address as the contact person of the household, i.e., the person whose identification number is used to identify the household members.

Cross municipal residence and workplaces. To find those households with at least one person working outside the residence municipality—indicating a need for vehicle ownership—we retrieve every registered person's residence and work municipalities. Workplace information includes the primary employment of employed residents aged 15–74 in November. Residence information consists of every resident in January. We make two simplified assumptions here. First, the residence place and workplace dates apply for the whole year. Second, those persons with missing data of either residence or work, including those under 15 and over 74 years old, reside and work in the same municipality. Any household with at least one person working outside the residence municipality receives a dummy value of 1.

Vehicle classifications and ownership. Hybrid, electric, hydrogen, and biofuel-powered vehicles seem promising options for the transition toward a low-carbon, sustainable private transport fleet[57,58]. Each engine type has its advantages and disadvantages. Except for BEVs, which are solely powered by electricity, other types emit carbon dioxide and other pollutants to different degrees[59–63]. Various powertrains will likely coexist in the future, while BEVs will most likely lead the way[64]. Some references and studies we cite collectively attribute electric vehicles (EVs) to battery electric vehicles (BEVs), plug-in hybrid electric vehicles (PHEVs) or plug-in electric vehicles (PEVs), and hybrid electric vehicles (HEVs). We use the following classification in our study to assign any registered vehicle in the country to the green or gray category:

- Gray: except for battery electric vehicles, privately owned passenger vehicles with fuel types such as gasoline (petrol), diesel, paraffin (kerosene), gas, hybrid gasoline, hybrid diesel, biodiesel, bio-gasoline, LPG-gas, CNG-gas, methanol, ethanol, and other fuel.
- Green: privately owned battery electric vehicles, solely powered by electricity. Any hybrid vehicle running on petrol or diesel is considered gray. Note that hydrogen-powered vehicles are green but omitted from the analysis because of negligible household ownership. The number of privately owned hydrogen cars in Norway was zero in 2005 and 212 in 2022 (see Fig. 2).

The ownership of all registered passenger vehicles by year is identified with a unique vehicle-person ID and linked to individual persons, indicating ownership as of December 31 each year. Since this key returns the status data at the end of the year, if a person deregisters or sells all their cars before the end of the year, this person will not have any connection to those deregistered or sold vehicles in microdata.no in that specific year. There is currently no way of looking at the short-term ownership or ownership within a year that has not lasted until the last day of the year. Furthermore, while a vehicle may have two or several owners, such as one owner and one co-owner, the data on microdata.no shows the main owner as the registered person that is linked to that vehicle (see Supplementary Note 5). Finally, gray and green vehicles are linked to households by the unique household number. Any household that has only owned gray vehicles, i.e., never owned any green vehicle, is assigned to the gray adopter population group. The other group, the green adopter population, consists of households with at least one green vehicle in any year, not necessarily all years (note that green adopters could also own gray vehicles). Furthermore, note that there might be years in this period when adopter households have not owned any vehicle. These two groups are mutually exclusive.

Potential endogeneity

Among the causes of endogeneity in the literature, omitted variables and simultaneity are more relevant to studies such as this research[49,65,66]. Endogeneity may be rooted in omitted variables when important variables correlated with the independent and dependent variables are left out of the model. This problem typically arises from three different categories. First, the variable may exist and is measurable but overlooked and not modeled[66]. This issue should not be a concern due to the comprehensive selection of independent variables. We have accounted for several socioeconomic factors, covering various potential influencing variables on the number of gray (emitting) and green vehicles (BEV) in households. Furthermore, in an adequate sample size, as large as the current study, the omitted variable can be assumed to be evenly distributed across all households (and thus, the predictor will not show systemic variation with the residual). Second, unobservable individual-specific variables such as environmental awareness, which are correlated with educational attainment, might affect the type of engine selection. Fixed effects models in panel data analysis handle unobserved heterogeneity to various degrees by accounting for such individual-specific or time-invariant effects[47,66]. Third, exogenous variables such as tax and subsidies (that may have a suppressing effect on the results), specific regional policies, or other unmeasured aspects (like social networks) could influence both the ownership of BEVs and emitting vehicles, thereby possibly leading to omitted variable bias. Incorporating influencing factors such as living in urban and residence-workplace proximity captures the essential elements in favor of providing a big picture in this study.

A more pressing issue within our study could be the simultaneity problem. Simultaneity occurs when the independent and dependent variables affect each other at the same time[49,65,66]. For example, it is plausible that a household's decision to purchase an emitting vehicle or a BEV influences their economic situation (through various factors like expenses and savings on fuel or taxes). In turn, their economic situation might influence their decision on vehicle purchase. This feedback loop between the choice of vehicles and socioeconomic status could lead to biased estimates in the regression model. While we have accounted for various socioeconomic factors, comprehensively capturing this simultaneous relationship's direction and intensity is complex. We employ instrumental variable (IV) regression analysis to address this challenge and mitigate probable endogeneity resulting from simultaneity[65,66].

Model specification. We employ the Hausman test to diagnose the model and check whether fixed effect (FE) or random effects (RE) estimation should be used in connection with panel regressions. The Hausman test provides a standard regression result for respective fixed and random effect estimation. *P* value based on chi-square diagnostics, an aggregate measure, indicates which variant is best for the current dataset. *P* values < 0.05, i.e., rejecting the null of the Hausman test, indicate systematic differences in the coefficient estimates and imply that the RE estimator is not consistent. According to the literature, the inconsistency of the RE estimator does not necessarily mean that FE restrictions are satisfied, and they should be checked with other advanced tests. Nonetheless, because of the currently available tests on the microdata.no platform, we assume that rejecting the null hypothesis corresponds to the fact that the fixed effect modeling fits the data best. In this sense, *p* values above the 0.05 limit indicate the opposite, implying that random effect modeling should be used[47,52]. The general form of an *entity* fixed effects regression model that the platform conducts is as in Eq. (1) (the formula and notations description are direct quotations[52,67]):

$$Y_{it} = \alpha_i + \beta X_{it} + u_i + e_{it} \ (i = 1, \ldots, n, \text{and } t = 2005, \ldots, 2021) \tag{1}$$

where:

Y_{it} is the outcome variable (for entity i at time t);

α_i is the unknown intercept for each entity (n entity-specific intercepts);

X_{it} is a vector of predictors (for entity i at time t);

β coefficient: for a given entity, when a predictor changes one standardized unit over time, the outcome will increase/decrease by β standardized units (assuming no transformation is applied);

u_i is the within-entity error term; and,

e_{it} is the overall error term.

In this study, we are interested in investigating which socioeconomic variables are significantly associated with Gray (i.e., emitting) and Green (i.e., BEV) ownership. Further, if significant, we want to know the contribution size relative to factors. To do so, the t values of the predictors and their size are considered as a measure of contribution to vehicle adoption.

Procedure to address simultaneity. Our approach to addressing simultaneity as a cause for endogeneity has several steps. First, if introduced to the model, we logically infer which variables may have simultaneity with the dependent variables—owned number of gray (emitting) or green vehicles (BEV). We suspect three independent variables have a simultaneity type of endogeneity with the independent variable—income, wealth, and debt. Specifically, income may exhibit simultaneity, as households with higher income levels may be more inclined to own multiple vehicles, both gray and green. The ownership of more vehicles could potentially enhance access to higher-paying jobs beyond the immediate residence, consequently expanding income prospects for these households.

Second, considering the underlying problem, we look for instrumental variables with no causal relation to ultimate dependent variables, i.e., owned gray vehicles for gray adopter households and owned green vehicles for green adopter households. To find valid instrumental variables, we follow the recommended conditions of instrument relevance, $\text{Corr}(Z_i, X_i) \neq 0$, and instrument exogeneity, $\text{Corr}(Z_i, u_i) = 0$ — X_i is the endogenous independent variable, Z_i is the candidate instrument, and u_i is the error term where the instrument is used to predict the independent variable. Regarding the strength of the instrument, we check whether a first-stage F-statistic exceeds the rule of thumb of 10, often considered an indicator of a model that has explanatory power—the larger the expected value of the F-statistic represents, the more information content contained in an instrument[49]. We face limitations in finding suitable candidates in our database that are available for all years, satisfactorily distributed over the population, and are thoroughly independent of the ultimate dependent variable— i.e., car ownership—to be used as instrumental variables (almost none are entirely independent of car ownership). In our case, household immigration background fulfills the validity requirements in relation to income—as an endogenous independent variable—and exogeneity with the error term in the first-stage regression. The F-statistic also appears to be satisfactory (see Supplementary Table 3). Thus, to avoid under-identified coefficients[49], we only include income as a potential simultaneous variable in the regression analysis, to be instrumented on household immigration background.

Finally, we run a manual two-stage IV regression analysis using predicted values for the potentially endogenous variable with the help of the instrumental variable on the panel (The microdata.no platform cannot currently run IV regression on panel data). One pitfall of using predicted values instead of real values of an independent variable is that standard errors in the results of this method are not accurate and tend to be larger compared with not applying the IV procedure. In addition to paying attention to R^2 values of IV regression, we consider the logic of the data we analyze[49,65] (see Supplementary Table 4).

Data availability

We use persons' socioeconomic and vehicle ownership data at www.microdata.no. This database is open to employees and students at universities and colleges, approved research institutions (recognized by the Research Council of Norway or Eurostat), ministries, and directorates. Interested researchers are encouraged to contact microdata.no to get access. The processed data used to create the figures in this research are deposited at https://doi.org/10.5281/zenodo.10615189 and openly available[68]. The online interactive Sankey diagram for green vehicles (BEVs) owned by Norwegian households from 2020 to 2022 is available at https://DavoodQorbani.github.io/research/2024_COMMSENV_Sankey/. This interactive figure is based on our analysis, exported from microdata.no, and is slightly modified regarding readability and visibility. No single data point is altered. The data of color-coded flows are revealed when the user hovers over them with a cursor. The relevant JavaScript codes are pulled from the Vega project at https://vega.github.io/.

Code availability

We use a custom code (https://doi.org/10.5281/zenodo.10615189) to analyze and process data for descriptive figures, which is central to the result of this paper[68]. The code needs to be run on the microdata.no platform, which uses syntax like the Stata software package[52,69]. This code uses database v.26 and is tested under the Rose 6.2.2 interface.

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References

1. Norwegian Ministry of Transport. Norway is electric. https://regjeringen.no/en/topics/transport-and-communications/veg/faktaartikler-vei-og-ts/norway-is-electric/id2677481/. (2021).
2. Alarfaj, A. F., Griffin, W. M. & Samaras, C. Decarbonizing, U.S. passenger vehicle transport under electrification and automation uncertainty has a travel budget. *Environ. Res. Lett.* **15**, 1–12 (2020).
3. Dimanchev, E., Qorbani, D. & Korpås, M. in *The 4Ds of Energy Transition: Decarbonization, Decreasing use, Decentralization, and Digitalization* (ed. Asif, M.) Ch. 8 (John Wiley & Sons, 2022).
4. IEA. Global energy review: CO_2 emissions in 2021. https://iea.org/reports/global-energy-review-co2-emissions-in-2021-2/ (2022).
5. IEA. Global CO_2 emissions from transport by sub-sector in the Net Zero Scenario, 2000–2030. https://iea.org/data-and-statistics/charts/global-co2-emissions-from-transport-by-sub-sector-in-the-net-zero-scenario-2000-2030 (2022).
6. Statistics Norway. 08940: Greenhouse gases, by source, energy product and pollutant 1990–2021. https://ssb.no/en/statbank/sq/10079229/ (2022).
7. Statistics Norway. Emissions to air. https://ssb.no/en/natur-og-miljo/forurensning-og-klima/statistikk/utslipp-til-luft/ (2022).
8. Norwegian Government. Better growth, lower emissions – the Norwegian Government's strategy for green competitiveness. https://regjeringen.no/en/dokumenter/bedre-vekst-lavere-utslipp--regjeringens-strategi-for-gronn-konkurransekraft-engelsk/id2575420/ (2017).
9. Norwegian Ministry of Transport. National transport plan 2022–2033. https://regjeringen.no/en/dokumenter/national-transport-plan-2022-2033/id2863430/ (2021).
10. Fevang, E. et al. Who goes electric? The anatomy of electric car ownership in Norway. *Transp. Res. Part Transp. Environ.* **92**, 102727 (2021).
11. Yang, A., Liu, C., Yang, D. & Lu, C. Electric vehicle adoption in a mature market: a case study of Norway. *J. Transp. Geogr.* **106**, 103489 (2023).
12. Münzel, C., Plötz, P., Sprei, F. & Gnann, T. How large is the effect of financial incentives on electric vehicle sales? – A global review and European analysis. *Energy Econ.* **84**, 104493 (2019).
13. Sæther, S. R. Mobility at the crossroads – Electric mobility policy and charging infrastructure lessons from across Europe. *Transp. Res. Part Policy Pract.* **157**, 144–159 (2022).
14. Earl, T., Poliscanova, J., Earl, T., Ambel, C. C. & Archer, G. Roadmap to decarbonising European cars. https://transportenvironment.org/discover/roadmap-decarbonising-european-cars/ (2018).
15. Keith, D. R., Houston, S. & Naumov, S. Vehicle fleet turnover and the future of fuel economy. *Environ. Res. Lett.* **14**, 021001 (2019).
16. Cambridge Econometrics. *European Transportation Roadmap Model (EUTRM) User Guide*. https://transportenvironment.org/wp-content/uploads/2021/10/2017_02_EUTRM_model_guidance_v1_3.pdf (2017).
17. Naumov, S., Keith, D. R. & Sterman, J. D. Accelerating vehicle fleet turnover to achieve sustainable mobility goals. *J. Oper. Manag.* **69**, 36–66 (2022).
18. Axsen, J., Cairns, J., Dusyk, N. & Goldberg, S. What drives the Pioneers? Applying lifestyle theory to early electric vehicle buyers in Canada. *Energy Res. Soc. Sci.* **44**, 17–30 (2018).
19. Anfinsen, M. Between stability and change: tensions in the Norwegian electric mobility transition. *Soc. Stud. Sci.* **51**, 895–913 (2021).
20. Hardman, S. & Tal, G. Understanding discontinuance among California's electric vehicle owners. *Nat. Energy* **6**, 538–545 (2021).
21. Figenbaum, E. & Kolbenstvedt, M. Learning from Norwegian battery electric and plug-in hybrid vehicle users – results from a survey of vehicle owners. https://toi.no/publications/learning-from-norwegian-battery-electric-and-plug-in-hybrid-vehicle-users-results-from-a-survey-of-vehicle-owners-article33869-29.html (2016).
22. Hardman, S., Shiu, E. & Steinberger-Wilckens, R. Comparing high-end and low-end early adopters of battery electric vehicles. *Transp. Res. Part Policy Pract.* **88**, 40–57 (2016).
23. Hardman, S. & Tal, G. Exploring the decision to adopt a high-end battery electric vehicle: role of financial and nonfinancial motivations. *Transp. Res. Rec.* **2572**, 20–27 (2016).

24. Westin, K., Jansson, J. & Nordlund, A. The importance of socio-demographic characteristics, geographic setting, and attitudes for adoption of electric vehicles in Sweden. *Travel Behav. Soc.* **13**, 118–127 (2018).
25. Zhuge, C. & Shao, C. Investigating the factors influencing the uptake of electric vehicles in Beijing, China: statistical and spatial perspectives. *J. Clean. Prod.* **213**, 199–216 (2019).
26. Ling, Z., Cherry, C. R. & Wen, Y. Determining the factors that influence electric vehicle adoption: a stated preference survey study in Beijing, China. *Sustainability* **13**, 11719 (2021).
27. Long, Z. & Axsen, J. Who will use new mobility technologies? Exploring demand for shared, electric, and automated vehicles in three Canadian metropolitan regions. *Energy Res. Soc. Sci.* **88**, 102506 (2022).
28. Plötz, P. & Dütschke, E. in *Who's Driving Electric Cars: Understanding Consumer Adoption and Use of Plug-in Electric Cars* (eds. Contestabile, M., Tal, G. & Turrentine, T.) Ch. 10 (Springer International Publishing, 2020).
29. Xing, Y., Tal, G. & Wang, Y. in *Who's Driving Electric Cars: Understanding Consumer Adoption and Use of Plug-in Electric Cars* (eds. Contestabile, M., Tal, G. & Turrentine, T.) Ch. 12 (Springer International Publishing, 2020).
30. Chen, C., Zarazua de Rubens, G., Noel, L., Kester, J. & Sovacool, B. K. Assessing the socio-demographic, technical, economic and behavioral factors of Nordic electric vehicle adoption and the influence of vehicle-to-grid preferences. *Renew. Sustain. Energy Rev.* **121**, 109692 (2020).
31. Jakobsson, N., Gnann, T., Plötz, P., Sprei, F. & Karlsson, S. Are multi-car households better suited for battery electric vehicles? – Driving patterns and economics in Sweden and Germany. *Transp. Res. Part C Emerg. Technol.* **65**, 1–15 (2016).
32. Saarenpää, J., Kolehmainen, M. & Niska, H. Geodemographic analysis and estimation of early plug-in hybrid electric vehicle adoption. *Appl. Energy* **107**, 456–464 (2013).
33. Aasness, M. A. & Odeck, J. Road users' attitudes towards electric vehicle incentives: Empirical evidence from Oslo in 2014–2020. *Res. Transp. Econ.* **97**, 101262 (2023).
34. Chakraborty, D., Bunch, D. S., Brownstone, D., Xu, B. & Tal, G. Plug-in electric vehicle diffusion in California: role of exposure to new technology at home and work. *Transp. Res. Part Policy Pract.* **156**, 133–151 (2022).
35. Abotalebi, E., Scott, D. M. & Ferguson, M. R. Can Canadian households benefit economically from purchasing battery electric vehicles? *Transp. Res. Part Transp. Environ.* **77**, 292–302 (2019).
36. Sprei, F. in *Who's Driving Electric Cars: Understanding Consumer Adoption and Use of Plug-in Electric Cars* (eds. Contestabile, M., Tal, G. & Turrentine, T.) Ch. 8 (Springer International Publishing, 2020).
37. Haustein, S. & Jensen, A. F. Factors of electric vehicle adoption: a comparison of conventional and electric car users based on an extended theory of planned behavior. *Int. J. Sustain. Transp*. **12**, 484–496 (2018).
38. Ruoso, A. C. & Ribeiro, J. L. D. The influence of countries' socioeconomic characteristics on the adoption of electric vehicle. *Energy Sustain. Dev.* **71**, 251–262 (2022).
39. Lee, J. H., Cho, M., Tal, G. & Hardman, S. Do plug-in hybrid adopters switch to battery electric vehicles (and vice versa)? *Transp. Res. Part Transp. Environ.* **119**, 103752 (2023).
40. Norwegian Tax Administration. Car prices: list prices as new (1994–2022). *The Norwegian Tax Administration*. https://skatteetaten.no/en/rates/car-prices---list-prices-as-new/ (2023).
41. United States Census Bureau. Wealth, asset ownership, & debt of households detailed tables: 2021. https://census.gov/data/tables/2021/demo/wealth/wealth-asset-ownership.html (2023).
42. Vergis, S. & Chen, B. Comparison of plug-in electric vehicle adoption in the United States: a state by state approach. *Res. Transp. Econ.* **52**, 56–64 (2015).
43. Ji, D. & Gan, H. Effects of providing total cost of ownership information on below-40 young consumers' intent to purchase an electric vehicle: a case study in China. *Energy Policy* **165**, 112954 (2022).
44. Chakraborty, D., Bunch, D. S., Lee, J. H. & Tal, G. Demand drivers for charging infrastructure-charging behavior of plug-in electric vehicle commuters. *Transp. Res. Part Transp. Environ.* **76**, 255–272 (2019).
45. Norwegian Public Roads Administration. Nasjonal reisevaneundersøkelse 2022 (National travel habits survey 2022). https://vegvesen.no/fag/fokusomrader/nasjonal-transportplan/den-nasjonale-reisevaneundersokelsen/reisevaner-2022/ (2023).
46. SuperCharge. supercharge.info. https://supercharge.info/data/ (2024).
47. Baltagi, B. H. *Econometric Analysis of Panel Data* (Springer, 2021).
48. Greene, W. H. *Econometric Analysis* (Pearson, 2019).
49. Stock, J. H. & Watson, M. W. *Introduction to Econometrics* (Pearson, 2020).
50. Hoffmeyer-Zlotnik, J. & Warner, U. Private household concepts and their operationalisation in cross-national social surveys. *Adv. Methodol. Stat.* **6**, 1–26 (2009).
51. Andreß, H.-J., Golsch, K. & Schmidt, A. W. *Applied Panel Data Analysis for Economic and Social Surveys* (Springer, 2013).
52. Sikt & Statistics Norway. *User Guide for the Analysis System Microdata.no*. https://microdata.no/manual/en/ (2024).
53. O'brien, R. M. A caution regarding rules of thumb for variance inflation factors. *Qual. Quant.* **41**, 673–690 (2007).
54. Dodge, Y. *The Concise Encyclopedia of Statistics* (Springer, 2008).
55. Menard, S. *Applied Logistic Regression Analysis* (SAGE Publications, 2002).
56. Statistics Norway. *Facts about Education in Norway 2022 – Key Figures 2020*. https://ssb.no/en/utdanning/utdanningsniva/artikler/facts-about-education-in-norway-2022/ (2022).
57. Jorgensen, K. Technologies for electric, hybrid and hydrogen vehicles: electricity from renewable energy sources in transport. *Util. Policy* **16**, 72–79 (2008).
58. Shafiei, E. et al. Potential impact of transition to a low-carbon transport system in Iceland. *Energy Policy* **69**, 127–142 (2014).
59. Mofijur, M. et al. Role of biofuel and their binary (diesel-biodiesel) and ternary (ethanol-biodiesel-diesel) blends on internal combustion engines emission reduction. *Renew. Sustain. Energy Rev.* **53**, 265–278 (2016).
60. Wagstrom, K. & Hill, J. in *Socioeconomic and Environmental Impacts of Biofuels: Evidence from Developing Nations* (eds. Gasparatos, A. & Stromberg, P.) Ch. 3 (Cambridge Univ. Press, 2012).
61. Bekel, K. & Pauliuk, S. Prospective cost and environmental impact assessment of battery and fuel cell electric vehicles in Germany. *Int. J. Life Cycle Assess.* **24**, 2220–2237 (2019).
62. van Renssen, S. The hydrogen solution? *Nat. Clim. Change* **10**, 799–801 (2020).
63. IEA. Global EV outlook 2020: entering the decade of electric drive? https://doi.org/10.1787/d394399e-en (2020).
64. Schiller, T., Kummer, P., Berdichevskiy, A., Weidenbach, M. & Sadoun, J. Future of automotive sales and aftersales: impact of current industry trends on OEM revenues and profits until 2035. https://deloitte.com/global/en/Industries/consumer/perspectives/future-of-car-sales-in-2035.html (2020).
65. Wooldridge, J. M. *Econometric Analysis of Cross Section and Panel Data* (MIT Press, 2010).
66. Hill, A. D., Johnson, S. G., Greco, L. M., O'Boyle, E. H. & Walter, S. L. Endogeneity: a review and agenda for the methodology-practice divide affecting micro and macro research. *J. Manag.* **47**, 105–143 (2021).

67. Torres-Reyna, O. Panel data analysis fixed and random effects using Stata (v. 6.0). https://princeton.edu/~otorres/Panel101.pdf (2007).
68. Qorbani, D. From gray to green: transition of passenger vehicle ownership in Norwegian households (Custom Script and Figures Data). *Zenodo* https://doi.org/10.5281/zenodo.10615189 (2024).
69. Sikt & Statistics Norway. Analysis tool - microdata.no. https://microdata.no/rose/ (2024).
70. Figenbaum, E. & Kolbenstvedt, M. Elektromobilitet i Norge – erfaringer og muligheter med elkjøretøy (Electromobility in Norway - experiences and opportunities with Electric vehicles). https://toi.no/getfile.php?mmfileid=33261 (2013).
71. Norwegian Ministry of Finance. Merverdiavgiftsfritaket for elbiler erstattes med en tilskuddsordning (The VAT exemption for electric cars is replaced by a subsidy scheme). *Regjeringen* https://regjeringen.no/no/aktuelt/merverdiavgiftsfritaket-for-elbiler-erstattes-med-en-tilskuddsordning/id2912423/ (2022).
72. Norwegian Tax Administration. Årsrundskriv for avgift på trafikkforsikringer 2023 (Annual notice for tax on traffic insurance 2023). *Norwegian Tax Administration (Skatteetaten)*. https://skatteetaten.no/en/rettskilder/type/rundskriv-retningslinjer-og-andre-rettskilder/avgiftsrundskriv/trafikkforskringsavgift-2023/ (2021).
73. Norwegian Tax Administration. Trafikkforsikringsavgift (Road traffic insurance tax). *Norwegian Tax Administration (Skatteetaten)*. https://skatteetaten.no/bedrift-og-organisasjon/avgifter/saravgifter/om/trafikkforsikringer/ (2022).
74. NRK. Nullutslippssone i Oslo tidligst fra 2025 (Zero emission zone in Oslo from 2025 at the earliest). *NRK* https://nrk.no/osloogviken/nullutslippssone-i-oslo-tidligst-fra-2025-1.16269170 (2023).
75. Norwegian Tax Administration. Motor vehicle taxes. *Norwegian Tax Administration (Skatteetaten)*. https://skatteetaten.no/en/business-and-organisation/vat-and-duties/car/ (2023).
76. Juven, O. 70 kroner i bompenger for elbiler (NOK 70 in tolls for electric cars). *NRK* https://nrk.no/osloogviken/70-kroner-i-bompenger-for-elbiler-1.14001977 (2018).
77. Martinsen, E. Mann kjørte med dukke i kollektivfelt (Man drove with doll in public transport lane). *NRK* https://nrk.no/osloogviken/mann-kjorte-med-dukke-i-kollektivfelt-1.13498710 (2017).
78. Korsnes, M. K. & Brunstad, S. B. No får elbileigarane parkeringsbot (Electric car owners now receive parking fines). *NRK* https://nrk.no/mr/no-far-elbileigarane-parkeringsbot-1.13301756 (2017).
79. NRK. Elbiler gratis på ferjer (Electric cars free on ferries). *NRK* https://nrk.no/mr/elbiler-gratis-pa-ferjer-1.6369854 (2008).
80. Myklebostad, M. & Brunstad, S. B. Fortsatt gratis for elbil på fergene (Here it is still free for electric cars). *NRK* https://nrk.no/mr/fortsatt-gratis-for-elbil-pa-fergene-1.13303176 (2017).
81. IEA. Oslo EVSE procurement installation. *IEA* https://iea.org/policies/6941-oslo-evse-procurement-installation (2017).
82. Norwegian Public Roads Administration. Hvem kan kjøre i kollektivfelt? (Who can drive in public transport lanes?). *Statens vegvesen* (*Norwegian Public Roads Administration*) https://vegvesen.no/trafikkinformasjon/langs-veien/trafikkregler/kollektivfelt/ (2021).
83. AutoPASS. Rates and discounts. *AutoPASS* https://autopass.no/en/user/rates-and-discounts/ (2023).

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Author contributions
D.Q. and H.P.L.M.K. were responsible for the study design and conception, and they conducted the analysis. D.Q. performed script (coding) and drafted the manuscript. S.-E.F. provided comments and feedback regarding the study design and analysis. Authors jointly read and revised the manuscript.

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Correspondence and requests for materials should be addressed to Davood Qorbani or Stein-Erik Fleten.

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