Applied Energy 319 (2022) 119246

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

Widespread range suitability and cost competitiveness of electric vehicles for ride-hailing drivers

Morteza Taiebat [a,b], Samuel Stolper [a], Ming Xu [a,b,*]

[a] School for Environment & Sustainability, University of Michigan, Ann Arbor, MI, USA
[b] Department of Civil & Environmental Engineering, University of Michigan, Ann Arbor, MI, USA

HIGHLIGHTS

- Investigate range and total cost of ownership of BEVs using comprehensive 2019 U.S. driving data on the Lyft platform.
- 86% of drivers could switch to a BEV250 without having to curtail their mileage on more than 5% of active days.
- While BEV100 is sufficient for most household vehicles in the US, BEV250 is a better choice for ride-hailing drivers.
- Range and lifetime cost should not be significant barriers to widespread EV take-up in the ride-hailing.

ARTICLE INFO

Keywords:
Electric vehicles
Ridesourcing
Ride-hailing
Fleet electrification
Travel pattern
Total cost of ownership
Range suitability
Stochastic simulation

ABSTRACT

Transportation network companies provide an increasingly significant share of mobility, which has prompted interest in curbing greenhouse gas emissions in the ride-hailing sector. Vehicle electrification offers the possibility of vast emissions reductions, but a number of factors are thought to constrain this transition. We investigate two such factors – battery electric vehicle (BEV) range and total cost of ownership – from 2019 driving data covering all U.S. drivers on the Lyft platform. We estimate that, for more than 86% of drivers, their daily travel needs can be met by a fully charged BEV with listed range of 250 miles (BEV250) on at least 95% of days. New and pre-owned BEVs both appear to be cost-saving for many drivers. We estimate that a $5,700 BEV purchase subsidy would make new BEVs cost-competitive to gas-powered vehicles for *all* drivers on the Lyft platform, holding annual mileage and vehicle prices constant. Our results suggest that range and lifetime cost should not be significant barriers to widespread EV take-up in the ride-hailing sector. More generally, they suggest that continued moderate subsidies for BEVs, information interventions, and targeting of such programs to ride-hailing drivers who stand to gain most from them will promote a faster transition in this sector. Driver-targeted outreach and information provision related to EV benefits, as well as expansion of charging availability and fast charging rates through local and federal policy, are additional valuable steps to encourage ride-hailing electrification.

1. Introduction

Transportation Network Companies (TNCs) or ride-hailing services [1] have brought about a new paradigm in personal travel that is rapidly reshaping the transportation sector. Ride-hailing platforms such as Lyft, Uber, and DiDi provide on-demand mobility services that complement and compete with personal vehicle ownership and transit use, changing urban travel patterns and the associated energy and environmental impacts. TNCs account for a small yet rapidly growing share of transportation miles [2] and have likely raised energy use and emissions by substituting for public transit, increasing "deadhead" miles, and inducing new travel demand [3–7]. The Union of Concerned Scientists (UCS), for example, finds that the average ride-hailing trip produces an estimated 69% more greenhouse gas (GHG) emissions than the trip it replaces [8]. California Air Resources Board estimates that the 2018 TNC vehicle fleet emitted 301 $CO_{2\text{-eq}}$ per passenger-mile traveled (PMT), approximately 50 percent higher than the statewide passenger vehicle fleet average of 203 $CO_{2\text{-eq}}$/PMT [9]. In 2018, California became the first U.S. state to regulate GHG emissions by TNCs, through the California Clean Miles Standard and Incentive Program (Senate Bill (SB) 1014). In 2021, California legislatures finalized a rule which mandates that 90% of ride-hailing miles traveled across the state take place in zero

* Corresponding author at: School for Environment & Sustainability, University of Michigan, 440 Church St, Ann Arbor, MI 48109, USA.
E-mail addresses: taiebat@umich.edu (M. Taiebat), sstolper@umich.edu (S. Stolper), mingxu@umich.edu (M. Xu).

https://doi.org/10.1016/j.apenergy.2022.119246
Received 23 November 2021; Received in revised form 2 April 2022; Accepted 2 May 2022
Available online 20 May 2022

emission vehicles by 2030.

Fleet electrification is widely viewed as a solution to the problem of large and increasing transportation-sector emissions, through the substitution of low- or zero-carbon electricity for emissions-intensive automotive fuels [10–15]. Consistent with this notion, Lyft recently announced a commitment to transition to 100% electric vehicles (EVs) on its platform by 2030 [16]. A few months later, Uber announced the same electrification goal for its US platform as well as a similar goal of full electrification internationally by 2040 [17]. A number of factors, however, are thought to constrain this transition. As of 2019, fewer than 0.5% of active TNC vehicles were estimated to be electric [18]. The upfront cost of an EV is currently higher than that of an internal combustion engine vehicle (ICEV), which elicits questions about the cost competitiveness of EVs. Ride-hailing drivers predominantly self-identify as low income and as a member of minority groups [19], which suggests the possibility that financing constraints limit EV uptake. In addition, EV batteries must be charged periodically, which, given the relative sparseness of the U.S. charging station network may induce "range anxiety" among some would-be EV users. Furthermore, the need to regularly charge an EV is an example of how the experience itself of owning and operating an EV differs from that of an ICEV. Relatedly, current limitations on the size or other non-price attributes of EVs may be a disincentive to their take-up.

In this study, we investigate the ability of currently available battery electric vehicle (BEV) models to meet the range needs of ride-hailing drivers and compete with ICEV and hybrid vehicles on total cost of ownership. We bring to bear a large, novel dataset: the universe of 2019 rides and drivers on the Lyft platform, which spans 110 million driver-days and over 1.8 million drivers. The absolute count of active drivers represented in this study remains the proprietary information of Lyft Inc. We report the analysis results based on the percentage of driver cohorts to comply with the data use agreement (see Note).

We estimate that more than 86% of all drivers on the Lyft platform in 2019 would have seen their daily travel needs met by a fully charged BEV with listed range of 250 miles (BEV250) on at least 95% of driving days. This high level of "range suitability" is not dependent on a fully charged battery; when we allow for incomplete initial states of battery charge, we nonetheless find that a BEV250 is sufficient to complete 82% of all observed driver-days. At the same time, we project that a moderate subsidy (or an equivalent purchase price reduction) of approximately \$5,700 for the upfront purchase would be necessary to make a new BEV250 cheaper over its use-period for all range-suitable drivers on the Lyft platform. Some high-mileage drivers would see total cost savings from a new BEV250 even without any subsidy. At estimated current prices, all drivers would see total cost savings from a pre-owned BEV, which has the lowest total cost of all vehicle types considered.

These findings together suggest that range and total cost should not be constraints on widespread BEV switching by TNC drivers. They also point to the importance of information campaigns to address misconceptions about BEV attributes, the value of targeting both information and subsidies to cost-effectively induce EV switching, and the notion that resources are better spent on charging technology and infrastructure than vehicle range expansion. The climate benefit of inducing widespread EV switching in the ride-hailing sector is high: if every BEV250-suitable driver on the Lyft platform drove a BEV250 in 2019, we project 5.72 million metric tons of $CO_{2\text{-eq}}$ avoided from tailpipe emissions (an estimated 77.2% reduction) annually (see Table S-6 for more details on tailpipe and life-cycle emissions reduction opportunities). This is equivalent to a 0.31% reduction in EPA's estimate of total transportation emissions in the US in 2018 [20].

2. Review of prior studies

EVs not only entail higher energy efficiency compared to ICEVs, but also can concentrate emissions from point sources of tailpipes to power plants for more efficient and effective emission control and, most importantly, help renewable energy integration [13]. However, transportation electrification is challenging due to decentralized operation, policy conflicts, infrastructure insufficiency, and consumers' lack of awareness, interest, and confidence, among other factors [14,15]. Recent studies have shown even aggressive adoption of EVs cannot alone meet the net zero emission economy targets [7,12]. The market penetration BEVs is currently hindered by their high cost, arguably short driving ranges, long charging time, and limited charging infrastructure [15,21]. The extent to which BEVs can be accepted by consumers depends on individual travel patterns (travel time, trip length, parking duration, etc.), BEV characteristics (driving range, charging rates, etc.), charging infrastructure access, economics, and a host of psychological factors [22].

Limited research has shown the potential for adoption of EVs among ride-hailing drivers. However, these conclusions were drawn largely based on using limited unrepresentative data, simulation, or proxy data such as data from taxi operations, because data from real-world ride-hailing operations are scarce. Chief among which is a new study suggested that electrifying a ride-hailing vehicle offers triple the emission reduction compared to switching a personal ICEV vehicle to BEV in California [10]. Yu et al. found that environmental benefits of electrifying ride-hailing can be further enhanced with clean electricity generation [23]. UCS suggested that ride-hailing with BEVs can reduce GHG emissions by 39% per passenger-trip compared to private ICEVs [8]. Studies from the International Council on Clean Transportation found that hybrid electric vehicle (HEV) is the least expensive option for ride-hailing drivers on per-mile cost basis and BEV will reach cost parity with ICEV by 2023–2025 even without subsidies [24,25].

A few previous studies have shed light on BEV range and cost considerations in specific contexts and for specific driver types. Tu et al. used GPS trajectories from 144,867 ride-hailing drivers in Beijing over one week to estimate that up to 55% of total distance driven by ride-hailing drivers can be met by 200-mile range BEV and ubiquitous home chargers (1.7 kW) [26]. Bauer et al. simulate ride-hailing patterns in New York and San Francisco using agent-based modeling and find evidence that BEVs can provide the same level of service at lower cost than ICEVs [27]. Pavlenko et al. estimate the total costs of EV ownership for several "representative" driver profiles [24]. Bauer et al. showed that BEVs can provide equivalent ride-hailing services to ICEVs at lower cost and the cost of charging infrastructure is not a significant barrier to ride-hailing electrification [27].

Our work expands on these previous studies by providing a more comprehensive empirical picture of BEV range suitability and cost considerations than has been previously possible. Tu et al. [26] is the only published empirical microdata-based study of range suitability in the ride-hailing sector, and there is no analogous pre-existing study of cost competitiveness. Our scope is far broader than Tu et al. [26]; we observe the entirety of a dominant TNC's rides and drivers nationally, for a full year. Our findings thus provide novel evidence on the barriers to fleet-wide electrification, to which both Lyft and Uber have committed to achieving by 2030. Moreover, our estimates have a lower variance than previous empirical analogs, because they are based on a longer time period of observed driving behavior.

3. Method and materials

We use anonymized, de-identified travel pattern data on all active, non-EV drivers in the US in 2019 on the Lyft platform; the full year of data ensures that our analysis accounts for seasonal variation in ride-hailing patterns. Our analysis sample includes all drivers with at least one active day on the Lyft platform in 2019. Observed vehicle-miles traveled (VMT) totals include mileage during "idling time" (or the "*P1*" segment, which covers travel in between occupied rides while the Lyft app is still open). We do not observe driving activity while the Lyft app is closed (known as *P0*), which includes personal travel as well as ride-hailing and other commercial (e.g., food and parcel delivery) activity through non-Lyft platforms.

To aid in the presentation and interpretation of results in this large dataset, we use unsupervised learning algorithms to identify distinct cohorts of drivers with shared travel patterns. Our procedure results in four cohorts: Ultra-High Mileage (UHM); High-Frequency High-Mileage (HFHM); Low-Frequency High-Mileage (LFHM); and Low-Frequency Low-Mileage (LFLM) (Fig. S-1). These cohorts account for 9%, 14%, 31%, and 46% of all drivers, respectively. We report characteristics and summary statistics of relevant variables in the dataset in Table S-1 and Fig. S-2.

Observing the distance traveled on the job every day by every driver on the Lyft platform makes it possible to characterize the suitability of electric vehicles to meet daily range needs as well as the total cost of BEV (versus ICEV) ownership. Other attributes certainly matter as well in the vehicle purchase decision [21,22,28,29]; however, the fact that ride-hailing driving is primarily done to earn money suggests that such drivers are likely to weigh range suitability and cost of ownership heavily in vehicle choice. Consistent with this notion, a recent survey finds that ride-hailing drivers rank BEV range limitation and economics as their top reasons for not choosing BEVs [30].

We use several definitions of BEV range suitability. Our primary definition is the ability of a BEV to meet a driver's daily VMT needs on 95% of days in the year (or, alternatively, fewer than 5% of her active days have total VMT higher than BEV range). We additionally characterize suitability according to 90% and 99% thresholds. To illustrate the pitfalls of focusing on *average* behavior, we also show the results of defining suitability as meeting a driver's average daily VMT need. Throughout our analysis, we assume that BEVs have an energy efficiency of 0.28 kWh/mile and 88% usable battery capacity on average [26]. Furthermore, we subtract 30 miles from the technical BEV range as a buffer to allow for VMT for personal use (the US average VMT for non-work was 20 miles per day in 2017 [31]). In our base specification, we assume that a BEV's State of Charge (SoC) is 100% at the beginning of the day and no charging occurs during the day. We conduct sensitivity analyses in which initial SoC is incomplete or partial mid-day charging is possible.

3.1. Data

We obtain anonymized data on the daily travel patterns of each driver on the Lyft platform in 2019. We omit drivers with no reported trips in the year, drivers of EVs and rental vehicles, and drivers with extreme outlier values for any of the relevant variables. For each driver, we observe daily total VMT, occupied VMT, number of trips completed, number of shifts, and shift hours. We also use the driver's state of residence in state-level calculations. The mileage data includes three segments: *P1* (driver waiting for a request); *P2* (driver driving to pick-up location); and *P3* (with at least one passenger in the vehicle). We calculate daily total VMT as the sum of these three and use *P3* to capture occupied VMT. To assess range suitability of BEVs in this dataset, we calculate, for each driver, average VMT as well as the 90th, 95th, and 99th percentiles of daily VMT. Table S-1 and Fig. S-2 show summary statistics of the key variables.

3.2. Driver cohorts

We create mutually exclusive "cohorts" of drivers exhibiting similar travel patterns using an unsupervised learning algorithm. We compare the performance of k-means, k-medoids, and hierarchical clustering and choose the k-means method with k = 4 for our main analysis [32] (Supplementary Note 1 provides more details on the driver clustering). Our clustering variables are number of active days, daily number of rides, daily total VMT, daily occupied VMT, and daily shift hours; we standardize all variables before clustering. Based on the relative attributes of each cohort, we use the following cohort names: Ultra-High Mileage (UHM); High-Frequency High-Mileage (HFHM); Low-Frequency High-Mileage (LFHM); and Low-Frequency Low-Mileage (LFLM) (Fig. S-1). Table S-1 includes summary statistics for key variables by cohort.

3.3. Total cost of ownership (TCO) model

We build a TCO model to calculate average annual ownership cost of vehicles of different types, total mileages, and commitment periods. We consider new (2020) and pre-owned (2017) ICEVs, HEVs, and BEVs; consistent with Pavlenko et al., we exclude plug-in hybrid electric vehicles, since they often operate similar to non-plug-in hybrid models and are challenged by relatively high fueling and maintenance costs and higher upfront costs [24]. For each vehicle type, we choose one representative vehicle model to evaluate. For ICEVs, and HEVs, we choose the Toyota Camry LE and Toyota Prius, respectively; these are currently the best-selling vehicles of their type overall as well as the most common vehicles of their type on the Lyft platform [30]. For new and pre-owned BEV250, we choose the Chevy Bolt, which is the most common BEV among ride-hailing drivers (the best-selling BEV overall is currently the Tesla Model 3) [30]. For pre-owned BEV100, we choose the Nissan Leaf, which is again the best-selling EV of its range on the used market [33].

We assume a 5% discount rate and calculate net present values for cash flows associated with future recurring costs in each year of ownership. We assume that the first year of ownership is the base year, that is, that costs in that first year are undiscounted. Our choice of discount rate is higher than the 3% rate frequently used in the transportation economics literature, because ride-hailing drivers tend to have relatively less income, which is commonly associated with a relatively higher discount rate. We use the following formulas to compute average annual total cost of ownership (AATCO):

$$AATCO_{CP}^{ICEVorHEV} = \frac{D_{CP}}{CP} + \frac{1}{CP}\sum_{i=1}^{CP}\left(\frac{I + \left(\frac{G_s}{MPG} + \phi(.)\right) \times (M_{TNC} + M_P)}{(1+r)^{i-1}}\right)$$

$$AATCO_{CP}^{BEV} = \frac{D_{CP}}{CP} + \frac{1}{CP}\sum_{i=1}^{CP}\left(\frac{I + (LCOC_s \times \varphi + \phi(.)) \times (M_{TNC} + M_P)}{(1+r)^{i-1}}\right)$$

$AATCO_{CP}^{ICEVorHEV}$ and $AATCO_{CP}^{BEV}$ are average annual total cost of ownership for ICEV or HEV and BEV, respectively. D_{CP} is the depreciation over the commitment period as described below. CP is the commitment period in years (3 or 5 years). i denotes year index and r is the discount rate (5%). I is the annual insurance cost. G_s is the 2019 average gas price ($/gallon) in state s where the vehicle operates and, analogously, $LCOC_s$ is the levelized cost of electricity ($/kWh) for BEV charging in state s as estimated in Borlaug et al [34] (Table S-5). MPG is the vehicle fuel economy (miles per gallon) and φ is the BEV energy efficiency (kWh/mile). $\phi()$ is the mileage weighted service and maintenance cost ($/mile) as described below. M_{TNC} is the annual mileage observed on the Lyft platform and M_P is the annual mileage for personal use of vehicle, which we assume to be 7300 miles per year [31]. We exclude taxes, registration costs, and fees given their high variability and that they do not contribute substantially to the comparative TCO (they are very similar among ICEVs, HEVs, and BEVs. This exclusion may slightly disadvantage BEVs, since in some regions BEVs receive discounts on registration and fees.

Depreciation. Depreciation depends on both mileage and vehicle age. Vehicles depreciate much faster at the beginning of their lifespan; the depreciation curve flattens in later years (of ownership). Prior research has shown that BEV cost-competitiveness increases in total mileage and commitment period in part because of a depreciation curve with a steeper head and flatter tail [35–37].

We calculate the depreciation of vehicles as the difference between a vehicle's manufacturer suggested retail price (*MSRP*) and its vehicle residual value (*VRV*) at the end of the commitment period. For simplicity, we assume BEV subsidies are directly deducted from *MSRP* as a point-of-sale rebate. For pre-owned vehicles, we use Kelly Blue Book average dealer estimates of resale price for vehicles listed as "certified pre-owned from certified dealer - fair purchase price on very good condition", with a typical mileage of 30,000 miles at the time of purchase.

For *VRV*, we use the alg.com Vehicle Residual Value tool, which provides an estimate of residual value based on mileage band and age for most vehicles in the market. We consider four annual mileages (10,000, 20,000, 30,000, and 40,000 miles) and ownership commitment periods of three and five years. The residual values of benchmarked vehicles are within a 3% margin of error compared to analogous Kelly Blue Book estimates. The residual value estimates for new and pre-owned vehicles based on annual mileage and commitment periods are presented in Table S-2 and Table S-3, respectively. We match the mileage band to the annual VMT of drivers and find the annual average depreciation for each vehicle based on three- and five-year ownership commitment. Since *VRV* is based on the undiscounted rate, the depreciation cost over the commitment period can be expressed as $D_{CP} = MSRP - \frac{VRV}{(1+r)^{CP-1}}$.

Insurance. Lyft provides drivers with insurance for *P1*, *P2* and *P3* segments of their mileage (dispatched and passenger on-board), but *P0* and personal mileage is paid by the driver. Several studies have attempted to estimate the TCO components of ride-hailing vehicles inclusive of insurance cost. The most widely used estimates come from Zoepf et al., who survey drivers about operating cost and provide a distribution of cost estimate (median combined cost of $0.13 per mile for maintenance, repair, and insurance) but do not break down by the components [38]. Henao and Marshall estimate annual insurance costs to be $1,500 [39]. Parrot and Reich estimate commercial insurance costs for ride-hailing drivers in New York City of $0.14/mile, which is higher than the national average. We opt for the American Automobile Association's estimate, with the assumption that insurance rate is not a function of mileage [40] as presented in Table S-4. Our estimation of annual insurance costs yields a median per-mile cost of $0.067/mile for ICEV based on the annual mileage of all drivers, which is slightly higher than Zoepf et al.'s survey estimates when accounting for service and maintenance (S&M) costs. Insurance cost is slightly lower for HEVs and BEVs relative to ICEVs as well as pre-owned models relative to new ones.

Service & Maintenance Costs. It is widely believed that service and maintenance (S&M) of BEVs are far less expensive than those of ICEV and HEV on average, given fewer parts that need routine maintenance. Reliable life cycle maintenance data from EVs are rare and usually reported in the form of a single estimate regardless of vehicle age and mileage [35]. Here, we develop a model which benefits from mileage-specific S&M costs for the whole lifecycle of a vehicle.

In the TCO model, $\phi()$ is a dynamic function which returns a mileage-weighted average S&M cost per mile for each vehicle technology based on a driver's annual mileage (observed and personal) and ownership commitment period. $\phi()$ is calculated based on the mileage-specific S&M costs for the lifecycle of vehicles represented in Fig. S-6. We assume that the useful life of a BEV is 200,000 miles and that of an ICEV or HEV is 150,000 miles [41]. For fair comparison, we augment an upfit cost of 2.04 ¢/mile after 150,000 miles for ICE and HEV, as suggested in Elgowainy et al. [41] Ranges of estimated S&M costs for different combinations of vehicle type, new vs. pre-owned, and commitment period length are shown in Fig. S-7.

Fuel and Electricity Costs. To produce estimates of per-mile energy costs, we first obtain EPA estimates of fuel economy for each vehicle model in our exercise. For new and pre-owned ICEV, we use 27 and 25 miles per gallon (MPG), respectively, as the combined (55% city, 45% highway) fuel economy. For new and pre-owned HEVs, we use 50 MPG. For new and pre-owned BEV, we assume an energy efficiency (φ) of 0.28 and 0.29 kWh per mile, respectively.

For gas price (G_s), we use the EIA 2019 average estimate in the driver's state, which includes taxes and is based on the weighted sales volume of three grades of gas, as shown in Table S-5 [42]. National average gas price in 2019 is $2.763/gal with median of $2.625/gal. The levelized cost of charging (LCOC) for BEV charging is adopted from a recent study from NREL [34] and matched by driver's state ($LCOC_s$). Baseline estimates of LCOC for each state are presented in Table S-5, which shows a national average of 0.150 $/kWh (exclusively charging at DCFC stations increases the national LCOC to 0.18 $/kWh, while the price falls to 0.11 $/kWh for drivers who only charged their BEV using a dedicated household outlet.). For simplicity, we assume G_s and $LCOC_s$ do not change over the ownership commitment period.

4. Range suitability of BEVs for ride-hailing drivers

Fig. 1 presents cumulative distributions of range suitability with respect to BEV battery size. In Panel A, we plot full-sample distributions for each of our four definitions of suitability; in Panel B, we reprint the full-sample distribution for our preferred definition alongside analogous distributions for the Low-Frequency Low-Mileage (LFLM) and Ultra-High Mileage (UHM) cohorts. Panel A shows that, for the great majority of drivers, their range needs are met on most or all days of ride-hailing activity. For example, a BEV250 satisfies 95% or more days of driving needs for 86.2% of all non-EV drivers on Lyft's platform in 2019. The corresponding number for the 90% and 99% thresholds are 92.4% and 74.7%, respectively. For context, there are currently several BEV250s on the market, including the Chevy Bolt, Tesla Model 3, Ford Mustang Mach E, and Kia Niro.

Three other facts are apparent from Fig. 1. First, assessment of range suitability using average behavior is misleading. According to Panel A, a 200-mile battery meets nearly every driver's average daily need – but at the same time, we calculate that such a battery size *fails* to meet a driver's needs on 48 days of the year, on average. Second, the marginal suitability effect of battery size decreases at higher battery sizes in the full set of drivers (Panel A). The right tail of ride-hailing driver activity is long: a battery size of 300 miles would be 99% range-suitable for 86.7% of drivers, but to provide the same level of suitability to nearly *all* (99.9%) drivers, a size of 590 miles would be needed. Third, there are wide differences in range suitability across the driver distribution. According to Panel B, a BEV250 is suitable for all LFLM drivers but only a quarter of UHM drivers.

We note two additional analyses that shed light on the sensitivity of range suitability to assumptions about BEV charging. First, we replicate the prior calculation while assuming that each driver takes advantage of a 30-minute daily partial charging via a 30 kW DC Fast Charger (DCFC), which is equivalent to a 90-mile range increase. There is an opportunity cost of mid-day charging, but the magnitude of this cost depends on the counterfactual activity of drivers. A recent survey of 732 BEV drivers on the Uber platform shows that a significant portion of drivers do engage in mid-day charging, with a mix of public level 2 chargers and DCFCs [30]. With 30-minute daily partial charging, our preferred estimate of BEV250 suitability increases from 86.2% to 97.7% of drivers (Fig. S-5).

Second, we investigate the extent to which observed days of ride-hailing activity can be met with less-than-complete States of Charge (SoCs), in acknowledgment of the fact that not all drivers are able to charge their vehicle to 100% before starting the day. We run a stochastic simulation with 10,000 iterations: in each iteration, we draw a random initial SoC uniformly distributed between 20 and 100% for each active driver-day and count the number of driver-days whose VMT can be met with BEVs of different battery size (otherwise we use the same assumptions as in our Fig. 1 analysis). Fig. 2 plots the empirical distribution (across the 10,000 iterations) of the percentage of driver-days with VMT less than the range of a BEV250 (or BEV100). The figure shows that, on average, 82% of all driver-days can be completed with a BEV250, while 40% can be completed with a BEV100. For the LFLM driver cohort, meanwhile, a BEV100 is sufficient for the completion of 71% of driver-days.

More generally, our simulation exercise suggests that the high degree

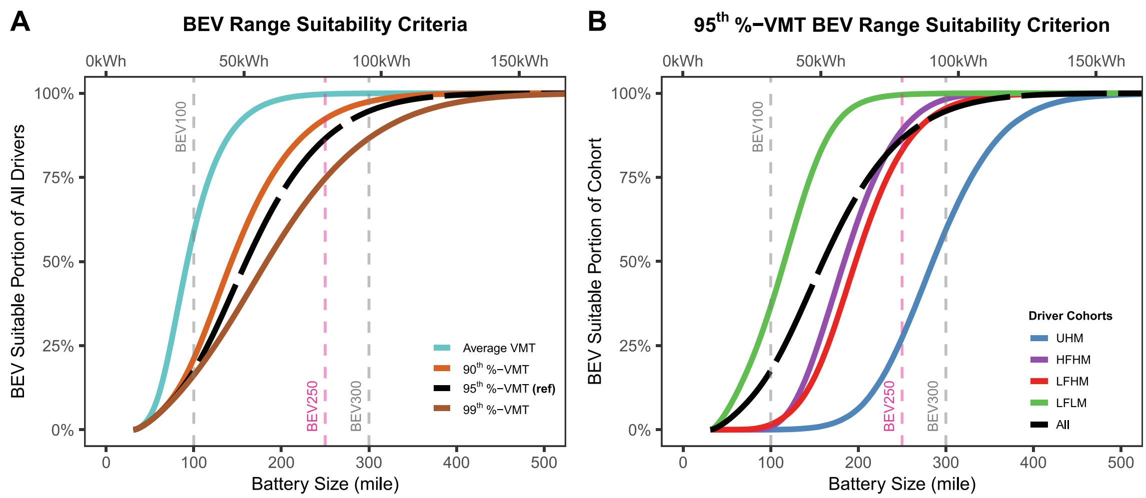

Fig. 1. (A) BEV range suitability for all drivers on the platform based on battery size (mile and kWh capacity) under different suitability criteria. 95th%-VMT BEV suitability indicates that the BEV range meets the daily VMT needs of a driver on 95% of her active days. 90th% and 99th% suitability criteria are analogous. "Average VMT" suitability indicates that daily VMT needs are met on a driver's average day. (B) BEV suitability with the 95th%-VMT metric overall and for specific cohorts (see text for cohort definitions).

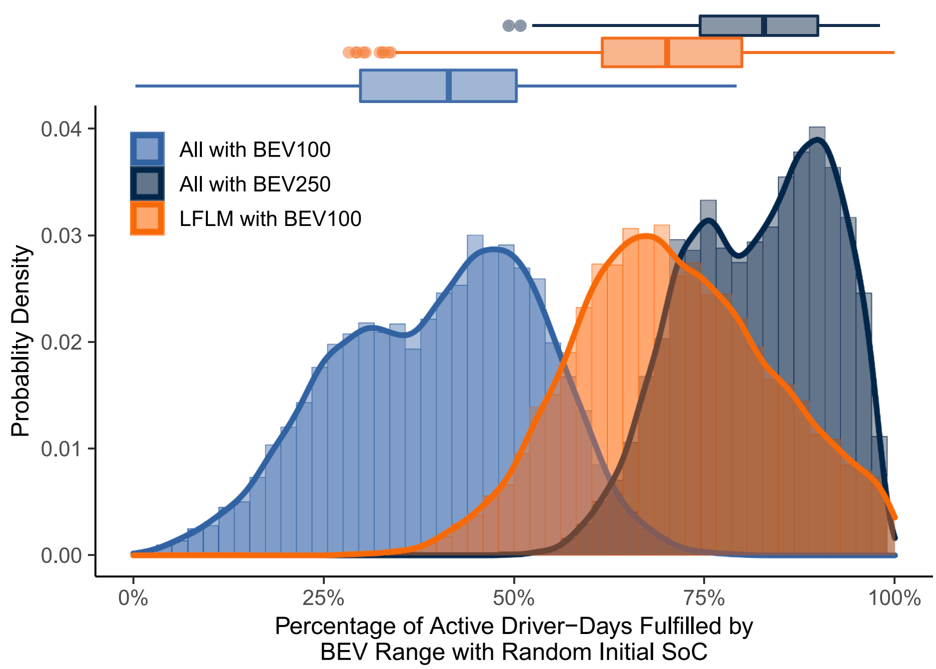

Fig. 2. Sensitivity of BEV suitability to initial State of Charge (SoC) based on stochastic simulation with 10,000 iterations. Initial SoC is uniformly distributed between 20 and 100%, and all other procedural details are the same as in Fig. 1. The average percentage of active days completed by BEV250 (BEV100) is 82% (40%). The simulation of specifically the LFLM driver cohort shows 71% of active days can be fulfilled with BEV100.

of BEV suitability implied by our main results is not overly sensitive to the assumption of 100% SoC. Needell et al. finds that for *household* vehicles in the US, relying only on night-time charging, a BEV with just under a 100-mile battery size could meet the travel demand of 87% of vehicle-days based on the 2009 National Household Travel Survey (NHTS) [43]. In contrast, we find that for ride-hailing drivers, while BEV100 can fulfill 40% of driver-days, less than 20% of drivers are range-suitable with it with 95th percentile-VMT criterion. While BEV100 is sufficient for most household vehicles in the US, BEV250 is a better choice for ride-hailing drivers.

To the extent that Lyft ride-hailing VMT and other sources of VMT are negatively correlated, we may be underestimating daily VMT by low-mileage ride-hailing drivers in our data. Those with high average daily mileage are more likely to be loyal drivers on the Lyft platform, and they have limited additional time for travel in the day by nature of their high observed Lyft VMT. Lower-mileage drivers, on the other hand, are more likely to be engaging in ride-hailing through other platforms and have more time for other commercial activity and personal use.

5. Total cost of ownership of BEVs

We utilize a Total Cost of Ownership (TCO) approach to model vehicle cost over the commitment period. TCO modeling is a standard tool in transportation economics for comparing different technologies on the grounds of cost [36]. In our analysis, TCO depends on the annualized fixed costs of capital and insurance, the marginal costs of service and maintenance (S&M) and fuel, and the levelized cost of electricity charging (LCOC). We estimate costs for a representative ICEV, HEV, and BEV model on the market at each battery range. LCOC reflects the average cost of charging given the monetized opportunity cost in level of access to charging infrastructure as well as electricity cost calculated at the state level [34]. We exclude taxes, registration costs, and other fees, which are very similar for ICEVs, hybrid electric vehicles (HEVs), and BEVs (this exclusion may slightly disadvantage BEVs in TCO comparisons, because there are rebates on such fees for BEVs in some states). We apply a 5% discount rate on expenses beyond the purchase year. A variety of state and federal government subsidies are available to most EV buyers, including, most prominently, a federal tax credit for EV purchases that is currently capped at $7,500, and some EV manufacturers have already hit this cap. To model the effect of these subsidies on TCO, we incorporate a point-of-sale rebate of varying sizes on all new BEV purchases in our analysis.

We begin by estimating TCO for different vehicle types, annual VMT, and commitment periods. We consider both new and used BEVs (of varying battery sizes), HEVs, and ICEVs. We vary annual VMT from 10,000 to 40,000. Following evidence on the average ownership commitment period among TNC drivers [39,44], we evaluate TCO over commitment periods of three and five years (a longer ownership commitment period would favor BEVs). We then divide TCO by total VMT over the ownership commitment period to obtain a "levelized cost" of ownership in dollars per mile.

Fig. 3 illustrates the per-mile TCO of new and pre-owned vehicles for different annual mileages and commitment periods. With an annual VMT of 10,000 – which is close to the annual average mileage of a personal vehicle in the US – a new pre-subsidy BEV250 costs nearly 27% more than a new ICEV for three years of ownership. However, as annual mileage and commitment period increase, BEV250 becomes increasingly cost-effective. 20,000 VMT per year is sufficient to make a pre-subsidy BEV250 cost less per mile than an ICEV with a five-year commitment period; 30,000 VMT is sufficient to do so for both commitment period lengths. Meanwhile, with a $10,000 purchase subsidy, which is roughly consistent with the combined value of current federal and state incentives for many BEV models, a new BEV250 consistently costs far less than a new ICEV. For example, with a modest annual VMT of 10,000, a five-year commitment period, and a $10,000 subsidy, a BEV250 costs nearly 29% less than ICEV. An HEV also consistently costs less than an ICEV and competes with BEV250 depending on mileage, commitment period, and subsidy level. Our cost estimates are consistent with those of Borlaug et al. [34] and Palmer et al. [36] but slightly larger in magnitude due to the shorter ownership commitment periods we use here. Several market research entities also report $6,000-$10,000 lifetime savings for BEVs compared to ICEVs, and even larger savings for pre-owned BEVs [37,45].

Notably, pre-owned BEVs cost less than pre-owned HEVs and ICEVs regardless of mileage and ownership commitment period, even without the aid of any purchase subsidy (for which pre-owned BEVs are ineligible). For instance, a pre-owned BEV100 (e.g., a Nissan Leaf) appears to be a very cost-effective option for those drivers whose daily VMT needs are met by a battery size of 100 miles. This represents a significant portion of drivers in the LFLM cohort and implies that, at currently observed vehicle prices, switching to a pre-owned BEV100 could significantly reduce total vehicle costs for the majority of ride-hailing drivers. The main reason why pre-owned BEVs have a greater relative cost advantage than new ones is that BEVs are currently considered semi-luxury vehicles; this induces a steep depreciation curve at the beginning of vehicle use and a flatter curve than those of ICEVs and HEVs from the third to fifth year of ownership [37].

Next, we apply our TCO analysis to the drivers in our ride-hailing dataset. Fig. 4 plots ranges of annualized savings produced by switching from an ICEV to a BEV. In Panel A, the BEV has a battery size of 250 miles and the commitment period is five years. We plot ranges and averages for the full sample as well as each cohort, excluding drivers for whom a 250-mile range does not meet our suitability criterion (Fig. S-8 and Fig. S-9 show analogous results using alternative assumptions). VMT is the largest source of variation in total costs across drivers, but cross-state differences in LCOC and the price of gasoline are also relevant (see Fig. S-11 and Supplementary Note 2 for state-specific analysis).

With no subsidy, a new BEV250 is costlier than a new ICEV for most but not all drivers. Overall, 8.3% of all 2019 drivers on the Lyft platform are projected to both find a BEV250 range-suitable and save money switching to it. High-mileage drivers, however, are more likely to find a BEV250 attractive on cost grounds. The analogous cohort-specific percentages of drivers for whom a BEV250 provides both suitable range and cost savings are 12.2% in the UHM cohort and 48.5% in the HFHM cohort. As Panel A of Fig. 4 shows, no driver loses more than $1,100 per year switching to a BEV, but a number of drivers *gain* more than $1,500 per year from a switch.

With a $10,000 purchase subsidy, *all* drivers on the Lyft platform are

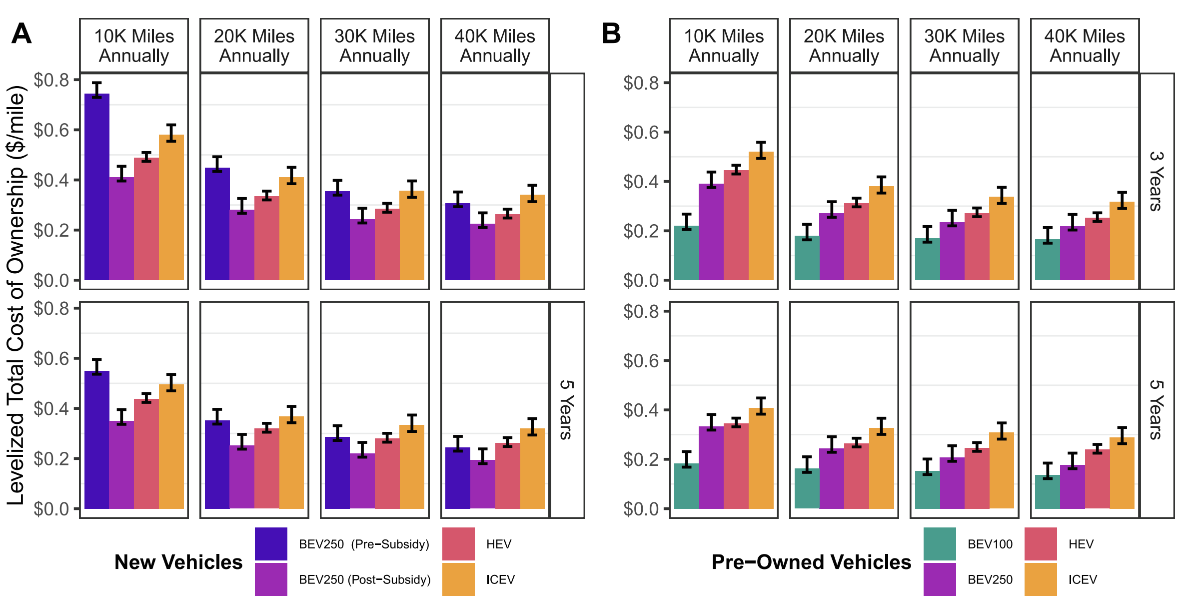

Fig. 3. Levelized (per mile) total cost of (A) new and (B) pre-owned vehicles for different annual mileages and commitment periods. The error bars represent the highest and lowest estimates with respect to variation of fuel and LCOC in different states. Per-mile cost includes depreciation, insurance, fuel/electricity, and S&M costs.

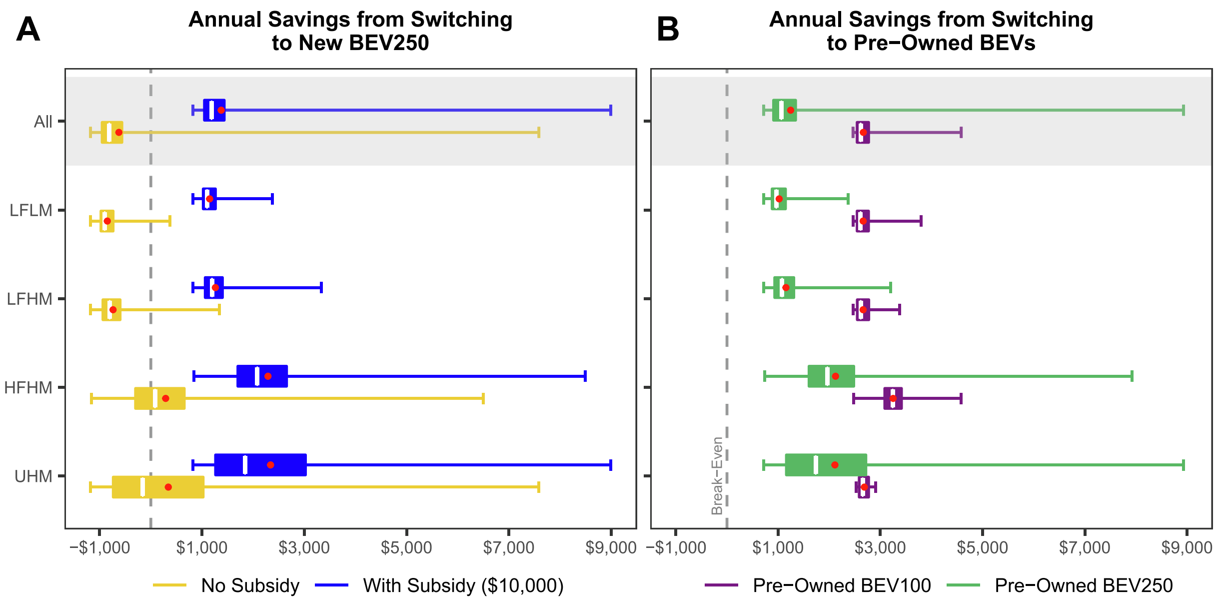

Fig. 4. The range and distribution of annual savings from ICEV to BEV for BEV-suitable drivers. (A) From new ICEV to BEV250 with and without purchase subsidies, under a 5-year commitment period. (B) From pre-owned ICEV to pre-owned BEV250 and pre-owned BEV100, under a 3-year commitment period. The red dots show the average annual savings for the whole population in the cohort. The boxes describe 25th percentiles (left hinge), medians (white line), and 75th percentiles (right hinge); whiskers describe absolute minimum and maximum. Savings distributions for other scenarios are shown in Fig. S-8 and Fig. S-9.

projected to save money switching to a BEV250, though only 86% of them also find a BEV250 range-suitable. The switch is projected to save an average of $1,325 annually among these drivers (Fig. S-10), though savings rises above $3,000 for some. Similarly, Panel B of Fig. 4 shows that switching to a pre-owned BEV100 or BEV250 (from a pre-owned ICEV) is projected to save money for all drivers at current purchase prices. Panel B also illustrates the value of battery right-sizing: LFLM and LFHM drivers uniformly save the most from a pre-owned BEV100, while some HFHM and UHM would find a BEV250 to be the cheaper option.

The purchase subsidy available to a potential BEV buyer is clearly very impactful in bringing BEVs to cost parity with ICEVs: a new BEV250 is projected to be range-suitable and cost-saving for 8.6% of drivers on the Lyft platform with no subsidy and 86.2% of drivers with a $10,000 subsidy. Given the magnitude of this effect, as well as uncertainty and geographic variation in what the subsidy level will be going forward, it is instructive to investigate how TCO moves with the subsidy level between $0 and $10,000. Fig. 5 precisely displays this relationship, overall and in each cohort, again under a five-year commitment period (Fig. S-12 repeats the experiment for a three-year commitment period). The average driver breaks even by switching to a new BEV250 with a subsidy of $3,200, though the right-skewed VMT distribution of ride-hailing drivers means only 26.5% of drivers actually break even at this subsidy level. However, a subsidy of $5,700 is enough to cause all range-suitable drivers to at least break even on the switch. The curves in Fig. 5 are capped below 100% (except in the case of the LFLM cohort) only because there are drivers in each cohort for whom a BEV250 does not provide suitable range. An equivalent reduction in vehicle purchase price due to battery cost cut has the same effect. The re-designed 2022 Chevrolet Bolt is projected to cost $5,500 less than the prior model [46]; our analysis implies that this price reduction brings nearly all range-suitable drivers to the break-even point on switching without any additional subsidy.

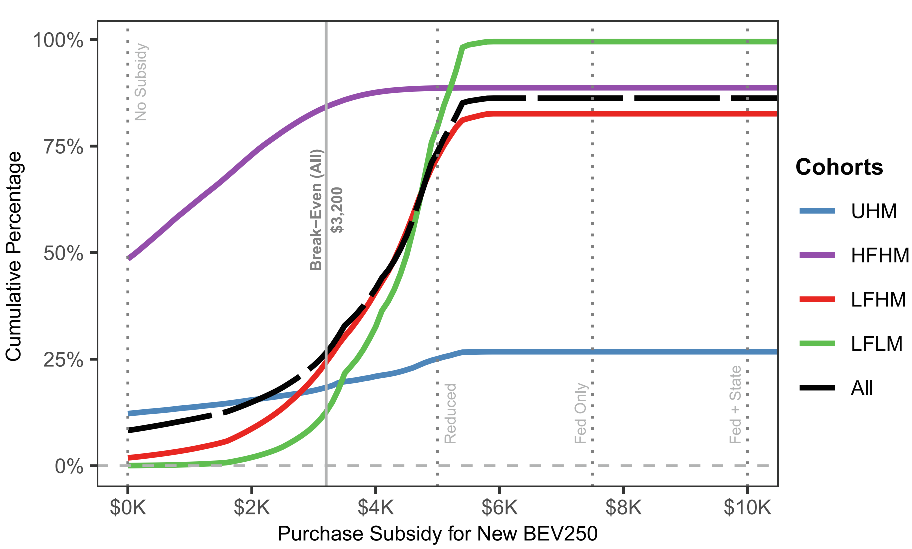

Fig. 5. Percentage of drivers in each cohort that both find a BEV250 range-suitable and break even under a 5-year ownership commitment, as a function of subsidy level. Curves that plateau below 100% have drivers for whom a BEV250 does not have suitable range. An average driver breaks even with a minimum of $3,200 purchase subsidy. Vertical lines indicate certain specific levels of subsidy. *Fed + State*: current level ($10,000) for some states; *Fed Only*: $7500 federal tax credit; *Reduced*: a scenario where tax rebate is reduced to $5,000.

6. Discussion and policy implications

Overall, our analysis suggests that range and total cost should not be seen as constraints on significant BEV take-up in the ride-hailing sector. We estimate that approximately 86% of drivers on the Lyft platform in 2019 could switch to a BEV250 – of which several models are currently on the market – without having to curtail their mileage on more than 5% of their active days. When we relax our assumption of 100% initial state of charge (SoC), the median percentage of driver-days (across 10,000 simulations) for which a BEV250 meets our suitability criterion remains high at 82%. Some of these drivers – in particular, high-mileage ones – are projected to save money by driving a new BEV250 even without a purchase subsidy. *All* range-suitable drivers are projected to at least break even with a subsidy of $5,700; the average savings at this subsidy level is $511 per year. Given that the federal tax credit program for EV purchase is expiring, maintaining this level of subsidy is crucial to making new BEVs cost-effective for the majority of ride-hailing drivers. Meanwhile, pre-owned BEVs offer significant savings and may be particularly attractive to those drivers who don't value the "luxury" attribute of new BEVs.

If all identified drivers who are BEV250-suitable (86% of all drivers) adopt BEVs, the sustainability benefits are staggering, as shown in Table S-6 and discussed further in Supplementary Note 3. This corresponds to 5.86 billion miles of electrified VMT on the Lyft platform annually, 62% of which come from the UHM and HFHM cohorts who save the most from electrification. Considering personal mileage, the total electrified VMT exceeds 17 billion miles annually, 41% of which are from the LFLM cohort, which accounts for nearly half of all drivers on the platform. The annual life cycle GHG emission reduction is more than 4.30 million metric tons of $CO_{2\text{-eq}}$ (5.72 from tailpipe reduction) using a conservative estimate of BEV battery production emissions. Specifically, the life cycle GHG emission reduction varies widely across states (Fig. S-13), depending on the average emission factors of electricity generation and aggregate electrified VMT, with the highest emission reduction in California, Texas, New York, and Florida. In contrast, switching to BEVs by BEV250-suitable drivers would lead to an additional 4.9 TWh of electricity consumption annually, which is equivalent to only 0.12% of US electricity generation in 2019.

These results have several implications for strategy and policy aimed at electrification. To the extent that drivers are unfamiliar with the technology or uninformed about range suitability and total costs of BEVs, information and awareness campaigns for potential EV buyers—specifically about available incentives and subsidies—may be effective at inducing a vehicle switch. This may be especially true in the ride-hailing sector, where drivers are more likely to be motivated by profit considerations and put correspondingly less weight on non-price vehicle attributes. The high resolution of our data and analysis shows the value of "targeting" here: high-mileage drivers may already be better off with a BEV, so changing perceptions among these drivers may be more likely to induce a vehicle switch; low-mileage drivers may, in some cases, be better off with a pre-owned BEV100.

Subsidies, too, could be targeted to good effect, to the extent that this is feasible. Not every driver needs the same subsidy level to be incentivized to switch. Moreover, our assumption of subsidy as a point-of-sale rebate has a significant equity implication. While EVs are competitive with ICEVs on *total* cost grounds, their higher upfront cost may prevent some financially constrained drivers (including those with low income, credit score, or tax appetite, or facing other barriers to financing mechanisms) from making the switch. Subsidies targeted and tailored to such drivers could help reduce this barrier. On top of increasing the manufacturer cap, the federal EV incentive program in 2021 has proposed switching the EV tax credit to point-of-sale rebate which makes EV subsides more available to low-income EV buyers, including ride-hailing drivers. More generally, the revelation (and communication) of widespread range suitability and cost competitiveness should free up TNCs and other entities in the transportation sector to prioritize other potential barriers to EV take-up. For instance, rather than investing in further range expansion of BEVs, companies and policymakers may more productively invest in charging technology and infrastructure to harness the battery sizes that are already suitable for most drivers.

Our work, its meaning, and its limitations suggest several avenues for future research on the electrification of cars on TNC platforms. First, discrepancies between perceived and actual range suitability and cost of ownership of BEVs point to the value of research on changing perceptions about such vehicles. Second, our study uses standard assumptions in the literature about access to charging infrastructure; accurately depicting current and projected access at a high resolution would improve future analyses of range suitability and total cost of ownership. Third, a TNC-wide transition to BEVs would very likely induce changes in purchase price (among other attributes), and future work to understand EV supply and demand dynamics could shed light on such changes. Fourth, although the current study investigates range suitability from the observed driver mileage, psychological factors associated with "range anxiety" of ride-hailing drivers merit further study. Finally, ride-hailing drivers predominantly self-identify as low-income and as members of a minority group [19]; research on policy design and corporate strategy to spur the electrification of ride-hailing should thus center their consequences for equity and justice, including through their effects on ride-hailing drivers.

Data Availability

The data on drivers' travel patterns which we use in this study are the property of Lyft Inc. and were made available through a data use agreement (DAU). Source data for each figure in the main text are provided in the following repository:

https://github.com/taiebat/TNC_EV_Suitability.

Note

This analysis has been conducted independent of Lyft Inc. (Lyft) and the data is provided through a Data Use Agreement (DAU) at the request of the authors. While this article is believed to contain correct information, Lyft does not expressly or impliedly warrant, nor assume any responsibility, for the accuracy, completeness, or usefulness of any information, apparatus, product, or process disclosed, nor represent that its use would not infringe the rights of third parties. Reference to any commercial product or process does not constitute its endorsement. This article does not provide financial, safety, medical, consumer product, or public policy advice or recommendation. Readers should independently replicate all experiments, calculations, and results. The views and opinions expressed are of the authors and do not necessarily reflect those of Lyft. This disclaimer may not be removed, altered, superseded, or modified without prior Lyft permission.

Declaration of Competing Interest

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

Acknowledgment

This material is based upon work supported by the National Science Foundation (Grant No. 1605202). The authors would like to sincerely thank Sam Arons, Paul Kauzmann, and Mike Xing for their significant contribution to conceptualization of the study and data acquisition, as well as helpful discussions. MT thanks the Sustainability and Policy Research teams at Lyft for providing the basis to conduct this study.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.apenergy.2022.119246.

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Supplementary Materials

Widespread Range Suitability and Cost Competitiveness of Electric Vehicles for Ride-hailing Drivers

Morteza Taiebat, Samuel Stolper & Ming Xu

https://doi.org/10.1016/j.apenergy.2022.119246

This file includes:

- Supplementary Note 1 – 3
- Table S-1 – S-6
- Fig. S-1 – S-13

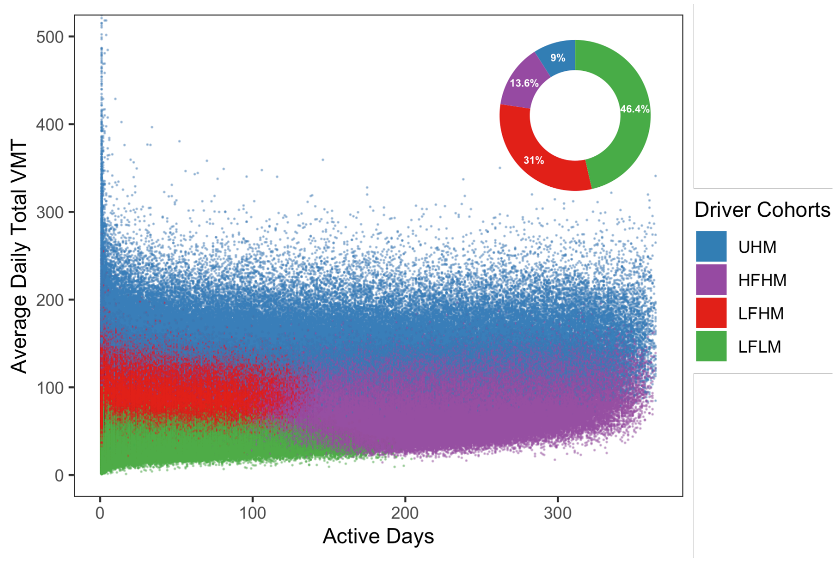

Fig. S-1. Near optimal and externally valid driver cohorts. *UHM*: Ultra High Mileage; *HFHM*: High Frequency High Mileage; *LFHM*: Low Frequency High Mileage; *LFLM*: Low Frequency Low Mileage.

Table S-1. Summary statistics of variables in the dataset for all drivers and by cohort.

	All	UHM	HFHM	LFHM	LFLM
Number of Active Days in 2019	**59**	124	190	36	24
Average Active-Day Number of Rides	**5.4**	12.4	5.6	6.4	3.2
Average Active-Day Observed VMT on Platform	**70**	145	77	86	43
Average Active-Day Occupied VMT	**25**	58	26	30	14
90th-percentile VMT	**123**	234	137	152	77
95th-percentile VMT	**139**	261	160	173	88
99th-percentile VMT	**165**	309	208	201	101
Average Active-Day Shift Duration (hr)	**3.54**	7.04	4.21	4.21	2.22
Observed Annual VMT on Platform	**5,112**	17,782	14,887	3,095	1,132
Total Annual VMT*	**12,412**	25,082	22,187	10,395	8,432

* Derived variable: annual observed VMT by Lyft plus 7,300 miles of personal miles.

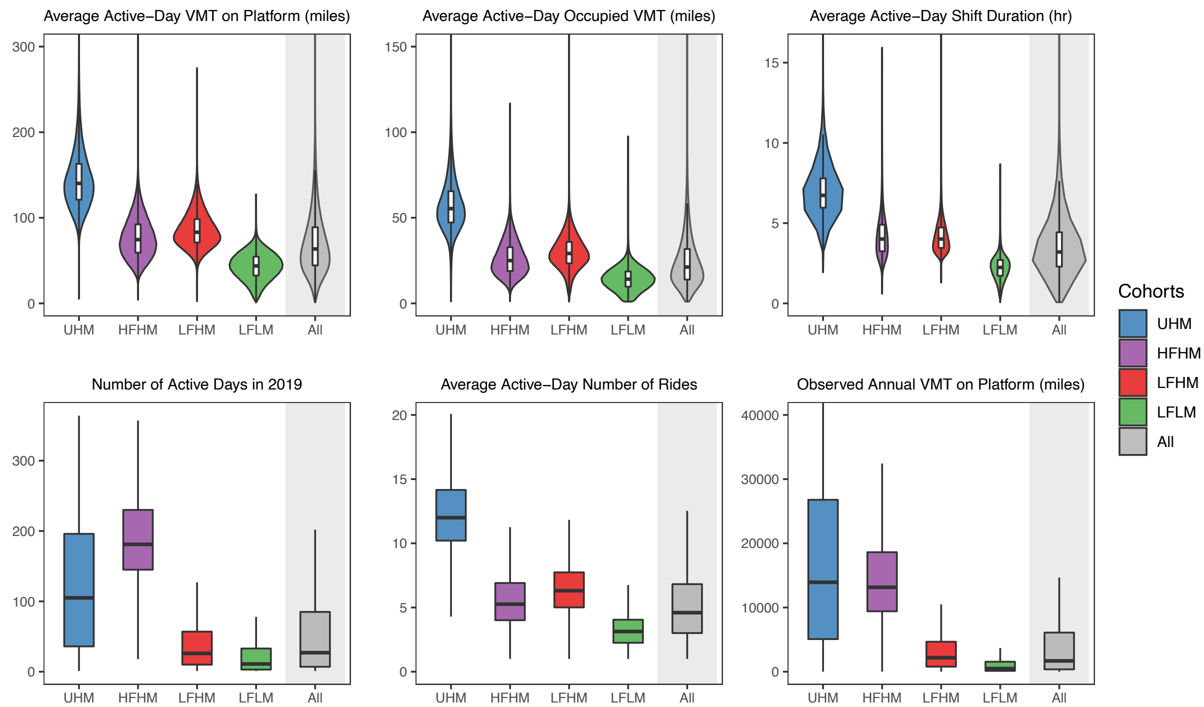

Fig. S-2. Distributions of selected variables in the dataset for all drivers and by cohort. The gray shade represents the distribution of variable for all drivers, regardless of cohort.

Supplementary Note 1: Driver clustering.

Based on computational efficiency and superior clustering power, we choose k-mean clustering, which minimizes within-cluster variances (squared Euclidean distances) of the aforementioned variables. Finally, we use several verification methods for checking the optimality of clusters (Fig. S-3). Both Elbow method and Silhouette width method suggest only two optimal clusters on selected variables and then marginal decrease in optimality with higher number of clusters (Fig. S-4). We use expert knowledge on average characteristics of resultant clusters to choose the near-optimal yet externally valid set of driver clusters. While the analysis is conducted at the individual driver level, some results are also reported on the cohort basis to provide a roadmap for identifying the ideal cohort of drivers for electrification efforts. Note that these cohorts based on the clustering method are not absolute, and drivers on the boundary of cohorts have travel patterns similar to those of either cohort.

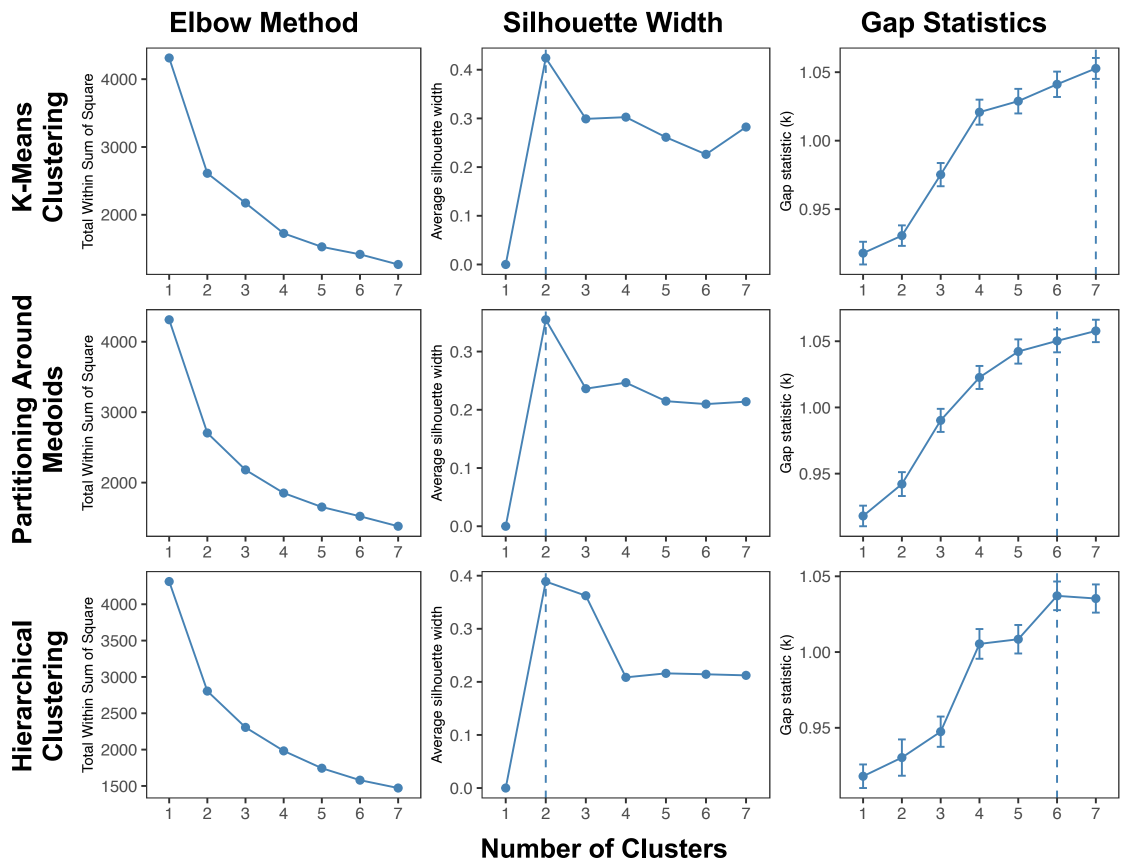

Fig. S-3. The performance of other unsupervised machine learning methods tested for defining the driver cohorts. Both Elbow method and Silhouette Width result in only two optimal clusters for all three algorithms. We use expert knowledge to choose four clusters as externally valid cohort without significantly losing the cluster optimality.

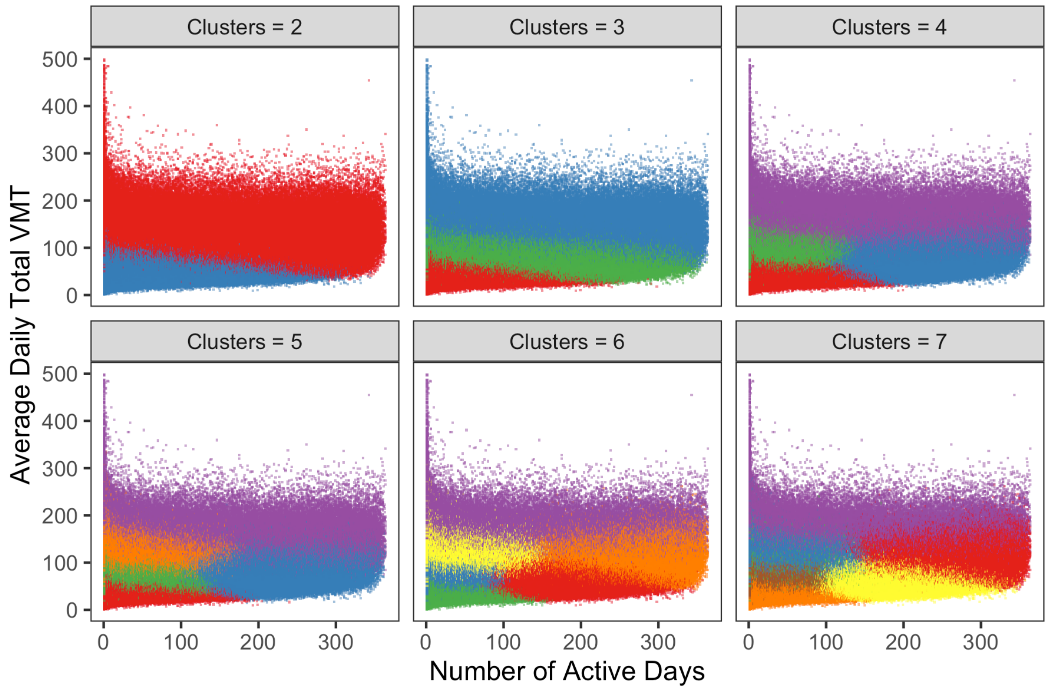

Fig. S-4. Results of different number of clusters on K-means clustering of cohorts on two variables. 4-cluster appears to have more external validity than others. The Greater number of clusters than 4 makes further cuts on low frequency low mileage drivers and does not improve the external validity.

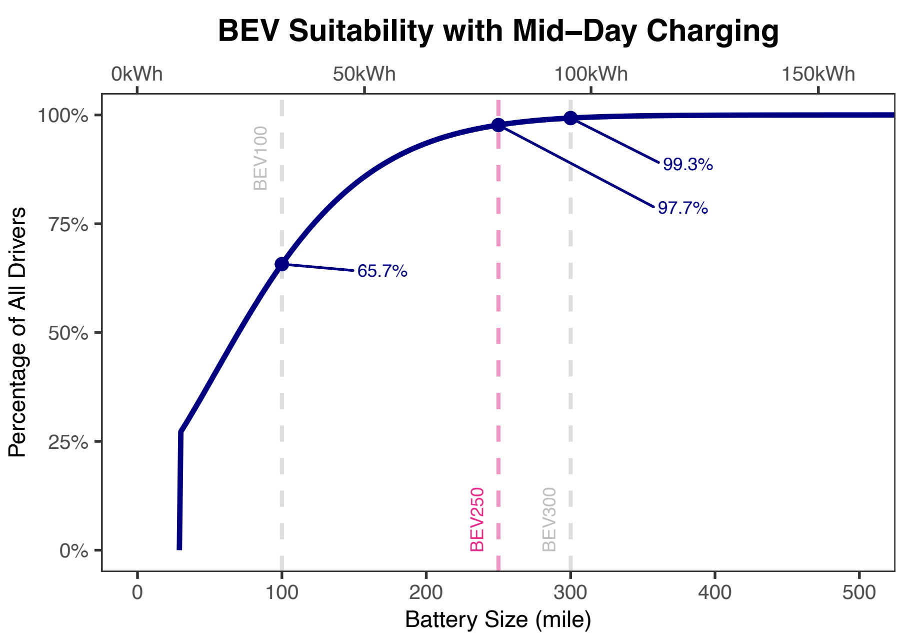

Fig. S-5. 95th%-VMT BEV Suitability with midday 30-minute charging at 30 kW DCFC. We use the full sample of drivers on the Lyft platform. The procedure for producing this figure is identical to that of Fig. 1, except for the allowance of an additional 30-minute midday charge.

Table S-2. The residual value (VRV) of new vehicles at the end of ownership commitment period from alg.com. The residual value is expressed as the percentage of MSRP.

New Models	ICEV	HEV	BEV250*
MSRP	$24,365	$27,280	$36,620
Mileage Per Year		3-Year Commitment	
10K miles/year	47%	56%	44%
20K miles/year	41%	51%	38%
30K miles/year	34%	45%	30%
40K miles/year	24%	39%	23%
		5-Year Commitment	
10K miles/year	32%	39%	34%
20K miles/year	23%	27%	23%
30K miles/year	10%	16%	13%
40K miles/year	1%	8%	8%

*For simplicity, we assume EV tax credits and subsidies are directly deducted from MSRP. The depreciation cost over commitment period is the difference between MSRP and residual value.

Table S-3. The residual value (VRV) of pre-owned vehicles at the end of ownership commitment period from alg.com

*Pre-owned Models**	ICEV	HEV	BEV250	BEV100
Pre-owned Certified Dealer Price	$15,632	$18,362	$19,144	$11,083
Mileage Per Year		3-Year Commitment		
10K miles/year	38%	49%	51%	61%
20K miles/year	29%	42%	40%	45%
30K miles/year	19%	33%	26%	26%
40K miles/year	9%	24%	13%	8%
		5-Year Commitment		
10K miles/year	32%	42%	33%	52%
20K miles/year	17%	29%	14%	25%
30K miles/year	2%	15%	2%	3%
40K miles/year	2%	2%	2%	3%

*Kelly Blue Book estimate corresponding to "Certified Pre-Owned from Certified Dealer - Fair Purchase Price on Very Good Condition", with typical mileage of 30K at the time of purchase.

Table S-4. Estimated annual insurance costs (I) for new and pre-owned vehicles. We assume the insurance rate is not a function of mileage, following the methodology of AAA.

	ICEV	HEV	BEV
New Models	$1,109	$1,200	$1,215
Pre-Owned Models	$964	$1,022	$1,001

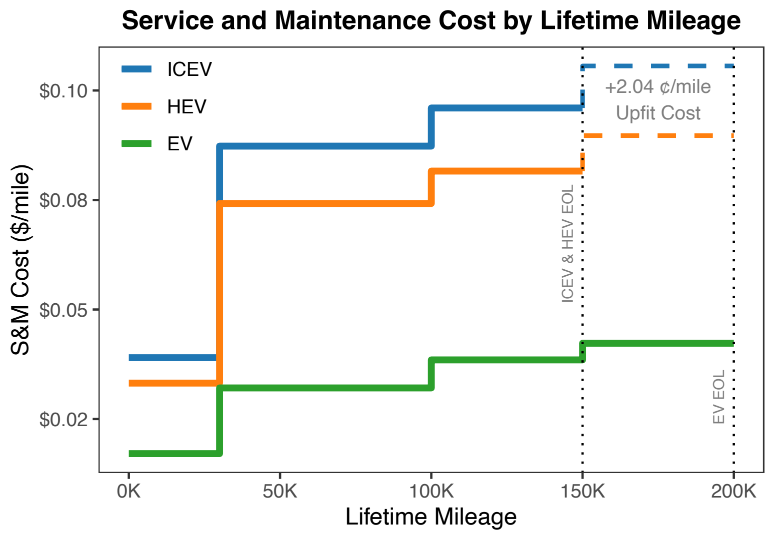

Fig. S-6. Service & Maintenance (S&M) costs per mile for different vehicle types. We assume that ICEV and HEV reach the end of their life (EOL) at 150,000 miles, while BEV reaches EOL at 200,000 miles. An upfit cost of $0.0204/mile is assumed for any mileage after 150,000 miles for ICEVs and HEVs. No vehicle in our analysis reaches over 200,000 miles under the assumption of a 3- or 5-year commitment period.

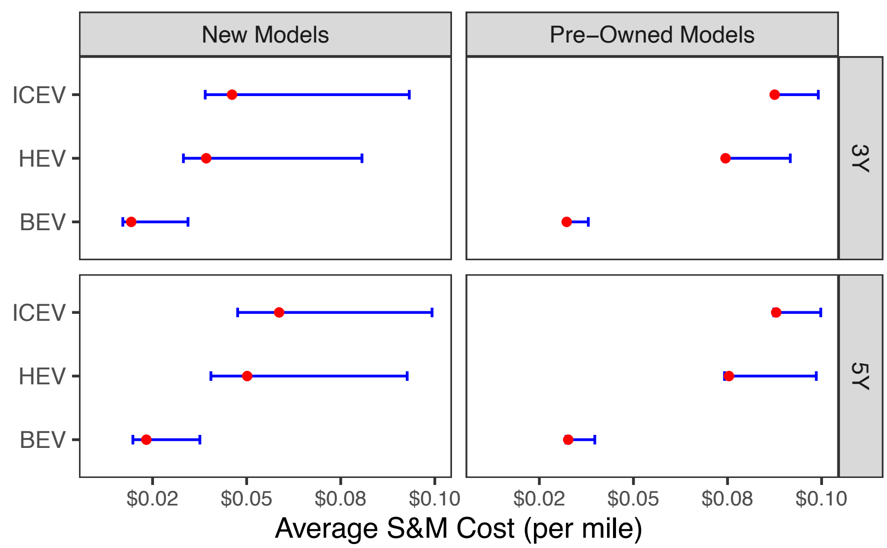

Fig. S-7. Range of mileage-weighted average S&M costs per mile for all drivers by model type, new vs. pre-owned, and commitment period length. The mileage-weighted average S&M cost additionally depends on annual mileage. Red points denote averages and whiskers show minimum and maximum.

Table S-5. 2019 average gas price and LCOC by state. Gas price includes taxes and is based on the weighted sales volume of three grades of gas, as calculated by the US Energy Information Administration.[1] The national average gas price in 2019 is $2.763/gal, and the median is $2.625/gal. LCOC is based on the central estimate of Borlaug et al. for each state.[2] The average LCOC is 0.15 $/kWh nationwide, with the highest costs in Hawaii and the lowest in the Oregon, Washington DC, Delaware, and Maine. For equivalent per mile cost, 0.28 kWh/mile and 27 mile/gal are used for energy efficiency of BEV and ICEV, respectively.

State	*LCOC ($/kWh)*	*Gas Price (G_s) ($/gal)*	*BEV per-mile LCOC ($/mile)*	*ICEV per-mile gas cost ($/mile)*
Alabama	0.13	2.369	0.0364	0.0877
Alaska	0.25	3.516	0.0700	0.1302
Arizona	0.12	3.101	0.0336	0.1149
Arkansas	0.13	2.332	0.0364	0.0864
California	0.18	3.968	0.0504	0.1470
Colorado	0.13	2.503	0.0364	0.0927
Connecticut	0.15	3.040	0.0420	0.1126
Delaware	0.10	2.625	0.0280	0.0972
District of Columbia	0.10	3.089	0.0280	0.1144
Florida	0.15	2.698	0.0420	0.0999
Georgia	0.12	2.552	0.0336	0.0945
Hawaii	0.31	3.944	0.0868	0.1461
Idaho	0.13	2.930	0.0364	0.1085
Illinois	0.16	2.637	0.0448	0.0977
Indiana	0.15	2.491	0.0420	0.0923
Iowa	0.12	2.576	0.0336	0.0954
Kansas	0.16	2.393	0.0448	0.0886
Kentucky	0.13	2.576	0.0364	0.0954
Louisiana	0.13	2.381	0.0364	0.0882
Maine	0.10	2.723	0.0280	0.1009
Maryland	0.17	2.711	0.0476	0.1004
Massachusetts	0.23	2.955	0.0644	0.1094
Michigan	0.18	2.515	0.0504	0.0931
Minnesota	0.14	2.527	0.0392	0.0936
Mississippi	0.15	2.357	0.0420	0.0873
Missouri	0.15	2.332	0.0420	0.0864
Montana	0.15	2.784	0.0420	0.1031
Nebraska	0.15	2.613	0.0420	0.0968
Nevada	0.11	3.504	0.0308	0.1298
New Hampshire	0.12	2.808	0.0336	0.1040
New Jersey	0.15	2.845	0.0420	0.1054
New Mexico	0.14	2.479	0.0392	0.0918
New York	0.12	3.053	0.0336	0.1131
North Carolina	0.13	2.576	0.0364	0.0954
North Dakota	0.14	2.552	0.0392	0.0945
Ohio	0.15	2.393	0.0420	0.0886
Oklahoma	0.12	2.259	0.0336	0.0837
Oregon	0.10	3.480	0.0280	0.1289
Pennsylvania	0.16	3.004	0.0448	0.1113
Rhode Island	0.22	2.894	0.0616	0.1072
South Carolina	0.16	2.589	0.0448	0.0959
South Dakota	0.16	2.381	0.0448	0.0882
Tennessee	0.15	2.442	0.0420	0.0904
Texas	0.15	2.332	0.0420	0.0864
Utah	0.15	2.943	0.0420	0.1090
Vermont	0.15	2.943	0.0420	0.1090
Virginia	0.11	2.491	0.0308	0.0923
Washington	0.14	3.578	0.0392	0.1325
West Virginia	0.16	2.723	0.0448	0.1009
Wisconsin	0.12	2.503	0.0336	0.0927
Wyoming	0.15	2.906	0.0420	0.1076

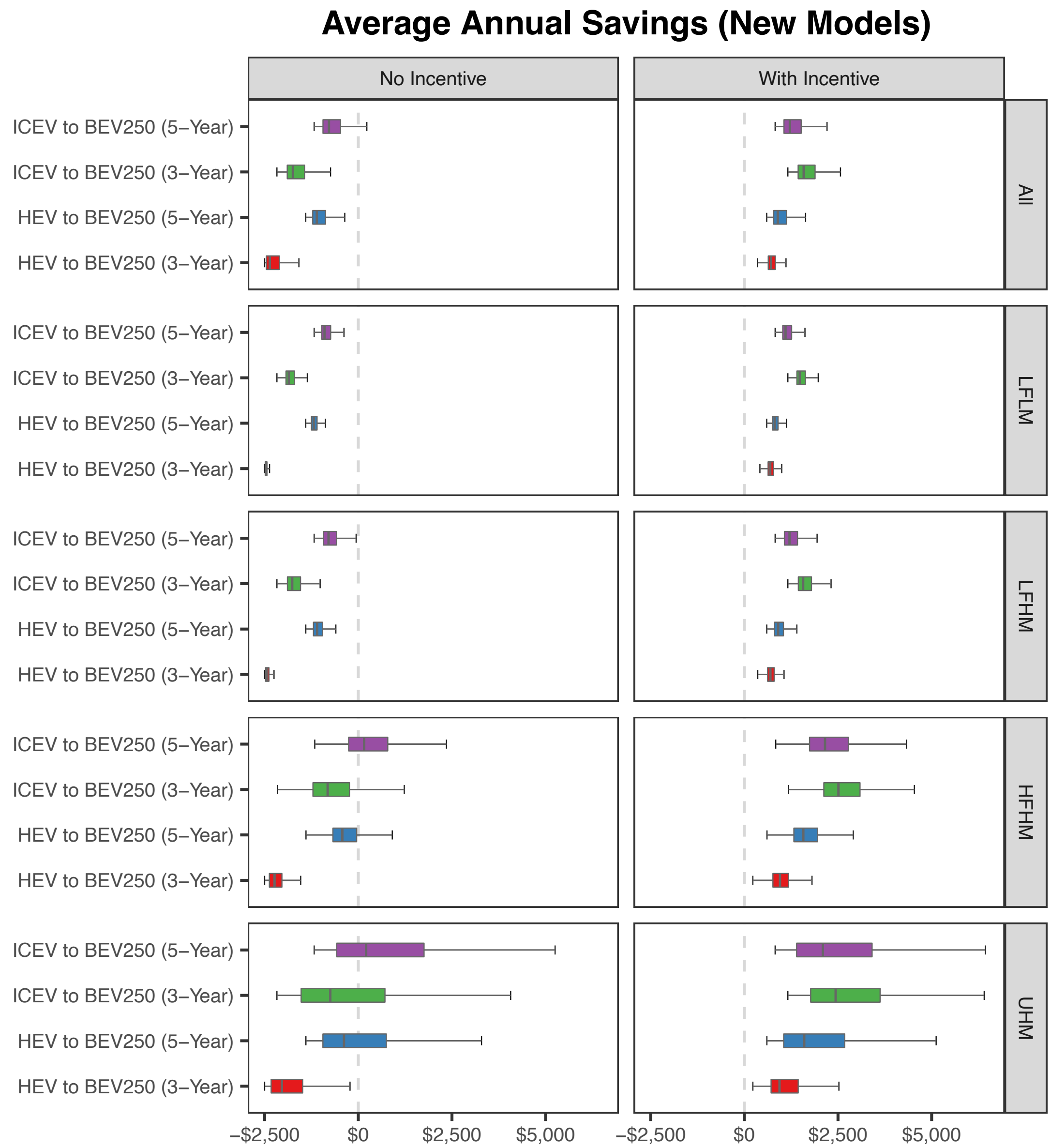

Fig. S-8. Distribution of average annual savings from switching to *new* BEVs under various scenarios. The range for all drivers is shown regardless of whether they are BEV suitable or not. Columns show with and without purchase subsidy and rows show the distribution for the cohorts. The boxes describe 25th percentiles (left hinge), medians, and 75th percentiles (right hinge) and whiskers describe 1.5 times the interquartile range.

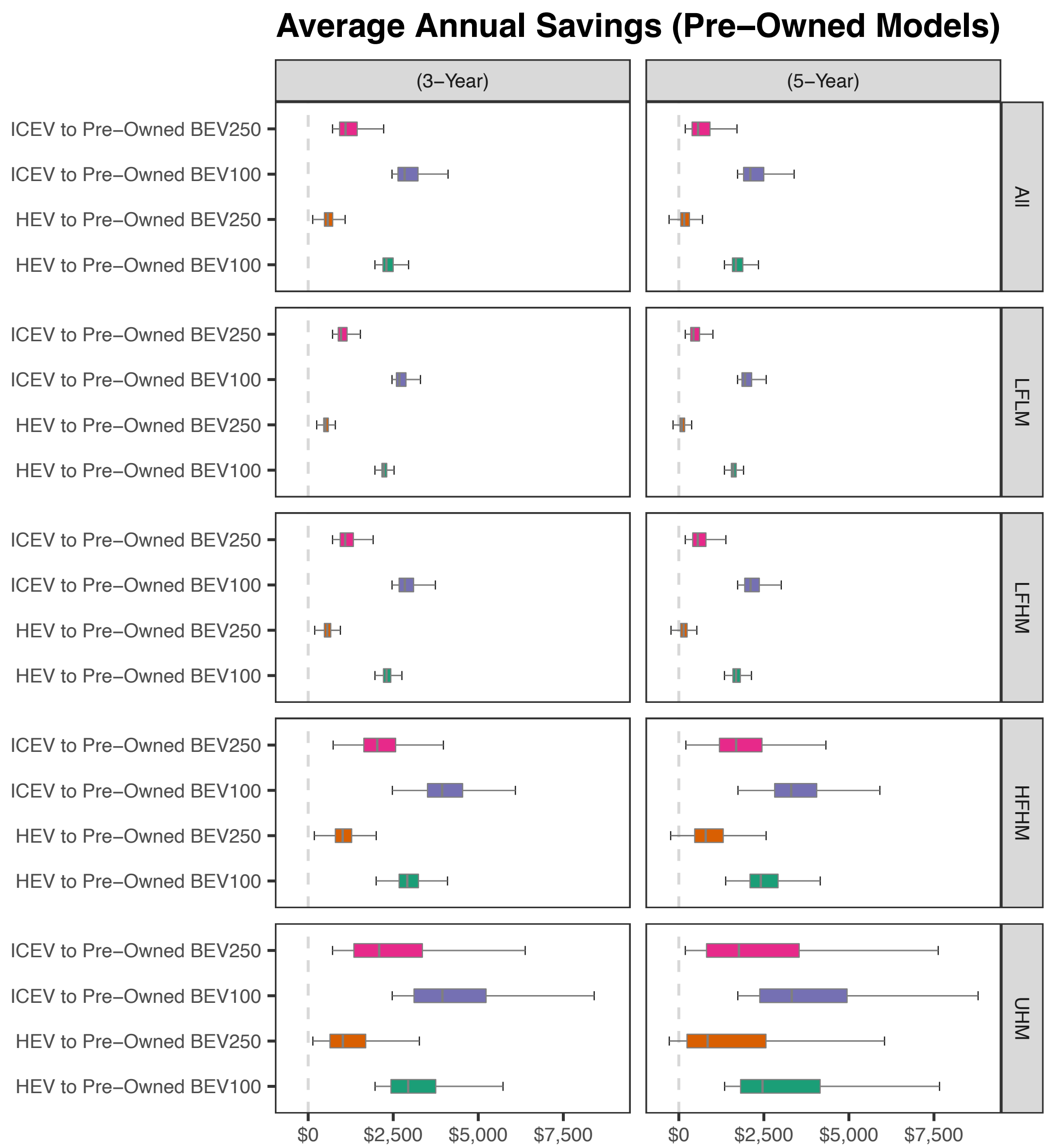

Fig. S-9. Distribution of average annual savings from switching to *pre-preowned* BEVs under various scenarios. The range for all drivers is shown regardless of whether they are BEV suitable or not. Columns show the average savings 3- and 5-year commitment period and rows show the distribution for the cohorts. The boxes describe 25th percentiles (left hinge), medians, and 75th percentiles (right hinge) and whiskers describe 1.5 times the interquartile range.

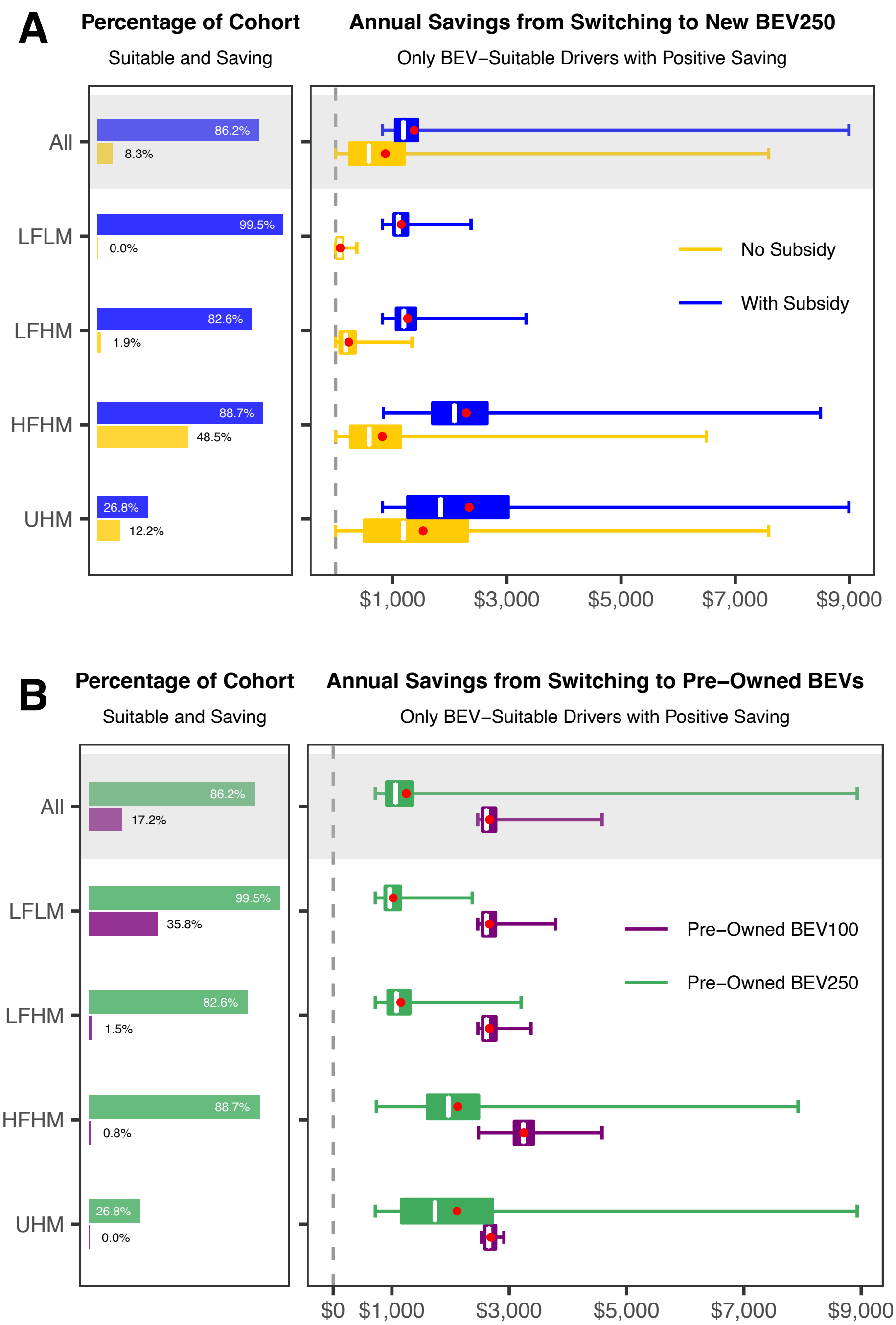

Fig. S-10. The range and distribution of annual saving from ICEV to BEV for BEV-suitable drivers with positive savings (Fig. 4 shows the full range). (A) From new ICEV to BEV250 with and without purchase subsidies under 5-year commitment period. (B) From pre-owned ICEV to pre-owned BEV250 and pre-owned BEV100 under 3-year commitment period. The red points show the average annual savings. The boxes describe 25th percentiles (left hinge), medians (white line), and 75th percentiles (right hinge) and whiskers describe absolute minimum and maximum.

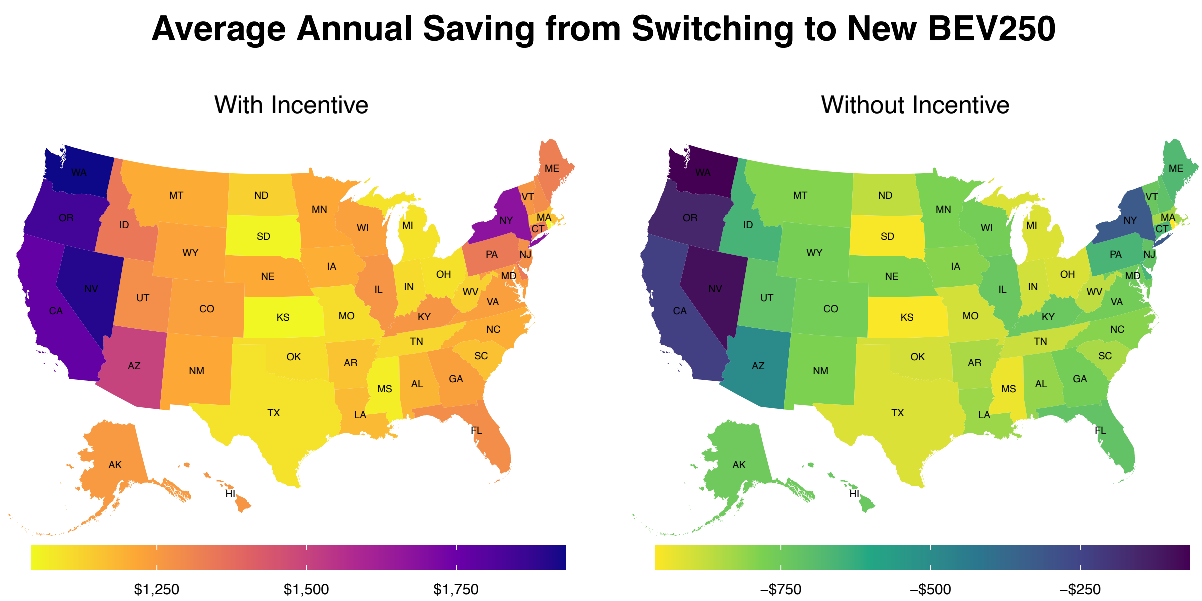

Fig. S-11. State-level average annual savings from new ICEV to new BEV250 with and without purchase subsidies under 5-year commitment period.

Supplementary Note 2: State-level average annual savings from new ICEV to new BEV250.

Fig. S-11 illustrates the state-level average annual savings from new ICEV to new BEV250 with and without purchase subsidies. With subsidies, states of WA, NE, OR, CA, and NY have the highest average annual savings. Without subsidies, Nevada's drivers return the highest savings, mostly due to the highest average mileage in the nation. States of KS, SD, MS, and RI have the lowest average annual savings in both cases. Note that, with subsidies, far more LFLM drivers in those states break even or save from switching to BEV, which changes the decomposition of the set of drivers in those states who are both BEV suitable and save from switching to BEVs.

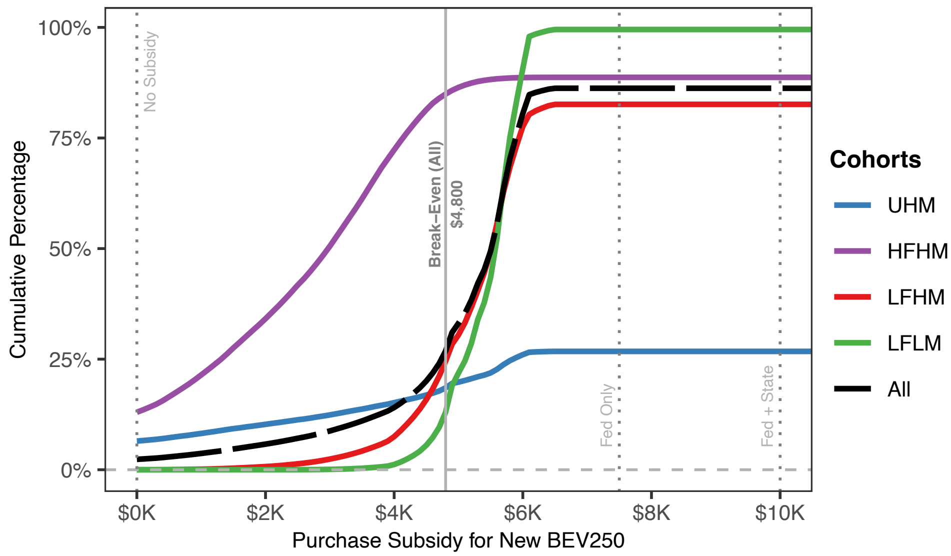

Fig. S-12. Percentage of drivers in each cohort that both find a BEV250 range-suitable and break even under a 3-year ownership commitment, as a function of subsidy level. Curves that plateau below 100% have drivers for whom a BEV250 does not have suitable range. An average driver breaks even with a minimum of $4,800 purchase subsidy. Vertical lines indicate certain specific levels of subsidy. *Fed + State*: current level ($10,000) for some states; *Fed Only*: $7500 federal tax credit; *Reduced*: a scenario where tax rebate is reduced to $5,000.

Supplementary Note 3: Sustainability implications.

The emissions conversion from gasoline to CO_2 is based on EPA measurements of 8,887 gr$CO_{2\text{-}eq}$ per gallon of gas and the fuel economy of replaced ICEV (27 miles per gallon). For the life-cycle GHG emissions we use BEV energy efficiency, data from state-level average emission factor of electricity generation from NREL's Cambium dataset [3] and per-mile vehicle cradle-to-grave emissions (including vehicle manufacturing and battery production and end of life) for ICEV and BEV. The estimate of state-level marginal emission factor of electricity generation is for year 2020 based on short-run mid-case scenario of NREL's Regional Energy Deployment System [3]. The US average marginal emission factor of electricity generation is 365.16 gr$CO_{2\text{-}eq}$/kWh but varies greatly among the states. As a point of comparison, our estimate of California's marginal emission factor for electricity generation is 192 gr$CO_{2\text{-}eq}$/kWh which is slightly higher than the estimate of Jenn [4] (186 gr$CO_{2\text{-}eq}$/kWh). We use a central estimate of 43 gr$CO_{2\text{-}eq}$/mile for ICEV and a conversative estimate of 144 gr$CO_{2\text{-}eq}$/mile for BEV including battery production for cradle-to-grave emissions excluding the use phase. Note that Cox et al., Hoekstra et al. and Elgowainy et al. estimate a range of 85-162 gr$CO_{2\text{-}eq}$/mile for BEV as use-phase excluded cradle-to-grave emissions [5–7].

Table S-6. Implications of electrification of all drivers who are BEV250-suitable and save from switching. All figures are based on annual estimate

	All	UHM	HFHM	LFHM	LFLM
Annual Avoided Tailpipe GHG Emissions (Million Metric Tons of $CO_{2\text{-}eq}$)	5.72	0.85	1.52	1.55	2.34
Annual Avoided Life-Cycle GHG Emissions (Million Metric Tons of $CO_{2\text{-}eq}$)	4.30	0.22	1.18	1.16	1.74
Annual Electricity Consumption (TWh)	4.86	0.24	1.30	1.33	1.99

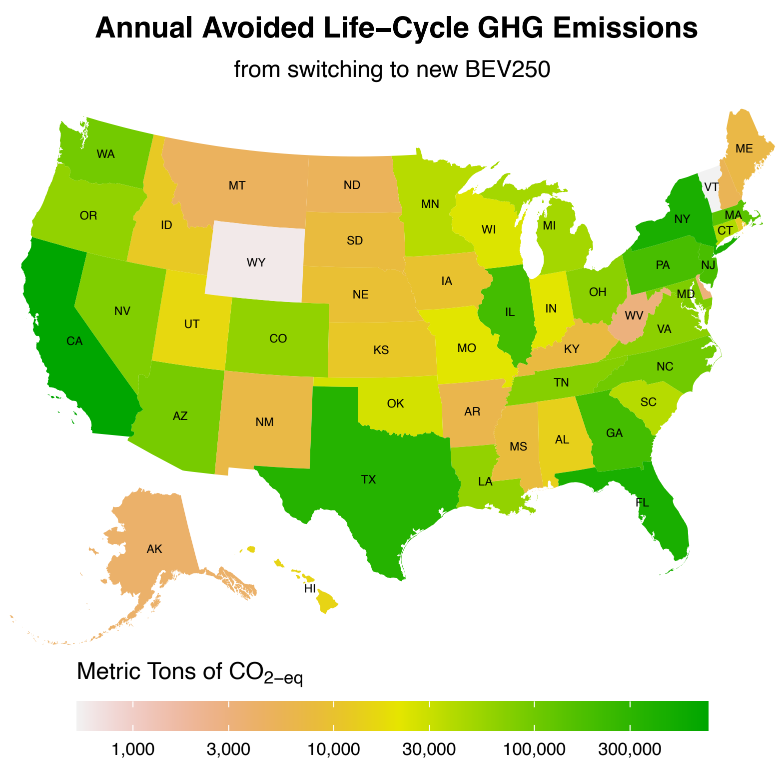

Fig. S-13. Annual avoided life-cycle GHG emissions from switching to new BEV250 across different states. We use average emission factor in each state and vehicle and battery life-cycle emissions.

Supplementary References

[1] U.S. Energy Information Administration (EIA). The State Energy Data System (SEDS). 2019.

[2] Borlaug B, Salisbury S, Gerdes M, Muratori M. Levelized Cost of Charging Electric Vehicles in the United States. Joule 2020;4:1470–85. https://doi.org/10.1016/j.joule.2020.05.013.

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[4] Jenn A. Emissions benefits of electric vehicles in Uber and Lyft ride-hailing services. Nat Energy 2020;5:520–5. https://doi.org/10.1038/s41560-020-0632-7.

[5] Cox B, Mutel CL, Bauer C, Mendoza Beltran A, van Vuuren DP. Uncertain Environmental Footprint of Current and Future Battery Electric Vehicles. Environ Sci Technol 2018;52:4989–95. https://doi.org/10.1021/acs.est.8b00261.

[6] Hoekstra A. The Underestimated Potential of Battery Electric Vehicles to Reduce Emissions. Joule 2019;3:1412–4. https://doi.org/10.1016/j.joule.2019.06.002.

[7] Elgowainy A, Han J, Ward J, Joseck F, Gohlke D, Lindauer A, et al. Cradle-to-Grave Lifecycle Analysis of U.S. Light Duty Vehicle-Fuel Pathways: A Greenhouse Gas Emissions and Economic Assessment of Current (2015) and Future (2025-2030) Technologies. Argonne, IL, 2016. https://doi.org/10.2172/1254857.