# Are we there yet? Evaluating the transition to EVs

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**Transitioning from internal combustion vehicles (ICEs) to battery electric vehicles (BEVs) is widely considered essential to achieve climate goals.[1–3] Although BEV adoption is rising, it varies substantially across regions and remains low in many countries despite significant investment from automakers and governments.[4,5] Prior research has emphasized behavioral impediments to adoption,[6–9] like range anxiety, and explored infrastructure design to support BEVs,[10,11] often relying on surveys or niche settings like car sharing.[12,13] However, little is known about how BEVs are used in everyday life, how their usage compares to ICEs, and how charging infrastructure shapes these patterns. Using a large dataset of U.S. vehicles, we demonstrate that BEVs are driven as much overall as ICEs but make about three fewer long-distance trips (≥150 km) per year. We find that increasing charging density to a moderate level reduces this long-distance trip gap more effectively than increasing charging reliability. We further show that convenient home-charging, rather than range anxiety, better explains differences between BEV recharging and ICE refueling. Our results can help automakers design more attractive service**

**offerings for BEV buyers, guide infrastructure providers and governments to improve charging access, and offer empirical evidence to inform public understanding and academic research on real-world BEV usage.**

Range anxiety—the concern that one's battery electric vehicle (BEV) will run out of charge before reaching its destination or a charging station—is widely recognized as a major deterrent to widespread BEV adoption.[14–16] Range, the distance a vehicle can travel on a full battery or fuel tank, is also a key factor thought to drive differences in how BEVs and internal combustion engine vehicles (ICEs) are used.[17,18]

BEVs generally have shorter ranges than ICEs, face fewer public chargers than gasoline stations in most areas, and take longer to recharge than ICEs take to refuel. While BEVs' share of new car sales in the United States grew more than 15-fold over the past decade, reaching nearly 8% in 2024,[4] they still constituted only 2% of vehicles on the road, less than 5% globally, and closer to 1% for most countries outside Europe or China.[5] BEV growth forecasts depend not only on how quickly battery costs decline and charging networks expand,[19] but also on consumer sentiment and drivers' perceptions of vehicle capabilities and benefits.[17,20–22] For example, *limited range per charge* and *time to charge* are two of the five most frequent deterrents to BEV adoption.[18] Increasing BEV market share—especially in conjunction with efforts to reduce the carbon intensity of electricity generation—is critical for governments to meet their national climate commitments and for automakers to meet their fleet emission targets.[1–3]

BEV original equipment manufacturers (OEMs) primarily focus on improving battery and vehicle technologies, supported by governments, utilities, and other firms that build out charging networks.[1,23] While we do not directly observe adoption decisions, much can be learned from the driving behavior of millions of BEVs already on the road to better understand the conditions under which different strategies to expand BEV market share are most effective. This includes analyzing how BEV usage patterns—such as driving and charging behavior—differ from those of ICEs, quantifying these differences, and examining the underlying factors that contribute to range anxiety and related behaviors.

To date, most research on range anxiety, BEV usage, and charging infrastructure has not used actual BEV data, which has been difficult to access and, until recently, unavailable at scale. Existing research, based on surveys and small-scale experiments, finds that range anxiety affects BEV drivers when their vehicle's remaining range drops below 15-75 kilometers or 20-25% state-of-charge (SOC),[6–9,24] and suggests this behavior reflects fear or a stress response. The literature further indicates that driver behavior is largely unaffected above this threshold, commonly referred to as *range buffer, comfort range,* or *safety range inventory.*[6]

Research aimed at optimizing BEV battery capacity or charging infrastructure[25,26] has often omitted range anxiety as a dimension, either viewing it as too difficult to quantify or by approximating BEV driver behavior using experimental data from ICEs.[27] Studies that have explicitly modeled range anxiety[12,28,29] employ widely differing approaches to capture its impact, possibly due to the empirical reality being unknown.

The limited empirical research on BEVs has mostly relied on secondary data sources, such as public infrastructure databases, transportation surveys, or odometer readings collected at (re)sale or maintenance visits – and has failed to produce a consensus on whether BEVs are driven differently than comparable ICEs.[30–33] Research based on public charging data shows that in regions where there is more availability of faster chargers, drivers tend to let their vehicles reach lower SOC levels before recharging—a pattern the authors attribute to reduced range anxiety.[12,29] And while range anxiety, as discussed above, is frequently cited as a major concern with BEVs, one survey of actual BEV drivers finds that only one in six exhibits it.[34]

In this study, we empirically evaluate how real-world BEV drivers operate and charge their vehicles, how their behavior differs from ICE drivers, and how charging infrastructure influences BEV drivers' decisions. We use large-scale, longitudinal U.S. passenger vehicle data to compare the mobility and charging behavior of BEVs and ICEs. We define *mobility* as the patterns of when and where vehicles are driven, and *repowering* as drivers' behavior regarding recharging BEVs or refueling ICEs. Our analysis draws on granular telemetry data provided by BMW Group (an OEM headquartered in Germany) spanning 319,471 vehicles—including 20,960 EVs—across 28 models. The dataset covers 252 million drives in the United States in 2023, totaling more than 3 billion kilometers (see Section 6 for details). By *drives*, we refer to the movement of a vehicle from one location to another from the moment its engine or motor starts until it stops. The dataset provides timestamps, vehicle locations, SOC, and other information at the start and end of each drive, enabling us to study granular usage patterns over time —a substantial advantage over most existing data sources.

We find that BEV mobility closely resembles that of ICEs across most dimensions, including annual distance driven. A key difference is that BEV drivers take slightly more shorter and medium trips (which account for 99% of all trips) but 34% fewer long trips (defined as 150 km or more). On average, the latter corresponds to about 3 fewer long trips per year for BEVs than ICEs (6.0 versus 9.1). We refer to the ratio of this difference to the number of BEV trips as the road-trip gap (in this case, $[9.1\text{-}6.0]/6.0 = 51\%$). We show that this road-trip gap is reduced more by bringing up charging density to moderate levels (as of 2023, 17% of trip destinations have zero stations within 5 km) than by increasing charger reliability. Yet, further raising station density beyond moderate levels does not further close the road-trip gap, which remains at 39% even for destinations with many, highly-reliable charging stations.

We further examine repowering behavior and find that BEVs are up to 80% more likely to be charged than ICEs are refueled at the same remaining range. We also show that this behavioral difference is entirely attributable to BEV drivers who engage in home-charging. When vehicles are operated away from their home area, BEVs and ICEs exhibit indistinguishable repowering patterns, which is surprising given the emphasis on range anxiety in public discourse, and the fact that in 2023 there were fewer public charging stations than gas stations in the US. Finally, we find that BEVs without home-charging engage in short public charging sessions (under 2 hours) 72% more often (and charge 104% more energy per year) than vehicles with home-charging. For longer or overnight public charging, the differences reduce substantially. These findings quantify how private charging access shapes public charging usage among BEV users.

Several stakeholders can benefit from these insights. OEMs could design new business models that support BEV drivers on the few days each year when they take longer trips (e.g., by offering portable range-extending solutions or short-term rentals of longer-range vehicles) and emphasize convenience when marketing home-charging offerings. Charging infrastructure developers and policymakers could more effectively increase BEV usage by, in some cases, adjusting their investment strategy to ensure (at least) a certain minimum charger density is available in more locations, rather than increasing installations in already densely covered areas - especially at common trip destinations. Those players could also use the insights from our analysis to tailor the mix of charger types to local needs. In areas with limited home-charging access (e.g., urban neighborhoods), faster public chargers designed for short sessions better align with usage patterns. In (suburban) areas where most BEV drivers have access to home-charging, less public charging infrastructure is needed overall; however, its users charge for longer sessions, which can be accommodated with slower speeds. Lastly, in an industry with rapid technology development, our findings provide public opinion and scholars with key facts about how drivers are actually using BEVs, and how their behaviors differ from ICE drivers in some respects and resemble them in others.

# 1 Mobility Behavior

We begin by comparing mobility behavior, since enabling mobility is the primary reason why people purchase vehicles. We then examine repowering behavior, the primary technological and infrastructure difference that affects the drivers of BEVs and ICEs.

A *trip* aggregates one or more drives (defined above) if they travel in the same direction, with the same passenger count, separated only by short breaks (see SI 6 for details). In our data, a trip averages 1.3 drives, and most trips consist of a single drive. Longer journeys are captured as one trip that typically consists of multiple drives.

Contrary to common claims,[31,33,35–37], we show in Table 1 that in aggregate BEV and ICE passenger vehicles exhibit largely similar usage patterns throughout the year across several dimensions including the average number of trips (996=19.11/7*365 for BEVs vs. 970 for ICEs), annual distance driven (17,956 vs. 17,922 km), distance and time per trip, and number of passengers. If anything, BEVs are used slightly more in our data. We also show that our sample of vehicles from a single OEM is similar to data from a US-wide survey of drivers across many OEMs (shown in the 'ADS 2022' column)[38].

**Table 1** Descriptive statistics of trips, comparing the sample's BEVs and ICEs as well as the US-wide survey data.

| | BEV | ICE | ADS 2022 |
|---|---|---|---|
| Avg. Number of Trips per Week | 19.11 (0.05) | 18.61 (0.04) | 17.08 |
| Avg. Distance per Trip (in km) | 18.02 (0.06) | 18.47 (0.05) | 19.62 |
| Avg. Number of Passengers in Car | 1.51 (0.00) | 1.48 (0.00) | 1.52[39] |
| Avg. Trip Duration (in minutes) | 23.49 (0.06) | 23.59 (0.05) | 24.50 |
| Avg. Number of Drives Per Trip | 1.27 (0.00) | 1.31 (0.00) | |

Sample averages for the key usage dimensions of interest (standard errors in parentheses). We include only vehicles for which the data contains at least 100 observations. ADS stands for American Driving Survey[38], a representative survey in which over 5,000 Americans report their daily driving patterns.

While the vehicles in our dataset tend to be more expensive than the average vehicle in the U.S., their ranges are comparable. Specifically, the average Manufacturer's Suggested Retail Price (MSRP) of base models in our data is nearly $70,000, compared to the average MSRP of new vehicles in the US, which is approximately $50,000[40]. Importantly, all BEVs in our data were manufactured in 2021 or later (ICEs 2018 or later), giving us access to modern BEVs with ranges that span approximately 350-650 km (or 220-400 miles, see Fig.A2), in line with the advertised 289-363 mile ranges of the 2024 Top 10 most sold BEVs in the US[41].

Given that range anxiety is inherently tied to driving distance, we examine the extent to which BEVs and ICEs differ in how often they are used for trips of varying lengths. We group trips by distance using 5-10 km bins for shorter trips and 25-50 km bins for longer trips. Fig.1, plots the annual number of trips that the average BEV or ICE has undertaken (left y-axes) within each bin distance (x-axis). Since shorter trips are much more common, we split the figure into two panels to scale their respective y-axes for easier readability. We use a dashed line (right y-axis) to convey the ratio between the average BEV and ICE values. For example, considering trips of 100-125 km (the smallest bin on the right panel), BEVs made approximately 5.6 trips in 2023 compared to 5.0 for ICEs, and the dashed line depicts the 1.1 ratio (5.6/5.0=1.1).

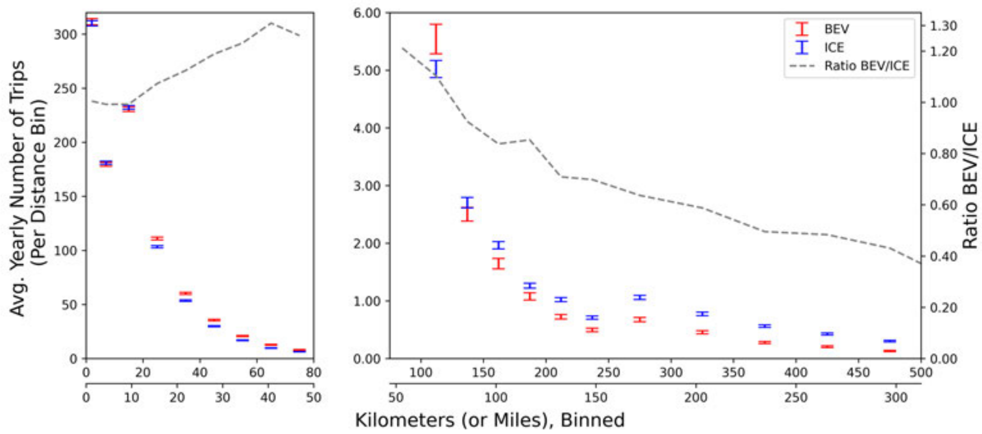


**Fig. 1** Average number of trips of a certain distance range (bin) that an ICE or BEV vehicle undertakes in a year, with 95% confidence interval. Bins are 5km wide from 0-10km, 10km wide from 10-80km, 20km wide from 80-100km, 25km wide from 100-250km, and 50km wide from 250-500km.

BEVs are used for up to 30% more trips than ICEs for shorter distances, but less frequently for longer ones. Here, "shorter" refers to trips of up to 150 km, which accounts for 99% of all trips and extends well beyond commuting and local use. Comparatively, BEVs make 25-45% fewer trips of 150-250 km length, and the divergence between BEVs and ICEs grows larger on trips beyond 250 km. Although ICEs undertake 51% more trips of at least 150 km per year than BEVs, the rarity of such trips means the absolute difference is modest: 3.1 trips annually (9.1 vs. 6.0). As shown in Fig. A1, this effect persists after controlling for location and vehicle-specific factors.

Interestingly, the $\approx 150$ km threshold–beyond which BEV usage is less frequent–is hundreds of kilometers shorter than the maximum range of the BEV models in our dataset, which varies from approximately 350 km to 660 km and averages 471 km (see Supplementary Fig. A2). Additionally, over the entire year, 72% of BEVs and 84% of ICEs in the dataset never drive farther in a day than the range of their battery or fuel tank allows. On average, BEVs (ICEs) exceed their full-charge (full tank) range on only 1.40 (0.47) days per year (see Supplementary Information B.1).

Consequently, the fact that BEVs are used less frequently than ICEs for long-distance trips (a phenomenon we call *road-trip gap*) does not seem to stem from technical limitations or insufficient battery capacity. Yet, if drivers can anticipate this road-trip gap, even a difference of $\approx 3$ annual long trips could saliently influence their decision to purchase a BEV. To overcome this adoption barrier, OEMs could offer complementary mobility services (e.g., range extenders or short-term access to longer-range vehicles), possibly even included in a BEV sales or leasing package. As discussed in the Supplementary Information Section B.1, on any given day throughout the year, no more than 1.0% (0.35%) of BEVs (ICEs) drive farther in a day than their vehicle's full-charge (full-tank) range allows. Sharing this fact—or enabling buyers to view their own trip history —could help ease their concerns about how often a BEV's limited range might adversely impact long-distance travel.

## 2 Long Trips and Infrastructure

To better understand the road-trip gap, we analyze how it varies with the availability and reliability of charging infrastructure at their destination. To control for some of the differences in mobility patterns and where BEV and ICE drivers live, we perform this analysis on a matched subsample of the data. Specifically, for each BEV, we identify a neighboring ICE whose approximated home location is less than $\approx 10$ km away (both locations share the same latitude/longitude when GPS coordinates are rounded to 1 decimal point) and shares key mobility characteristics—total miles driven, number of trips, average passenger count, and number of weeks observed in our data (see method section 6.1 for details).

Without matching, the road-trip gap in the full sample is 31% for trips between 150-250 km and 109% for trips exceeding 250 km, consistent with the previous analysis. With matching, the road-trip gap reduces to 24% and 90%, respectively, but remains substantial in magnitude, indicating that the gap is not solely driven by differences in who adopts BEVs and ICEs.

Using the matched pairs of BEV and ICE users and a large-scale dataset of charging station locations that also contains a measure of the station's reliability[42], we analyze how the presence and reliability of charging stations at the destination influence drivers' likelihood of taking long trips. Charging reliability, especially, has attracted increased attention in recent years[15,18,42].

In Fig.2, we divide the average vehicle's share of long-distance trips (>150 km) into nine (3x3) subcases. First, we categorize the density of charging stations by the number of stations within a 5 km radius of the trip's destination (0-2, 3-10, and 10+ stations). Second, we categorize the average reliability of these charging stations as low, moderate, or high based on whether those stations' average reliability score falls within the lower, middle, or upper third of all destinations. Reliability scores are based on user comments from the *Plugshare* platform, with higher scores reflecting fewer reliability concerns (see Section 6 for details). We then report the road-trip gap within each cell: the relative likelihood of ICEs making such trips versus BEVs (see Fig. A3 for the absolute trip counts). For example, in our matched sample, the average ICE makes 2.03 long-distance trips per year to destinations with 3-10 stations and high average reliability, compared to 1.48 such trips for BEVs —a 37% road-trip gap.

Fig. 2 shows that the road-trip gap is largest (55-58%) for trips to destinations with low charging density (0-2 stations), and declines by around 30% to 39-42% for trips to medium charging density destinations (3-10 stations). The road-trip gap does not decrease substantially more for trips to destinations with high density (over 10 stations). Moreover, across destinations with similar charging density, differences in average charging reliability do not appear to affect the road-trip gap. Even at high-reliability destinations with moderate or high charging density, a 39% road-trip gap remains.

For OEMs and policy makers interested in closing the road-trip gap, our findings indicate that ensuring moderate charging density (3 or more stations) at many destinations is a more effective approach than having fewer destinations with higher charging reliability. Destinations play a greater role in road-trips for BEVs, due to the increased time it takes to charge along the way. While our measure of average charging station reliability at long-distance destinations does not directly appear to affect

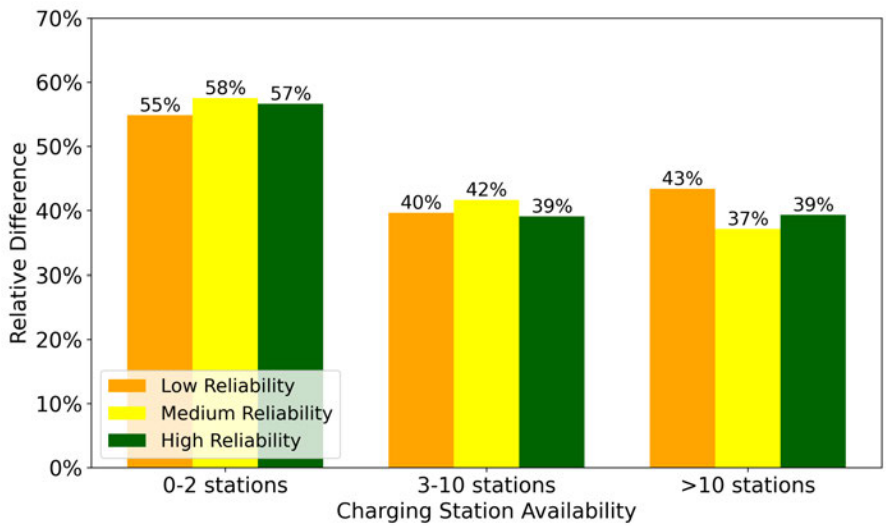


**Fig. 2** This figure shows how much more frequently ICEs are used than BEVs (annually) for long trips (≥150 km) to destinations featuring low-, medium-, or high-reliability charging infrastructure. For example, at destinations with 0-2 charging stations, ICEs are used 55% more than BEVs when charger reliability is low.

the road-trip gap, if drivers experience reliability issues on shorter trips, that could anchor their reliability expectations and help explain why the road-trip gap remains at 39%, even at destinations with high charging density and reliability.

# 3 Charging Behavior

Another facet impacting BEV users is how repowering—increasing the amount of stored energy in a vehicle—differs between BEV charging and ICE refueling. Due to their lower range, BEVs need to be repowered more frequently than ICEs to travel the same distance. Moreover, as shown in Fig. A5, even after controlling for a vehicle's remaining range at the end of a drive, BEV drivers are consistently more likely to repower their car than ICE drivers. This difference is most pronounced when the remaining range is between 75 and 250 km, where BEV drivers repower 42-78% more frequently than ICE drivers. Yet, contrary to much of the survey and experimental literature,[7,29,43,44] BEV users exhibit a higher charging propensity across the entire spectrum of remaining range.

To understand why BEV users have a higher propensity to repower than ICE users even when their vehicles have hundreds of kilometers of remaining range, we decompose repowering behavior by where it occurred. In Fig. 3, we compare ICEs (blue lines) to just those BEVs that have access to home-charging (red lines). Here, we find that BEV users who charged their vehicle more than 1 km from the driver's approximated home location (red line with filled square markers), which we categorize as *away from home*, exhibit very similar repowering behavior as ICE users who refueled away from home (blue line with unfilled square markers). For example, when vehicles are shut off with only 50-75 km of range remaining in locations away from home, ICE users refuel 50% of the time, which is very similar to the 42% of the time among users of BEVs with home-charging. In fact, BEVs are slightly *less* likely to be charged than ICEs with comparable remaining range when away from home (see Fig.3 where the blue line with unfilled squares is consistently above the red line with filled squares). This indicates that when away from home, BEVs are repowered in surprisingly similar ways to ICEs (see supplementary Fig. A6 for BEVs without home-charging who, irrespective of their distance to home, charge similarly to BEVs or ICEs far from home).

In contrast, the difference described earlier is nearly entirely attributable to repowering vehicles that are *close to home* —defined as within 1 km of their approximated home location—where only BEVs have the option of repowering at home. Again, consider vehicles shut off with only 50-75 km of range remaining but this time when they are close to home, ICE users refuel 21% of the time (blue line, unfilled dots), whereas users of BEVs with home-charging charge almost 69% of the time (red line, filled dots), about 3.5 times the rate of ICE users. Overall, when

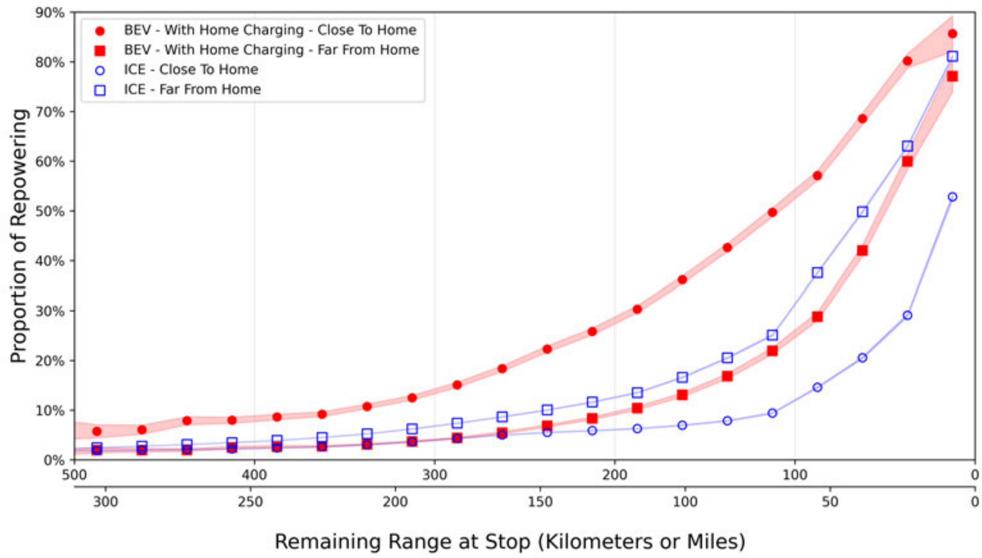


**Fig. 3** Charging proportion, as a function of remaining range and vehicle type, as well as home-charger and distance to home. A vehicle is considered close to home if it is within 1 km of its home location; otherwise, it's far from home. The shaded areas represent the 95% confidence interval. The remaining range is binned in 25 km intervals and each bin is plotted at its midpoint.

(close to) home with the same remaining range, BEVs are repowered up to four times more than ICEs.

In summary, the findings suggest that increased convenience or accessibility of home-charging, rather than range anxiety, might be driving the observed differences in repowering behavior between BEVs and ICEs (see Fig. A6 for additional detail), as BEVs are charged only as often (or even less frequently) than ICEs when away from home. OEMs can leverage this information to market BEVs bundled with home-charging options by highlighting the ease it provides. Electric utilities, OEMs, and EV charging providers can use our insights on where and how frequently BEVs are plugged in to better quantify the value of smart charging applications–such as vehicle-to-home and vehicle-to-grid–where connection frequency and location are critical. For regulators and researchers, recognizing that BEVs charge more frequently than ICE vehicles refuel–not because drivers are averse to remaining range falling below a certain threshold (the predominant framework in the literature) but because they face a different set of repowering options —can help update public opinion on how much of a concern range anxiety truly is for current-day BEV users.

## 4 Public Charging Usage

While BEVs can be charged at home, not all users have access to home-charging, and even those who do also use public charging infrastructure. Previous studies have found positive spillovers from public EV charging such as increased local retail revenue[45,46] and have examined how public charging stations are being integrated into daily life at workplaces, hotels, and other destinations.[43,47] Yet, the frequency and duration of BEV drivers' use of public charging are not well understood, despite being key factors for station developers considering how many chargers of each type and speed to install in different locations.

Using our granular data, we analyze the frequency and duration of public charging by BEV users, defined as charging at least 1 km from home, and examine how this reliance on and use of public infrastructure differ depending on the availability of home charging. Notably, charging times for BEVs are bimodal and have a pronounced long tail (see Appendix Fig.A7). Fig.4 compares the average number of public charging sessions per year for BEV drivers with and without home-charging.

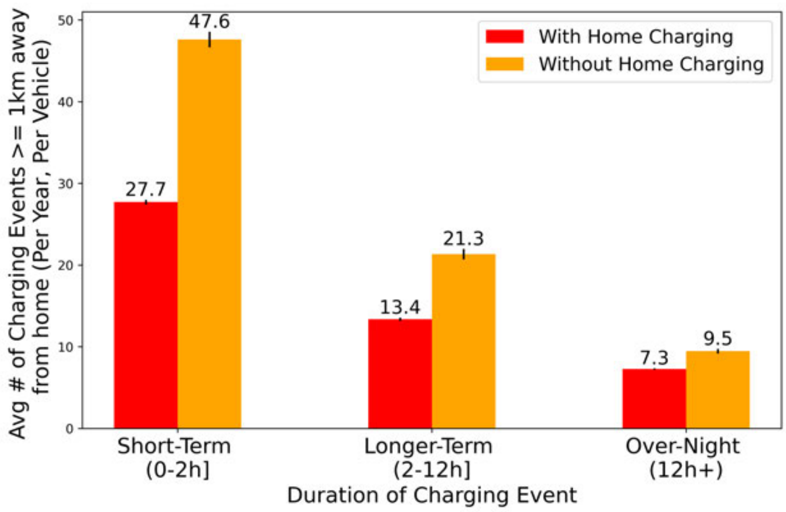


**Fig. 4** Number of times BEVs recharge in public, split by duration of charging event and having a home charger. Error bars indicate standard errors.

BEVs that lack access to home-charging presumably use public charging more than BEVs with home-charging. Our data enables us to reveal how much more, and how these two groups of BEVs use of public charging differently. To compare their charging durations, we categorize the length of charging sessions into short (up to 2 hours), long (2-12 hours), and overnight (over 12 hours, which in 98% of cases includes midnight). Considering short sessions, BEVs that lack home-charging use public stations 72% more often than those with home-charging (47.6 vs 27.7 times per year)—roughly two additional sessions per month (see Table A3 for descriptive statistics). Interestingly, this difference shrinks as session duration increases. For overnight charging sessions away from home (e.g., at hotels), the difference is only 30% (9.5 vs 7.3 times per year).

Because charging network operators and utilities earn revenue and design stations based on the energy consumed, we additionally report the amount of energy delivered (in kilowatt-hours (kWh)) per charging event. BEVs without home-charging draw 19% more energy during short-term sessions than BEVs with home-charging, but only 6% more during over-night sessions (see Table A3). This short-term charging difference appears attributable mainly to BEVs without home-charging using faster chargers, as initial battery state and charging duration are similar (within 2-3%) for both groups (see Table A3). These results show that limited access to home charging shifts BEVs toward shorter, more frequent fast-charging sessions, leading to 104% higher annual energy consumption from short-term public charging. This helps quantify the revenue opportunity of targeting such users.

## 5 Conclusion

In this study, we empirically examine how BEVs are used and repowered in real-world settings, how their use compares with ICEs, and how charging infrastructure affects these behaviors. By analyzing a large-scale telemetry dataset of hundreds of thousands of U.S. vehicles, we provide rare empirical insights that reveal everyday use of BEVs and ICEs, moving beyond surveys and small-scale experiments that have dominated prior BEV research.

Our analysis shows that BEVs are driven as frequently as ICEs and cover similar or slightly greater annual distances, and that BEVs are used for three fewer long-distance trips ($\geq$150 km) per year than ICEs (6.0 vs. 9.1 on average). We find that the latter road-trip gap is diminished on trips to destinations with at least moderate charging density, and that greater density is more important than increased charger reliability in reducing the gap. We further demonstrate that BEV recharging differs from ICE refueling primarily because of convenient access to home-charging. When away from home, BEVs are less likely to charge than ICEs are to refuel at comparable remaining range levels. Lastly, we show that BEVs without home-charging rely far more on short-duration public charging than BEVs with home-charging.

Our results can help ground BEV discussions in empirical evidence on real-world usage and charging patterns. They can provide OEMs with insights to design business models that address the differences in long-distance travel between BEVs and ICEs, and to market BEVs' capability to be used very similarly to ICEs for 99% of trips, along with the convenience of new repowering options (e.g., at home). For policymakers and charging providers, the results indicate that ensuring at least moderate charging density near trip destinations can boost BEV usage for longer trips.

We acknowledge certain key limitations in our study. First, our dataset is limited to a single year (2023) and a single, premium OEM (BMW) in the U.S., with BEVs having similar battery ranges. These factors might limit the generalizability of our results across geographies with other regulations and across manufacturers that produce and sell vehicles to different customer segments. Second, user behavior may change in the future as battery technology and charging capabilities evolve. Finally, while our telemetry data is highly granular, it does not capture the decision-making process of vehicle users—including why some adopted a BEV in the first place. Together, these limitations provide opportunities for future research.

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# 6 Methods

***High-Level Summary of Dataset***

We use a 2023 dataset from an OEM that contains driving information of 319,471 U.S. passenger vehicles—20,960 BEVs and 298,511 ICEs. The dataset includes vehicle model and type, and for every instance the vehicle's engine/motor started or stopped in 2023, the date and time, geo-location (GPS coordinates rounded to 2 decimal points), remaining range, and state-of-charge/fuel level. For each trip, we observe the vehicle's fuel consumption, distance traveled, number of passengers, average outside temperature, and driver identification number. All data are anonymized to prevent re-identification. Collectively, the data encompasses 252,439,903 drives (vehicle movements), about 5% of which are by battery electric vehicles (BEVs), allowing us to compare the usage and charging behavior of internal combustion engine vehicles (ICEs) and BEVs. The data includes 28 vehicle models that collectively traveled 3.4 billion miles over 72.5 million hours, across all U.S. states.

To qualify for inclusion in the dataset, vehicle owners must have agreed to share their telemetry data with the OEM, and completed at least 100 trips in 2023. The OEM deployed the telemetry technology required to appear in the data with vehicles produced in 2018 or later, and so our dataset includes only vehicles since model year 2018 (BEVs from 2021 and later). We treat all engine (or motor) versions of the same vehicle as the same model (e.g., the 5 series model includes both the 530i and 540i), except sport versions (branded as M-models - M for Motorsport) that are considered distinct models because they feature different interiors, sell at higher prices, and are developed separately.

**Table 2** High-level summary of the dimensions of the drives dataset.

| | |
|---|---|
| #BEVs | 20,960 |
| #ICEs | 298,511 |
| Total # Vehicles | 319,471 |
| # Different Models (Engine Versions) | 28 (84) |
| Total # Kilometers Driven | 3,397,123,944 km |
| Total # Miles Driven | 2,123,202,465 miles |
| Total # Drives | 252,439,903 |
| Total # Hours (Years) Driven | 72,503,587 (8,277) |

***Drives and Aggregating Trips to Drives***

A *drive* describes the technical definition of a vehicle session, based on automatically generated sensor data. A new drive ID is recorded as soon as the in-car display (head unit) is powered on and the vehicle starts moving. Once the vehicle is locked, the head unit shuts down, at which point the drive ends. This shutdown process may take a few minutes (≈3 minutes). When the vehicle is unlocked and moved again after shutdown, a new drive ID is assigned. However, if the car is restarted before the head unit fully powers down, the previous drive session continues.

Drives are aggregated to trips based on four different conditions: (1) standing time (i.e., time a vehicle is standing between two drives), (2) seat occupancy, (3) fuel level, (4) ratio of standing time and trip duration, as well as bearing vector (the direction of travel).

Successive drives will be summed up to trips if:

1. - The stand time in between drives is less than 15 minutes AND
   - The number of passengers remains the same

   OR
2. - The stand time in between drives is less than 15 minutes AND
   - The vehicle starts the new drive with more fuel than it ended the previous drive.

   OR
3. - The combined mileage of successive trips is > 75 km AND
   - The number of passengers remains the same AND
   - The change in bearing (the bearing of a drive is defined as the vector from its start location to its end location) between the successive drives is less than 15° and the ratio between standing time and the combined duration of the drives is less than 0.5 or the change in bearing between the successive drives is between 15° and 165° and the ratio between standing time and the combined duration of the drives is less than 0.25.

Successive drives that do not meet any of these three sets of criteria are considered separate trips.

#### *Characterizing Repowering*

We define a car as having been repowered (recharged or refueled) between successive drives if the state of charge or fuel level (the ratio of liters in the fuel tank to the fuel tank's capacity) is more than 2% higher at the start of the successor drive than it was at the end of the prior one. The 2% threshold prevents misclassifying a small fluctuation in the charge or fuel level as a repowering event caused by other factors, such as temperature changes.

#### *Characterizing Proximity to Home*

Due to data privacy concerns, we do not directly observe a vehicle user's home location. We observe a distance calculation indicating how far a vehicle is from its (approximated) home location at the beginning and end of a drive. The OEM, which has access to more granular GPS information and additional data points, calculates this estimated home location for each vehicle. They shared distance to that location but in a coarsened way: the OEM rounded it to the nearest 2 km increment, coding this distance as 0 km when the car is within 1 km of its home location or 2 (4,6,...) km when the vehicle is farther away. Throughout the paper, we categorize vehicles as *close to home* ($\leq$ 1 km distance) versus *far from home* (>1 km distance). When a vehicle is within 1 km of its estimated home location (i.e., distance to home = 0), we refer to this as its *(approximated) home location*.

#### *Characterizing Home-Charging*

We characterize a vehicle as having home-charging if, for all charge events that it performs within 1 km of the approximated home location, the standard deviation of the rounded GPS coordinates is less than 0.003 in both latitude and longitude, which equates to 300 meters latitude and 240 meters longitude (approximately, as translating degrees and meters differs for latitude). Low latitude/longitude variability indicates a consistent charging location close to home. Our approach and the 0.003 cutoff were validated in collaboration with the OEM. Based on this analysis, approximately 88% of BEVs in our sample have home-charging, very close to the 86% reported 2024 US-wide survey average.[1]

#### *Charging Station Data and Reliability*

We use data from Plugshare (see https://company.plugshare.com/data.html for Plugshare's data tool), an online community where BEV users can exchange information about charging locations, electric mobility, and their charging experiences. BEV users can access and leverage this data via the Plugshare App or website to plan trips or find charging locations. Plugshare's crowdsourcing model for charging information means that stations are updated regularly. The 53,932 stations in Plugshare's data that opened by December 31, 2023 provide a more encompassing view of charging locations than the U.S. Department of Energy's (DoE) Alternative Fuels Data Center (AFDC)[2] database that contains 45,546 stations in the U.S.. For each charging station from Plugshare, we observe its location, opening date, charger type, and number of chargers at the station.

When calculating the number of chargers in an area (e.g., within 5 km of a destination or GPS coordinate), we add all charger types (Level 1, 2, and 3) to calculate the total number of chargers, and include only stations opened on or before December 31, 2023. As robustness checks, we also conducted our analysis on the impact of density and reliability of charging stations around a destination (see Fig. 2) only using stations that are in the AFDC data, we also ran the analysis on just the Level 3 "fast-charger" stations. For both robustness checks, all results continue to hold.

We augment this station data with reliability information derived from analyzing user reviews on Plugshare for each station.[3] The reliability scores are calculated as the proportion of all reviews of a station in a given year (which include concerns about reliability) that lack such concerns, and thus range from 0-1 for each charging station. For each destination, we average the reliability scores of all charging stations within 5 km around the destination. We refer the reader to 3 for more details of how the reliability metric is calculated.

We classify destination reliability as low, medium, or high, based on whether the score is in the lower, medium, or upper third of all long-trip destinations (1,903,116 long trips in our data exceed 150 km). Average reliability scores between 0.00-0.61 fall into the lower third, 0.61-0.77 into the middle third, and 0.77-1.00 into the upper third.

We use a similar approach to classify charging station density. Of the observed destinations, the lowest third has 0-2 charging stations, the middle third has 3-10 charging stations, and the highest third has more than 10 charging stations. If a destination has no charging stations in its vicinity (within a 5 km radius), which is true for about 17% (319,503 of 1,903,116) long trip destinations, we set the reliability value at that destination to be equal to the closest destination with a reliability value.

### 6.1 Matching Procedure

In our dataset, we match BEVs to ICEs using k-2-k coarsened exact matching (CEM).[4] For each BEV, we try to find one corresponding ICE vehicle that matches on the (coarsened) variables. One matching criterion is the latitude and longitude of a vehicle's approximated home location (see *Characterizing Proximity to Home* above). To strike a balance between matching a large share of BEV vehicles and ensuring that each matched pair is sufficiently similar in their approximated home location, we round the latitude and longitude coordinates to 1 decimal and exactly match BEV-ICE pairs on these rounded values. This means that each matched BEV-ICE pair have home locations that are within the same $\approx$ 11 km x 8.5 km grid on a map, and thus can reach the same long-distance destination in similar distance/time. (A 0.1 degree latitude difference between two locations with the same longitude corresponds o 11.1 km of distance, and a 0.1 degree longitude difference (given the spherical nature of the globe) corresponds to 11.1 km at the equator and about 8.5 km in the United States. The average distance between approximated home locations across our matched pairs is 4.6 km (2.9 miles).

Beyond approximated home location, we also coarsen and match on a) total miles driven, b) average passenger count, c) number of trips made, and d) the number of weeks each vehicle is observed in the dataset. The cutpoints for total miles driven were 0, 1000, 5000, 10000, and 20000, 99999. The cutpoints for average passenger count were 1.00, 1.25, 1.50, 2.00, 2.50, and 5.00. The cutpoints for number of trips made were 0, 250, 500, 750, 1500 and 9999. The cutpoints for the number of weeks observed were 0, 8, 24, and 53. In order to avoid potential differences in long trip frequency (trips $\geq$ 150 km) impact our matching, we match vehicles based on their behavior on only those trips shorter than $150km$ (which includes over 99% of all trips). This CEM approach enabled us to develop 15,792 matched BEV-ICE pairs, successfully matching 74% of BEV vehicles (15,792 out of 21,438) in a manner we believe offers a reasonable trade-off between match quality and sample coverage.

The resulting matched subpopulations (on the trips shorter than 150 km) are very similar on their matched dimensions as shown below (with standard errors in parentheses):
The average number of trips for matched BEVs is 491.3 trips (2.45) , compared to 498.6 trips (2.54) for matched ICEs.
The t-test statistics are t = 2.0702 and p = 0.03844.
The average distance driven for matched BEVs is 7430.0 km (49.98), compared the matched ICEs average of 7282.6 km (47.93) for matched ICEs.
The t-test statistics are t = -2.3875 and p = 0.0170.
The average BEV passenger count for matched BEVs is 1.48 (0.00), compared to 1.47 (0.00) for matched ICEs.
The t-test statistics are t = -1.0591 and p = 0.2896.
The average length of time vehicles were observed in the data for matched BEVs is 26.8 weeks (0.10), compared to 28.2 (0.11) for matched ICEs.
The t-test statistics are t = -10.1062 and p = 0.0000.

### 6.2 Mobility Behavior - Regression Analysis

As discussed in Section 1, and shown in Fig. A1,we analyzed how frequently BEVs and ICEs are driven different distances, controlling for the vehicle's home state and the degree of urbanization at its approximated home location (using an Urbanity Index (UI), see[5]), and clustering standard errors at the vehicle level. We estimate the linear, random-effect (by vehicle ID) panel regression shown in Equation 1, where the unit of analysis is vehicle $i$ - distance bin length $m$ (e.g., 0-10 km). Count$_{im}$ is vehicle $i$'s annualized number of trips (or drives) (where we scaled the observed value to 52 weeks when we observe the vehicle for fewer weeks) of binned length $m$. distance_bin$_{im}$ is a set of binary variables for the different bins $m$, $BEV_i$ is a binary variable that is equal to 1 if the vehicle $i$ is electric, and 0 otherwise. $X_i$ contains a vector of vehicle-specific controls, including the home state and the UI. We include random-effect $\mu_i$ and cluster standard $\varepsilon_{im}$ by vehicle $i$. In Fig.A1, we show the margins for $\gamma_i$, i.e., the marginal effects of a BEV on the number of trips of that length, made per week.

$$\text{Count}_{im} = \alpha + \sum_m \beta_m \text{ distance\_bin}_{im} + \sum_m \gamma_m \text{distance\_bin}_{im} \times \text{BEV}_i + X_i + \mu_i + \varepsilon_{im}. \tag{1}$$

## Method References


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# Appendix A Extended Data

**Table A1** Descriptive statistics of BEV and ICE usage

| BEVs n=20,960 | Total Miles Driven | Avg. Miles Per Trip | Avg. # Passengers | Total # Trips | Total # Drives | Weeks In Data |
|---|---|---|---|---|---|---|
| Min. | 436.0 | 2.8 | 1.0 | 100.0 | 107.0 | 2.0 |
| Median | 6,750.0 | 16.2 | 1.4 | 419.0 | 526.0 | 25.0 |
| Average | 8,521.8 | 18.0 | 1.5 | 487.4 | 617.3 | 26.2 |
| Max. | 70,858.0 | 104.3 | 5.0 | 2,835.0 | 5,248.0 | 52.0 |
| Std.Dev. | 6,591.5 | 8.8 | 0.4 | 305.4 | 394.9 | 12.9 |
| **ICEs n=298,511** | **Total Miles Driven** | **Avg. Miles Per Trip** | **Avg. # Passengers** | **Total # Trips** | **Total # Drives** | **Weeks In Data** |
| Min. | 0.0 | 0.0 | 1.0 | 100.0 | 103.0 | 2.0 |
| Median | 8,784.0 | 16.6 | 1.4 | 524.0 | 679.0 | 34.0 |
| Average | 10,386.3 | 18.5 | 1.5 | 595.9 | 775.6 | 31.9 |
| Max. | 115,270.0 | 185.5 | 5.0 | 3,149.0 | 6,400.0 | 52.0 |
| Std.Dev. | 7,329.8 | 9.2 | 0.4 | 371.6 | 492.6 | 13.7 |

Statistics of the full dataset's variables that were used in the vehicle matching procedure (see Section 6.1 for details and post-match statistics). Across these dimensions, in aggregate, BEVs, and ICEs are used in very similar ways, with differences being either statistically insignificant or statistically significant but small in magnitude.

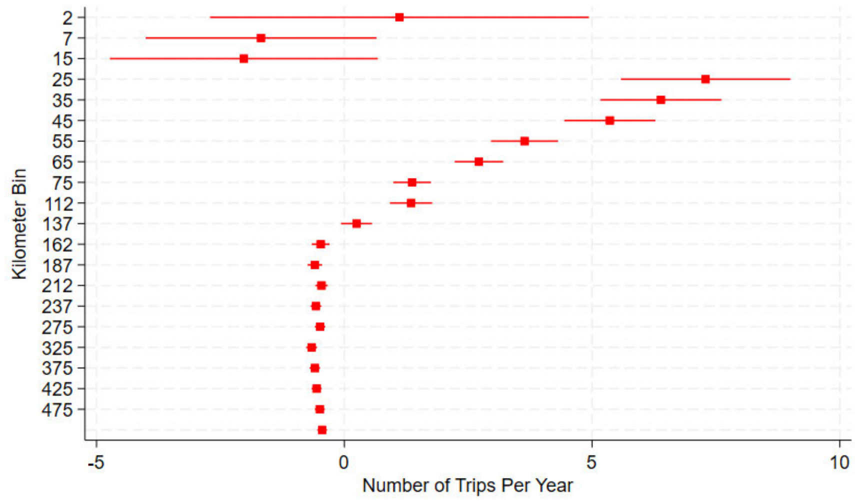


**Fig. A1** Marginal effect of a vehicle being a BEV on the number of trips it undertakes per year (per bin). Positive marginal effects of a BEV going on more trips than an ICE, negative values indicate fewer trips. Panel regression as specified in Section 6.2. Error bars show 95% confidence interval. Directionally, we find the same effects as in the main result in Fig. 1 after controlling for vehicle-specific fixed effects and clustering standard errors. Electric vehicles are driven slightly more on shorter trips (up to 125 km) and less on long-distance trips (longer than 150 km).

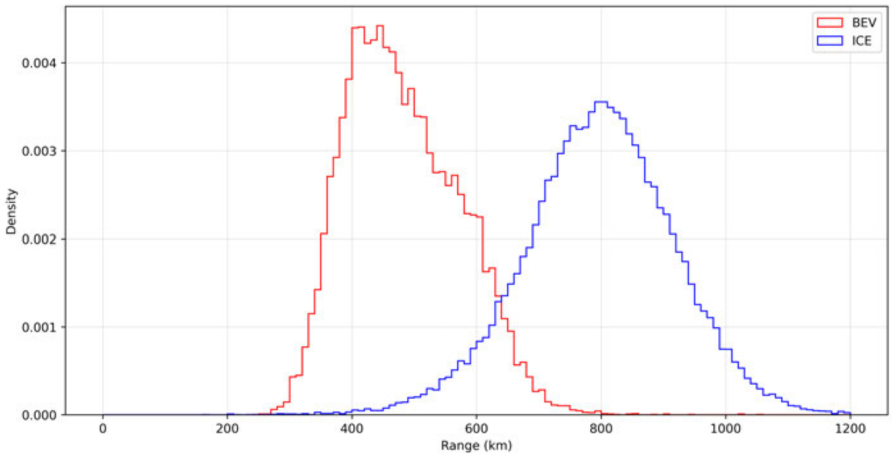


**Fig. A2** Histogram of the distribution of vehicles' maximum observed range of BEVs (red) and ICEs (blue). A vehicle's maximum observed range is the highest (predicted) remaining range at the start of the trip that was recorded across all observations in the data. The average (median) BEV in our sample has a maximum observed range of 471 km (482 km) or approximately 300 miles, about 60% of the average (median) ICE with 798 km (799 km) or approximately 500 miles.

**Table A2** Proportion of vehicles' trips of length 150-250 km, or beyond 250km

| **Pr. Trip Length 150-250km** | | All Destinations | # Charge Stations at Destination 0 − 2 | 3 − 10 | 10+ |
|---|---|---|---|---|---|
| Full Sample | ICE | 0.59% | 0.21% | 0.19% | 0.19% |
| | BEV | 0.45% | 0.12% | 0.14% | 0.19% |
| | *Ratio* | *1.31x* | *1.70x* | *1.41x* | *1.00x* |
| Matched Sample | ICE | 0.49% | 0.12% | 0.15% | 0.22% |
| | BEV | 0.40% | 0.09% | 0.12% | 0.18% |
| | *Ratio* | *1.24x* | *1.31x* | *1.23x* | *1.22x* |

| **Pr. Trip Length ≥250km** | | All Destinations | # Charge Stations at Destination 0 − 2 | 3 − 10 | 10+ |
|---|---|---|---|---|---|
| Full Sample | ICE | 0.49% | 0.17% | 0.16% | 0.16% |
| | BEV | 0.24% | 0.06% | 0.08% | 0.10% |
| | *Ratio* | *2.09x* | *2.77x* | *2.04x* | *1.69x* |
| Matched Sample | ICE | 0.40% | 0.11% | 0.12% | 0.17% |
| | BEV | 0.21% | 0.05% | 0.07% | 0.09% |
| | *Ratio* | *1.90x* | *2.17x* | *1.78x* | *1.85x* |

We show the difference in the proportion of going on trips between 150-250 km distance and exceeding 250 km, split by BEVs and ICEs. We show the values, both for the full dataset and the matched sample. The third column in the table shows the results for all destinations, and the column to the right shows the results split by the number of charging stations within 5 kilometers of the trip destination.

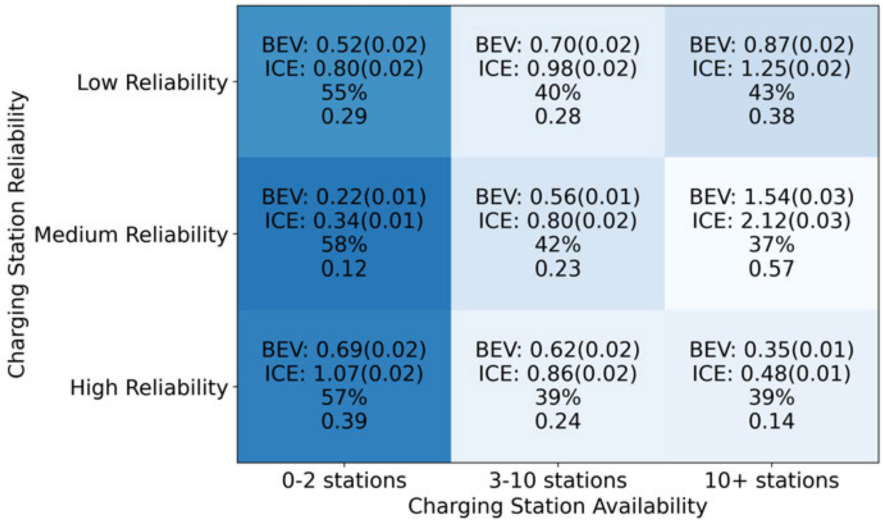


**Fig. A3** Statistics for long trips (≥150 km) by BEV and ICE vehicles in the matched sample to destinations with charging infrastructure that varies by charging density (number of chargers within 5 km of the destination) (x-axis) and the average reliability of those chargers (y-axis). Each cell reports average values across all destinations that share its charging infrastructure parameters: The average number of trips per year that a BEV or ICE undertake to such destinations with # in parentheses; the relative difference in these averages ([ICE-BEV]/BEV), and the difference in the number of trips between the two averages. For example, the top-right cell focuses on trips to destinations with more than 10 chargers, whose average reliability is low. In our matched sample, the average BEV makes 0.87 trips to such destinations per year, and the average ICE makes 1.25 such trips, which is 43% more ([1.25-0.87]/0.87=143%), with the difference being 0.38 trips per year. The BEV and ICE numbers here are used to create Fig. 2.

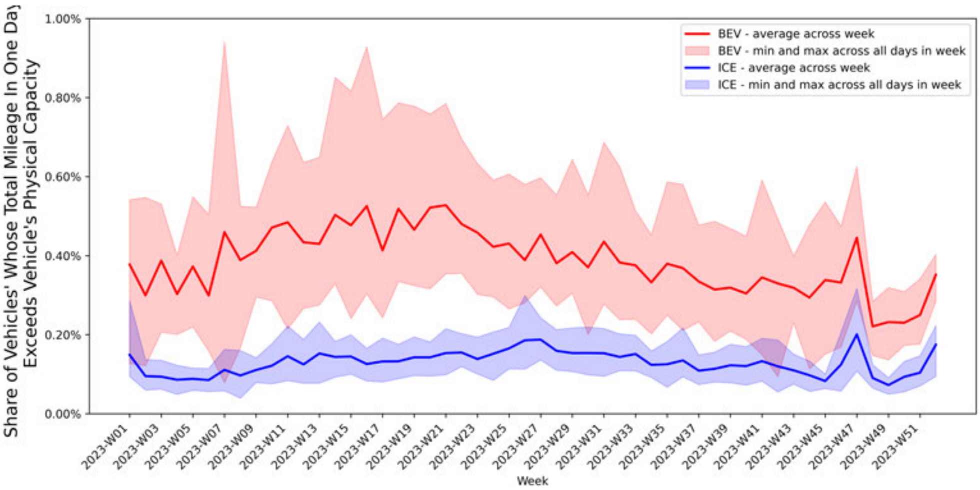


**Fig. A4** Plot of the fraction of vehicles in the full dataset whose distance traveled exceeds the vehicle's capacity. A vehicle's capacity is defined as the vehicle's median range, conditional on the charge/fuel level being at or above 99%. We plot weekly ICE and BEV averages as lines, and the shaded areas represent each week's lowest and highest values. The fluctuations across days (i.e., the shaded areas) are largely due to cars being more likely to exceed their range capacity (i.e., to be driven for very long distances) on weekends. For ICEs, the week with the highest share of vehicles traveling further than their fuel tank capacity was Thanksgiving week in the United States, with the highest day (peak of blue shaded area) being November 26, 2023, which was Thanksgiving Sunday. On that day, 0.32% of ICEs drove farther than they could on a single tank, 2.5 times more than the average across the year of 0.13%. The share of BEVs that exceed their range on any given day fluctuates between 0.2% and 1.0% throughout the year, with an average of 0.38%. Thus, on average, BEVs exceed their range three times more frequently than ICEs (0.38% / 0.13% = 2.92), but BEVs and ICEs do so rarely. In our dataset, 72% of BEVs and 84% of ICEs never travel more in a day than their vehicles' capacity allows.

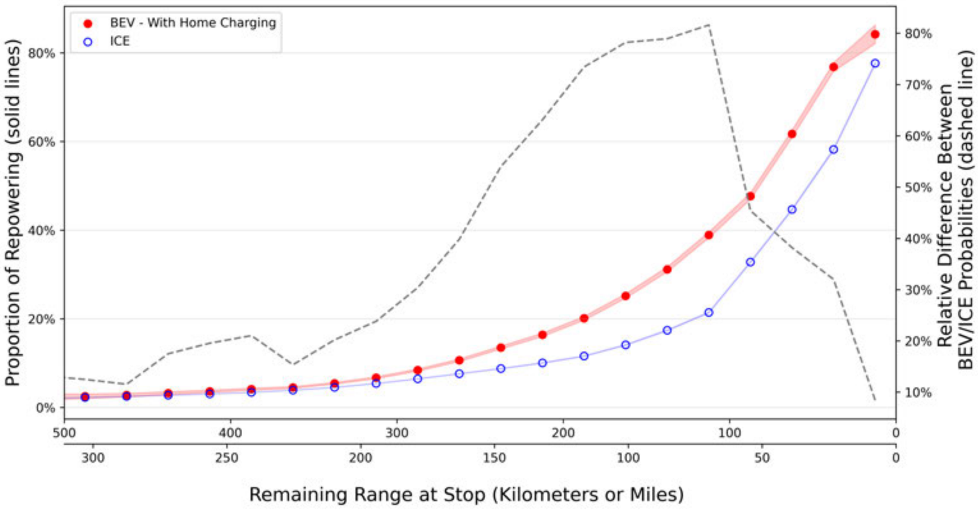


**Fig. A5** Charging proportion, as a function of vehicle type and remaining range. The shaded areas represent the 95% confidence interval. Remaining range values are binned in 25 km intervals and each bin is plotted at its midpoint. For example, when vehicles stop with 100-125 km range remaining, an ICE vehicle (blue, unfilled dot) is refueled 22% of the time, whereas a BEV (red, filled dot) is recharged 39% of the time, or 1.8 times more often.

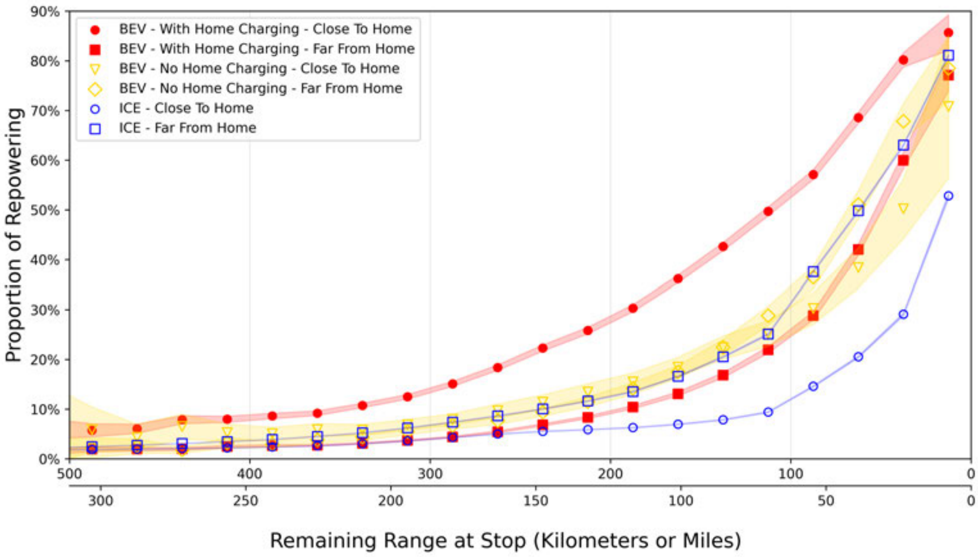


**Fig. A6** Charging proportion, as a function of remaining range and vehicle type, including BEVs without home-charging (compare Fig. 3 that only showed ICE and BEV with access to home-charging). The shaded areas represent the 95% confidence interval. The remaining range is binned in 25 km intervals and each bin is plotted at its midpoint. Close to home is defined as locations that are less than 1 km from the approximated home location, while far from home is for locations further than 1 km from the approximated home location.

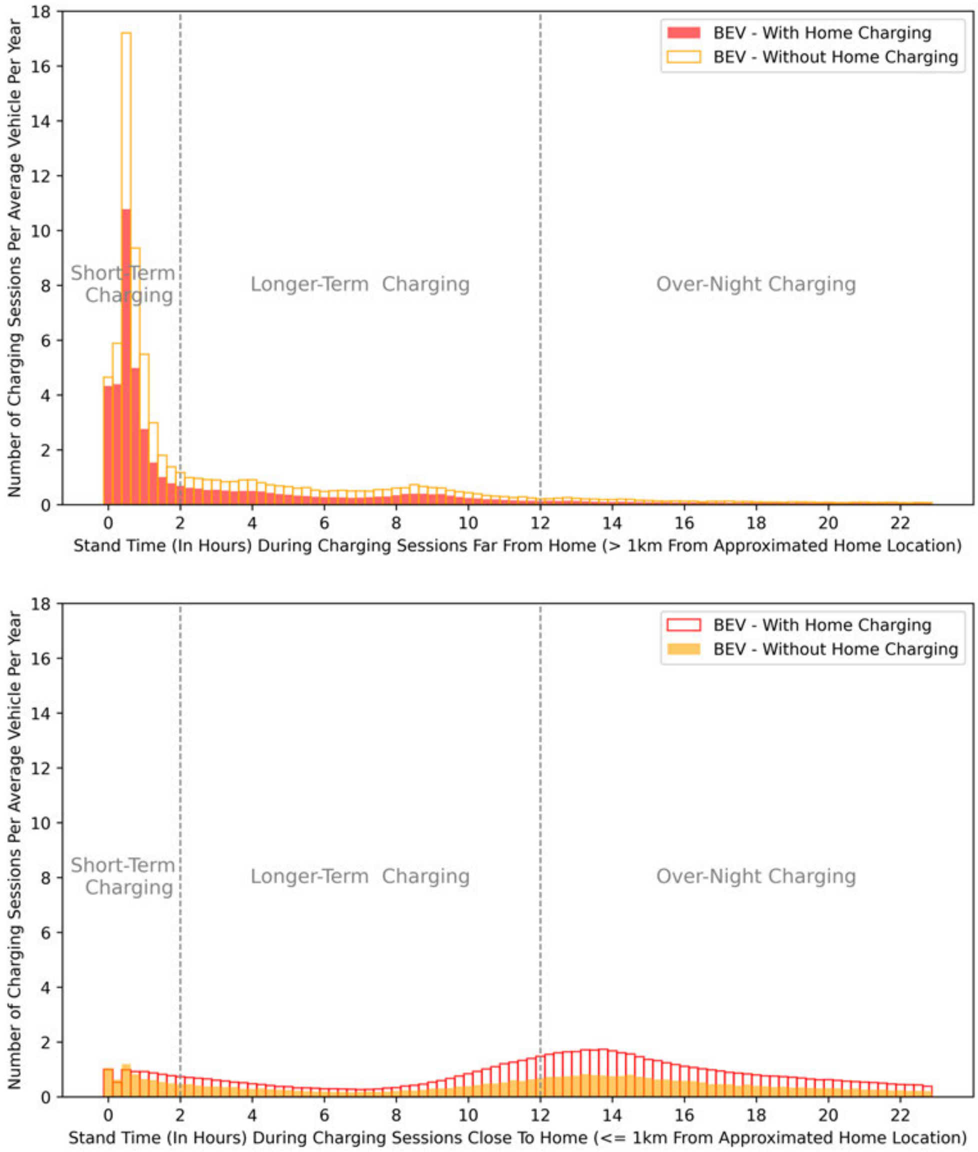


**Fig. A7** Distribution of how long vehicles are parked when repowering. We report the so-called *stand time*—the time a vehicle spends standing between drives—during which the state of charge of the battery or fuel tank increases. The stand time is expressed in units of hours. Because our analysis in the main paper focuses on how public charging infrastructure is used, we only include charging events that occurred at least 1 km away from a vehicle's approximated home location in the top panel of the figure. For additional context, the bottom panel of the figure shows the same analysis, but for charging events close to home (i.e., less than 1 km from the approximated home location.). As becomes evident from the comparison of the top and bottom panels, the usage of chargers far and away from home differs substantially, with charging close to home being used more by BEVs with home chargers and skewed towards more over-night charging than the charging use away from home for both groups of BEVs. Please refer to Section 4 and Table A3 for our detailed discussion on the differences in public charging (e.g., charging away from home).

**Table A3** BEVs' charging event statistics for all recharging events away from home (>1 km from approximated home location), split by duration of charge event, and a vehicle having access to home-charging or not. Standard errors in parentheses. Relative differences are calculated as the ratio of the absolute difference divided by the home-charging value. Stand time durations are winsorized at the 95th percentile. The "empty capacity at start of charge" is calculated as (1-SOC/100) multiplied times the battery capacity of a vehicle. It thus represents the amount of energy that could be charged if the vehicle remained plugged in until the battery reached 100% charge.

| | Home-Charging | Short-Term ($\leq$ 2 hrs) | Longer-Term (2 – 12 hrs) | Over-Night ($\geq$ 12 hrs) |
|---|---|---|---|---|
| Count of Charging Events | Yes | 27.72 (0.28) | 13.37 (0.20) | 7.28 (0.09) |
| | No | 47.62 (0.96) | 21.35 (0.64) | 9.47 (0.28) |
| | Abs. Diff | 19.90 | 7.98 | 2.19 |
| | Rel. Diff | 72% | 60% | 30% |
| Average Charge per Event (in kWh) | Yes | 22.58 (0.10) | 17.32 (0.10) | 25.01 (0.11) |
| | No | 26.79 (0.26) | 20.80 (0.25) | 26.50 (0.27) |
| | Abs. Diff | 4.21 | 3.48 | 1.49 |
| | Rel. Diff | 19% | 20% | 6% |
| Average Duration per Event (in minutes) | Yes | 45.55 (0.14) | 325.17 (1.00) | 2,434.17 (7.74) |
| | No | 47.03 (0.35) | 325.94 (2.46) | 2,269.21 (19.21) |
| | Abs. Diff | 1.48 | 0.76 | -164.95 |
| | Rel. Diff | 3% | 0% | -7% |
| Average Empty Capacity in Battery At Start of Charge (in kWh) | Yes | 44.85 (0.13) | 38.78 (0.14) | 41.00 (0.13) |
| | No | 45.93 (0.31) | 40.31 (0.34) | 41.76 (0.33) |
| | Abs. Diff | 1.08 | 1.53 | 0.76 |
| | Rel. Diff | 2% | 4% | 2% |

# Appendix B Supplementary Information (SI)

## B.1 SI - Exceeding Physical Capacity of Vehicle

Related to Section 1, where we analyzed how often BEVs and ICEs undertake long trips, Figure A4 shows how often a vehicle's total daily mileage exceeds its capacity. We calculate a vehicle's capacity as the median range observed for that vehicle in the dataset when its tank or battery is 99% or 100% full. Using the median value of a fully charged/fueled vehicle accommodates some variation in the vehicle's effective range, which can vary based on temperature, road conditions, elevation profile, and more. We henceforth refer to a day when a vehicle's total mileage exceeds its range as *capacity-limited*.

We study how often BEVs and ICEs undertake long trips for two reasons. First, this dynamic proxies how frequently physical vehicle characteristics limit mobility, which could influence usage and adoption decisions. Second, by better understanding the timing and frequency of such events, OEMs can make better decisions about if/what new business models could be offered (e.g., providing rentals) to address these limitations.

We find that throughout the 2023 observational period, 72% of BEVs and 84% of ICEs never traveled farther in a day than their battery or fuel tank range allows. Conversely, 28% of BEV users experienced at least one *capacity-limited* day in the year, compared to 16% of ICE users. This is largely due to the difference in the range of vehicle technologies (see Fig. A2). The average BEV user experienced 1.40 such days in the year, compared with 0.47 for ICEs. The distributions are long-tailed, and there is more variation among BEV users (standard deviation of 2.5 days for BEVs vs. 1.1 days for ICEs).

Shifting from the vehicle/user perspective to the fleet perspective, we study the fraction of all vehicles that exceed the range of a single charge/tank on any given day.

As we show in Fig. A4, 0.2-1.0% of BEVs (between 1 in 100 to 1 in 500) are capacity-limited on any given day, compared to only 0.05-0.32% of ICEs (1 in 300 to 1 in 2,000). On an average day, 0.13% of ICEs exceed their range, compared to 0.38% of BEVs. Both ICEs and BEVs are capacity-limited more often on weekends, as longer trips occur predominantly during that time. The day with the highest share of ICEs exceeding their range capacity (0.32%) was November 26, 2023—Thanksgiving Sunday in the United States (where our observations are from), a day when many Americans return home from visiting relatives or friends. For BEVs, we observe a spike on that day as well, although the share of vehicles exceeding capacity varies more throughout the year. This is largely due to the fact that the BEV fleet is more than an order of magnitude smaller and the continual addition of new vehicles into our dataset, which gradually changes the fleet's composition over time.