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Article

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Replacement of internal combustion engine vehicles by electric vehicles in Chinese ridesharing markets

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Increasing concerns about greenhouse gas emissions and local air pollution have motivated the search for sustainable transportation alternatives. Electric vehicles (EVs) offer a promising solution, yet their potential to replace internal combustion engine vehicles (ICEVs) in high-utilization ridesharing fleets remains insufficiently understood. This study analyzes data from a major ridesharing platform in Beijing, comparing EVs and ICEVs across car-sharing and private car-hailing modes. We find that at the driver level, EVs and ICEVs demonstrate comparable order completion in car-sharing, while EVs exhibit significantly lower daily mileage. Order-level regression analysis reveals that EVs, in private ride-sharing, exhibit a higher propensity to complete long-distance orders. We also find that mainstream 2015 EVs could cover the majority of daily ICEV travel patterns, with higher substitutability in car-sharing. These findings provide a benchmark for evaluating progress in the ongoing electrification of shared mobility.

Greenhouse gas (GHG) emissions, being considered as the main driver of anthropogenic climate change, are the most concerning global environmental issue[1,2]. Local air pollutants, such as SO_2 and NO_X, have also escalated, aggravating morbidity and mortality in cardiovascular and cardiopulmonary illnesses[3]. Therefore, leading economies, including China, are increasingly concerned about controlling greenhouse gas emissions[4]. Decarbonization in transport has long been recognized as a crucial step. Aiming for a sustainable transportation system, new renewable energy fuels and electric vehicles (EVs) emerge as a prospective trend[5].

With the rapid global expansion of the sharing economy, ridesharing companies have emerged as a key component of transportation systems through a business model that connects peers via third-party platforms to share vehicles[6–8]. Car owners share their spare car resources on a third-party platform to provide passenger services and collect money in return, with a lower threshold to allow amateur drivers to provide travel services[9]. The global ridesharing market value is projected to reach US$216bn in 2028[10]. Given the significant contribution of ridesharing vehicles to total vehicle kilometers traveled (VKT), developing an environmentally friendly ridesharing market is profound and necessary. Among the numerous energy-saving and low-carbon vehicle technologies, EVs have sparked great interest in ridesharing as an alternative to internal combustion engine vehicles (ICEVs) because of their emission reduction utility[11–13].

Despite the expected environmental benefits[14–17], EV adoption in ridesharing faces many barriers, including technology constraints, personal preference, and charging infrastructure[1,18–20]. In developing EV markets, EVs may be more expensive than ICEVs[21]. Although vehicle price and battery costs are decreasing each year, an EV's initial price often remains a dominant deterrent to large-scale EV adoption[22]. Moreover, EVs' lifetime costs, such as perceived depreciation, excessive charging cost, and maintenance, can be perceived as a major cost component of EVs[23–25]. Ridesharing drivers are likely more sensitive to these factors as ridesharing vehicles typically travel 100,000 kilometers annually, significantly exceeding private vehicle usage[26]. Technologically, limited battery range and insufficient maximum driving range cause range anxiety and significantly contribute to driver resistance to EV adoption[24,27]. The management and distribution of charging stations also pose challenges to widespread EV adoption[28,29], while time spent and recharging uncertainty can discourage ridesharing drivers from choosing EVs for commercial use[21,30,31]. Furthermore, drivers may be concerned about passengers' preference for ICEVs[32].

These barriers obscure EVs' true substitution potential in ridesharing, particularly in countries with developing EV markets[33,34]. However, empirical evidence regarding EVs' substitution potential in ridesharing remains scarce. While studies show EVs are typically driven less than ICEVs in private contexts[14,35–37], evidence from commercial fleets is mixed and limited. Although the study suggests shared electric vehicles typically

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accumulate lower daily and annual mileage[38], research on Hamburg's taxi fleet indicates that 89% of taxis could transition to full electrification[39]. A recent study has also shown that with current EV battery technology and range, EVs can handle most regular daily travel[40]. Combined with the limited accessibility of ridesharing travel data in previous studies, this creates significant uncertainty about EVs' actual operational performance and their feasibility as ICEV replacements.

Against these backgrounds, and given China's position as the global leader in EV adoption[41], this study uses unique 2015 data from Beijing to address two concrete research questions: Do EVs exhibit comparable performance to ICEVs in ridesharing applications? Do EVs serve different orders compared with ICEVs? We focus on two main modes in the ridesharing market: car-sharing and private car-hailing. In *car-sharing*, the drivers who provide the service release travel information first, and passengers who share similar destinations decide whether to use the service and which to use. In contrast, vehicles in the *private car-hailing* are predominantly used to carry passengers for profit. Drivers engage in private car-hailing to earn a living or supplement their income with regular work schedules and sensitivity to monetary factors, while car-sharing drivers expect partial coverage of travel expenses with unpredictable and infrequent schedules.

Through a dual-level analysis of driver behavior and order characteristics, this study provides an early and granular assessment of EV substitutability by comparing usage patterns and estimating trip coverage potential, including deadheading mileage. Our findings are as follows. At the driver level, we observe no significant difference between EVs and ICEVs in the car-sharing fleet in terms of order volume and travel distance. In contrast, within the private car-hailing fleet, EV drivers exhibit significantly lower daily order mileage and total mileage compared to ICEV drivers, yet they maintain significantly longer platform online hours. These marked daily disparities, however, diminish when viewed over weekly and monthly aggregates. At the order level, the vehicle type (EV vs. ICEV) shows no significant association with trip distance in car-sharing. For private car-hailing, however, full-time EV drivers are associated with significantly longer order distances.

We then assess the feasibility of EVs substituting for ICEVs. We calculate the cumulative distribution function (CDF) of daily travel distances. The results show that in the car-sharing fleet, EVs could cover 96.5% of ICEV trips under the most conservative range assumption. However, when the estimated deadheading distance is included, this coverage rate drops to 90.6%. The impact of deadheading is more pronounced in the private car-hailing fleet: under the most conservative range scenario, EVs could cover only 61.8% of ICEV trips based on order distance alone, and this coverage falls to 39.4% after accounting for deadheading. These findings indicate that effective operation of EVs in private car-hailing would likely require mid-shift charging, which also explains why EV drivers exhibit longer daily online hours yet shorter total travel distances.

Furthermore, EVs demonstrate a significantly higher likelihood of completing orders exceeding 100 km compared to ICEVs. While the data is from 2015, a period of early EV market development, it establishes a crucial benchmark. The findings provide foundational insights into the challenges and opportunities of integrating EVs into high-utilization fleets, offering enduring value for understanding the longitudinal dynamics of this transition.

Results

Driver-level comparison

We begin by comparing the usage patterns of EVs and ICEVs at the driver level within the car-sharing fleet. The analysis incorporates data from 86 EV drivers and 6573 ICEV drivers, aggregating their daily order records over the observation period from December 2015 to January 2016. We examine several key performance metrics: order mileage, total mileage, number of orders, and total order revenue. Specifically, order mileage, number of orders, and total order revenue are calculated by aggregating all orders completed by a driver within each weekly or monthly interval. Total mileage refers to the sum of the order mileage plus the estimated deadhead distance traveled between consecutive orders on a given day, representing the driver's total travel distance from the first to the last trip.

Given the relatively sparse daily driving records in the car-sharing fleet, we conducted our comparative analysis at both weekly and monthly levels. Descriptive statistics and the results of Welch's t-tests are presented in Table 1. Figure 1 displays boxplots illustrating the working patterns of EV and ICEV drivers, while Fig. 2 shows the 95% confidence intervals for the mean differences between the two groups. As illustrated in Fig. 1, the total distance and order distance traveled by EV drivers are consistently lower than those of ICEV drivers at both weekly and monthly intervals. The distribution for EVs also shows a greater number of outliers, a pattern likely attributable to the smaller sample size of EV drivers. However, as indicated by the confidence intervals in Fig. 2, these observed differences are not statistically significant.

For the private car-hailing fleet, our dataset comprises daily online hours and order completion records for 12 EV drivers and 2,948 ICEV drivers during the observation period. Here, online time refers to the total duration a driver was registered and available for service on the platform each day. Order mileage is the sum of distances from all orders completed by a driver on a given day, while total mileage extends this measure by adding the estimated deadhead distance traveled between consecutive orders. We also calculated the daily number of orders. These daily records were further aggregated to construct weekly and monthly driver-level profiles, enabling a comparative analysis of work patterns between EV and ICEV drivers. Descriptive statistics and results of Welch's t-tests are presented in Table 2. Figure 3 provides boxplots comparing EVs and ICEVs at daily, weekly, and monthly intervals, while Fig. 4 displays the corresponding 95% confidence intervals for the mean differences.

Our analysis for private car-hailing fleet reveals significant differences at the daily level. EV drivers recorded a significantly longer average online time (6.60 hours) compared to ICEV drivers (5.72 hours) ($p = 0.002$, Cohen's d = 0.25). This indicates that EV drivers, on average, maintain

Table 1 | Descriptive statistics and t-test results: car-sharing fleet (EVs vs. ICEVs)

	Variable	EV		ICEV		Mean difference	t	*p*	Cohen's_d
		Mean	Sd	Mean	Sd				
Weekly	Total Fee (CNY)	61.81	76.81	74.44	64.62	−12.63	−1.97	0.05	−0.18
	Order Number	2.31	2.56	2.70	2.18	−0.39	−1.80	0.07	−0.16
	Total Distance (km)	58.91	83.54	72.47	75.27	−13.56	−1.82	0.07	−0.17
	Order Distance (km)	39.63	52.86	47.99	45.40	−8.36	−1.86	0.07	−0.17
Monthly	Total Fee (CNY)	108.60	180.61	144.74	169.62	−36.14	−1.55	0.13	−0.21
	Order Number	4.05	6.21	5.24	5.90	−1.19	−1.47	0.15	−0.20
	Total Distance (km)	103.51	191.66	140.91	192.11	−37.41	−1.42	0.16	−0.19
	Order Distance (km)	69.62	122.63	93.31	116.00	−23.69	−1.49	0.14	−0.20

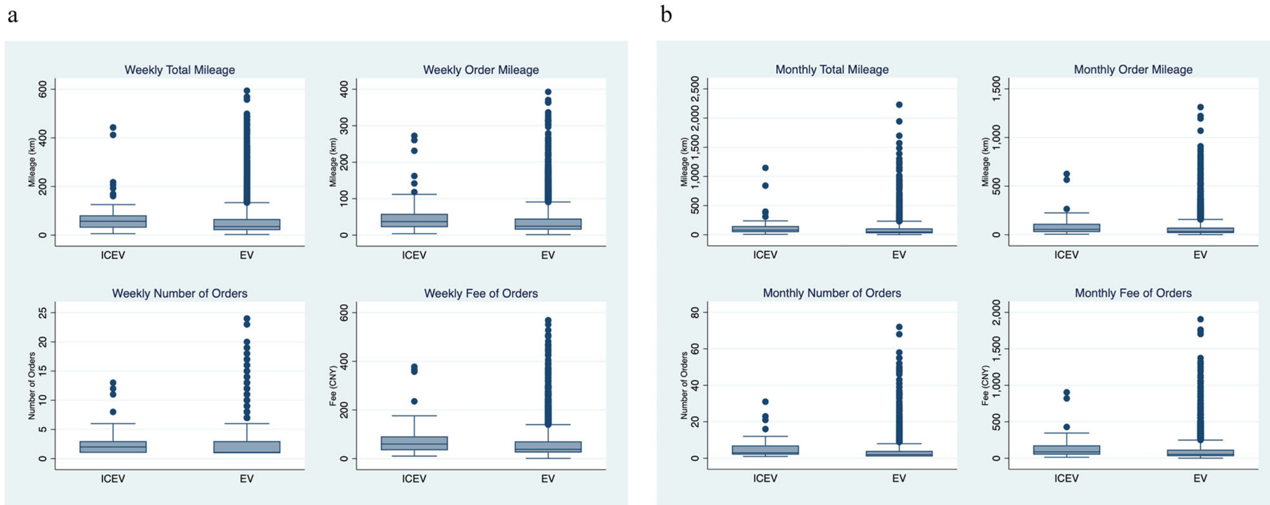
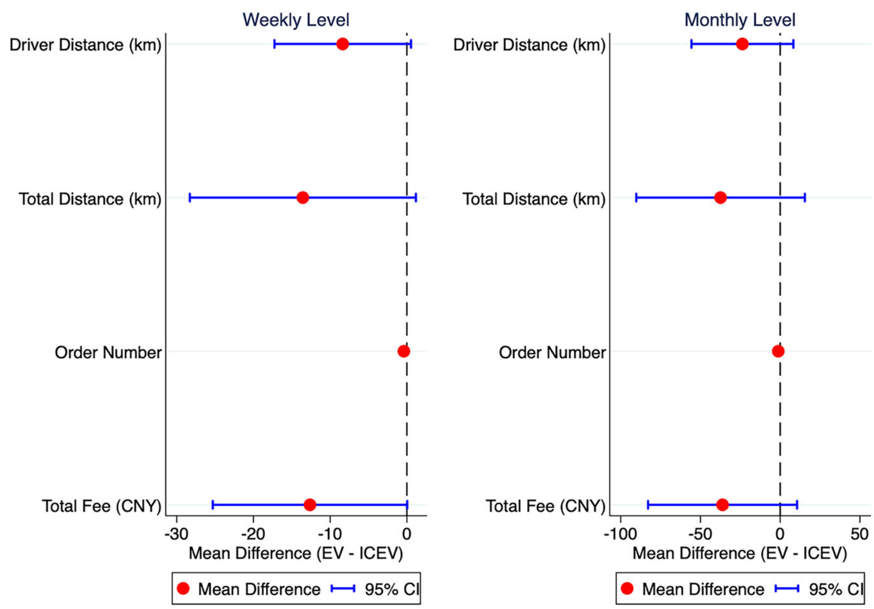


Fig. 1 | Boxplots for EV and ICEV drivers' travel patterns in the car-sharing fleet. **a** indicates the weekly comparison of travel patterns between EV and ICEV drivers, and **b** indicates the monthly comparison of travel patterns between EV and ICEV drivers.

Fig. 2 | 95% Confidence intervals for mean differences. EVs vs. ICEVs in car-sharing.



longer availability on the platform. In contrast, no significant difference was found in the daily number of orders completed.

In the private car-hailing fleet, regarding travel distance, EV drivers exhibited significantly lower daily order mileage (69.23 km vs. 88.54 km for ICEVs; $p = 0.001$, Cohen's $d = -0.33$). After incorporating deadheading distance (i.e., the distance traveled between two consecutive orders without passengers), EV drivers' total mileage (104.20 km) remained significantly lower than that of ICEV drivers (132.60 km) ($p = 0.001$, Cohen's $d = -0.32$). However, when aggregated to weekly and monthly levels, although the directional patterns persist—EVs show lower mileage and longer online time—these differences are no longer statistically significant. This attenuation is likely due to the substantial reduction in sample size (number of driver-weeks or driver-months) after temporal aggregation, which diminishes statistical power.

Order-level comparison

To address our second research question (i.e., Do EVs serve different orders compared with ICEVs?), we shift our unit of analysis to the individual order and conduct a series of regression analyses on order distance, including variants that incorporate deadhead mileage.

For the car-sharing fleet, we first estimate the relationship between vehicle type and order distance (i.e., the mileage traveled for an order). The regression results are presented in Table 3. Model 1 is a baseline specification controlling only for date fixed effects and vehicle brand. In Models 2 and 3, we sequentially add controls for whether the trip occurred during a peak hour (peak_hour) and for driver activity level (active_driver, defined as having completed more than 10 orders during the observation period). Model 4 replicates the full specification of Model 3 but uses the sum of the order distance and the subsequent deadhead distance as the dependent variable. As shown in the results, the vehicle type (EV vs. ICEV) has no statistically significant effect on the distance of car-sharing orders across all specifications. Furthermore, we introduced interaction terms (EV × peak_hour and EV × active_driver) into the models, none of which yielded significant coefficients. Additionally, we performed logistic regressions, classifying orders exceeding 50 km as long_trip and those exceeding 100 km as very_long_trip. These analyses also found no significant effect of vehicle type on the likelihood of a trip being long-distance.

Table 2 | Descriptive statistics and t-test results: private car-hailing fleet (EVs vs. ICEVs)

	Variable	EV		ICEV		Mean difference	t	p	Cohen'd
		Mean	Sd	Mean	Sd				
Daily	Total mileage (km)	104.20	82.89	132.60	92.51	-28.39	−3.53	0.001	−0.32
	Order mileage (km)	69.23	56.07	88.54	62.38	−19.31	−3.56	0.001	−0.33
	Number of orders	9.66	6.97	10.22	6.49	−0.56	−1.00	0.320	−0.08
	Online time (hour)	6.60	3.93	5.72	3.15	0.88	3.20	0.002	0.25
Weekly	Total mileage (km)	349.18	362.15	452.19	438.26	−103.00	−1.47	0.151	−0.26
	Order mileage (km)	232.07	244.41	301.96	297.35	−69.89	−1.47	0.151	−0.26
	Number of orders	32.40	33.45	34.85	33.15	−2.45	−0.46	0.648	−0.07
	Online time (hour)	22.15	21.04	19.52	15.46	2.63	1.06	0.296	0.14
Monthly	Total mileage (km)	780.41	1123.73	928.17	1359.86	−147.76	−0.47	0.642	−0.12
	Order mileage (km)	518.66	755.08	619.81	910.28	−101.14	−0.48	0.634	−0.12
	Number of orders	72.40	105.38	71.53	104.30	0.88	0.04	0.971	0.01
	Online time (hour)	49.51	66.33	40.06	48.04	9.44	0.85	0.405	0.16

Order mileage refers to the total distance of all orders completed by a driver on a given day, whereas total mileage is calculated by adding the estimated deadhead distance between consecutive orders to account for travel without passengers.

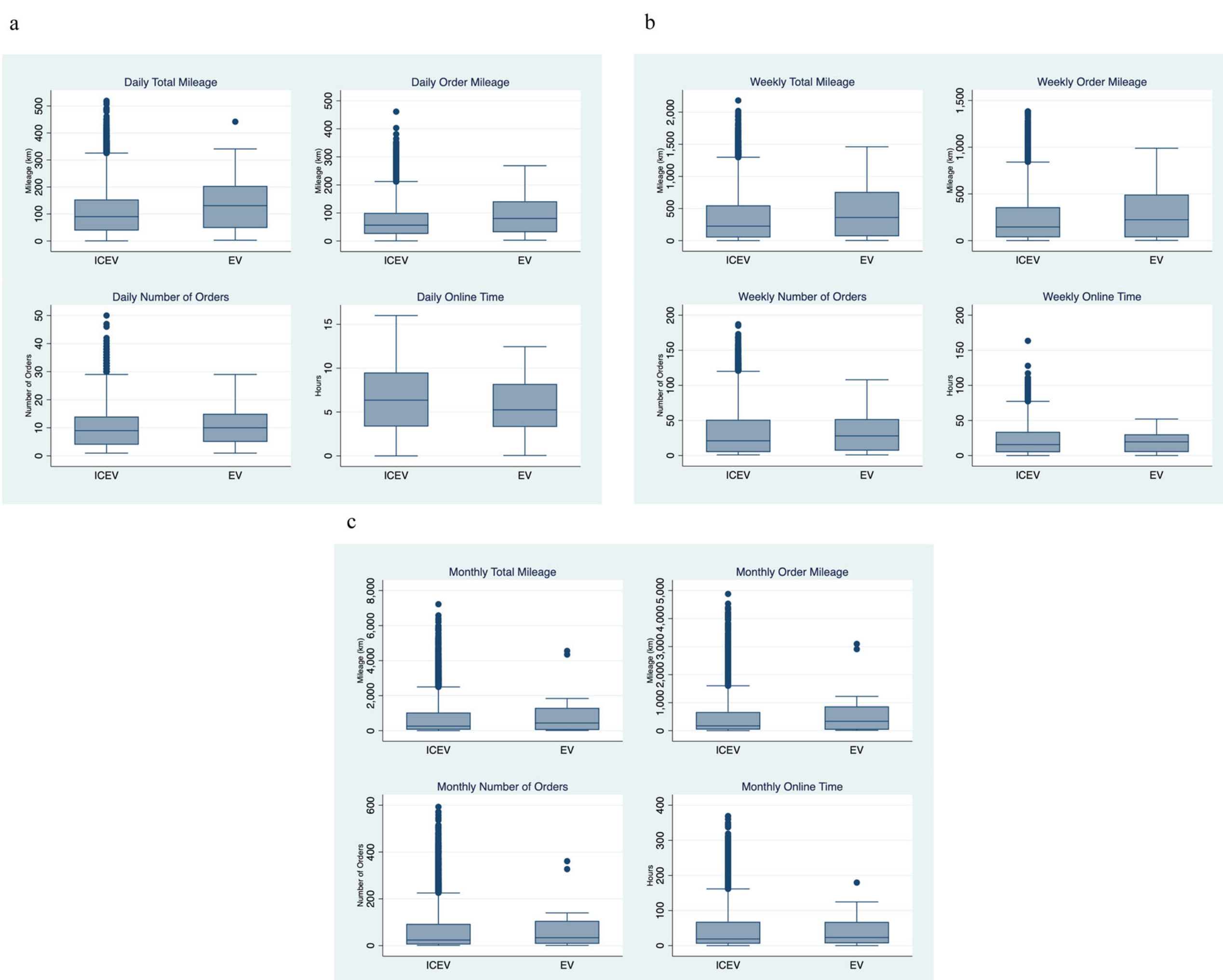


Fig. 3 | Boxplots for EV and ICEV drivers' travel patterns in the private car-hailing fleet. **a** indicates the daily comparison of travel patterns between EV and ICEV drivers, **b** indicates the weekly comparison of travel patterns between EV and ICEV drivers, and **c** indicates the monthly comparison of travel patterns between EV and ICEV drivers.

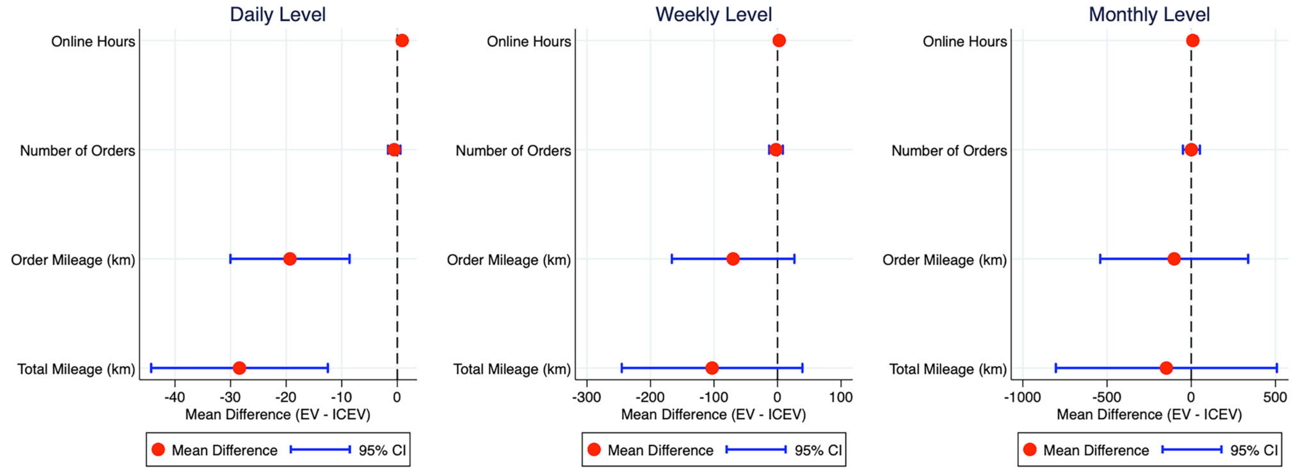


Fig. 4 | 95% Confidence intervals for mean differences. EVs vs. ICEVs in private car-hailing.

Table 3 | Regression results for order distance in car-sharing

DV = order distance	(1)	(2)	(3)	(4)
VARIABLES	Model 1	Model 2	Model 3	Model 4
EV	0.460	0.516	0.515	1.370
	(0.541)	(0.543)	(0.543)	(0.905)
peak_hour		−0.682***	−0.693***	−1.532***
		(0.192)	(0.193)	(0.311)
active_driver			−0.193	0.659**
			(0.196)	(0.321)
Constant	17.15***	18.77***	18.86***	30.97***
	(0.0958)	(0.328)	(0.336)	(1.007)
Observations	12,500	12,500	12,500	12,500

Robust standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. *Order distance* indicates the mileage traveled for an order; *EV* indicates that the driver operates an EV (vs. ICEV); *peak_hour* indicates that the trip occurred during a peak hour; *active_driver* indicates that the driver completed more than 10 orders during the observation period.

For the private car-hailing fleet, we estimated regression models at the order level, using both the order mileage and the total mileage (order mileage plus the subsequent deadhead distance) as dependent variables. Model 1 serves as the baseline, controlling for date fixed effects and vehicle brand. Models 2 and 3 incrementally introduce controls for driver type (a binary indicator full_time for drivers active more than 20 days per month) and for trips occurring during peak hours (peak_hour). In Model 4, the dependent variable is switched to total mileage, which incorporates deadhead distance. The regression results are summarized in Table 4.

The results indicate that, compared to ICEV orders, EV orders are associated with a significantly longer travel distance. The estimated increase is 1.36 km ($p < 0.001$) for order mileage and 2.026 km ($p < 0.001$) for total mileage. We also find that a driver's full-time status exerts a significant positive effect on order distance. We further investigated interaction effects. As shown in Model 7, while the standalone coefficient for EV is not significant, the interaction term EV × full_time is positive and significant. This indicates that orders completed by full-time EV drivers are, on average, 1.613 km longer ($p < 0.001$) than those completed by comparable full-time ICEV drivers. In contrast, the interaction between EV and peak_hour is not statistically significant. Finally, we performed logistic regressions to examine the propensity for long-distance trips. The results show a positive but statistically insignificant relationship between EVs and the probability of a long_trip (distance > 50 km; coefficient = 2.601). However, for very_long_trip (distance > 100 km), the association with EVs is strongly positive and significant (coefficient = 28.24, $p < 0.001$).

Discussion

This study evaluates the potential for EVs to substitute for ICEVs in ride-sharing by analyzing driver-level and order-level data from car-sharing and private car-hailing services in Beijing, China.

At the driver level, we find no significant heterogeneity between EVs and ICEVs in the car-sharing mode. Specifically, after aggregating order data to weekly and monthly levels, we observe that EV drivers' order mileage, both with and without deadheading distance, tends to be lower than that of ICEV drivers, while the average number of orders shows little difference. These differences, however, are not statistically significant, potentially due to the limited sample size of EV drivers ($N = 86$) in this fleet. In contrast, significant heterogeneity emerges in the private car-hailing fleet. Aggregating daily order records, we find that EV drivers' total mileage, whether including deadheading or not, is significantly lower than that of ICEV drivers. Despite no significant difference in the number of daily orders, EV drivers spend an average of 0.88 more hours online per day than their ICEV counterparts. By examining the charging time and maximum single-trip range of each EV model present in our 2015 dataset (see Table 5), we note that the typical fast-charging duration for these vehicles was around one hour. We therefore infer that charging time likely contributes to the extended online hours observed among EV drivers, as drivers may remain logged on the platform while waiting for or undergoing charging. When daily metrics are aggregated to weekly and monthly levels, similar directional patterns persist, but the differences lose statistical significance. This attenuation is again likely attributable to reduced sample size and the relatively short observation window of two months in our dataset.

Within the private car-hailing fleet, our order-level analysis reveals that EVs complete trips of significantly greater distance than ICEVs. Further investigation into the interaction between vehicle type and driver commitment shows that while full-time driver status alone is associated with a slight reduction in trip distance (−0.42 km), and the standalone EV coefficient is not significant, the interaction term EV × full_time is positive and significant (1.898 km). This suggests that the tendency for EVs to serve longer trips is particularly pronounced among full-time drivers. A subsample analysis confined to full-time drivers confirms this pattern, showing a significant positive relationship between EVs and trip distance ($\beta = 1.494$, $p < 0.001$). We further explore whether EVs are disproportionately assigned to or select into long-distance orders. Logistic regression results indicate that EVs have a significantly higher likelihood of completing very long trips (>100 km) compared to ICEVs, while no significant difference exists for long trips (>50 km). This phenomenon could be partially attributed to a potential reluctance among ICEV drivers to accept very long trips, possibly

Table 4 | Regression results for order distance in private car-hailing

DV = order distance	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	Model1	Model2	Model3	Model4	Model5	Model6	Model7
EV	1.360***	1.328***	1.319***	2.026***	−0.119	1.556***	−0.0857
	(0.212)	(0.212)	(0.212)	(0.327)	(0.521)	(0.302)	(0.527)
full_time		−0.436***	−0.400***	−0.611***	−0.456***		−0.420***
		(0.0620)	(0.0619)	(0.0865)	(0.0624)		(0.0622)
peak_hour			−0.589***	-1.262***		−0.601***	−0.601***
			(0.0226)	(0.0356)		(0.0224)	(0.0224)
EV*full_time					1.613***		1.898***
					(0.569)		(0.579)
EV*peak_hour						−0.583	−0.751*
						(0.408)	(0.415)
Constant	6.994***	7.529***	7.690***	12.11***	7.429***	7.631***	7.650***
	(0.0176)	(0.0691)	(0.0693)	(0.0978)	(0.0626)	(0.0630)	(0.0633)
Observations	279,355	279,355	279,355	279,355	279,355	279,355	279,355

Robust standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. *Order distance* indicates the mileage traveled for an order; *EV* indicates that the driver operates an EV (vs. ICEV); *full_time* indicates that the driver works for more than 20 days per month; *peak_hour* indicates that the trip occurred during a peak hour.

Table 5 | EV performance indicators in car-sharing and private car-hailing modes

Trip mode	EV type	Range	Quick-charge time	Normal charge time	Number
Car-sharing	Tesla Model S	390 km	1 h	10 h	5
	BAIC-New energy EV series	160 km	1 h	8 h	16
	BAIC-New Energy	150 km	1 h	8 h	15
	Smart fortwo	145 km		6–7 h	9
	DENZA	253 km	1 h	5 h	4
	Byd e6	300 km	1.5 h	8 h	8
	Jianghuai iev	240 km	2 h	8 h	27
	Chery eQ	151 km	0.5 h/	10 h	2
Private car-hailing	BAIC-New Energy ES210	175 km	1 h	5 h	2
	BAIC-New Energy EV Series	160 km	1 h	8 h	4
	Jianghuai -iEV5	170 km	1 h	8 h	3
	Smart fortwo	145 km	1 h	6–7 h	3

due to economic or operational considerations. More importantly, it demonstrates that, despite concerns regarding range and charging, EVs in the ridesharing context are not systematically excluded from the longest orders and can, in fact, cover extensive travel demands.

We further examine the feasibility of EV substitution in ridesharing by assessing whether range limitations are a primary constraint. To do so, we estimate the proportion of daily driving patterns that could be accommodated by typical EVs under different range assumptions. We consider three range scenarios reflective of the 2015 market: (i) a conservative case (93 km), representing older or smaller EVs; (ii) an intermediate case (139 km), accounting for contingent factors such as suboptimal weather or driving conditions; and (iii) an average case (185 km), reflecting the typical maximum range of mainstream EVs at the time. Given that our data were collected during winter, when battery performance is often reduced, we apply a 20% reduction to each nominal range threshold to approximate cold-weather capacity degradation[40]. This adjustment yields effective daily ranges of approximately 74 km, 111 km, and 148 km for the three scenarios, respectively. Although drivers could partially mitigate range limits through opportunistic charging during the day, our analysis deliberately adopts a worst-case assumption, that no daytime charging occurs, to provide a conservative estimate of substitutability under the most constrained operational conditions.

The feasibility of EV substitution in private car-hailing fleets is illustrated in the left panel of Fig. 5 and in Table 6. When deadheading distance is excluded, a mainstream EV could cover 61.8% of ICEV daily trips under the most conservative range scenario (74 km). Under the intermediate and average scenarios (111 km and 148 km, respectively), the range limit does not constrain 80.2% and 91.0% of ICEV daily trips. After incorporating estimated deadheading distance, these coverage rates decline substantially to 39.4%, 57.0%, and 72.5% for the conservative, average, and intermediate scenarios, respectively.

The feasibility of EV substitution in car-sharing fleets is illustrated in the right panel of Fig. 5 and in Table 6. For trips completed in car-sharing mode, when deadheading distance is excluded, our analysis shows that 96.5% of ICEV daily trips could be accommodated by EVs even under the shortest (conservative) range assumption. The proportion of long trips exceeding an EV's range remains low across both ideal and suboptimal operating conditions. Specifically, range limits would not restrict 99.5% of ICEV daily trips under the average range scenario, and still 98.9% under the intermediate scenario (see Table 6). After accounting for estimated

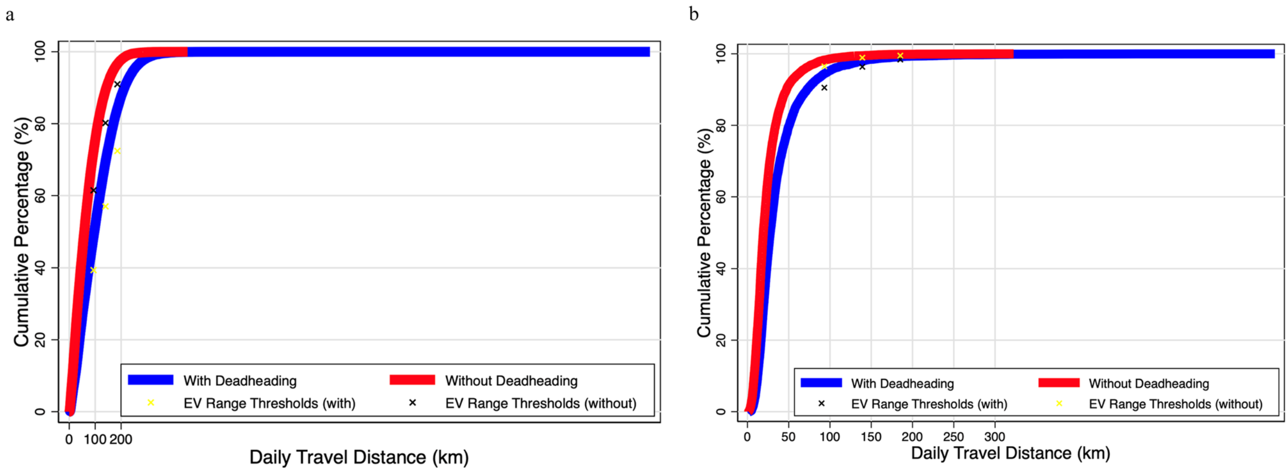


Fig. 5 | Cumulative distribution function of drivers' daily mileage. **a** indicates the cumulative distribution function for the private car-hailing fleet, and **b** indicates the cumulative distribution function for the car-sharing fleet.

Table 6 | Percentage of daily trips made with ICEVs that are below the assumed EV ranges

	Conservative (77 km)	Intermediate (111 km)	Average (148 km)
ICEV (private car-hailing)	61.8% (39.4%)	80.2% (57.0%)	91.0% (72.5%)
ICEV (car-sharing)	96.5% (90.6%)	98.9% (96.4%)	99.5% (98.4%)

Percentages in parentheses indicate coverage rates when ethe stimated deadheading distance is included.

deadheading distance, these coverage rates adjust to 90.6%, 96.4%, and 98.4% for the conservative, intermediate, and average range thresholds, respectively.

The foregoing analysis reveals a pronounced contrast in substitution feasibility between the two ridesharing modes. In the private car-hailing fleet, under conditions of restricted charging access and adverse environmental factors (simulated by our conservative range assumptions), the coverage rate of EVs for ICEV trips is substantially lower. The incorporation of deadheading distance has a particularly strong negative impact on this feasibility. This finding directly helps explain the driver-level pattern observed earlier: EV drivers achieved lower daily mileage yet maintained longer online hours. The logical implication is that these drivers likely needed to interrupt service for mid-shift charging, increasing platform availability time without a proportional increase in productive travel distance. In stark contrast, within the car-sharing fleet, EV coverage of ICEV daily travel remains high even under the most conservative estimates, indicating a strong inherent compatibility in this peer-to-peer mode.

Synthesizing these findings with our order-level analysis yields a nuanced picture. Despite the aggregate mileage and coverage constraints in private car-hailing, EVs actually completed orders of significantly greater average distance than ICEVs, especially among full-time drivers, and showed a higher propensity to serve very long-distance trips (>100 km). This indicates that for individual trip fulfillment, EVs' range and charging requirements did not functionally restrict their operational scope.

In conclusion, while EVs demonstrate clear potential to substitute for ICEVs in both car-sharing and private car-hailing contexts, the critical determinant of feasibility is not the vehicle's range per se, but the flexibility and accessibility of charging opportunities. However, our assessment of substitution feasibility does not model the dynamic interactions of battery state-of-charge, charging station queueing, or spatial accessibility, which are critical for real-world fleet management; future research incorporating high-resolution telematics and charging logs is needed to develop operational simulations that can optimize dispatch and infrastructure use under these constraints.

While this study provides a detailed empirical assessment of EV operational performance, a key limitation arises from the age of the data. Our analysis is based on vehicle technology and market conditions from 2015, a period representing the early developmental stage of both the EV and ridesharing industries. Since then, substantial advancements have been made in battery energy density, driving range, and fast-charging infrastructure. Consequently, the absolute range constraints and coverage gaps quantified here likely overstate the limitations of current-generation EVs. Nonetheless, this analysis establishes an important benchmark, and the identified operational challenges, particularly the interplay between charging logistics, deadheading distance, and driver productivity, remain relevant for understanding the integration of EVs into high-utilization fleets, even as the underlying technology improves.

Based on our empirical findings, we propose the following targeted recommendations to accelerate the substitution of ICEVs with EVs in ridesharing. First, policymakers should strategically focus charging infrastructure investment on hubs and corridors with high ridesharing activity, particularly to serve the private car-hailing sector. This directly addresses the critical need for accessible, fast-charging options that minimize drivers' non-revenue downtime, which our study identifies as a key constraint on EV productivity in this mode. Second, recognizing the distinct operational patterns between car-sharing and private car-hailing, support mechanisms should be tailored. For car-sharing, where range is less constraining, policies can focus on broader consumer incentives (e.g., purchase subsidies, preferential licensing). For private car-hailing, policies and platform rules should jointly address operational feasibility, for example, through targeted charging subsidies for professional drivers, or platform algorithms that intelligently match EVs with shorter trips and integrate charging breaks into shift planning.

Methods

To compare the usage of EVs and ICEVs in ridesharing, we use order-level and driver-level data obtained from Didi, a dominant Internet taxi company in China. This company was launched in China in 2015 and provides ridesharing services by matching customers and private drivers based on an intelligent dispatch system[42]. Our data include car type, driver profiles, and order profiles for both private car-hailing and car-sharing modes. The data were collected in Beijing, China, from December 5, 2015, to January 5, 2016, and are not publicly available. Incomplete and inconsistent data were removed from the sample. The final dataset includes 86 EVs and 6573 ICEVs in car-sharing and 12 EVs and 2948 ICEVs in private car-hailing. The number of EVs in the dataset is comparable to the number being used in a car-sharing fleet in Germany, which has 91 EVs out of a total of 1727 distinct vehicles[38].

Data sources and processing

For each mode, we utilize two datasets: driver registration information and order records. The driver data contains anonymous IDs, vehicle brand/model, and city, allowing us to identify the powertrain (EV/ICEV). For drivers in private car-hailing, the platform recorded drivers' online time, which indicates the total duration a driver was logged into and available on the platform. The order data include order IDs, matched driver/passenger IDs, timestamps, and GPS coordinates for trip origins and destinations. To calculate travel distances, we used the Gaode Maps API to compute the actual road mileage for each order based on its GPS coordinates. We also estimated the deadheading (empty) distance between consecutive orders for the same driver using the same API, by calculating the distance between the drop-off point of one trip and the pickup point of the next.

Variable calculation

In car-sharing, for each driver and day, we calculated the daily number of orders, total order mileage, and total mileage. Total mileage is defined as the sum of order mileage and the estimated deadheading mileage for that day. These daily records were then aggregated by driver_id to construct weekly and monthly driver-level profiles.

In private car-hailing, we computed each driver's daily number of orders, order mileage, and total mileage (order + deadhead). From these daily figures, we derived driver-level averages for daily mileage and mileage per order by dividing the respective totals by the number of days worked and the number of orders.

These constructed variables form the basis for our comparative analysis of usage patterns between EVs and ICEVs across the two service modes. To test for statistically significant differences in these aggregated metrics, we applied Welch's t-test, which is appropriate for comparing groups with unequal variances and sample sizes.

Statistical modeling: order-level analysis

To further examine how trip characteristics differ between EVs and ICEVs, we estimate a series of regression models at the order level, focusing on two dependent variables: order mileage and total mileage (order mileage plus the subsequent deadheading distance). For linear regression models with interaction terms, the baseline specification is as follows:

$$Mileage_{ijt} = \beta_0 + \beta_1 EV_i + \gamma X_{ij} + \delta_t + \varepsilon_{ijt} \tag{1}$$

where $\mathrm{Mileage}_{ijt}$ is either the order distance or total distance for order j completed by vehicle/driver i at time t; EV_i is a binary indicator for electric vehicles; $\mathbf{X}_{ij}$ is a vector of controls including driver type (full-time status), whether the trip started during a peak hour, and vehicle attributes; and δ_t represents date fixed effects.

To explore heterogeneous effects, we extend the model by including interaction terms between the EV dummy and key driver/trip characteristics:

EV × Full-time/Active-driver: To test whether the effect of EV on trip distance is amplified for professional drivers in private car-hailing / active drivers in car-hailing.

EV × Peak Hour: To examine if EVs serve trips of different lengths during high-demand periods. To assess whether EVs are more likely to serve long-distance orders, we estimate logistic regression models of the form:

$$\log\left(\frac{P(LongTrip_{ijt} = 1)}{1 - P(LongTrip_{ijt} = 1)}\right) = \beta_0 + \beta_1 EV_i + \gamma X_{ij} + \delta_t \tag{2}$$

We define two distinct outcome variables: (1) Long Trip: Order distance greater than 50 km. (2) Very Long Trip: Order distance greater than 100 km. These models use the same set of control variables and fixed effects as the linear specifications, allowing us to isolate the relationship between vehicle type and the propensity to complete extended journeys.

Data availability

The dataset used in this study is commercially sensitive and proprietary to the ride-sharing company. The authors do not have permission to share data.

Code availability

The underlying code for this study is available to qualified researchers on request from the corresponding author.

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Author contributions

X.C. acquired funding, administered the project, provided supervision and resources, drafted the original manuscript and participated in reviewing and editing the manuscript. Y.R. conducted data analysis, drafted the original manuscript, and participated in reviewing and editing the manuscript. M.K. developed the conceptualization, designed the methodology, and participated in reviewing and editing the manuscript. J.P. contributed to the methodology and participated in reviewing and editing the manuscript. T.W. drafted the original manuscript and participated in reviewing and editing the manuscript. All authors commented on the results and contributed to the final version of the manuscript.

Competing interests

The authors declare no competing interests.

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