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Net Change in Energy Use from Ridehail Services in Five California Regions

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Abstract: Previously, we estimated the net change in energy use from ridehail services in Austin Texas. This estimate was based, in part, on assumptions regarding the number of rides involving two pooled parties and the distance drivers commuted into their service area to begin their driving day. The recent release of a year's worth of Uber ridehail rides provided to California agencies, as well as recent surveys of driver commute behavior and the previous mode replaced by ridehail services, have enabled more accurate estimates of the net change in energy use from ridehail services statewide and in five regional markets. We find that the net reduction in energy use from more-efficient vehicles and pooled rides does not offset the additional increase in commute and between-ride deadhead kilometers and replacing more efficient modes with ridehail services. The net result is a 96% increase in statewide energy use (ranging from a 75% to a 123% increase in each region).

Keywords: ridehailing; deadhead; Uber; vehicle kilometers traveled; electric vehicles

1. Introduction

Prior to the onset of the coronavirus (COVID-19) pandemic in early 2020, ridehail services had become an established travel mode in urban areas. Ridehail services provided by transportation network companies (TNCs) such as Lyft and Uber connect individuals seeking a ride with nearby drivers via a smartphone application (app). Since they were first introduced in the early 2010s, observers have been concerned about the impact ridehail services might have on a variety of issues, including traffic congestion, energy use and greenhouse gas emissions, criteria pollutant emissions, ridership on public transit systems, worker's rights for drivers, and passenger and driver safety. In particular, federal, state, and local agencies are investigating whether these services can deliver on their potential to reduce traffic congestion, energy use, and emissions, or if they may actually exacerbate the problems they were purportedly created to solve.

Several previous studies have shown that ridehail services impact transportation patterns, particularly in urban areas. For example, one study estimates that ridehail vehicles accounted for 15% of all vehicle trips and 9% of all person trips within San Francisco [1], while another estimates that since their introduction, such vehicles accounted for half of the increase in traffic congestion in downtown San Francisco [2]. A study of the use of ridehail services in seven major U.S. cities found that 21% of adults used these services and 24% used them on a weekly or daily basis [3]. And a 2016 study estimated that 21% of urban and 15% of suburban residents in the U.S. had used ridehail services [4].

There are six aspects of ridehail services that can affect VKT and, ultimately, energy use [5]. On the one hand, ridehail services can reduce energy use in three ways, which occur over the short, medium, and long term. In the short term, sharing a ride with another party, referred to as pooling, can reduce VKT by as much as 50% compared to two travelers driving their separate personal vehicles along a similar route. However, pooled ridehail services are not available in all markets. In the medium term, by concentrating VKT in a smaller number of vehicles, their owners have an incentive to purchase more-efficient vehicles since the lower per-kilometer fuel costs will more quickly offset the higher initial



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purchase price of a more efficient vehicle. In the long term, riders may dispose of an existing vehicle and may eliminate some trips in a personal vehicle once they no longer have to pay the fixed costs of owning and maintaining that vehicle.

On the other hand, ridehail services can lead to increases in energy use in several ways, including via empty or “deadhead” travel, or by replacing travel that would previously have been undertaken in a more efficient travel mode. Deadhead kilometers, which is travel in a ridehail vehicle without a passenger, can offset at least some of the energy benefits of the ridehail service and can lead to more traffic congestion. The first type of deadheading is the distance ridehail drivers travel to commute into (and out of) urban areas to begin (and end) their driving shift before turning on (or after turning off) the ridehail app, which can be considered “commute deadheading” (because the CPUC’s reporting requirements for TNCs do not include commute deadheading, this VKT is informally referred to as Period 0 (or P0) kilometers). The second type of deadheading is “between-ride deadheading”, which includes additional kilometers driven: (1) to take advantage of surge pricing, TNCs pay drivers (and charge passengers) based on greater anticipated passenger demand, accounting for when drivers circle areas waiting for a ride request (both of which the California Public Utilities Commission, or CPUC, refers to as Period 1 (or P1) kilometers); and (2) to pick up a passenger after accepting a ride request (which the CPUC refers to as Period 2 (or P2) kilometers). The CPUC refers to the VKT between passenger pick up and drop off as Period 3 (or P3) kilometers.

Whether ridehailing increases VKT and energy use depends on what mode of travel the ridehail trip replaced. A similar fraction of conventional taxi VKT, or perhaps even more, is taken up by deadhead kilometers when compared with TNC vehicles, as taxis are more likely to circle in areas seeking riders, while ridehail vehicle drivers can potentially park between rides while awaiting a subsequent ride request through the smart phone app. Trips in private vehicles may add additional VKT while drivers search for parking at the end of a trip, whereas ridehail drivers never search for parking other than finding a safe location at which to drop off their passengers. In theory, ridehail deadheading can be reduced by TNCs managing the number of ridehail vehicles in service, thereby matching driver supply more closely with anticipated passenger demand [6].

The other aspect of ridehail services that may increase energy use is when a ridehail trip replaces a trip in a more energy-efficient travel mode; for example, a trip taken on public transit replaced by a trip in a ridehail vehicle could increase the amount of per-passenger energy consumed during that trip (although a ridehail trip that replaces a transit trip likely increases accessibility by delivering the traveler directly to their destination rather than to a transit stop a short walk from their destination). In addition, ridehail services may induce new travel; that is, they may generate a trip that otherwise would not have been taken if not for the availability of a ridehail service. Conversely, ridehail services may supplement fixed-route public transit service by providing first/last-mile travel to or from transit stops, thus extending the reach of the transit system to travelers who normally would not take transit. An analysis of transit ridership data before and after Uber entry found that overall ridership increased by 5% two years after entry, ranging from a 7% increase to an 8% decrease depending on the size of the city and its transit system [7]. In addition, TNCs encourage more part-time drivers, as opposed to fewer full-time drivers in conventional taxi service, which reduces the average number of rides each driver or vehicle provides, leading to potential increases in traffic congestion. Increased traffic congestion, with more stop-and-go driving, has been shown to slightly increase energy use [8].

A few studies have estimated deadheading from ridehail services using a variety of data sources and methods, as summarized in [9]. These studies estimate that 36% to 45% of all ridehail VKT are deadhead kilometers, although none of these studies accurately account for all of the deadhead kilometers driven by ridehail vehicles. Based on the RideAustin dataset described below [10], it is estimated that 37% of all ridehail VKT are deadhead kilometers. While their estimate did assume that ridehail drivers commuted an additional two miles at the beginning and end of each shift, their between-ride deadhead VKT was

based on the straight-line distance between the end of each ride and the start of each subsequent ride rather than the actual distance measured on the road network. Based on data obtained from Uber, ref. [11] found that the average percentage of ridehail vehicle kilometers without a passenger—excluding commuting deadheading—in five cities ranged from 36% in Los Angeles to 45% in Seattle. In a non-peer-reviewed report, ref. [12] estimated that 40% of the VKT of weekday ridehail rides that either began or ended in downtown Manhattan were from between-ride deadheading. Researchers downloading data from the Uber and Lyft public-facing APIs estimated that 20% of the VKT of ridehail rides that started and ended within San Francisco’s financial district were from deadheading [1]. In addition to excluding commute deadheading, this analysis also understates the share of between-ride deadheading as the distance between where a ride was requested and where the passenger was picked up was attributed to passenger VKT rather than to deadhead VKT.

A previous analysis estimated the net energy impact of ridehail services based on nearly 1.5 million individual rides over 11 months in Austin provided by RideAustin, a local non-profit ridehailing service that started operation when Lyft and Uber left the Austin market [5]. Analyses of these individual ride data indicated that 26% of all RideAustin VKT was included under between-ride deadheading. Combined with a simple estimate that 19% of all ridehail VKT was for commute deadheading VKT, the study estimated that a total of 45% of all ridehail VKT was from deadheading. The RideAustin data also indicated that the RideAustin vehicles were 3.2 KPL more efficient than the average vehicle registered in the Austin area. Using assumptions regarding the extent of pooling (15% or 30% of all rides are pooled, and half to all of the VKT of shared trips are overlapping VKT) and surveys in the literature regarding transport modes replaced by ridehail services in other cities, the study estimated that the RideAustin ridehail services resulted in a 41%-to-90% net increase in energy use based on low- and high-energy assumptions regarding pooled rides and mode replacement.

In 2018, the California Air Resources Board (CARB) and CPUC adopted regulatory requirements for ridehail services providers (TNCs), called the Clean Miles Standard (CMS) (<https://ww2.arb.ca.gov/our-work/programs/clean-miles-standard/about>, (accessed 11 August 2024)). As part of the CMS rulemaking process, the agencies required all TNCs operating in California to provide data on every individual ride their drivers provided in 2018. CARB published a review of these data in 2019 [13]; in the review, the CARB estimated that ridehail services increased CO₂ emissions by 50%, based on a combination of the following: (1) a 39% increase in VKT from deadheading; (2) a 7%-lower-than-average occupancy rate; and (3) use of vehicles that are substantially more efficient than the overall California fleet (having 5.5 higher average KPL). Some limitations of the CARB’s estimate of the net energy use of ridehail services are as follows: (1) only between-ride—i.e., not commute—deadheading were included (although CARB did adjust for overlapping VKT from drivers driving for more than one ridehail service); (2) the CARB did not account for average kilometers traveled by vehicle age when estimating the fuel efficiency of the overall California fleet; and (3) the CARB based its occupancy assumption on a survey of trip diaries maintained by 31 TNC drivers during 2754 rides.

In this paper, we update the previous analysis of the impact of ridehail services on travel and net energy use that was conducted on a relatively small number of trips in Austin [5]. In this updated analysis, we use a publicly available dataset on observed, real-world data on all individual trips provided during a six-month period by a single TNC throughout California. This expansive dataset allows for a more thorough analysis of ridehail services in several regions with different characteristics regarding travel demand and the supply of alternative travel modes (such as public transit). We also take advantage of recent surveys of ridehail driver and passenger behavior conducted in California, which allow us to estimate commute deadheading and what travel modes were replaced by ridehail services more precisely. To our knowledge, this is the most extensive analysis of real-world ridehail travel conducted to date, with the results providing important insights into how ridehail services influence energy use in different urban contexts.

2. Materials and Methods

Table 1, adapted from [5], summarizes the six aspects of ridehail services that influence energy use and lists the data and methods used in this analysis to estimate the net effect of ridehail services on energy use. The first three aspects in the table likely reduce VKT and/or energy use, while the last three likely increase VKT and energy use, compared to travel prior to the advent of ridehail services.

Table 1. Aspects of changes in VKT and energy use from ridehail services and methods used in this analysis (adapted from [5]).

Aspect of Ridehail Services	Method Used in This Analysis
Decreases in energy use	
1. More fuel-efficient vehicles	Measured by comparing rated fuel economy of Uber fleet with that of overall registered fleet
2. Pooled rides	Measured using fraction of rides provided that were pooled; distance of overlapping VKT from pooled rides estimated
3. Car-shedding and fewer trips	Not estimated
Increases in energy use	
4. Between-ride deadheading	Measured using actual travel distance between end of previous ride and start of next ride (P1 and P2 distance)
5. Commute deadheading	Estimated based on recent driver surveys in SF and LA
6. Mode replacement	Estimated based on recent passenger surveys in SF and LA

In 2013, the CPUC required TNCs operating in the state to provide annual reports on their operations, which included, among other things, detailed data on all individual rides provided [14,15]. The CPUC recently made public the available data on 156 million completed rides by drivers for Uber from September 2019 through August 2020 (Lyft provided similar data on 61 million rides to the CPUC; however, pending a lawsuit, the location, date/time, and distance of the segments of each ride are not included). These data include the location (ZIP code), date, and timestamp of four segments for over 156 million accepted ridehail rides for when the driver received and accepted a ride request and when the driver picked up and dropped off the passenger(s). Two location fields are provided: ZIP code, and census block; however, the census block field contains only the last five digits of the census block, so the data can only be used to locate the ridehail vehicle at the ZIP code level. The ZIP code where the driver first turned on the app/dropped off the passenger of the previous ride is also provided, but not when that occurred.

The CPUC data provide information on the timing, length, and duration of each individual ride; whether a pooled ride was requested and matched with another request; and the year, make, and model of the vehicle in which the ride occurred. Each ride also includes the duration and distance of three segments of each ride, which can be used to estimate the deadhead kilometers occurring prior to a driver picking up a passenger. For our analysis, we use only the first six months of these data, through February 2020 (we refer to this period as that before shelter-in-place orders were imposed in California, or “pre-SIP”), to assess the net energy impact of ridehail services prior to the economic shutdown in response to the COVID-19 pandemic.

Our analysis improves on the previous analysis, being based on data from all 133 million individual rides provided by Uber over a six-month period throughout California. We use these rich data to estimate decreases in energy use from pooling rides and more-efficient vehicles and increases in energy use from between-ride deadheading. We also take advantage of two recent surveys of TNC drivers and passengers, conducted by UC Berkeley in San Francisco and Los Angeles in 2017 [16]. These surveys allow for detailed estimates of the increase in energy use from commute deadheading and mode replacement induced by ridehail services in California. The more comprehensive data on individual rides, provided by the largest TNC in the U.S., coupled with more-recent driver and passenger surveys

conducted in California cities, allow us to make the most comprehensive analysis of the net energy impact of replacing travel with ridehail services to date. We also examine what impact ridehail services have had on different regions of the state, which have different density and transportation system characteristics.

UC Berkeley worked with Uber and Lyft and the Natural Resources Defense Council (NRDC) to design a survey instrument for ridehail passengers, which the two TNCs sent via email to 8630 ridehail passengers in San Francisco, Los Angeles, and Washington DC in the summer of 2016. The purpose of the survey was to understand how ridehail users changed their travel behavior, including what travel mode the most-recent ridehail trip replaced, whether they changed their vehicle holdings, and their annual VKT in their personal vehicles. The TNCs contacted passengers who used their service at least seven times in the past year, with at least half of those trips within one of the three cities. Participation invitations were randomly distributed across five weekdays to ensure that the sample had a random distribution of the most recent trip taken according to the day of week. We used the information from the survey on what mode the respondent would have taken for their most-recent ridehail trip if ridehail services were not available (UC Berkeley contracted with a survey software company to conduct a general population survey on a stratified random sample of 1650 respondents in total in the three urban areas to compare the demographics of ridehail and non-ridehail users, as well as their use of public transit, vehicle ownership, and other travel behavior). UC Berkeley conducted a second survey—again with Uber, Lyft, and the NRDC—of 5034 Uber and Lyft drivers in the fall of 2016 to elicit information on, among other things, each driver’s home ZIP code, the market in which they primarily drove for a TNC, and the distance they typically drove before logging into the ridehail app. The purpose of the driver survey was to learn more about the distance drivers commuted into their primary service area to begin their driving shift. We used the average distance between the driver’s home location and their primary ridehail market to estimate driver commute deadheading VKT.

We use the CPUC data to estimate the increased energy use from between-ride deadhead VKT and the decreased energy use from pooled rides. Vehicle fuel economy of the Uber vehicles is compared with that of all vehicles registered in California to estimate the decreased energy use from more-efficient vehicles. Deadhead VKT attributed to drivers’ commutes at the beginning and the end of their shifts is estimated using the UC Berkeley driver survey, while the UC Berkeley passenger survey is used to estimate the increase in energy use from ridehail services replacing other modes of travel. The impact of ridehail services in California on net energy use, based on the estimates of five of the six aspects, shown in Table 1, are estimated, both statewide and for five regions in the state. Four scenarios are also investigated to understand the effect of some assumptions used in the baseline estimate.

The following sections describe the detailed methods used to estimate the change in energy use from the five aspects of ridehail services mentioned above: more-efficient vehicles, pooled rides, between-ride and commute deadheading, and mode replacement. Each ride in the CPUC Uber dataset was grouped into one of five regions of California based on the ZIP code the passenger was in when requesting a ride (San Francisco Bay Area, Los Angeles, San Diego, Sacramento, and Central Valley; the remaining rides were combined into an “other” category). About half of the rides occurred in the Los Angeles region, one third in SF Bay Area, 8% in San Diego, and 2% each in the Sacramento, Central Valley, and other regions. A total of 65% of the ridehail trips in the “other” region occurred in the five smaller cities, namely, Chico, Monterey, San Luis Obispo, Santa Barbara, and Santa Cruz. Only rides that were provided during the six months between September 2019 and February 2020 were included to reflect the trends in ridehail services prior to the shelter-in-place order California adopted in response to the COVID pandemic in mid-March 2020.

2.1. Decreased Energy Use from More-Efficient Vehicles

Because they tend to drive their vehicles more than the average driver, TNC drivers have an additional incentive to own newer and more-efficient vehicles than the average

driver. To estimate the decrease in energy use from more-efficient ridehail vehicles, we compared the characteristics of the Uber fleet to those of the average vehicle in each of the California regions using two public databases of vehicle registrations provided by the CARB [17] and the California Energy Commission (CEC) [18].

For each individual ride in the CPUC Uber dataset, the ridehail vehicle year and make/model is included. Although Uber provided unique identification for individual drivers and the vehicle identification numbers (VINs) for their vehicles to the CPUC, those data have been excluded from the public dataset. Plug-in hybrid, battery electric, and fuel cell electric vehicles can be identified by their model names. However, while some hybrid electric models can be identified, the CPUC Uber data do not distinguish between hybrid and non-hybrid versions of the same model (the models in the Uber dataset for which hybrid versions are not identified are Honda Civic, Toyota Avalon, Chevrolet Malibu, Hyundai Sonata, Kia Optima, and Ford Fusion). The distribution of Uber rides, by vehicle type, powertrain, or model year, is virtually identical to the distribution of the total VKT of the Uber rides.

The CARB registration data provide vehicle type (car, LDT1, LDT2), powertrain (PHEV, BEV, FCEV), and model year by county but not make/model or all powertrains (i.e., hybrid electric vehicles are not identified). The CEC registration data provide the powertrains, including hybrid electric vehicles, also by county, but not model year or vehicle type.

The left panel in Figure 1 shows that the model year distribution of vehicles used by Uber drivers is quite similar among the five regions, with the ride-weighted average vehicle age being one year older in Sacramento (model year: 2014) than in Los Angeles (model year: 2015). The model year distribution is quite skewed, with 50% to 60% of all Uber vehicles being five years old or younger (i.e., model year 2016 or newer in 2020). Note that Uber restricts the age of vehicles their drivers can use such that the oldest model year in the CPUC Uber dataset is 2004.

The model year distributions for CARB registrations were weighted by the average VKT by vehicle age schedule for cars and light trucks that the EPA uses in its MOVES model [19]. The right panel in Figure 1 indicates that the VKT-weighted, overall California vehicle fleet is, on average, one to two years older than the Uber fleet in each region based on the DMV vehicle registrations provided by the CARB. And the model year distribution of all registered vehicles is less skewed than that for Uber vehicles, with five years' old or newer vehicles accounting for only 33% to 42% of 2016 or newer vehicles and only 23% to 34% of vehicles from all model years. Note that the average model year of the California fleet only considers model year 2004 and newer vehicles; the VKT-weighted average model year of the statewide California fleet, considering all vehicles, is 2008, or seven years older than the ride-weighted average Uber vehicle (2015).

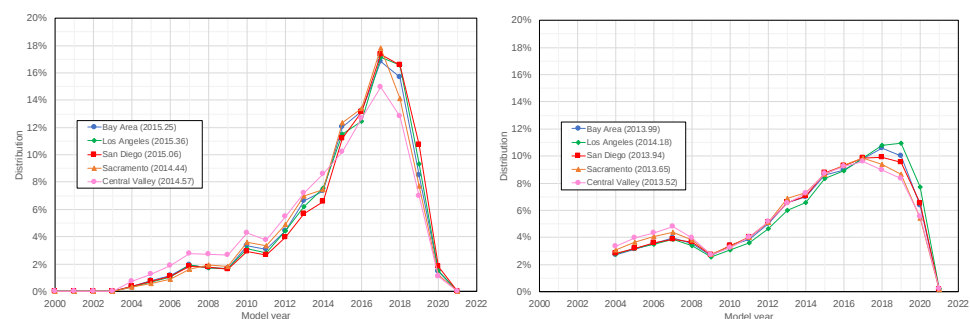


Figure 1. Model year distribution of vehicles: Uber rides (left) and CA registrations (right).

A total of 21% of all ICE cars in the CPUC Uber dataset are actually models that have a hybrid version that is not identified. Based on the fraction of models with a hybrid version that is identified in the dataset, we assumed that 20% of these are hybrid vs. non-hybrid versions (this assumption increases the fraction of all Uber rides statewide that are in hybrids from 18.2% to 20.8%).

Figure 2 compares the distribution of Uber rides with the distribution of vehicle registrations for 2020 from the CEC by vehicle powertrain. The fraction of Uber rides in hybrid electric vehicles is much higher than the fraction of hybrid electric vehicle registrations in each region. Uber rides in hybrid electric vehicles range from 12% of all rides in the Central Valley to 25% of all rides in the Bay Area, but hybrid electric vehicle registrations range from only 2.2% in the Central Valley to only 5.8% in the Bay Area. Conversely, fewer Uber rides were provided in plug-in hybrid and battery electric vehicles than the fraction of registered vehicles with those powertrains. This is likely because of the relatively higher initial cost, shorter range, and longer recharge time of battery electric vehicles compared to hybrid electric vehicles, which would limit the amount of time for which the vehicles could be used to generate revenue for their drivers. The net effect is that substantially fewer vehicles used for Uber rides had gasoline internal combustion engines than registered vehicles in each region, resulting in a reduction in the energy use per kilometer of travel.

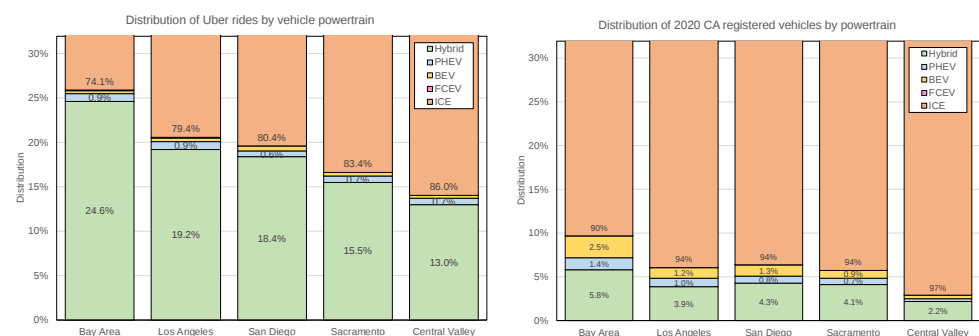


Figure 2. Distribution of vehicle powertrain: Uber rides (left) and CA registrations (right).

We obtained the average real-world fuel economy by vehicle model year, type, and powertrain from the EPA [20] (ref. [20] includes average fuel economy by vehicle type for all powertrains combined; the EPA provided us with the average fuel economy by vehicle type and powertrain (gasoline, diesel, compressed natural gas, liquified petroleum gas, battery electric, hybrid electric, plug-in hybrid electric, and hydrogen fuel cell)). The U.S. average sales-weighted fuel economy (in kilometers per liter) by model year, vehicle type, and powertrain are shown in Figure 3 (internal combustion engine vehicles), Figure 4 (hybrid and plug-in hybrid electric vehicles), and Figure 5 (battery electric and hydrogen fuel cell vehicles).

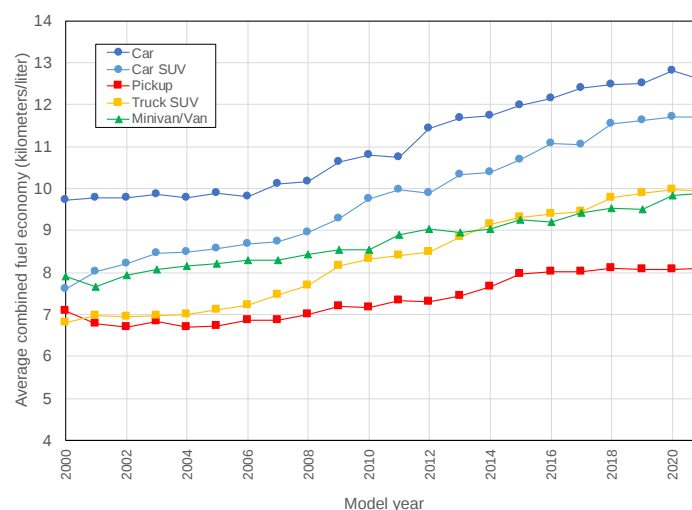


Figure 3. Average internal combustion engine fuel economy by model year and vehicle type, weighted by U.S. sales (combined city/highway kilometers of miles driven per liter of fuel used).

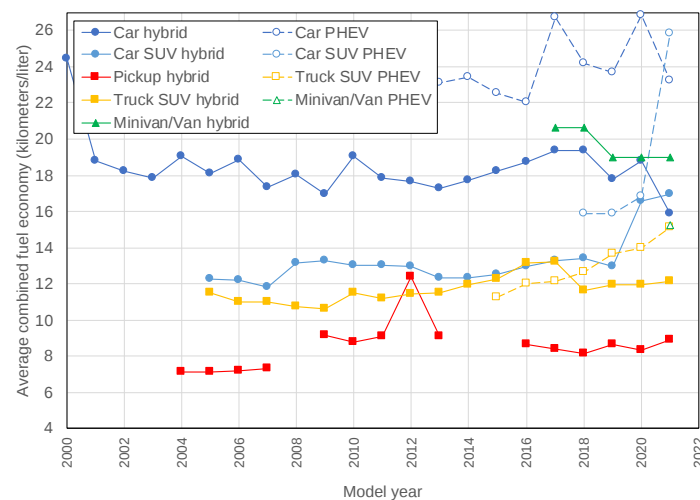


Figure 4. Average hybrid electric and plug-in hybrid electric fuel economy by model year and vehicle type, weighted by U.S. sales (combined city/highway kilometers of miles driven per liter of fuel used).

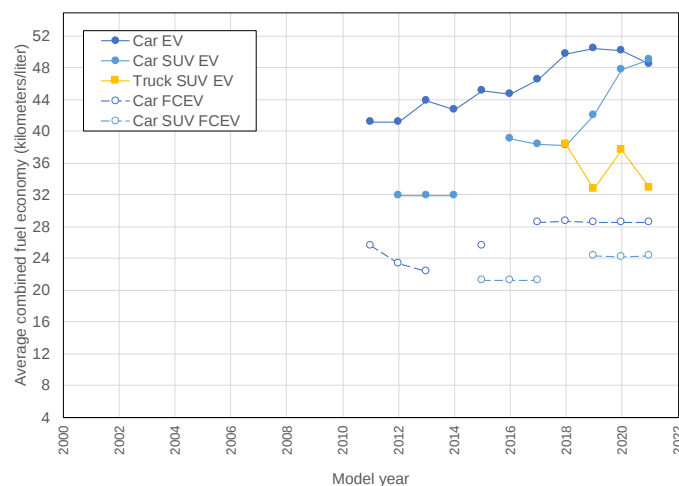


Figure 5. Average battery electric and hydrogen fuel cell vehicle fuel economy by model year and vehicle type, weighted by U.S. sales (combined city/highway kilometers of miles driven per liter of fuel used).

We estimated the average fuel economy in 2020 by vehicle type and powertrain, as shown in Table 2 for vehicles with internal combustion engines and in Table 3 for hybrid electric, plug-in hybrid electric, battery electric, and hydrogen fuel cell vehicles. For the Uber fleet, we used the distribution by vehicle type and powertrain based on the vehicle models after adjusting for models with a hybrid electric version that is not identified in the Uber database. For the California fleet, we used the distribution of California vehicle registrations by vehicle type and powertrain between 2013 and 2018 from a proprietary registration database compiled by IHS Markit (previously R.L. Polk and Co.), linearly extrapolated to 2020. We calculated the average model year as of 2020 for all vehicle types and powertrains from the same two datasets. The distributions and average model year were weighted by actual VKT from the Uber dataset (the distribution of the Uber fleet by model year is essentially identical irrespective of whether the fleet is weighted by the number of rides provided or by total VKT) and the average VKT by vehicle age schedule for cars and light trucks that the EPA uses in the MOVES model [19]. We then assigned the EPA sales-weighted average fuel economy from Figures 3–5 for each average model year shown in Tables 2 and 3 and multiplied the average fuel economy by the distributions by vehicle

type and powertrain to obtain a weighted average fuel economy in 2020 by powertrain for both the fleet of Uber vehicles and all registered vehicles in California, shown in red font in Tables 2 and 3. The fleet of Uber ICE vehicles has a fuel economy 2.5 KPL higher than that of all vehicles registered in California due to a higher fraction of cars vs. other vehicle types (80% vs. 51%) and a fleet that is, on average, one year younger (2013 vs. 2012) than the overall California fleet. Uber hybrid vehicles have a slightly higher average fuel economy than the overall California fleet because of the higher fraction of cars vs. car-based SUVs (crossover utility vehicles, or CUVs).

Table 2. Distribution, average model year, and average EPA fuel economy (kilometers/liter) by ICE vehicle type for Uber vehicles and all vehicles registered in California (2018 IHS Markit extrapolated to 2020).

Vehicle Type	Type Distribution		Average MY		Average EPA KPL	
	Uber	CA	Uber	CA	Uber	CA
Car	79.6%	50.6%	2013	2012	11.7	11.5
Crossover utility vehicle	15.3%	21.9%	2013	2015	10.3	10.7
Pickup	0.3%	14.7%	2013	2009	7.4	7.2
Sport utility vehicle	1.8%	7.7%	2011	2008	8.4	7.7
Minivan	3.0%	3.5%	2011	2010	8.9	8.5
Van	0.0%	1.6%	2016	2011	9.2	8.9
Wtd average			2013	2012	11.3	10.2

The average fuel economy of Uber and California vehicles by powertrain from Tables 2 and 3 were then applied to the distribution of Uber rides and all vehicles registered (from the CARB registration data) in each of the five California regions. The registrations of all California vehicles were weighted by the average of the car and light truck average VKT by vehicle age, taken from the annual VKT by age schedules.

Table 3. Distribution, average model year, and average EPA fuel economy (kilometers/liter) by ICE vehicle type for Uber vehicles and all vehicles registered in California (2018 IHS Markit extrapolated to 2020).

Vehicle Type	Powertrain	Type Distribution		Average MY		Average EPA KPL	
		Uber	CA	Uber	CA	Uber	CA
Car	Hybrid	19.93%	2.45%	2014	2014	17.7	17.7
	PHEV	0.87%	0.26%	2015	2017	23.4	23.4
	BEV	0.38%	0.85%	2017	2018	46.5	49.7
	FCEV	0.05%	0.10%	2018	2018	28.6	28.6
CUV	Hybrid	0.82%	0.21%	2018	2018	13.4	13.4
	PHEV	0.00%	0.02%	2019	2018	15.9	15.9
	BEV	0.02%	0.13%	2018	2018	38.3	38.3
	FCEV	0.00%	0.00%	2019	NA	21.3	21.3
Wtd average Car + CUV	Hybrid			2014	2014	17.5	17.3
	PHEV			2015	2017	23.3	22.8
	BEV			2017	2018	46.1	48.2
	FCEV			2018	2018	28.6	28.6

2.2. Decreased Energy Use from Pooled Rides

TNCs like Uber often allow parties to request a match with another party in order to share the ride and reduce the cost; this ride sharing is often referred to as pooling. The CPUC Uber dataset includes whether a pooled ride was requested and whether a pooled ride request was matched for each ride. During the study period, Uber allowed pooled rides only in the SF Bay Area, LA, and San Diego markets in California. The CPUC Uber

data provide whether, for each ride, the passenger requested a pooled ride and whether that request was successfully matched. Table 4 indicates that only 16% of riders requested a pooled ride; 64% of those requests were successfully matched, for an overall pooling rate of 10% of all rides. Riders in the Bay Area more frequently requested a pooled ride than in LA or San Diego, with a higher successful match rate.

Increasing the rate of matched pooled rides would have little effect on energy use unless a substantial portion of the VKT of two pooling parties overlaps. And riders are less likely to request a pooled ride over a non-pooled ride if the increased wait and travel times exceed the value of the reduced fare. Pooling has the potential to overlap duplicate VKT on longer trips from locations that generate a lot of trips (such as from San Francisco International Airport to downtown San Francisco or the East or South Bays or major events). However, parties making those trips are more likely to consist of two or more passengers and are therefore less likely to request a pooled ride (and they may be constrained by TNC limits on the total number of passengers allowed in a vehicle).

To estimate the effect of pooling on reducing energy use, we multiplied the overall pooling rates from Table 4 by 34% based on the following assumptions. Imagine two solo rides of 1 km each; if two-thirds (0.67 km) of each ride is pooled, and 0.33 km of each ride is not pooled, the total combined VKT of the two pooled rides is 1.33 km, and 1.33 km is 66% of, or 34% less than, two solo rides of 1 mile each. This pooling adjustment factor results in VKT reductions from pooling of 4.8% in the Bay Area, 2.8% in Los Angeles, and 1.6% in San Diego. We tested the effect of these pooling assumptions on our results in a sensitivity analysis, as described in Section 3.

Table 4. Requested and successful pooling rates by region.

Region	Pool Request Rate	Pool Rate	
		Overall	Of Requested
Bay Area	21.2%	14.3%	67.5%
Los Angeles	13.0%	8.3%	64.2%
San Diego	12.9%	4.9%	38.0%
Total	15.9%	10.2%	63.9%

2.3. Ridehail VKT and Increased Energy Use from Between-Ride Deadhead VKT

For the Clean Miles Standard (CMS), the CPUC and California Air Resources Board (CARB) define three segments of ridehail rides, as shown in Table 1. The time/distance the driver spends commuting into a service area to begin their driving shift (and out of a service area at the end of their driving shift) is informally referred to as Period 0 (or P0). We refer to VKT accrued during P0 as commute deadhead VKT.

The CPUC Uber data include the actual distance driven, as measured via the vehicle GPS via the TNC app over the road network, between three time periods for each ride, which refer to Periods 1, 2, and 3 in the CMS regulation developed by the CPUC and the CARB. The three periods are as follows: (1) between when the driver turns on the app or completes the previous ride and when the driver accepts the next ride request (Period 1, or P1); (2) between when the driver accepts the ride request and picks up the passenger (Period 2, or P2); and (3) between when the driver picks up and drops off the passenger (Period 3, or P3). In addition to the actual distance driven during each of these periods, the CPUC Uber data also include the location (the ZIP code) of each of these waypoints, as well as where the driver receives the ride request. The time of each of these waypoints, except for the time when the driver turns on the app or completes the previous ride, is also included. Table 5 shows a sample record from the dataset.

Table 5. Sample record from the CPUC Uber dataset.

Variable	Value
VehicleMake	MAZDA
VehicleModel	MAZDA3
VehicleYear	2009
AppOnOrPassengerDroppedOffZIP	92592
TripReqRequesterZIP	92592
TripReqDriverZIP	92592
TripReqDate	20191221 19:29:56
PeriodOneMilesTraveled	1.11
ReqAcceptedDate	20191221 19:29:59
ReqAcceptedZIP	92592
PassengerPickupDate	20191221 19:33:39
PeriodTwoMilesTraveled	0.50
PassengerPickupZIP	92592
PassengerDropoffDate	20191221 19:49:08
PassengerDropoffZIP	92590
PeriodThreeMilesTraveled	8.00
Pool_Request	N
Pool_Match	N
TotalAmountPaid	14.3
Tip	0
SurgePricing	N
VehicleOccupancy	.

Figure 6 shows the average VKT by ride segment and the fraction of deadhead kilometers (from Table 5, P1 + P2 VKT divided by P1 + P2 + P3 VKT) for each region in the state. The percentage of total VKT that qualifies as between-ride deadhead VKT ranges from 27% in the Bay Area and Los Angeles to 40% in the Central Valley.

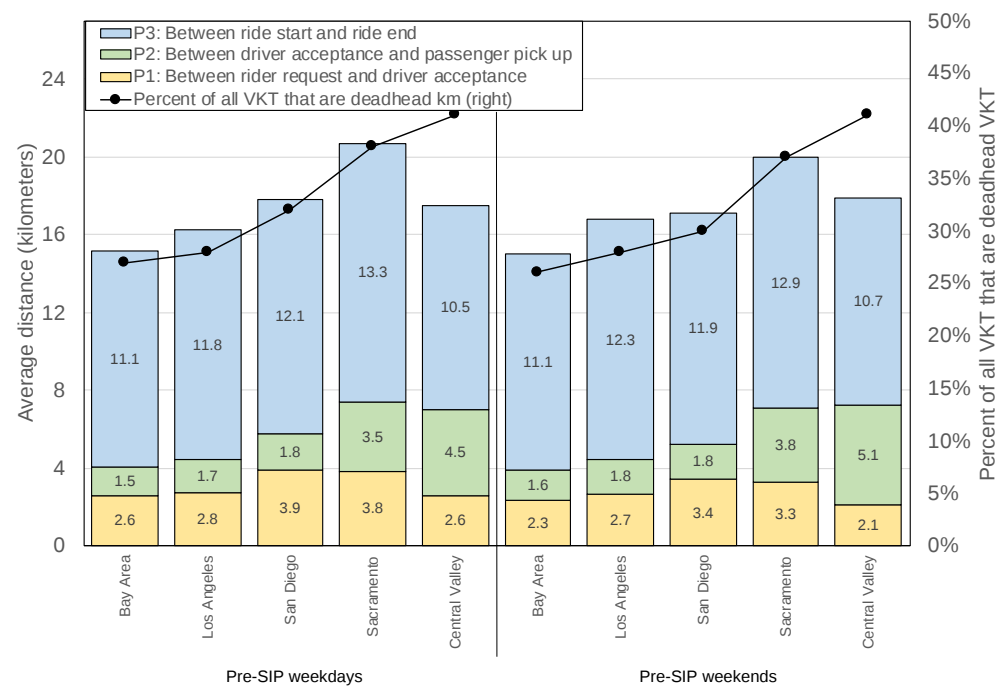


Figure 6. Average VKT by ride segment and percent deadhead kilometers by time period, week-day/weekend, and region.

2.4. Increased Energy Use from Commute Deadhead VKT

Many analyses of the effect of ridehail services on energy use do not include the distance drivers travel without passengers at the start (or end) of their driving shift, which we call commute deadheading [5]. At the start of their shift, drivers travel some distance from their residence to an area with anticipated demand, where they then turn on the app to receive their initial ride request. Similarly, at the end of their shift, drivers turn off the app and travel from the location of their last passenger drop-off to their home.

The CPUC requires TNC operators to provide the home address for each of their drivers; however, this information was redacted from the publicly available dataset. We make use of the recent survey of TNC drivers in three cities [16]. Table 6 shows the distribution of TNC drivers by the distance from their origin (presumably their home) to their primary passenger market for three ridehail markets (San Francisco, Los Angeles, and Washington DC). Nearly 20% of TNC drivers in the SF Bay Area live more than 48 km from their primary market, whereas only 11% of drivers in Los Angeles and Washington DC live more than 48 km from their primary market. The authors assigned the assumed average distance to each distance bin based on the midpoint of each distance bin and calculated the average distance for drivers to their primary ridehail market. The average commute distance for ridehail drivers is 31 km in the SF Bay Area and 23 km in the Los Angeles (and Washington DC) area. These calculated average distances agree with the average distance cited elsewhere in the NRDC report.

To calculate the commute deadhead VKT, we multiplied the average number of drivers per day in each service area by the average (roundtrip) commute VKT in each service area. We assumed a one-way commute distance of 31 km for the SF Bay Area and 23 km for all other California regions.

Table 6. Distribution of distance from TNC driver's home location and primary passenger market for three TNC service areas.

Distance (Kilometers)	Assumed Average Distance (Kilometers)	SF	LA	DC
0	0	10.0%	6.0%	9.0%
0 to 8	4.0	24.0%	24.0%	20.0%
8 to 16	12.1	13.0%	19.0%	23.0%
16 to 24	20.1	13.0%	17.0%	12.0%
24 to 32	28.2	9.0%	10.0%	10.0%
32 to 40	36.2	5.0%	8.0%	10.0%
40 to 48	44.3	5.0%	5.0%	6.0%
48 to 64	56.3	6.0%	4.4%	7.0%
64 to 97	80.5	7.0%	4.0%	3.0%
97 to 129	112.7	2.0%	1.4%	0.3%
129 to 161	144.8	3.0%	1.0%	0.0%
161 to 241	201.2	1.0%	0.1%	0.0%
241+	257.5	0.4%	0.0%	0.0%
Total		98.4%	99.9%	100.3%
Average		30.6	22.5	21.7

2.5. Increased Energy Use from Mode Replacement

A major source of increased energy use from ridehail services is the previous mode the ridehail service replaced. This information is generally only available from surveys of travelers who use ridehail services.

Figure 7 shows the distribution of travel modes replaced by ridehail services taken from five studies. Refs. [3,21] present surveys that were conducted in several U.S. cities ([21]: Austin, Boston, Chicago, Los Angeles, San Francisco, Seattle, and Washington DC; [3]: Boston, Chicago, Los Angeles, New York, San Francisco Bay Area, Seattle, and Washington DC); [22] presents a survey conducted in Austin after the largest TNCs, Uber and Lyft, left that market in 2016; [23] presents a 2018 survey of California ridehail users using both

private and pooled ridehail service; and [16] presents surveys conducted in three cities in 2016 and 2017. The distribution of replaced travel modes varies substantially among these surveys, in part because they do not all use the same definitions of replaced travel modes. There may also be differences in the sampling of survey respondents or the specific wording of the questions asked in each survey. In particular, the shares of drive alone and walk/bike trips replaced by ridehail trips were quite different in the [3,21] surveys, even though six of the same seven cities were included in each. The [16] surveys show fairly consistent results, with most ridehail passengers forgoing public transit (rail or bus, from 36% in DC to 22% in Los Angeles), followed by taxi services (from 37% in DC to 29% in San Francisco), and driving alone (from 18% in Los Angeles to 7% in DC). A relatively large portion of ridehail passengers previously car pooled in Los Angeles (20% compared to only 7% in San Francisco and 6% in DC). Between 4% (DC) and 8% (Los Angeles) of ridehail passengers would not have taken the trip if ridehail services were not available.

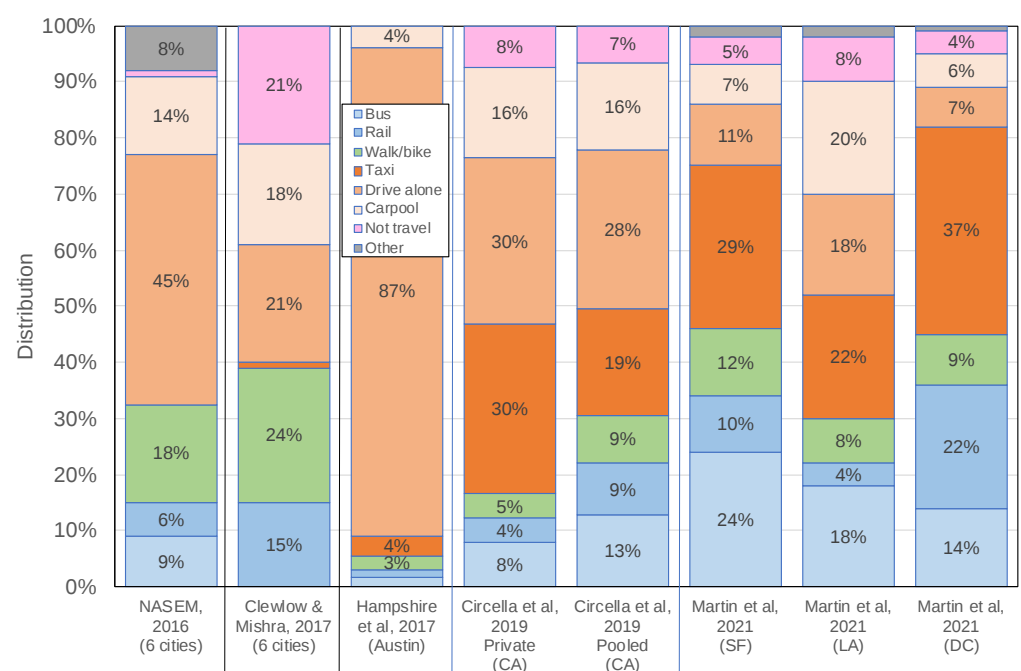


Figure 7. Distribution of travel modes replaced by ridehail services: five studies. Sources: NASEM, 2016 [21]; Clewlow & Mishra, 2017 [3]; Hampshire et al., 2017 [22]; Circella et al., 2019 [23]; and Martin et al., 2021 [16].

Table 7 summarizes the assumptions we used with respect to the mode replaced for each of the five regions. The distributions of replaced modes for the San Francisco Bay Area and Los Angeles are taken from the [16] survey results shown in Figure 7. We assume that the San Diego and Sacramento regions have the same replaced mode shares as Los Angeles. For the Central Valley, we assume zero mode share for commuter/transit rail and half of the replaced mode shares of Los Angeles for all modes except drive alone; the remaining replaced mode is assumed to be drive alone (60%).

Table 8 shows the assumptions regarding the average distance of each trip replaced by a ridehailing service by mode of the replaced trip. Average trip distances by mode were taken from [24] for the Bay Area, Los Angeles, San Diego, and Sacramento regions, as shown in the top portion of Table 8. The average distance of carpool trips was assumed to be the same as a personal vehicle trip in [24] (e.g., 15.1 km in the Bay Area), while the average trip distance of taxi, other, and induced travel trips were assumed to be the same distance as the average Uber trip in each region (e.g., 11.1 km in the Bay Area). Trip distances for the Central Valley and other regions were assumed to have the longest distance in the other four regions for each mode (i.e., 14.5 km for transit buses, as in the [24] for Sacramento).

The average trip distance across all modes in each region was calculated based on the distribution of modes replaced by ridehail trips in Table 7. In most regions, the resulting weighted average distance was higher than the average distance of the replacing Uber ride (e.g., 12.6 vs. 11.1 in the Bay Area). In the bottom portion of Table 8, the average trip distance for all modes other than taxi, other, and induced travel trips were then adjusted by the same scaling factor so that the weighted average distance of all trips by all modes matched the average Uber trip distance. The scaling factor varied from 82% in the Bay Area to 99% in the Central Valley to 107% in the Other region.

Table 7. Assumptions regarding distributions of replaced travel mode by region.

Replaced Travel Mode	Region				
	SF Bay Area	Los Angeles	San Diego	Sacramento	Central Valley
Transit bus	24%	18%	18%	18%	9%
Commuter/transit rail	10%	4%	4%	4%	0%
Walk/bike	12%	8%	8%	8%	4%
Taxi	29%	22%	22%	22%	11%
Drive alone	11%	18%	18%	18%	60%
Carpool	7%	20%	20%	20%	10%
Not travel	5%	8%	8%	8%	4%
Other	2%	2%	2%	2%	2%
Total	100%	100%	100%	100%	100%

Table 8. Assumptions regarding average trip distance (in kilometers) by travel mode and region.

Replaced Travel Mode	Region					
	SF Bay Area	Los Angeles	San Diego	Sacramento	Central Valley	Other
Average Uber ride distance	11.1	12.0	12.0	13.2	14.8	16.4
Transit bus	11.1	12.2	8.8	14.5	14.5	14.5
Commuter/transit rail	31.0	29.7	25.2	42.6	0.0	0.0
Walk/bike	1.3	1.3	1.1	1.6	1.6	1.6
Taxi [†]	11.1	12.0	12.0	13.2	14.8	16.4
Drive alone	15.1	15.0	15.2	15.7	15.7	15.7
Carpool *	15.1	15.0	15.2	15.7	15.7	15.7
Not travel [†]	11.1	12.0	12.0	13.2	14.8	16.4
Other [†]	11.1	12.0	12.0	13.2	14.8	16.4
Estimated wtd average	12.6	13.0	12.3	14.6	14.9	15.5
Scaling factor	82%	89%	96%	86%	99%	107%
Transit bus	9.1	10.8	8.5	12.4	14.3	15.5
Commuter/transit rail	25.4	26.4	24.2	36.6	0.0	0.0
Walk/bike	1.0	1.1	1.1	1.3	1.5	1.7
Taxi [†]	11.1	12.0	12.0	13.2	14.8	16.4
Drive alone	12.4	13.4	14.6	13.5	15.6	16.8
Carpool *	12.4	13.4	14.6	13.5	15.6	16.8
Not travel [†]	11.1	12.0	12.0	13.2	14.8	16.4
Other [†]	11.1	12.0	12.0	13.2	14.8	16.4
Estimated wtd average	11.1	12.0	12.0	13.2	14.8	16.4

Note: Average trip distances for transit bus, commuter/transit rail, walk/bike, and drive alone are taken from the NHTS for the SF Bay Area, Los Angeles, San Diego, and Sacramento regions. Average trip distances for these modes in the Central Valley and other regions are assumed to be the highest of the NHTS distances in the other four regions. * Average distance for carpool trips is assumed to be the same as for drive alone. [†] Average distances for taxi, other, and induced travel trips are all assumed to be the same as the Uber average distance in that particular region.

Table 9 shows the assumptions we used for the average energy use (in passenger kilometers of travel per gasoline liter equivalent) of the replaced mode for each of the five regions. Energy use of transit bus and commuter/transit rail are taken from the reported fuel use and passenger kilometers of travel (PKT) for the transit agencies providing transit, i.e., bus, transit rail, and commuter rail in each region [25]. Ref. [25] provides fuel use in gasoline liter equivalents (GLE) for all fuels but electricity; electricity use is provided in kilowatt hours and converted to GLE by multiplying by a factor of 0.03 [26]. We grouped GLE and PKT for (1) bus, commuter bus, bus rapid transit, and trolleybus from [25] into a transit bus category; (2) light rail, streetcar rail, and cable car into a transit rail category; and (3) commuter rail, heavy rail, monorail, and hybrid rail into a commuter rail category. The transit mode GLE and PKT values for each region are shown in the top rows of Table 9, while the bottom rows of Table 8 show the passenger kilometers per liter for all travel modes. The passenger kilometers per liter values for non-transit modes in Table 9 are taken from Tables 2 and 3 above. Drive alone values are based on the average model year and average fuel economy by model year from the overall registered fleet in each region from Tables 2 and 3. For taxi and “other modes”, which we assume are rental cars, we use the average fuel economy for the Uber fleet from Tables 2 and 3. We assume that the average fuel economy for car pool trips is twice that of the drive alone values for each region.

Table 9. Assumptions regarding average passenger kilometers (PKT) of travel per gasoline liter equivalent (GLE) by travel mode and region.

Measure	Region				
	SF Bay Area	Los Angeles	San Diego	Sacramento	Central Valley
Gasoline liter equivalent (millions)					
Transit bus	85.93	299.90	37.49	15.68	19.39
Transit rail	10.33	17.67	5.63	3.76	0
Commuter rail	56.96	41.84	4.73	0	0
Passenger miles of travel (millions)					
Transit bus	1370	3092	349	120	154
Transit rail	328	745	353	102	0
Commuter rail	3612	1004	93	0	0
Average passenger kilometers per gasoline liter equivalent (PKT/GLE)					
Transit bus *	15.9	10.3	9.3	7.7	7.9
Commuter/transit rail *	58.6	29.4	43.1	27.2	0.0
Walk/bike	0	0	0	0	0
Taxi **	13.1	12.8	12.7	12.5	12.3
Drive alone **	11.8	11.1	11.1	11.0	10.6
Carpool **	23.6	22.2	22.3	21.9	21.1
Not travel	0	0	0	0	0
Other (rental car) **	13.1	12.8	12.7	12.5	12.3

* Transit bus, transit rail, and commuter rail values aggregated from individual full reporter transit agencies in each region from the 2019 National Transit Database. Commuter/transit rail is the PKT-weighted average of the transit rail and commuter rail values for each region. ** Drive alone values based on California registrations, and average fuel economy by average model year, vehicle type, and powertrain from Tables 2 and 3 (average model year). Taxi and other (rental car) values based on Uber registrations and average fuel economy from Tables 2 and 3. Carpool values are twice those of the drive alone values for each region, assuming one passenger in addition to the driver.

Figure 8 compares the magnitude of the change in energy use resulting from ridehail services replacing other travel modes, using the low-energy case. Ridehail services that replaced driving alone in all regions, as well as travel on transit bus in all regions except the Bay Area, actually reduces energy use; the Uber ridehail vehicles have higher average fuel economy and use less fuel than either the average California vehicle or transit buses (transit buses in the Bay Area are more efficient (15.9 PKT/GLE) than the average Uber vehicle (13.1 PKT/GLE), so ridehail trips that replace transit bus trips in the Bay Area result in an increase in energy use). However, ridehail services increases energy use for trips taken

by other replaced modes. In the SF Bay Area, 66% of the net change in energy use comes from replacing trips on transit bus and commuter/transit rail, another 15% from induced travel that would otherwise not have occurred, and 11% from replacing carpool trips. In the other regions, induced travel and replaced carpool trips account for the largest net change in energy use from ridehail services, followed by replaced commuter/transit rail trips. Figure 8 indicates that in the Central Valley, over 60% of the net change in energy use from mode replacement comes from decreased energy use from ridehail services replacing solo driving and travel in transit buses. This decreased energy use offsets the increased energy use from induced travel and replaced carpool travel in the Central Valley.

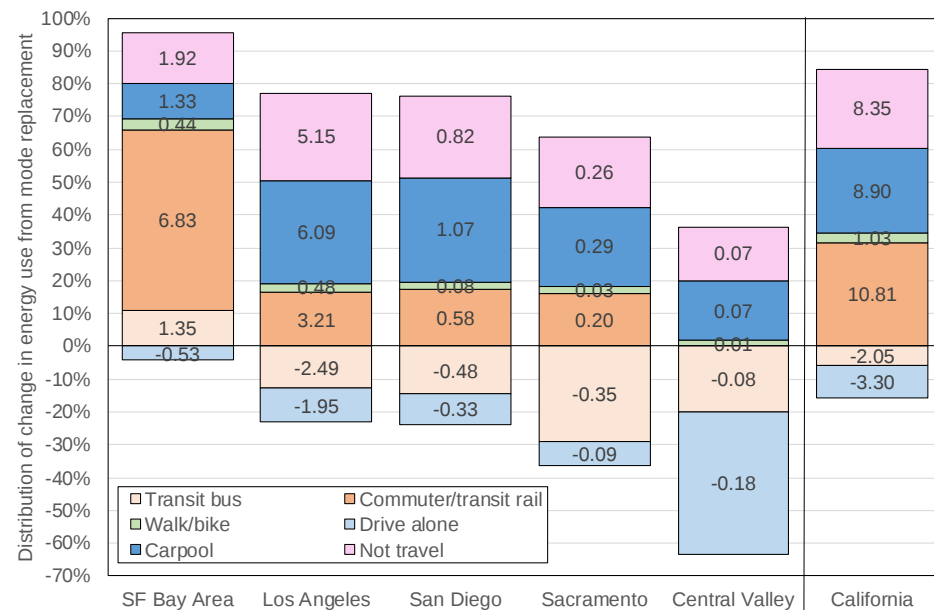


Figure 8. Percent change in energy use from baseline by mode replaced by ridehail services and region: low-energy case (values shown are change in absolute mGLE).

3. Results

We estimate the overall net impact of ridehail services on energy use, accounting for both increases (from between-ride and commute deadheading miles and replaced modes) and decreases (from ridehail vehicles being more efficient than the in-use fleet and the pooling of rides) in energy use, making use of the detailed CPUC data on individual Uber rides and recent surveys of ridehail drivers and passengers conducted in California by UC Berkeley.

First, the energy use of ridehail rides is estimated by multiplying the fuel economy of the average model year of the Uber fleet from Tables 2 and 3 by the VKT of ridehail rides, including deadheading and commuting, for each region. Then, the baseline energy use of each replaced trip is estimated by allocating the total VKT of ridehail rides to the modal distribution of trips that are replaced by ridehail rides (Table 7) based on the average distance by mode (Table 8), including additional travel induced by ridehail services. The passenger kilometers of travel per gasoline liter equivalent of each replaced mode (Table 9) is then applied to these distributions to estimate the baseline energy use of the replaced trips (we assume the same distance of replaced trips on transit vehicles as the ridehail ride, even though the transit trip would likely have been shorter than the ridehail ride directly to the traveler's destination (a transit trip would involve walking to and from the transit stop to the destination)). The analysis is conducted for each of the five regions and other areas in California and then summed to estimate statewide energy use with and without ridehail service.

Figure 9 and Table 10 summarize the net effect of the five aspects of ridehail services that affect energy use in millions of gasoline liters equivalent (mGLE) for the five regions in California and statewide (we do not estimate the effect of ridehail services on the retirement of personally owned vehicles over the longer term and the subsequent elimination of discretionary trips). The “pre-ridehail energy use” in Table 10 refers to the energy use of travel if ridehail services were not available. For reference, the CARB estimates that in 2020, light-duty vehicles used 10,594 mGGE (or 40,098 mGLE) energy annually statewide (<https://ww2.arb.ca.gov/ghg-inventory-data> (accessed on 11 August 2024)). Our analysis of the CPUC Uber data implies that the Uber fleet accounted for 0.5% of the energy use from on-road light-duty vehicles in California in 2020 (92.9 statewide mGLE from Table 10 times by 2 for a full year and divided by 40,098 mGLE total annual energy use from light-duty vehicles = 0.46%). Our estimate compares favorably with the CPUC’s estimate that TNCs were responsible for 0.8% of GHG emissions from light-duty vehicles in California between November 2016 and October 2017 [13]. The effect of each of the five ridehail factors from Table 1 on energy use are shown separately in the top portion of Table 10 and summed as “net energy use”. The bottom portion of Table 10 calculates the percentage difference from the pre-ridehail energy use for each factor and total energy use. Note that the “mode replacement” estimate in Figure 9 and Table 10 assumes that all previous modes are replaced with a personal vehicle with the average fuel economy of the existing on road fleet to avoid double-counting the benefit of more-efficient Uber vehicles in the “mode replacement” category. The additional reduction in energy use from replacing these modes with the average Uber vehicle is estimated in the “more-efficient vehicles” category in the figure and table. Figure 8 shows the percentage change in energy use from replacing the previous mode with the average Uber vehicle, which is more efficient than the average California vehicle.

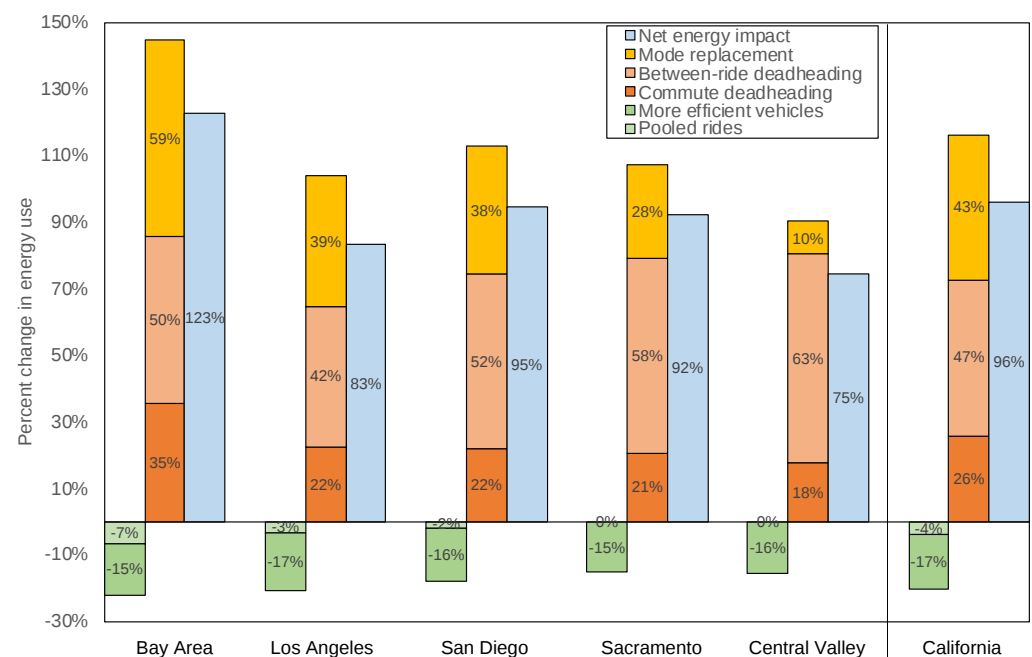


Figure 9. Energy impact of five aspects of ridehail services and their net impact in California by region.

Figure 9 and Table 10 indicate that on the one hand, ridehail services doubled energy use statewide (116% increase) from increased VKT from between-ride (47%) and commute (26%) deadheading, replacing trips that were previously made by more efficient modes (43%). This increase in energy use ranged from a 90% increase in the Central Valley to a 145% increase in the Bay Area. On the other hand, ridehail services reduced energy use statewide by 21% from higher fleet efficiency (−17%) and pooled rides (−4%). This decrease in energy use ranged from a 16% decrease in the Central Valley to a 22% decrease

in the Bay Area. The net effect is a 96% increase in energy use statewide, ranging from a net 75% increase in the Central Valley to a net 123% increase in the Bay Area.

We tested the sensitivity of our baseline results in Figure 9 and Table 10 to four changes in our assumptions; the effect on the baseline results in Table 10 are shown in Table 11 (Tables A1–A4 in the Appendix A show all the values included in Table 10, with the changes from the baseline estimate for each scenario identified by shading in each table). The first scenario assumes a larger decrease in energy use from ridehail services by assuming a greater reduction in VKT from pooled rides and allows for pooling in Sacramento, the Central Valley, and other areas of the state, where Uber did not allow pooling in 2019. We assumed that pooling is made available in the Sacramento region at the same overall pooling rate as in San Diego (4.9%) and in the Central Valley and other regions of the state at half that rate (2.4%). In this scenario, we also assumed that each party in a pooled trip had the same origin and destination, such that the pooled trip reduced the VKT of two separate trips by 50%, an extremely generous assumption, as compared to the 34% VKT reduction from pooling in the baseline case.

The top panel in Table 11 (and Table A1) indicates that the alternate pooling assumptions would have very little impact on the net change in energy use from ridehailing, i.e., from an 88.9 (96%) net increase in mGLE under the baseline results to an 87.1 (94%) net increase statewide. Extending pooling to the regions of the state that currently do not have it (Sacramento, Central Valley, and other regions), albeit at lower match rates than in the Bay Area and Los Angeles, reduces ridehail VKT and net energy use by only a few percentage points.

Table 10. Net change in energy use from ridehail services in California by region (millions of gasoline liters equivalent).

Aspect	Bay Area	Los Angeles	San Diego	Sacramento	Central Valley	Other	Total
Pre-ridehail energy use	26.48	51.65	8.43	2.84	1.75	1.70	92.85
1. Pooled rides	−1.75	−1.65	−0.15	0.00	0.00	0.00	−3.55
2. More-efficient vehicles	−4.08	−8.94	−1.37	−0.43	−0.27	−0.28	−15.37
4. Commute deadheading	9.38	11.61	1.86	0.59	0.31	0.30	24.05
5. Between-ride deadheading	13.29	21.85	4.41	1.66	1.10	1.17	43.47
6. Mode replacement	15.63	20.22	3.24	0.80	0.17	0.25	40.32
Net energy use	32.48	43.09	7.98	2.62	1.30	1.45	88.92
Percent difference from pre-ridehail energy use:							
1. Pooled rides	−7%	−3%	−2%	0%	0%	0%	−4%
2. More-efficient vehicles	−15%	−17%	−16%	−15%	−16%	−16%	−17%
4. Commute deadheading	35%	22%	22%	21%	18%	18%	26%
5. Between-ride deadheading	50%	42%	52%	58%	63%	69%	47%
6. Mode replacement	59%	39%	38%	28%	10%	15%	43%
Net energy use	123%	83%	95%	92%	75%	85%	96%

The second scenario considers that driver and ride data reported by ridehail operator, rather than aggregated by driver, overstate between-ride VKT when a driver has multiple ridehail apps open. The CARB’s analysis of TNC ride data from 2018 found that 22% of all vehicles driven for a TNC worked for at least two TNC companies at the same time and estimated that 11% of all VKT were overlapping VKT when a driver was accruing apparent P1 miles for one TNC while they were driving P2 or P3 miles for another TNC [13]. To account for overlapping VKT by drivers working for multiple TNCs, we subtracted 11% of all VKT in the CPUC Uber data from the between-ride deadhead VKT (based on reported P1 and P2 VKT).

The second panel in Table 11 (and Table A2) indicates that removing 11% of all VKT reduces the amount of between-ride deadhead VKT by 39% statewide, ranging from a 27% decrease in the Central Valley to a 41% decrease in the Bay Area and Los Angeles. Accounting for overlapping VKT decreases the net change in energy use from ridehailing from an 88.9 (96%) net increase in mGLE under the baseline results to a 71.9 mGLE (77%) net increase. These reductions in between-ride deadhead VKT range from a net 57% increase in the Central Valley to a net 102% increase in the Bay Area.

The third scenario assumes a larger increase in energy use from ridehail services by assuming that all taxi services replaced by ridehail services were provided by hybrid electric vehicles rather than vehicles with the fuel efficiency of the average Uber vehicle. Many cities require that a portion of the taxi fleets operating in their area use hybrid electric vehicles; as noted above, 21% of the Uber fleet statewide was made up of hybrid electric vehicles, ranging from 25% in the Bay Area to 13% in the Central Valley.

Table 11. Four scenarios of net change in energy use from ridehail services in California by region (millions of gasoline liter equivalent). Only rows where values change from the baseline estimate in Table 10 are shown; all values in Table 10 under each of the four scenarios are included as Tables A1–A4 in Appendix A.

Scenario and Aspect	Bay Area	Los Angeles	San Diego	Sacramento	Central Valley	Other	Total
Scenario 1: More pooling							
1. Pooled rides	−2.61	−2.46	−0.23	−0.07	−0.02	−0.02	−5.41
Net energy use	31.62	42.28	7.90	2.55	1.28	1.43	87.06
1. Pooled rides	−10%	−5%	−3%	−3%	−1%	−1%	−6%
Net energy use	119%	82%	94%	90%	73%	84%	94%
Scenario 2: Remove 11% overlap VKT							
Pct decrease in P1 + P2 VKT	−41%	−41%	−35%	−31%	−27%	−26%	−39%
5. Between-ride deadheading	7.82	12.93	2.88	1.15	0.80	0.87	26.45
Net energy use	27.01	34.18	6.45	2.11	1.00	1.15	71.90
5. Between-ride deadheading	30%	25%	34%	40%	46%	51%	28%
Net energy use	102%	66%	77%	74%	57%	68%	77%
Scenario 3: 100% hybrid taxis							
Baseline	23.59	47.71	7.80	2.63	1.69	1.68	85.10
6. Mode replacement	18.51	24.16	3.87	1.01	0.23	0.28	48.06
Net energy use	35.36	47.03	8.61	2.83	1.36	1.48	96.67
6. Mode replacement	78%	51%	50%	38%	14%	17%	56%
Net energy use	150%	99%	110%	107%	80%	88%	114%
Scenario 4: 41% more TNC EVs							
Share of EVs	51.8%	34.4%	40.0%	37.0%	27.5%	35.0%	40.8%
1. Pooled rides	−0.76	−0.87	−0.08	0.00	0.00	0.00	−1.70
2. More-efficient vehicles	−24.70	−36.97	−6.22	−1.92	−0.97	−1.03	−71.81
4. Commute deadheading	4.07	6.11	0.91	0.30	0.18	0.16	11.72
5. Between-ride deadheading	5.76	11.50	2.15	0.83	0.63	0.61	21.49
Net energy use	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1. Pooled rides	−3%	−2%	−1%	0%	0%	0%	−2%
2. More-efficient vehicles	−93%	−72%	−74%	−68%	−56%	−60%	−77%
4. Commute deadheading	15%	12%	11%	10%	10%	9%	13%
5. Between-ride deadheading	22%	22%	26%	29%	36%	36%	23%
Net energy use	0%	0%	0%	0%	0%	0%	0%

The third panel in Table 11 (and Table A3) indicates that this scenario reduces the baseline emissions in the baseline estimate in Table 10, i.e., from 92.9 to 85.1 mGLE, as the all-hybrid taxi fleet is more efficient than the taxi fleet in the baseline estimate. This scenario increases the additional energy use from modal shift, i.e., from a 40.3 mGLE (43%) increase statewide in the baseline estimate to a 48.1 mGLE (56%) increase, and from an overall 88.9 mGLE (96%) net increase to a 96.7 mGLE (114%) net increase statewide. The net change in energy use under this scenario ranges from a net 80% increase in the Central Valley to a net 150% increase in the Bay Area.

The CPUC and the CARB have adopted the Clean Miles Standard (CMS), which requires that 90% of ridehail P3 VKT be in zero-emission (e.g., electric) vehicles by 2030 (the CMS also sets a declining CO₂ per passenger kilometer traveled emission standard for ridehail services). Both Uber and Lyft have made commitments to use all-electric-vehicle fleets in the U.S. by 2030 (<https://www.uber.com/us/en/about/sustainability/> (accessed on 11 August 2024); <https://www.lyft.com/impact/electric> (accessed on 11 August 2024)). The bottom panel in Table 11 (and Table A4) shows the additional share of the Uber fleet in each region that would have to be EVs in order to offset the increased energy use from ridehail services from commute and between-ride deadheading and mode replacement: 41% statewide, ranging from 28% in the Central Valley to 52% in the Bay Area.

Increasing the fraction of EVs in the ridehail fleet has an effect on all aspects of ridehail energy use except mode replacement (recall that the mode replacement category only accounts for the change in energy use relative to the average efficiency of the current California fleet; the more-efficient Uber fleet is accounted for in the more-efficient vehicles category). The largest decrease from the baseline estimate comes from more-efficient vehicles (from the 15.4 mGLE decrease in Table 10 to a 71.8 mGLE decrease statewide) and changes the combined a 67.5 mGLE increase in energy use from commute and between-ride deadheading with a combined 33.2 mGLE increase. On the other hand, increasing the fraction of EVs in the ridehail fleet by 41% slightly reduces the energy savings from pooled rides, i.e., from a 3.6 decrease in mGLE statewide to a 1.7 mGLE decrease. For these calculations, we assumed that the average fuel economy of the on-road California fleet remains the same as in the baseline; any increases in the average fuel economy of the on-road fleet would reduce the estimated energy benefits from increasing the fraction of the ridehail fleet that is electric. California recently adopted a regulation to phase out sales of all new ICE vehicles by 2035, at which point 20% could be PHEVs and the remaining 80% must be BEVs.

4. Discussion

While the fraction of Uber rides in hybrid electric vehicles is much higher than the fraction of hybrid electric vehicle registrations, fewer Uber rides were provided in plug-in hybrid and battery electric vehicles than the fraction of registered vehicles with those powertrains. This is likely because of the relatively higher initial cost, shorter range, and longer recharge time of battery electric vehicles compared to hybrid electric vehicles. These factors limit the amount of time during which battery electric vehicles could be used to generate revenue for their drivers. The net effect is that substantially fewer vehicles used for Uber rides had gasoline internal combustion engines than registered vehicles in each region, resulting in a reduction in the energy use per kilometer of travel.

Our analysis of six months of 156 million Uber rides in California in 2019 indicates that ridehail services result in a net 99% increase in energy use throughout the state. While ridehail services consistently resulted in a net increase in energy in metropolitan areas with different characteristics, this increase does vary among the areas. Ridehail services have a larger negative impact in the San Francisco Bay Area, which has a comprehensive public transit system with a larger share of travel met by commuter/transit rail, than in less-dense metro regions such as Los Angeles, where ridehail services replaced more carpool trips. The net increase ranges from 123% in the San Francisco Bay Area to 75% in the Central Valley. Increased energy use from commute deadheading is highest in the San Francisco Bay Area

(35%) and lowest in the Central Valley and other regions of the state (18%), presumably because drivers are willing to commute longer distances to access a large pool of potential riders in large urban areas. On the other hand, increased energy use from between-ride deadheading is highest in the other (69%), Central Valley (63%), and Sacramento (58%) regions, and lowest in the large urban areas surrounding Los Angeles (42%), the Bay Area (50%), and San Diego (52%), presumably because there is less demand for ridehail services and greater distances between passengers in those less dense areas. The increase in energy use from ridehail services replacing other modes is lowest in the Central Valley (10%) and other regions of the state (15%), most likely because ridehail services there mostly replace driving in personal vehicles, which are less efficient than public transit or walking/biking. The increase in energy use from mode replacement is largest in the San Francisco Bay Area (59%) as more of the net energy increase came from ridehail replacing many more trips taken by transit bus and commuter/light rail, which, in the Bay Area at least, use much less energy per passenger kilometer than a ridehail trip. The increase in energy use from ridehail replacing other modes in Los Angeles, San Diego, and Sacramento (28% to 39%) is mostly due to ridehail replacing a large number of carpool trips and, to a lesser extent, inducing additional travel that otherwise would not have occurred in the absence of ridehail services.

Even ignoring commute deadheading, which may have occurred if ridehail drivers had another occupation with a similar commute distance, ridehail services would increase net energy use by 70% statewide (ranging from a net increase of 57% in the Central Valley to 87% in the Bay Area).

Our estimate of the net increase in energy use from ridehail services in California is closer to our earlier high energy (90% increase) estimate than our low energy (41% increase) estimate in Austin. Our estimate of the energy increase from commute and between-ride deadheading (73% combined) is virtually the same as our earlier estimate in Austin (72% combined), as is our estimate of more-efficient vehicles (a 17% decrease in California and a 13% decrease in Austin). However, our estimate of increased energy use from mode replacement (43%) is higher than our high energy estimate (38%) in Austin, while we estimate a much smaller decrease in energy use from pooled rides in California (a 4% decrease) than in Austin (a 30% and 7% decrease in the low and high energy estimates, respectively).

Our current estimate of the net increase in energy use from ridehail services is substantially higher than the 2019 estimates made by the CARB. The CARB estimated that ridehail services result in a net 50% increase in CO₂ emissions after eliminating duplicate VKT from drivers using multiple platforms. While our baseline estimate results in a 96% net increase in energy use statewide, our reducing overlapping VKT scenario results in a 77% net increase in energy use statewide, which is closer to, but still substantially higher than, the CARB estimate.

The CARB estimate is based on 39% of all ridehail VKT being between-ride deadheading; statewide, we estimate that 25% of all ridehail VKT is between-ride deadheading, and 13% commute deadheading. Excluding commute deadheading, we estimate that between-ride deadheading accounts for only 28% of ridehail VKT in our baseline estimate and sensitivity scenarios 1, 3, and 4, and only 19% of ridehail VKT in our sensitivity scenario 2, which removes 11% of overlapping VKT.

CARB found that the fuel economy of the TNC fleet was 13 KPL higher than the CA fleet (39.7 vs. 26.7 KPL); we found only a 4.1 KPL difference statewide (30.3 vs. 26.2 KPL). It is not clear why the CARB estimated such a high fuel economy from TNC vehicles; perhaps their TNC fleet average fuel economy is based on vehicles and not weighted by the number of rides provided or kilometers driven. Our estimates of both the California fleet and the statewide Uber fleet are both weighted by kilometers driven (estimated according to vehicle type and model year for the California fleet), measured for individual trips in the Uber fleet.

The CARB's survey of trip diaries of 31 TNC drivers, providing 2754 rides, indicates that only 12% of all TNC rides surveyed were pooled, which is slightly higher than the observed 10.2% pooled rides in the three regions that allowed pooling in 2019. The CARB's survey indicated that pooled rides had only a slightly higher occupancy rate than non-pooled rides (1.57 vs. 1.54 passengers per ride). This was also observed in the 2019 CPUC Uber data (1.08 vs. 1.06 passengers per ride), but with lower overall occupancy rates than from the CARB survey.

The four scenarios we analyzed indicate that extending pooled ride service throughout the state and better matching the travelers in pooled rides such that each pool reduces total ride VKT by 50% has minimal effect on the net increase in energy use statewide or in the regions that currently do not have pooling. Removing 11% of between-ride deadhead VKT to account for drivers that are driving a passenger for one TNC, which appears as waiting for a ride request from a second TNC, reduces the statewide net energy increase somewhat (i.e., from a 96% increase to a 77% increase). But assuming taxi fleets are all hybrid vehicles, thereby reducing the benefit from replacing taxi trips with ridehail trips, increases our estimate of the net energy increase (i.e., from a 96% increase to a 114% increase). Assuming no additional adoption of EVs in the overall California fleet, we find that ridehail fleets would have to increase the fraction of EVs in their fleets by at least 41% statewide to offset the energy increases from deadhead VKT and mode replacement associated with ridehail services in California.

As our analysis is based on observed data on all rides provided by Uber over a six-month period throughout California, our estimates of the relative efficiency of ridehail vehicles, the fraction of ridehail rides that are pooled, and the amount of between-ride deadheading are extremely accurate. However, our estimates of the travel mode replaced by ridehail services and the distance drivers commute into their primary service area to begin their driving shift are based on surveys of relatively small samples of ridehail passengers and drivers. While there are no comprehensive data on the demographic characteristics of ridehail passengers or drivers, which could be used to determine whether the survey respondents are representative of all ridehail passengers or drivers, UC Berkeley created the survey instruments, conducted the sampling, and analyzed the responses jointly with Uber and Lyft, as well as NRDC, an environmental advocacy organization [16]. We believe that the participation of these organizations, with different objectives in the design and implementation of these surveys, resulted in survey results that are as accurate and unbiased as possible.

Some caveats to our estimates: First, our estimate of ridehail services replacing personal vehicle trips does not consider the slight decrease in energy use from eliminating the need to park a personal vehicle at some distance from the ultimate destination. By providing point-to-point transportation, ridehail services not only eliminate the additional energy use and time from parking but also provide more convenient transportation. In essence, ridehail services trade off the time spent walking to or from where a personal vehicle is parked with wait time for the ridehail driver to arrive at the pick up location. Similarly, ridehail services can reduce overall travel time for travelers that previously rode public transit.

Second, we do not account for travelers changing their destinations and therefore likely increasing the distances of their trips when replacing a public transit, bike, or walk trip with a ridehail ride. The extent to which ridehail services result in travelers accessing locations further away, thereby increasing the VKT from the trip taken via the replaced mode, would result in an even larger increase in the energy use of ridehail services.

Third, we randomly replace vehicles in the Uber fleet with EVs, which have a much higher fuel economy. This scenario does not consider how ridehail drivers might change their behavior when driving an EV. EVs will likely have longer and, depending on their range, perhaps more frequent refueling events, which could impact how intensively they are driven for ridehail service.

Fourth, our Scenario 1 estimate of the effect of pooling on VKT and energy use takes advantage of actual pooling match rates but has to assume what fraction of total VKT of two solo ridehail trips is replaced by a single pooled ridehail trip. It is not clear whether the data TNCs report to the CPUC could be used to estimate the fraction of the VKT of each pooled ride with one or two parties in the vehicle; this information is necessary to better estimate the effect of pooling on reducing ridehail VKT and energy use.

Fifth, since many drivers have multiple ridehail apps open simultaneously, between-ride deadhead (Period 1) VKT reported by one TNC could be between-passenger pickup and drop off (Period 3) VKT for another TNC. The CARB used detailed data from all ridehail providers to estimate that 11% of deadhead VKT overlapped multiple providers; we used this assumption for our Scenario 2 estimates. If, in the future, the CPUC were to include detailed data on rides provided by Lyft, as well as vehicle VIN or license plate data for all individual rides, the amount of overlapping VKT could be estimated more precisely.

Finally, not owning a personal vehicle may induce travelers to forgo some trips altogether that they would otherwise have taken, although this potential long-term change in behavior is difficult to quantify. The [16] survey of ridehail passengers found that 2.5% of ridehail passengers disposed of a personal vehicle at least partially because of the presence of ridehail services, and that 7.8% were less likely to purchase a vehicle in the next few years because of ridehail services. On the other hand, less than 1% of passengers acquired a vehicle at least partially because of ridehail services. These results conflict with a study that found that the introduction of ridehail services in over 240 U.S. cities resulted in a net increase in the number of registered vehicles, possibly as a result of individuals purchasing or leasing a vehicle explicitly to drive for ridehail service. The UC Berkeley survey also includes ridehail passengers' estimates of the number of annual kilometers they drove in personal vehicles that were disposed of or anticipated kilometers in vehicle acquisitions they delayed because of the existence of ridehail services (as well as how many additional kilometers respondents drove in personal vehicles they acquired because of ridehail services). However, the survey did not ask those same respondents how many of those kilometers in personal vehicles were replaced by ridehail trips, or the distance of those trips, or how many replaced trips that were not taken at all. Whether ridehail services result in a net increase or decrease in VKT over the long term as households forego personal vehicle ownership in exchange for shared mobility services is still an open research question.

This analysis demonstrates that prior to the COVID-19 pandemic, the vehicles used for ridehail services tended to be more efficient than the personal vehicles they replace, in part because of a higher fraction of cars (vs. light trucks) and hybrid electric (vs. gasoline) vehicles. However, ridehail drivers were not adopting the cleanest technologies available, i.e., battery electric and plug-in hybrid electric vehicles, at a faster rate than the average Californian. And the potential energy savings from separate travelers pooling their travel in a single ride was not being realized, with only 10% (at best) of all ridehail rides being pooled. This analysis indicates that at least prior to the COVID-19 pandemic, these aspects did not, and likely cannot, overcome the increased energy use from deadhead VKT that ridehail vehicles travel to reach their passengers and from the replacement of low-energy modes, such as walking/biking and public transit, with ridehail services. The economic shutdown in response to the COVID-19 pandemic drastically reduced all travel, especially in travel modes using shared vehicles such as public transit and ridehailing services. Future research is needed to assess whether our estimates of the net effect of ridehailing services on energy use will continue as ridehail services evolve as society recovers from the COVID-19 pandemic.

Our methodology described in this paper can be replicated in any area to estimate the impact of the provision of ridehail services on net energy use, using local data where available. Our results, based on observed detailed data on all individual ridehail trips provided in a region, can be used to calibrate or validate models that simulate ridehail services, such as regional agent-based models of multimodal travel options (BEAM [27] and

POLARIS [28]). Our results can also be used by local and state policymakers in California and elsewhere to assess the contribution of ridehail services to energy use and emissions, both statewide and in cities such as San Francisco and Los Angeles, which have different population densities, transportation systems, and travel trends. The contribution of the five aspects of ridehail services to the net increase in energy use from replacing other modes can be used to estimate the expected effectiveness of policies with which to reduce the carbon footprint of ridehail services. Such policies can range from comprehensive policies, such as the California Clean Miles Standard, to more limited policies, such as pricing incentives to encourage pooling or reduce between-ride deadhead VKT, or the provision of purchase or lease incentives to TNC drivers to encourage their use of electric vehicles.

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Appendix A

Tables A1–A4 show all results for the four sensitivity analyses summarized in Table 11, with the changes from the baseline estimate (in Table 9) for each scenario identified by yellow shading.

Table A1. Net change in energy use from ridehail services in California by region; more pooling (millions of gasoline liters equivalent).

Aspect	Bay Area	Los Angeles	San Diego	Sacramento	Central Valley	Other	Total
Pre-ridehail energy use	26.48	51.65	8.43	2.84	1.75	1.70	92.85
1. Pooled rides	−2.61	−2.46	−0.23	−0.07	−0.02	−0.02	−5.41
2. More-efficient vehicles	−4.08	−8.94	−1.37	−0.43	−0.27	−0.28	−15.37
4. Commute deadheading	9.38	11.61	1.86	0.59	0.31	0.30	24.05
5. Between-ride deadheading	13.29	21.85	4.41	1.66	1.10	1.17	43.47
6. Mode replacement	15.63	20.22	3.24	0.80	0.17	0.25	40.32
Net energy use	31.62	42.28	7.90	2.55	1.28	1.43	87.06
Percentage differences from pre-ridehail energy use:							
1. Pooled rides	−10%	−5%	−3%	−3%	−1%	−1%	−6%
2. More-efficient vehicles	−15%	−17%	−16%	−15%	−16%	−16%	−17%
4. Commute deadheading	35%	22%	22%	21%	18%	18%	26%
5. Between-ride deadheading	50%	42%	52%	58%	63%	69%	47%
6. Mode replacement	59%	39%	38%	28%	10%	15%	43%
Net energy use	119%	82%	94%	90%	73%	84%	94%

Table A2. Net change in energy use from ridehail services in California by region; remove 11% overlap VKT (millions of gasoline liters equivalent).

Aspect	Bay Area	Los Angeles	San Diego	Sacramento	Central Valley	Other	Total
Pct decrease in P1 + P2 VKT	−41%	−41%	−35%	−31%	−27%	−26%	−39%
Pre-ridehail energy use	26.48	51.65	8.43	2.84	1.75	1.70	92.85
1. Pooled rides	−1.75	−1.65	−0.15	0.00	0.00	0.00	−3.55
2. More-efficient vehicles	−4.08	−8.94	−1.37	−0.43	−0.27	−0.28	−15.37
4. Commute deadheading	9.38	11.61	1.86	0.59	0.31	0.30	24.05
5. Between-ride deadheading	7.82	12.93	2.88	1.15	0.80	0.87	26.45
6. Mode replacement	15.63	20.22	3.24	0.80	0.17	0.25	40.32
Net energy use	27.01	34.18	6.45	2.11	1.00	1.15	71.90
Percentage differences from pre-ridehail energy use:							
1. Pooled rides	−7%	−3%	−2%	0%	0%	0%	−4%
2. More-efficient vehicles	−15%	−17%	−16%	−15%	−16%	−16%	−17%
4. Commute deadheading	35%	22%	22%	21%	18%	18%	26%
5. Between-ride deadheading	30%	25%	34%	40%	46%	51%	28%
6. Mode replacement	59%	39%	38%	28%	10%	15%	43%
Net energy use	102%	66%	77%	74%	57%	68%	77%

Table A3. Net change in energy use from ridehail services in California by region; 100% hybrid taxis (millions of gasoline liters equivalent).

Aspect	Bay Area	Los Angeles	San Diego	Sacramento	Central Valley	Other	Total
Pre-ridehail energy use	23.59	47.71	7.80	2.63	1.69	1.68	85.10
1. Pooled rides	−1.75	−1.65	−0.15	0.00	0.00	0.00	−3.55
2. More-efficient vehicles	−4.08	−8.94	−1.37	−0.43	−0.27	−0.28	−15.37
4. Commute deadheading	9.38	11.61	1.86	0.59	0.31	0.30	24.05
5. Between-ride deadheading	13.29	21.85	4.41	1.66	1.10	1.17	43.47
6. Mode replacement	18.51	24.16	3.87	1.01	0.23	0.28	48.06
Net energy use	35.36	47.03	8.61	2.83	1.36	1.48	96.67
Percentage differences from pre-ridehail energy use:							
1. Pooled rides	−7%	−3%	−2%	0%	0%	0%	−4%
2. More-efficient vehicles	−17%	−19%	−18%	−16%	−16%	−17%	−18%
4. Commute deadheading	40%	24%	24%	22%	18%	18%	28%
5. Between-ride deadheading	56%	46%	57%	63%	65%	70%	51%
6. Mode replacement	78%	51%	50%	38%	14%	17%	56%
Net energy use	150%	99%	110%	107%	80%	88%	114%

Table A4. Net change in energy use from ridehail services in California by region; 41% more TNC EVs (millions of gasoline liters equivalent).

Aspect	Bay Area	Los Angeles	San Diego	Sacramento	Central Valley	Other	Total
Share of EVs	51.8%	34.4%	40.0%	37.0%	27.5%	35.0%	40.8%
Pre-ridehail energy use	26.48	51.65	8.43	2.84	1.75	1.70	92.85
1. Pooled rides	−0.76	−0.87	−0.08	0.00	0.00	0.00	−1.70
2. More-efficient vehicles	−24.70	−36.97	−6.22	−1.92	−0.97	−1.03	−71.81
4. Commute deadheading	4.07	6.11	0.91	0.30	0.18	0.16	11.72
5. Between-ride deadheading	5.76	11.50	2.15	0.83	0.63	0.61	21.49
6. Mode replacement	15.63	20.22	3.24	0.80	0.17	0.25	40.32
Net energy use	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Percentage differences from pre-ridehail energy use:							
1. Pooled rides	−3%	−2%	−1%	0%	0%	0%	−2%
2. More-efficient vehicles	−93%	−72%	−74%	−68%	−56%	−60%	−77%
4. Commute deadheading	15%	12%	11%	10%	10%	9%	13%
5. Between-ride deadheading	22%	22%	26%	29%	36%	36%	23%
6. Mode replacement	59%	39%	38%	28%	10%	15%	43%
Net energy use	0%	0%	0%	0%	0%	0%	0%

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