Transportation in Transition:
Data-Driven Sustainability Assessment of Automated, Electric, and Shared Mobility

by

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Abstract

Emerging technologies in transportation, including vehicle automation, electrification, and shared mobility, are poised to transform the mobility paradigm, transportation markets, and travelers' behavior in the coming decades. While improvement in safety, mobility, and energy efficiency yields large benefits to the society, the sustainability outcomes and the net effect of these technologies on energy usage and the environment are unclear. With the transition still in its infancy, there is an opportunity to work proactively to ensure that these emerging technologies develop sustainably. This research broadly focuses on leveraging the synergies of these emerging technologies to improve transportation system efficiency and sustainability. It is intended to shed light on how they impact travel pattern, energy use, and economics of mobility.

This dissertation begins by examining the interactions between connected and automated vehicle (CAV) technology and the environment. Net positive environmental impacts are expected at the vehicle, transportation system, and urban system levels, but a greater vehicle utilization and shifts in travel patterns could cause an energy "rebound effect." Using an econometric model of vehicle miles traveled (VMT) choice under income and time constraints; I estimate elasticities of VMT demand with respect to fuel and time costs. The estimated elasticities are then used to simulate VMT and energy use impacts of full, private CAV adoption under a range of possible changes to the fuel and time costs of travel. I forecast a 2-47% increase in travel demand for an average household. This presents a stiff challenge to policy goals for

reductions in energy use, traffic congestion, and local and global air pollution, as CAV use increases.

Next, I investigate the nexus of electrification and shared mobility by determining range suitability and cost competitiveness of battery electric vehicles (BEVs) for ride-hailing drivers using the 2019 driving data on the Lyft platform. I estimate that, for more than 86% of drivers, their daily travel needs can be met by a fully charged BEV with listed range of 250 miles on at least 95% of days. The results suggest that range and lifetime cost should not be significant barriers to widespread BEV take-up in the ride-hailing business.

Machine learning techniques are utilized to understand the sharing behavior in ride-hailing trips, using a novel dataset from all ride-hailing trips in Chicago in 2019. I find that the travel impedance variables (trip cost, distance, and duration) collectively contribute to 95% and 91% of predictive power in predicting the propensity to share and successful matching, respectively. This implies that pricing signals are more effective to encourage ride sharing. Building on these findings, I provide empirical evidence on the short-run effects of incentives for shared travel in ride-hailing. Using data on all ride-hailing trips in Chicago for eight months from 2019-2020, the effect of a new congestion fee policy change on ridership is estimated. I show that a $1.15 rise in the relative price of a private ride is associated with a 22% relative rise in willingness to share. I find no evidence of a drop in TNC person-trips overall, which indicates that the policy effect is mainly to induce substitution from private to shared rides. The insights from this research can provide guidance to steer the development of these emerging technologies towards desired societal and environmental outcomes and inform short- and long-term policymaking for their sustainable adoption.

Chapter 1. Introduction

1.1. Background

The transportation sector is a vital element of the U.S. economy, comprising roughly 9% of its gross domestic product (GDP) or 1.9 trillion USD annually [1]. It is also currently the largest contributor to greenhouse gas (GHG) emissions among the U.S. economic sectors [2] and the fastest-growing source of GHG emissions and energy consumption globally. Transportation directly generated over 7 gigatons of carbon-dioxide equivalent ($GtCO_2$ eq) GHG emissions worldwide in 2010, or 23% of total global energy-related GHG emissions [3]. In 2019, the transportation sector accounted for 28.5% of total national energy-related GHG emissions in the U.S., according to the U.S. Environmental Protection Agency (EPA) [2]. Recent data from the U.S. Energy Information Administration (EIA) also shows that carbon dioxide (CO_2) emissions from the U.S. transportation sector (1,893 million metric tons or MMt) surpassed CO_2 emissions from the electric-power sector (1,803 MMt) from October 2015 through September 2016 [4]. This is the first time that transportation-sector CO_2 emissions have regularly exceeded CO_2 emissions from the electric power sector since the late 1970s on a 12-month rolling basis. The most recent data from the U.S. EPA confirms that the transportation sector remained as the largest source of emissions since then [5]. In absence of transportation decarbonization, this trend is likely to continue if growth in renewable energy lowers fossil fuel-based electricity generation, leading to continued reduction of power sector emissions.

Within the transportation sector, road-based travel is responsible for the largest share of CO_2 emissions, GHG emissions, and energy use compared to other modes of transportation such as aviation, rail, and marine. Passenger cars, light-duty trucks (including sport utility vehicles, pickup trucks, and minivans), and freight trucks emitted 41.6%, 18.0%, and 22.9%, respectively, of total U.S. transportation-sector GHG emissions in 2018 [2]. Given that emissions from the transportation sector increased more in absolute terms than emissions from any other sector from 1990–2018, transportation emissions must be a key focus of mitigation efforts. Strategic development and deployment of new technologies to curb the environmental impacts of road-based travel can therefore go a long way towards alleviating the environmental impacts and enhancing sustainability and social equity of the transportation sector overall.

1.2. Emerging Technologies in Transportation Sector

Emerging technologies, including vehicle automation, connectivity, electrification, and shared mobility are poised to reshape the transportation sector. Some researchers went as far as describing these technologies as "revolutions" and "disruptions" [6–8]. These transformations have a potential to help or hinder the environmental, economic, and equity implications of future road-based travel, depending on the direction of development, consumer attitudes, and policies [9,10]. A rapidly growing body of research has investigated the potential implications on deploying vehicle automation, connectivity, electrification, and shared mobility. The consensus among recent studies is that only a converging deployment of vehicle automation, connectivity, electrification and shared mobility can radically improve the sustainability of transportation sector (Figure 1-1). In the following, I explain these transformative technologies and elaborate on their potential trade-offs in improving transportation system efficiency, sustainability, and social equity.

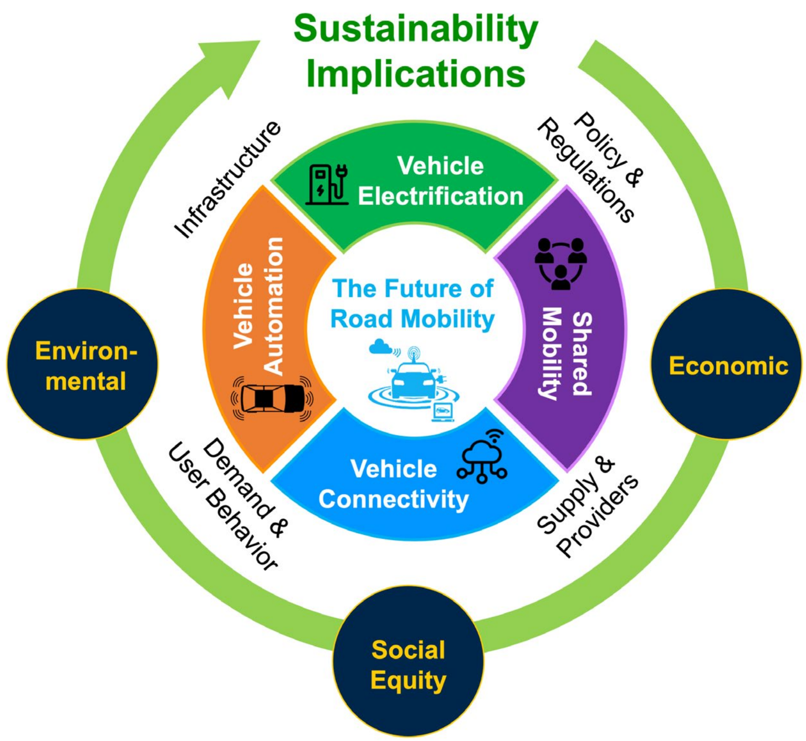

Figure 1-1. The emerging technologies in the transportation sector and the drivers to sustainable adoption.

1.2.1. Vehicle Connectivity and Automation

Vehicle connectivity and automation are separate technologies that could exist independent of each other but have strong complementary attributes. Connectivity refers to a vehicle's capacity to exchange information with other vehicles and infrastructure. This capacity can be realized through Vehicle-to-Vehicle (V2V), Vehicle-to-Infrastructure (V2I), and other cooperative communications networks. Vehicle connectivity is a key enabler of vehicle automation. Vehicle automation refers to any instance in which control of a vehicle capability normally overseen by a human driver is ceded to a computer. Examples of automation commonly seen in vehicles on the market today include cruise control, adaptive cruise control, active lane-keep assist, and automatic emergency braking. A fully automated vehicle can navigate itself by sensing and interacting with the driving environment to reach its destination without human intervention [11–13]. The terms "autonomous" and "automated" are often used interchangeably in the literature, but merit distinction. The former (a subset of the latter) refers to a vehicle capable of navigating without direct input from a human driver, with limited or no communication with other vehicles or infrastructure, while the latter indicates broader classes of vehicle automation. Here, the term "CAV technology" refers to vehicle technology with high levels of automation as well as connectivity capabilities. These two facets of CAV technology are expected to develop in concert.

The Society of Automotive Engineers (SAE) International's J3016 taxonomy classifies vehicle automation by level of driver intervention and/or attentiveness required for operation [14]. To avoid redundancy and confusion, the U.S. National Highway Traffic Safety Administration (NHTSA) agreed to adopt the SAE's categorization, instead of relying on vehicle capabilities [15]. In 2016, the NHTSA proposed mandating V2V connectivity capability on all new cars and light-duty trucks, citing significant potential safety benefits [16]. On September 12, 2017, the U.S. Department of Transportation released updated federal guidelines for the deployment of highly automated vehicle technologies [17]. These guidelines focus on road safety performance and mobility services, without addressing environmental impacts.

The primary purpose of CAV technology is to increase transportation safety and provide better mobility services [17]. However, vehicle connectivity and automation will also inevitably and significantly change the environmental profile of the transportation sector. A growing body of literature has examined the possible environmental implications of CAVs, and has found large uncertainty based in part on the shortage of real-world data for CAV operations [10,18–24].

CAV technology could facilitate either dramatic decarbonization of transportation or equally dramatic increases in transportation-sector emissions. The net environmental impacts of CAV technology depend on lawmaking and decisions at the international, federal, state, and local levels. CAV technology is at the early stage of development. Thus, a forward-looking perspective is needed to properly design, plan, and develop a CAV system that provides both better mobility service as well as desired societal and environmental outcomes.

1.2.2. Vehicle Electrification

Electrification is an indispensable (yet not entirely sufficient) approach towards decarbonizing future mobility. The Intergovernmental Panel on Climate Change declares that electric modes of transportation would "need to displace fossil-fuel powered passenger vehicles by 2035−2050 to remain in line" with pathways to hold global warming to 1.5°C [25]. Electric vehicles (EVs) not only entail higher energy efficiency compared to internal combustion engine vehicle (ICEVs), but also can concentrate emissions from point sources of tailpipes to power plants for more efficient and effective emission control and most importantly to help increase renewable energy integration [26]. If coupled with clean energy, EVs can dramatically cut transportation emissions. Many studies examining the environmental externalities of vehicle electrification have found that EVs usually improve environmental outcomes and remove local pollution from urban cores [27,28]. The specific environmental impacts of EVs are largely determined by when cars are charged and where and how chargers are integrated into the electric grid [29,30]. Emissions from power generation for EVs might in some cases be higher than tailpipes emissions from ICEVs. However, moving emissions from a large number of individual vehicle tailpipes to a few centralized power plants is likely to reduce emission mitigation costs, improve energy efficiency, and help integrate renewable energy in power generation [26,27].

On the other hand, the transportation sector is among the most difficult sectors for electrification and decarbonization, due to decentralized operation, policy conflicts, infrastructure insufficiency, and consumers' lack of awareness, interest, and confidence among other factors. Recent studies have shown even aggressive adoption of EVs cannot alone meet the net zero emission economy targets [31,32]. The market penetration of BEVs is currently hindered by their high cost, arguably short driving ranges, long charging times, and limited charging infrastructure [33,34]. The extent to which BEVs can be accepted by consumers depends on individual travel patterns (travel times, trip length, parking duration), BEV characteristics (driving range, charging rates), charging infrastructure access, economics, and a host of psychological factors [35]. Despite potential benefits, the actual environmental impacts of EVs are affected by many factors, such as unregulated charging, Vehicle-to-Grid (V2G) communications, charge speed, and the degree to which users overcome range anxiety.

There is considerable uncertainty surrounding the rate at which EV technology will continue to advance as well as the rate at which consumer demand for EVs will grow. As such, projections of expected EV deployment over the next two decades vary considerably. While experts disagree about how rapidly EV fleets will expand, there is general consensus that EVs have the potential to interact positively with new transportation technologies and mobility business models [36].

1.2.3. Shared Mobility

Substitution from private to shared mobility reduces congestion, energy use, local air pollution, and global greenhouse gas emissions [6,37,38]. Shared mobility is an effective way to reduce VMT by combining trips that are temporally and spatially similar, generating many benefits including efficiency improvements, fleet downsizing, congestion reduction, energy conservation, and emissions alleviation. On-demand shared mobility services, commonly known as "Transportation as a Service" (TaaS) [39,40] offered by Transportation Network Companies (TNCs) offer flexible, efficient, and convenient mobility, promoted as a remedy for private vehicle dependency, traffic congestion, high parking costs, and environmental pollution. Ride-hailing or ridesourcing is a "prearranged and on-demand (are not allowed to street hail) transportation services for compensation in which drivers and passengers connect via digital applications" [41]. The explosive increase in the adoption of ride-hailing (or ridesourcing) services such as Lyft, Uber, and DiDi can be attributed to the ease of access using a smartphone application along with a higher availability compared to regulated, traditional taxi services [42–45]. TNCs account for a small yet rapidly growing share of transportation miles [46]. Some analysts predict a rapid move from private car ownership to TaaS in the next decade, via on-demand ride-hailing platforms [47] (Figure 1-2).

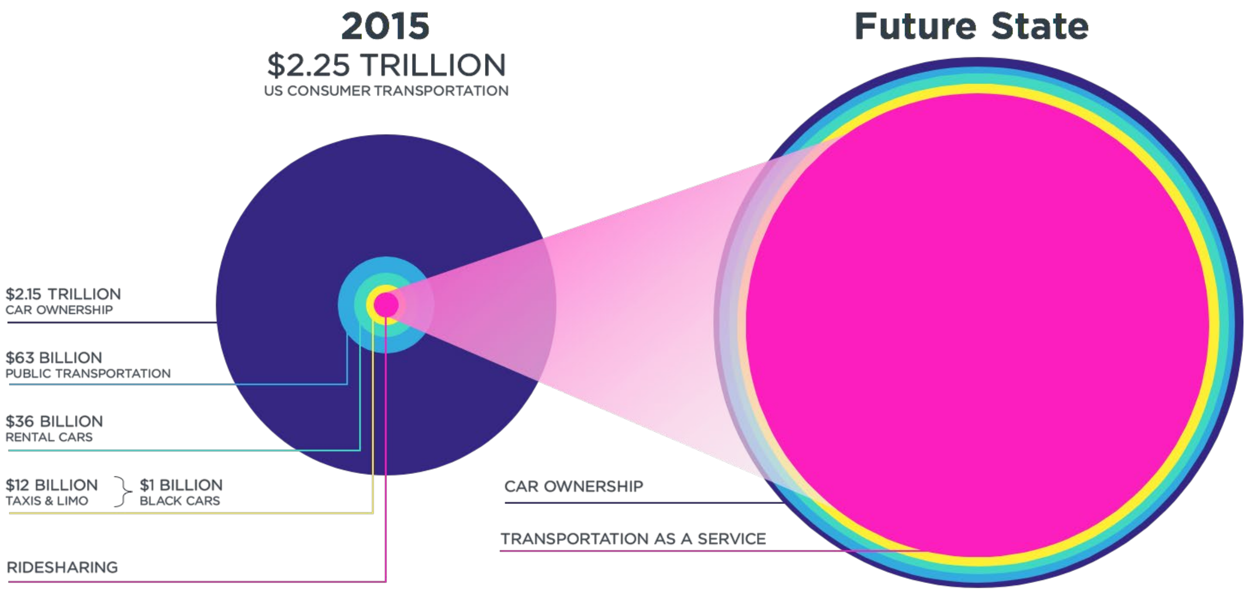

Figure 1-2. The expected rapid growth of Transportation-as-a-Service (TaaS). Source: Bureau of Labor Statistics and Morgan Stanley Research [47].

Recent empirical evidence reveals that the unintended consequences of ride-hailing services may outweigh some benefits by undermining public transportation [48,49], drawing mode share from other more sustainable transportation means [38,50], increasing vehicle ownership [51,52], VMT and deadheading miles [43,53], and leading to aggravated congestion in urban areas [54]. In large U.S. ride-hailing markets it is estimated that 7-13% of total traffic in core counties is attributed to TNCs, while they serve only 2-3% of regional trips [46]. Ride sharing or pooling, in which a rider shares all or some portion of the trip with other passengers, has the potential to mitigate negative impacts of solo ride-hailing by consolidating VMT from multiple spatiotemporally matching trips. The rate of sharing is a key factor in determining the sustainability of ride-hailing compared to other transportation alternatives, especially for future autonomous on-demand mobility services [9,39,55].

1.3. Synergy of Emerging Technologies for Sustainable Transportation

The emerging mobility technologies have significant potentials to enhance smart and sustainable transportation if their development and deployment are converging. Shared mobility, vehicle automation, and electrification have complementary features; they collectively address each other's practical barriers. The economic and environmental impacts of each individual technology are examined in various studies. The synergetic environmental effects and mutual economic benefits, however, have received less attention. Thus, those impacts for smart and sustainable mobility are still relatively nascent. The research presented in this dissertation reflects my contributions to a better understanding of the sustainability implications and synergetic effects of these technologies. Readers are referred to Taiebat & Xu (2019) [33] for a more detailed discussion on synergies of vehicle electrification, automation and shared mobility.

1.4. Structure of the Dissertation and Contributions

My dissertation broadly focuses on system-level analyses of vehicle automation, electrification, and shared mobility, by understanding how they impact travel pattern, energy use, and economics of mobility. The goal of this research is to provide guidance for technology and policy development by leveraging emerging mobility modes to improve **transportation system efficiency**, **sustainability,** and **social equity**. With the transition still in its infancy, there is an opportunity to work proactively to ensure that vehicle automation, electrification and shared mobility technologies develop sustainably and avoid unintended energy, environmental, and equity consequences.

The research presented in this dissertation has been published, or is currently under consideration at the following journals with these co-authors:

- **Chapter 2**: Taiebat, M., Brown, A.L., Safford, H.R., Qu, S. and Xu, M., 2018. A review on energy, environmental, and sustainability implications of connected and automated vehicles. *Environmental Science & Technology*, *52*(20), pp.11449-11465. (Among top 10 most downloaded articles in ES&T for 12 consecutive months)
- **Chapter 3**: Taiebat, M., Stolper, S. and Xu, M., 2019. Forecasting the impact of connected and automated vehicles on energy use: a microeconomic study of induced travel and energy rebound. *Applied Energy*, *247*, 297-308.
- **Chapter 4**: Taiebat, M., Stolper, S. and Xu, M., 2021. Widespread range suitability and cost competitiveness of electric vehicles for ride-hailing drivers. *Under Review*.
- **Chapter 5**: Taiebat, M., Amini, E. and Xu, M., 2021. Sharing Behavior in Ride-hailing Trips: A Machine Learning Inference Approach. *Transportation Research Part D: Transport and Environment*.
- **Chapter 6**: Stolper, S., Taiebat, M., and Xu, M., 2021. Ridesharing incentives to reduce externalities from energy use. *Manuscript in Preparation*.

The remainder of the dissertation is organized as follows. Chapter 2 is intended to foster understanding and discussion of the likely and potential environmental implications of CAV technologies by reviewing existing studies and identifying key research needs. I define environmental impacts broadly in this chapter, including not only downstream emissions and wastes, but also upstream resource and energy demands. I also discuss some socioeconomic aspects of CAV adoption that are associated with energy and the environment. The review includes some environmental impacts that could be realized through vehicle automation alone, but most impacts require automation in conjunction with connectivity. I begin by developing a holistic framework for analyzing different levels of interactions between CAVs and the environment (Section 2.1). I then survey the quantitative results of relevant studies and critically evaluate the key assumptions and conclusions of each (Section 2.2).

In Chapter 3, I use an econometric model to forecast the induced travel and rebound from CAVs using data on existing travel behavior. I develop a microeconomic model of VMT choice under income and time constraints; it is then used it to estimate elasticities of VMT demand with respect to fuel and time costs, with fuel cost data from the 2017 United States National Household Travel Survey (NHTS) and wage-derived predictions of travel time cost. I find evidence that wealthier households have more elastic demand, and that households at all income levels are more sensitive to time cost than to fuel cost. I use the estimated elasticities to simulate VMT and energy use impacts of full, private CAV adoption under a range of possible changes to the fuel and time costs of travel. I forecast a 2–47% increase in travel demand for an average household.

Chapter 4 investigates the range suitability and cost competitiveness of BEVs for ride-hailing drivers using 2019 driving data on the Lyft platform. I estimate that, for more than 86% of drivers, their daily travel can be met by a fully charged BEV with listed range of 250 miles for at least 95% of days. New and pre-owned BEVs both appear to be cost-saving for many drivers. I estimate that a $5,700 BEV purchase subsidy would make new BEVs cheaper than gas-powered vehicles for all Lyft drivers, holding annual mileage and vehicle prices constant. The results suggest that range and lifetime cost should not be significant barriers to widespread EV take-up in the ride-hailing business.

In Chapter 5, I use machine learning techniques to under the sharing behavior in ride-hailing trips, using a novel dataset from all ride-hailing trips in Chicago in 2019. I find that the travel impedance variables (trip cost, distance, and duration) collectively contribute to 95% and 91% of the predictive power in determining whether a trip is requested to share and whether it is successfully shared, respectively. This implies that pricing signals are most effective to encourage riders to share their rides.

Building on these findings, in Chapter 6, I provide empirical evidence on the effects of incentives for shared travel in ride-hailing. The city of Chicago has implemented a congestion pricing policy in the ride-hailing sector, incentivizing shared ridership. I use data on all ride-hailing trips in Chicago for eight months from 2019-2020 to estimate the effect of this policy change on ridership. I find that willingness-to-share (WTS) in Chicago's ride-hailing trips has been on a downward trend but rose suddenly and precipitously after the introduction of the congestion pricing policy. I show that a \$1.15 rise in the relative price of a private ride is associated with a 2.4 percentage points rise in WTS without a statistically significant reduction in ridership. The results suggest that governments may be able to drive reductions in energy use and its externalities through strengthening the incentive to share ride-hailing trips.

Finally, in Chapter 7, I identify knowledge gaps, draw conclusions on the findings and offer recommendations for future research in the nexus of sustainability and emerging mobility technologies.

Chapter 2. Energy, Environmental, and Sustainability Implications of Connected and Automated Vehicles

2.1. Levels of Interactions between CAVs and the Environment

CAV technology interacts with the environment at different scales and levels of complexity. I define four levels of interactions between CAVs and the environment—the *vehicle* level, *transportation system* level, *urban system* level, and *society* level—as illustrated in Figure 2-1. Interactions generally increase in complexity from the vehicle level to society level and may stem from CAV technology directly or CAV-facilitated effects.

The most direct and well-studied interactions occur at the vehicle level. At this level, connectivity and automation physically alter vehicle design and operation. At the transportation system level, CAV technology can drastically change how vehicles interact with each other in the driving environment. At the urban system level, CAV-based transportation interacts with a wide range of infrastructure in the urban environment such as roads, power grids, and buildings, thereby altering how urban systems utilize resources and energy and generate emissions and waste. Finally, how the public perceives and how the government regulates CAVs can have profound effects at the society level.

Generally, higher-level interactions will have farther-reaching implications despite often receiving less attention (Table 2-1). Higher-level interactions are also more difficult to quantify and are associated with greater uncertainty. Many important questions at high levels are beyond the scope of quantitative or predictive modeling and must instead be addressed qualitatively. Because research focusing on CAV environmental implications is just emerging in recent years, a large body of literature is in the form of reports and white papers. In order to make this review as comprehensive as possible, this analysis is based on not only peer-reviewed studies but also reputable reports and documents containing consensus quantitative results. Key sources are classified based on scope in Table 2-2.

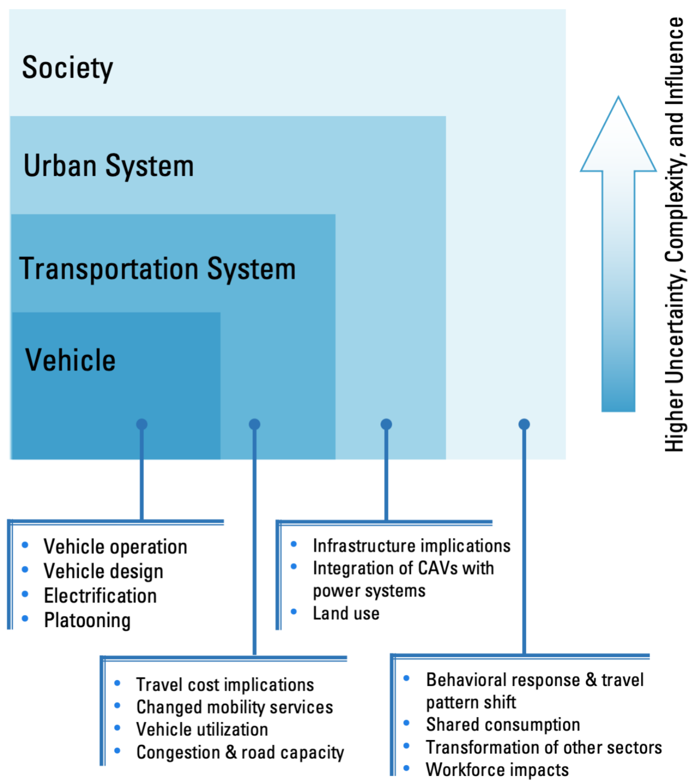

Figure 2-1. Levels of interactions between CAVs and the environment and corresponding major influence mechanisms.

Table 2-1. Summary of key environmental impacts at each level of CAV-environment interaction.

	Major Influencing Mechanisms	Positive Impacts	Negative Impacts	Sources
Vehicle	• Vehicle operation • Vehicle design • Electrification • Platooning	• Higher energy efficiency - Optimal driving cycle - Eco-routing - Reduce cold starts - Less idling - Less speed fluctuations - Powertrain downsizing - Self-parking • Safety enabled vehicle light-weighting • Vehicle right-sizing • Complementary electrification benefits • Platooning	• Faster highway speeds • Additional ICT equipment needs for navigation and communication • Aerodynamic shape alteration • Higher auxiliary power requirement	[10,11,19,20,22,56–61]
Transportation System	• Travel-cost implications • Changed mobility services • Vehicle utilization • Congestion and road capacity	• Greatly reduced human labor costs • Promotion of shared mobility • Integration with mass transit • Fleet downsizing • Increased effective roadway capacity • Decongestion • Fewer crashes and less accident-related traffic • Syncing with traffic lights	• Higher vehicle utilization rate • More frequent and longer trips result in greater vehicle-miles traveled • More unoccupied travel (for parking, between trips, etc.) • Congestion increases due to induced travel • Competition with mass transit	[10,19,20,22,37,56,58,62–70]
Urban system	• Infrastructure implications • Integration of CAVs with power systems • Land use	• Changes in land-use patterns • Reduced need for parking infrastructure • Integration with power systems through vehicle electrification • Reduced need for highway lighting and traffic signals	• Increased urban sprawl • Need for large, energy-intensive data centers	[20,63,71–74]
Society	• Behavior response and travel pattern shift • Shared consumption • Transformation of other sectors • Workforce impacts	• Promotion of shared consumption • Spillover effects to other sectors	• Induced travel demand and rebound effect • Transportation modal shift (e.g., rail/aviation to road travel) • Gradual unemployment and job displacement	[22,56,64,75–80]

Table 2-2. Classification of relevant CAV studies by scope.

	Study	Vehicle	Transp. Sys.	Urban sys.	Society
*	Alonso-Mora et al. [63]		✓		
	Anderson et al. [13]	✓	✓	✓	✓
*	Auld et al. [64]		✓		
*	Bansal and Kockelman [76]				✓
	Barth et al. [58]	✓	✓		
*	Bauer et al. [81]	✓	✓		
	Brown et al. [20]	✓	✓	✓	✓
*	Chen et al. [70]		✓	✓	
*	Chen et al. [82]	✓			
*	Childress et al. [56]		✓	✓	✓
*	Crayton and Meier [83]				✓
*	Fagnant and Kockelman [68]	✓	✓		
*	Fox-Penner et al. [84]			✓	
	Fulton et al. [85]	✓	✓		
*	Gawron et al. [23]	✓			
*	Gonder et al. [86]	✓			
	Greenblat & Shaheen [37]	✓	✓	✓	✓
*	Greenblatt and Saxena [19]	✓	✓	✓	
*	Harper et al. [78]				✓
*	Heard et al. [87]				✓
*	Kang et al. [62]	✓	✓	✓	
*	Kolosz and Grant-Muller [73]		✓	✓	
*	König and Neumayr [88]				✓
*	Kyriakidis et al. [79]				✓
*	Lavrenz and Gkritza [89]	✓		✓	
*	Li et al. [74]	✓		✓	
	Liu et al. [90]	✓			
*	Lu et al. [65]		✓	✓	
*	Malikopoulos et al. [91]	✓	✓		
*	Mersky and Samaras [57]	✓			
*	Moorthy et al. [92]		✓		
	Prakash et al. [93]	✓			

	Rios-Torres and Malikopoulos [59]	✓	✓		
	Stephens et al. [22]	✓	✓	✓	✓
*	Stern et al. [67]	✓			
*	Wadud [94]		✓		✓
*	Wadud et al. [10]	✓	✓	✓	✓
*	Wang et al. [95]	✓			
*	Wu et al. [96]	✓			
*	Zakharenko [97]		✓	✓	
*	Zhang et al. [98]			✓	
*	Zhang et al. [99]		✓		

Asterisk (*) indicates publication in a peer-reviewed journal. Sorted alphabetically based on first author.

2.2. Environmental Impacts of CAV at Each System Level

2.2.1. Vehicle Level

At this level, the direct environmental effects of CAV technology on a per vehicle basis are considered. These effects can also manifest in fleets. Many studies have focused on the vehicle-level and show that individual CAVs are generally more energy efficient and generate less emissions than conventional vehicles [10,19,22]. These benefits at the vehicle-level can be attributed to four major factors: operation, electrification, design, and platooning.

Vehicle operation: A number of references discuss the potential for vehicle automation to improve car-centric energy efficiency by optimizing vehicle operation: i.e., by maximizing the operation of vehicles at the most efficient mode [13,20,58,69]. Efficient driving broadly translates into improved fuel economy, reduced energy consumption, and abated tailpipe emissions. Higher driving efficiency can be achieved in CAVs through a variety of mechanisms, including optimal driving cycle, dynamic eco-routing, less idling, reducing cold starts, trip smoothing, and speed harmonization [10,20,67,68,96]. These mechanisms are discussed below.

Different human drivers in identical situations make different real-time decisions, often leading to sub-optimal results [12]. In CAVs, eliminating heterogeneity between drivers and improving driving decision-making helps optimize the driving cycle. Barth and Boriboonsomsin reported that, even when drivers remain "in the loop" of vehicle operation (i.e., at a level of involvement less than conventional driving but one that falls short of full automation), providing dynamic feedback to drivers results in up to 20% fuel savings and decreased CO_2 emissions without a significant increase in travel time [69]. The information gathered from vehicle connectivity also enables optimal route selecting, widely known as dynamic eco-routing [58,69,100]. Gonder et al. estimated the potential energy savings of eco-routing in a Chevy Bolt at around 5% [86]. Trip smoothing and speed harmonization are other practices that aim to minimize repeated braking-acceleration cycles through intelligent speed adaption, smooth starts, fewer speed fluctuations, and eliminating unnecessary full stops.

CAV technology substantially facilitates and amplifies these practices. Wu et al. estimated that partial automation in conjunction with connectivity can reduce fuel use by 5-7% compared to human driving when automation enables vehicles to closely follow recommended speed profiles [96]. At the fleet level, cooperative communications between vehicles can further reduce energy use, with up to 13% fuel savings and 12% reductions in CO_2 emissions reported in experiments [58]. Prakash et al. suggested that 12-17% reduction in fuel use can be achieved when a CAV is trailing a lead vehicle with the specific objective of minimizing accelerations and decelerations [93]. Based on experiments, Stern et al. found that introducing even a single CAV into traffic dampens stop-and-go patterns, resulting in up to 40% reductions in total traffic fuel consumption [67]. Rios-Torres and Malikopoulos developed a simulation framework for mixed traffic (CAVs interacting with human-driven vehicles) and reported that the fuel-consumption benefits of CAVs increase with higher CAV penetration [59]. Chen at al. suggested a wider range of changes in fuel consumption (between -45% to +30%) that would result from transitioning from conventional to CAV fleets at the U.S. national level [82].

Less idling and fewer cold starts can help reduce energy waste and mitigate emissions. Cold starts are a major contributor to a number of criteria air pollutants from the transportation sector, including volatile organic compounds (VOCs), NO_x, and CO [58,101]. Simulations demonstrated fewer cold starts for shared automated taxis [68]. In such vehicles, since no aggressive acceleration is needed, powertrains can also be downsized. This is especially relevant for automated shared mobility services in urban areas where more energy use is due to acceleration rather than from high-speed wind resistance [10]. Self-parking features also save time and limit braking-acceleration cycles, reducing energy intensity by approximately 4% [20].

On the other hand, some attributes of CAVs may result in more energy consumption. Radar, sensors, network communications, and high-speed internet connectivity require higher auxiliary power from vehicles, which manifests as greater power draw and consequently higher energy consumption [102]. Energy demands for connectivity components, sensing, and computing equipment can significantly alter the overall energy efficiency of CAVs [23]. Additionally, improved safety in CAVs may induce higher highway speeds. Since aerodynamic drag forces increase quadratically with speed, higher highway speeds result in higher fuel consumption above a certain threshold [58]. For instance, a speed increase from 70 to 80 mile per hour (MPH) is reported to increase average energy use by 13.9% per mile [103]. Wadud et al. and Brown et al. suggested that typical driving at above-optimal speeds tends to decrease overall fuel economy by 5%-22% [10,20]. This decrease may offset—and indeed, overwhelm—increases in engine efficiency. It is conceivable that improved safety in CAVs could enable relaxation of speed limits for roadways where vehicles are currently restricted to below-optimal speeds, resulting in some energy savings. This point received less attention in the literature.

The extent to which CAV-related increases in vehicle energy consumption will offset gains in energy efficiency is unclear. CAV technology could lead to substantial net improvements in fuel economy and emissions reduction if the negative effects are minimized and the positive realized. Mersky and Samaras raised the question of how to test and measure fuel efficiency of CAVs by updating EPA rating tests [57]. They developed a method for testing fuel economy of CAVs using the existing EPA test procedure and showed that fuel economy differences for the CAV tests range from -3% to +5% compared to the current EPA testing procedure.

Electrification: Many studies examining the environmental externalities of vehicle electrification have found that electric vehicles (EVs) usually improve environmental outcomes and remove local pollution from urban cores [27,28]. The specific environmental impacts of EVs are largely determined by when cars are charged and where and how chargers are integrated into the electric grid. Emissions from power generation for EVs might in some cases be higher than tailpipes emissions from vehicles with internal combustion engines. However, moving emissions from a large number of individual vehicle tailpipes to a few centralized power plants is likely to reduce emission mitigation costs, improve energy efficiency, and help integrate renewable energy in power generation [27]. Offer et al. demonstrated that plug-in hybrid electric vehicles (PHEVs) and battery electric vehicles (BEVs) have much lower life-cycle costs and emissions compared to fuel cells or internal combustion engines vehicles [104]. Despite potential benefits, the actual environmental impacts of EVs are affected by many factors, such as unregulated charging, Vehicle-to-Grid (V2G) communications, charge speed, and the degree to which users overcome range anxiety. The effects of these factors remain uncertain and require more research.

CAV technology can provide a strong complement to EV technology, potentially solving some of the challenges of EV development [20]. In electric CAVs, on-board energy management strategies can be explicitly designed and implemented to take advantage of synergies between electrification and automation. For instance, an electric CAV could optimize route selection and driving cycle to reduce battery draining, maximize energy recovery via regenerative braking, and extend the battery life.

CAVs can also mitigate the range restriction of EVs by matching appropriately ranged vehicles to individual trips,[70] and take advantage of the energy and environmental benefits brought by vehicle electrification. Offer argued that even if electric CAVs substantially increase vehicle utilization, they will have a large positive impact on transport decarbonization and will curb global GHG emissions by improving the economics of electrification [60]. Shared automated electric vehicles (SAEVs) magnify benefits by orders of magnitude [84]. Greenblatt and Saxena suggested that electric automated taxis can reduce per-mile GHG emissions by more than 90% compared to using conventional vehicles for daily travel [19]. Bauer et al. simulated the operation of SAEVs in NYC, and found that under the current power-grid mix, SAEV fleet would generate 73% fewer GHG emissions and consume 58% less energy than a non-electrified automated fleet [81].

Vehicle design: The size and weight of a vehicle have direct impacts on the vehicle’s fuel economy, and consequently on its overall environmental performance. The composition of the vehicle body indirectly influences the life-cycle environmental impacts of the vehicle via resource and energy requirements associated with the supply chain. CAV engineering is expected to enable a number of efficiency-improving design practices, such as vehicle right-sizing and safety-enabled vehicle light-weighting. On the other hand, more carbon-intensive materials are needed in CAVs, which could increase overall per-vehicle weight as well. Differences in CAV design strategies among automakers and the evolution of CAV design over time add uncertainties to analysis of CAV-related environmental impacts.

(a) Vehicle light-weighting: A number of recent studies have addressed the life-cycle environmental impacts of vehicle light-weighting using alternative materials. Several report that each 10% reduction in vehicle weight yields on average a direct fuel economy improvement of 6-8% [20,105]. In a highly connected and automated vehicle system, transportation safety can be significantly improved by eliminating human errors in driving. As a result, once CAVs make up the vast majority of on-road active vehicles, crashworthiness of vehicles becomes less crucial, and vehicles can become smaller with less safety equipment. Safety features contributed to 7.7% of total vehicle weight in an average new U.S. vehicle in 2011 [10]. If these features could be safely removed, an estimated 4.6-6.2% improvement in fuel economy could be realized [20]. Moreover, environmental impacts associated with the life-cycle of the eliminated vehicle safety features could also be avoided.

Reduced safety equipment in CAVs also leads to more optimal and smaller powertrains, further improving fuel economy. Wadud et al. suggested “de-emphasized performance” as another potential option that would further downsize the powertrain of CAVs and save up to 5% of fuel consumption [10]. Conventional vehicles typically have power capabilities far in excess of their average power requirements to satisfy occasional high-performance demands such as freeway merging. The ability of CAVs to smooth speed profiles, coupled with the high potential of CAVs to serve in shared mobility services, means that peak power demand could be significantly reduced.

(b) Vehicle right-sizing: Another opportunity that could be realized from widespread use of CAVs is vehicle “right-sizing”. According to 2017 National Household Travel Survey, single and double-occupant vehicle trips respectively accounted for 58% and 25% of total annual vehicle-miles-traveled (VMT) in passenger trips made in the U.S., and the average occupancy of light-duty vehicles was just 1.67 passengers [106]. There is significant potential for vehicle size optimization by matching specific vehicles to specific trips to avoid wasted capacity and thus associated environmental impacts. In the case of automated taxis or shared automated vehicles (SAVs), a vehicle could be dispatched based on a passenger’s needs (e.g., a smaller vehicle for a solo traveler). Greenblatt and Saxena studied trip-specific (i.e., right-sized) automated taxis based on the average proportion of occupants and total VMT. They concluded that trip-specific automated taxis could improve the fuel efficiency of fleets by 30-35% [19]. Wadud et al. investigated an extreme scenario in which all trips occur in optimally sized vehicles. In this scenario, solo travelers travel in single-occupant CAVs with the energy efficiency of motorcycles (half the fuel economy of a compact car), two-person groups travel in compact cars, groups of 3–4 travel in mid-size vehicles, and groups of 5 or more travel in minivans. They reported that such a scenario would yield fuel savings of 45% [10]. While right-sizing 100% of vehicle trips may be an unrealistic goal, this demonstrates the high potential of CAV right-sizing for improving fuel economy and consequently reducing environmental impacts.

(c) ICT equipment and aerodynamic shape alteration: Figure 2-2 shows a schematic view of information and communications technology (ICT) devices that could be added onto a generic CAV. Manufacturing ICT devices is highly carbon-intensive [107], which increases GHG emissions associated with vehicle manufacturing. Moreover, additional ICT devices in CAVs are expected to consume more auxiliary power, which implies more operational energy use [102]. Although highly uncertain, Gawron et al. suggested that CAV subsystems and ICT equipment could increase a vehicle's life-cycle primary energy use and GHG emissions by 3-20% due to increases in power consumption, weight, and data transmission [23].

Furthermore, adding ICT devices such as GPS antennae and LIDAR (Light Detection and Ranging) could alter vehicle aerodynamics. ICT devices can create sharp edges and increase frontal projected area, both generate turbulence around the vehicle at high speeds and force the vehicle to consume more energy to maintain its performance. This could dramatically reduce CAV fuel efficiency at high speeds. There is no empirical data to evaluate how significantly add-on ICT devices affect aerodynamics and efficiency, but the magnitude of impacts can be roughly approximated using effects of roof racks on conventional vehicles. Chen and Meier reported that a roof rack can increase a passenger car's fuel consumption by up to 25% [108]. Future CAV designs could integrate ICT equipment into the vehicle body better than the example shown in Figure 2-2, potentially improving aerodynamics.

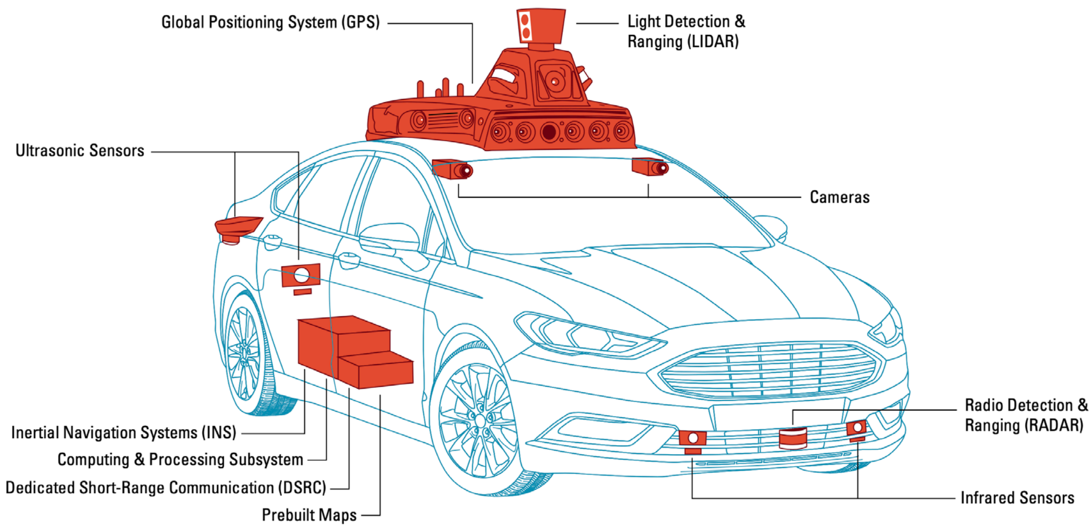

Figure 2-2. Key technologies and additional ICT devices in a generic CAV for navigation and communication. This figure is a generalized model based on components and subsystems described in the literature [13,109] Actual engineering designs will vary among automakers and vehicle models, and future designs are likely to change as CAV engineering advances.

Platooning: is synchronized movement of two or more vehicles trailing each other closely. Platooning reduces aerodynamic drag for following vehicles, making the whole platoon more efficient. Aerodynamic drag forces are proportional to the second power of speed, meaning that platooning is most effective in high speeds. Since platooning is practically viable for highways, adoption of this technique could yield significant fuel savings and emissions reductions. The magnitude of benefits depends on a number of platoon-specific characteristics, including cruising speed, speed variations, vehicle trailing space, vehicle shape (baseline aerodynamics), platoon size, the fraction of time spent on the highway, and the control algorithms used by the vehicles [58,110]. Vehicles in the middle of a platoon realize the largest energy-efficiency gains, while gains are smaller for vehicles at the front and rear of a platoon. Longitudinal controls, sensing, and V2V communications make it possible for CAVs to safely trail each other at close distances, enabling platooning [11]. Due to the relatively slow reaction time of humans, platooning is not safe when the driver is in the loop (i.e., when driving is not fully automated).

A number of studies have experimentally shown the energy and emission effects of drag minimization by vehicle platooning [95,111,112]. Many of these experiments have focused on trucks. Given the large frontal area and high percentage of highway cruising mileages in commercial heavy-duty trucks, truck platooning would yield substantial energy savings [113]. Tsugawa reported that a 3-truck platoon traveling at 80 km/h achieves a 10% drop in energy consumption (relative to three trucks traveling conventionally) when there is a 20-meter gap between trucks, and a 15% drop when the gap narrows to 5 meters [114].

For platoons containing mixed vehicle types separated by half- to full-vehicle lengths, the drag reduction is reported between 20 and 60% [115]. Wang et al. showed that a higher penetration rate of intelligent vehicles (similar to CAVs) in a tight platoon (i.e., a platoon with a very small gap between vehicles) could result in lower nitrogen oxide emissions [95]. Barth et al. projected 10-15% energy savings for platoons operating at separations of less than 4 meters [58].

Platooning in dedicated lanes results in the highest environmental benefits. However, there are still beneficial opportunities for groups of two or more CAVs to platoon on mixed-use roads or lanes [20]. Platooning can also mitigate congestion and expand roadway capacity (discussed in Section 3.2.4). Although the environmental benefits of platooning have been proven, research is needed to quantify expected benefits at various CAV penetration scenarios. Realizing benefits also requires new engineering design for safe platoon maneuvers—including exiting a platoon and merging—for various vehicle types.

2.2.2. Transportation System Level

Large-scale penetration of CAVs will change transportation network loads [116] and consequently environmental impacts associated with the transportation system. The net result is difficult to predict, particularly for different levels of CAV market penetration. Major mechanisms by which CAVs affect environmental impacts of the transportation system include changing travel cost, changing mobility services, and influencing congestion and roadway effective capacity.

Travel-cost implications: CAVs allow passengers who would normally be driving to instead occupy travel time with a variety of activities such as working, reading, watching movies, or eating. By substituting driving for productive or leisurely activities, the perceived cost of in-vehicle time (often called "value-of-travel time" (VOTT) or "willingness to pay" to save travel time) could be diminished. Moreover, eliminating the labor cost of human drivers in transportation services reduces direct travel cost and hence expands access to transportation services for lower-income individuals and households. This socioeconomic benefit could have accompanying environmental benefits if transportation services become cheap enough that lower-incomes substitute transportation services for private vehicles and if transportation services employ energy-efficient CAVs, since lower-income households tend to drive less efficient vehicles [38]. However, lowered travel cost is expected to increase travel demand, a key effect that could yield undesired consequences.

Many studies have attempted to analyze the general cost of travel in CAVs. It is found that SAEVs could profitably reduce fees charged to passengers by up to 80% compared with a ride-on-demand trip today, a drop that would make SAEVs price-competitive with mass transit [117]. Chen and Kockelman suggested that the total cost of charging infrastructure, fleet ownership, and energy for SAEVs ranges from $0.42 to $0.49 per occupied mile of travel [71], which is substantially lower than current costs of traveling in taxis or ride-hailing services. Greenblatt and

Saxena showed per-mile operation cost of high-VMT SAEVs are about one fifth of typical per-mile taxi fares [19]. Lu et al. found that automated taxis (electric and conventional) could reduce daily commute costs by over 40% but increase total transportation-related energy consumption and emissions in Ann Arbor, MI [65].

Bosch et al. provided a more conservative estimate, indicating that shared and pooled CAV travel is likely to be only slightly less expensive than personal vehicle travel in terms of per-passenger-kilometer cost. This is due to the higher capital cost and cleaning and maintenance needs of shared fleets. They also asserted that private ownership of CAVs might be cost-competitive, despite the general assumption that SAV-based travel is cheaper than private CAV-based travel [118]. Wadud analyzed the total cost of ownership for CAVs and implications for different levels of income. The study concludes that full automation in personal vehicles offers substantial benefits for the wealthy who have a higher value of time and drive more frequently. In contrast, full automation in commercial taxis is beneficial to all income levels [94].

The upshot is that while reducing travel costs is a positive externality likely to improve access to affordable travel options, transit equity, and consumer welfare, it may result in higher levels of energy consumption and environmental impacts at the transportation system level due to rebound effects (discussed further in Section 3.4). This may offset some efficiency benefits of CAVs at the vehicle-level. Moreover, the lower cost of CAV travel may discourage travelers from ride-sharing, since the cost savings associated with SAVs over private CAVs may not be substantial enough to be worth the extra hassle and reduced privacy [118].

Changed mobility services: CAVs could reshape mobility services by promoting shared mobility and interacting with mass transit, as discussed below.

(a) Shared mobility: Large-scale penetration of CAVs has the potential to shift the transportation system from relying on privately-owned vehicles to a new system relying primarily on on-demand shared mobility services, [37], commonly known as "Mobility as a Service" (MaaS) [38]. Shared mobility is an effective way to reduce VMT by combining trips that are temporally and spatially similar, generating many benefits including efficiency improvements, fleet downsizing, congestion reduction, energy conservation, and emissions alleviation. These benefits are maximized by combining shared mobility and vehicle automation.

CAVs can help boost car-sharing by improving user experience, avoiding vehicle unavailability and inaccessibility [119]. Kang et al. proposed a system-optimization framework for automated EV sharing, and suggested higher profitability and lower emissions per passenger-mile of operation compared to conventional car-sharing services [62]. CAVs can also help improve ride-sharing efficiency. Ride-sharing is intended to improve vehicle occupancy by filling empty seats in vehicles with riders on similar routes. Compared to car-sharing, ride-sharing is more dynamic and reliant on real-time matching [120]. Ride-sharing is particularly suited to CAV fleets that can continuously re-route based on real-time ride requests. Since SAVs have not yet been tested in the real world, most studies examining the topic have attempted to simulate the impact of implementing a SAV fleet in a specified area using agent-based models rather than empirical data [68,70,121].

There are several ways in which combining shared mobility with CAVs can reduce travel costs. First, shared mobility systems spread ownership costs (i.e., depreciation, financing, insurance, registration, and taxes) and operational costs across a large user base [38]. Second, the shift from personally owned vehicles to on-demand SAVs could maximize capacity utilization and improve vehicle utilization rate. For instance, the average daily parking time of current private vehicles is more than 90%,with the average daily driving of approximately 30 miles [20]. However, a SAV could travel more than 200 miles and complete around 20 trips per day on average, which translates into a more efficient vehicle utilization [65,70,122]. Third, high vehicle occupancy decreases energy use per passenger-mile-traveled, which reduces the fuel cost for each passenger. Finally, a transportation system that integrates SAVs can benefit from the efficiency of centralized planning. Decisions made at fleet management businesses are more likely to consider fuel costs and prioritize efficiency compared to individual vehicle owners, who are likely to prioritize the utility of their vehicles [75].

A number of studies find similar or lower costs for SAVs compared to current taxi services which on average cost approximately $0.80 to $5.75 per passenger-mile [37,65,75,81]. Fagnant and Kockelman conducted various simulations and found that the per-mile cost of a SAV fleet is around $1.00 [68]. Chen at al. estimated that the per-mile cost of a SAEV fleet ranges from $0.75 to $1.00 [70]. Bauer et al. reported the range of $0.29 to $0.61 per revenue mile of SAEV operation as a replacement for NYC taxis, which is an order of magnitude lower than the cost of present-day service [81].

SAVs also make it possible to decrease total fleet size and/or number of vehicles operating at a given time. This yields traffic and environmental benefits by reducing congestion, increasing highway capacity, and lowering emissions (further discussed in Section 3.2.3). Alonso-Mora et al. showed that introducing high-capacity CAVs with dynamic ride-sharing could substantially downsize the NYC taxi fleet. They demonstrated that using ten-passenger-capacity CAVs could serve 98% of the travel demand with a mean waiting time of 2.8 minutes while shrinking the taxi fleet to 15% of its present size. SAVs also make it possible to decrease the size of the private vehicle fleet while meeting current travel demand. Studies showed that one SAV could feasibly replace anywhere from 5 to 14 private vehicles [65,68,70,123,124]. The replacement rate of SAEVs depends on battery capacity and charger availability [71,122]. SAEVs have lower replacement rates than SAVs because SAEVs need to be charged, a process that takes longer than conventional refueling. Hence more SAEVs than SAVs are needed to meet the same travel demand, since there must be sufficient SAEVs available to provide service while other SAEVs are charging [122].

(b) Interaction with mass transit: Besides providing door-to-door mobility service, CAVs could interact with other transportation modes such as public transit. CAVs offer a convenient option for short, frequent trips, such as traveling from subway stops and bus stations to work or home. Integrating CAVs with mass transit therefore provide a promising solution to the "first/last-mile" problem, making mass transit more convenient which can in turn reduce vehicular travel [125]. Moorthy et al. found that traveling via public transit with CAV last-mile service could reduce energy consumption by up to 37% compared to traveling with personal vehicle [92]. If automation could be expanded to buses and rail, labor cost savings could be passed onto passengers via lower trip fares, thereby improving the competitiveness of mass transit. CAV services could also be used by transit agencies in public-private partnerships to supplement or replace costly services such as low-ridership bus lines or paratransit [13].

In contrast, CAV adoption could decrease the number of mass transit users since inexpensive CAVs could compete with transit systems. Similarly, low-cost, CAV-enabled shared mobility may result in less ridership for mass transit. Less revenue for mass transit has a disproportionate impact on low-income population, since low-income population tends to rely on transit more heavily than higher-income population [38]. Further studies are needed to quantify the likely impact of CAVs in this regard.

Vehicle utilization: In a CAV-enabled transportation system, more people would likely be willing to travel extended routes by car [80,126]. since the burden of driving is eliminated. Given that CAVs, unlike human drivers, do not need to rest, their deployment is likely to increase vehicle utilization and/or vehicle-hours-traveled. This translates to increased total VMT, energy use, and emission.

Some studies have also found that replacing personal vehicles with SAVs will generate unoccupied VMT (e.g., as a vehicle returns to its origin after dropping off passengers), leading to higher total VMT at the transportation system level. The extent to which total system-wide VMT will change largely depends on how frequently trips are shared [65]. Fagnant and Kockelman found that if rides are never shared, a SAV-only fleet will generate 8.7% more VMT compared to a private-vehicle-only fleet, but allowing dynamic ride-sharing in a SAV fleet reduces this figure to 4.5% [123]. Similarly, Zhang et al. showed that a pooling SAV fleet generates 4.7% less VMT than a non-pooling SAV fleet [124]. Taking realistic traffic flows into account, Levin et al. reported that empty repositioning trips made by SAVs without dynamic ride-sharing increase congestion and travel time by 3-20% [127]. SAEVs could also drive to remote locations for charging, resulting in higher VMT. Loeb et al. estimated that travel to charging stations accounts for about 32% of unoccupied VMT in SAEV fleets [122]. Zhang et al. suggested that private CAVs can also generate unoccupied VMT if they reduce the number of household vehicles while maintaining the current travel patterns. For instance, a privately-owned CAV could take one member of household to work, return home unoccupied, and then take another member to school. This study estimated that such relocation could increase total VMT for privately-owned vehicles by around 30% [99].

It is possible that the adverse environmental effects of CAV-related VMT increase at the transportation system level could be offset by CAV-related efficiency gains at the vehicle-level [56,80]. It is important to note that most studies on CAV utilization assume a low SAV adoption rate (around 10%) [122–124]. Increasing SAV penetration is likely to save system-wide VMT compared to a private-vehicle-only fleet, since more opportunity is available to consolidate sharable VMT and reduce unoccupied travel of SAVs due to the reduced need of vehicle relocation between trips. Moreover, some argue that CAVs could help avoid unnecessary "cruising for parking" VMT through automated navigation and parking [20]. Increasing the waiting time deemed tolerable for automated taxis would further reduce total VMT and required fleet size [65,81].

Congestion and road capacity: Traffic congestion and idling contribute to additional energy use and emissions. Every new vehicle on the road uses capacity and increases congestion. Constructing new roads and lanes is one way to alleviate congestion. However, research has demonstrated that induced vehicle travel (shifts from other modes, longer trips and new vehicle trips) often consumes a significant portion of new capacity added to congested roads [128]. Alternative, arguably more sustainable options are to encourage mixed-land use and promote ridesharing. Since SAVs can replace conventional cars at a higher rate and increase vehicle utilization efficiency (both leading to fleet downsizing), they can reduce congestion without adding road capacity. CAVs can expand effective road capacity by not only decreasing the number of vehicles on road, but also right-sizing vehicles [10]. Vehicle right-sizing will substantially reduce the fraction of fleets composed of large vehicles traveling frequently with few passengers [19,75]. While the impacts of vehicle right-sizing and fleet downsizing on improving road capacity are intuitive and frequently mentioned, quantitative estimates are missing from the literature.

Traffic jams resulting from collisions can cause congestion too. The safety improvements of CAVs is estimated to reduce congestion by 4.5% through decreasing crash frequency [80]. CAV technology can also alleviate congestion and improve effective roadway capacity by allowing vehicles to safely reduce following distance (headway), use existing lanes and intersections more efficiently by maintaining shorter distances between vehicles [116,129], travel in coordinated platoons, take routes that avoid traffic jams and low speed zones [20], and also dampen stop-and-go traffic waves [67]. Another benefit is that CAVs can operate on a flat speed range 30-70 MPH on arterial roadways, which helps reduce traffic congestion [69]. Finally, CAV technology enables vehicles to synchronize movement with traffic signals, which reduces frequent acceleration and deceleration at intersections. Some studies have suggested that it may be ultimately possible to achieve "signal-free" transportation systems under high CAV penetration [91,116]. Realizing such systems require major infrastructure overhauls as well as technical solutions to address pedestrian movement.

Multiple studies consider the aforementioned points in their simulations. Auld et al. applied an integrated model to analyze the impact of different market penetrations of CAVs on performance of the transportation network and changes in mobility patterns for the Chicago region. They presented a scenario in which CAVs could yield an 80% increase in road capacity with only 4% induced additional VMT [64]. Li et al. found high-CAV-penetration scenarios can reduce carbon monoxide, $PM_{2.5}$, and energy consumption in urban areas by up to 15% due to reduced congestion or increased road capacity [74].

It is possible that vehicle automation could increase travel demand, thereby offsetting decongestion benefits. Zakharenko held that the impact of induced travel is unlikely to be very large, since CAVs and SAVs are expected to operate far more efficiently even if their utilization increases [97]. Additional research is needed to estimate the expected effects of increased travel demand on road congestion and capacity at various CAV penetration levels.

2.2.3. Urban System Level

Today's urban systems have largely been designed to accommodate privately-owned and driven cars. CAVs can reshape urban systems and infrastructure in several ways. Due to improved communications, CAVs may require less infrastructure such as traffic lights, parking lots, and road lanes. CAVs can also resolve charging-infrastructure challenges, thereby supporting vehicle electrification. However, CAVs will require additional ICT supports, though such supports could potentially be integrated into existing streetlights, signs, and other transportation infrastructure. There are also concerns that CAVs could encourage sub-urbanism and urban sprawl [97].

Infrastructure implications: Deployment of CAVs will revolutionize the conventional urban infrastructure. V2I and higher safety capabilities of CAVs may render much existing infrastructure obsolete, while requiring new types to be installed. The net environmental impacts of CAV-related changes in infrastructure are largely unknown. The following sections summarize what is known and highlight priority research areas.

(a) Existing infrastructure (lighting and traffic signals): Because CAVs may not need lighting for navigation or signaling, it may be possible to save energy by reducing the number and/or utilization of road lights and traffic lights. There is no direct data on the energy demand of road lighting and traffic signals in the U.S. The EIA estimates that in 2015, about 404 TWh of electricity was used for residential and commercial lighting [130]. This was about 15% of the total electricity consumed by both of these sectors and about 10% of total U.S. electricity consumption. Based on the Department of Energy's report on U.S. Lighting Market Characterization [131], I estimate that highway lighting (excluding traffic signals) consumes around 1% of electricity generated in the U.S. Thus, reducing road lighting by 30% would save 16.5 TWh of energy, 11 MMTs of CO_{2eq}, and around $1.65 billion annually. As a comparison, in the UK, road lighting and traffic signals consume 2.5 TWh of electricity annually, representing 0.73% of total annual electricity consumption [132].

Nevertheless, navigation is not the sole purpose of road lighting. Many passengers may not feel safe on dark roads even if CAVs can drive without risk. Some studies proposed replacing conventional road lights with intelligent and adaptive systems [133,134]. These systems could turn lights on when a CAV approaches and dim or turn lights off when the roadway is empty. V2I capabilities of CAVs facilitates such technology. Future research should examine the potential for reducing road lighting at various levels of CAV penetration from cost, maintenance, and passenger-comfort standpoints. Research should also consider different technical scenarios. For instance, the ongoing transition to light-emitting diode (LED) street lighting is increasing efficiency and so lessens the impact of eliminating lighting altogether.

<u>(b) New infrastructure requirements:</u> Communication and data transmission are essential to CAV operations. CAVs depend on high frequency of information exchange for finding pick-up locations, efficient routing, and arriving safely at the final destination. All this communication and data processing requires significant computational resources and large-scale infrastructure (e.g., datacenters). The life-cycle of ICT infrastructure is energy intensive and generates a variety of environmental impacts [107,135,136]. Kolosz and Grant-Muller considered embodied emissions of roadside infrastructure and datacenters for the Automated Highway System (AHS), a system that accommodates vehicles with intelligent speed adaptation features. They reported that, despite these emissions, AHS would save an expected 280 kilotons of CO_{2eq} over 15 years of operational usage in the M42 corridor, the UK's busiest highway. This is because AHS-enabled optimization of vehicles on highways reduces emissions to an extent that offsets infrastructure-related emissions [73]. More research is needed to quantify the expected net energy use and life-cycle environmental impacts of a typical datacenter for management and communications of CAV fleets.

Integration of CAVs with power systems: Vehicle automation and electrification are mutually reinforcing. Integrating CAVs with urban power systems can offer multiple environmental benefits [137]. Fleets of CAVs can help promote vehicle electrification by resolving challenges such as range anxiety, access to charging infrastructure, and charging time management, since connected vehicles are always aware of the availability and location of charging options [71,84].

Automated charging infrastructure enables more efficient energy management and facilitates vehicle-grid integration and uptake of renewable electricity in transportation sector [138]. Some prototypes of charging robotic arms and mechanisms have recently been introduced to automatically plug into EVs and control the charging process. Wireless Power Transfer (WPT) is a nascent technology that can complement CAVs [139]. When wireless charging is combined with CAVs, it becomes possible to automatically rotate vehicles on charge transmitter pads without human intervention. Removing this labor cost for service would make SAEVs cheaper. In addition, CAVs could navigate themselves to wireless charging spots to top up at reduced energy rates during off-peak hours. Chen et al. investigated the charging-infrastructure requirements of SAEVs and concluded that by replacing attendant-serviced charging with automated wireless charging, the operational cost of SAEV fleets drops by 20-35% [70].

A step beyond stationary WPT is in-motion dynamic charging, in which embedded transmitters in roadways wirelessly charge vehicles as they are moving, extending maximum range and/or reducing the required size and cost of batteries [139]. Lavrenz and Gkritza studied the automated electric highway systems (AEHS) powered by inductive charging loops embedded in the roadway and estimated that AEHS would decrease fossil-fuel energy use by more than 25% and emissions by up to 27% [89].

An interesting potential use of electric CAVs is as mobile energy storage units for excess electricity generated by utility-scale power plants. Under such a scheme, CAVs would automatically charge (take up power) at off-peak hours when rates and demand are low and discharge (release power) back to the grid during peak hours or in case of an electricity storage. Such bidirectional power transfer could be managed by CAV communications with the power grid and would be particularly useful in facilitating increased penetration of intermittent renewable energy like wind and solar. One caveat is that frequent charging and discharging of vehicle batteries might result in accelerated battery degradation [139]. Another is that some consumers might be reluctant to allow their privately-owned vehicles to be leveraged in such a manner, even if financial incentives were provided [140].

It is also important to note that the charging patterns of SAEVs and privately-owned CAVs might be very different from charging patterns of human-driven EVs including privately-owned EVs as well as EVs owned by transportation network companies [62,81]. SAEVs might need more frequent charging given their higher utilization rate. The impacts of different charging patterns on the grid and associated environmental consequences are uncertain and require further investigation.

Land use: Because CAVs can navigate themselves to and from dedicated parking areas, increased CAV penetration reduces the need for parking located close to all destinations and hence the total amount of space needed for parking overall [98]. Nourinejad et al. noted that CAVs can park in much tighter spaces, reducing needed parking space by what they found to be an average of 67% [141]. Similarly, Zhang and Guhathakurta suggested that SAVs could reduce parking land by 4.5% in Atlanta at penetration as low as 5% [72]. Avoiding the construction of new parking could also have substantial environmental benefits. Chester et al. reported that parking construction can add 6-23 g CO_{2eq} per passenger-kilometer-traveled to the total life-cycle emissions of a vehicle (typically about 230 to 380 g CO_{2eq}) and increase sulfur dioxide and PM_{10} emissions by 24-89% [142].

Eliminating obsolete transportation infrastructure could enable denser development in urban areas [20]. However, there are concerns that CAVs could encourage sub-urbanism and urban sprawl, especially for people with lower perceived values of travel time. According to Bansal et al., deployment of CAVs will likely result in long-term shifts in which people choose to relocate their homes [76]. Large families or those who tend to take advantage of lower land prices in suburbs may use CAVs to reside further from urban cores [143]. Zakharenko provided a comprehensive overview of how urban areas could be altered by CAV deployment [97]. Such qualitative discussion is common in the literature, but more quantitative analyses are needed to inform land-use policies and urban planning.

2.2.4. Society Level

The potential environmental implications of vehicle automation are the largest at the society level, but the magnitude and direction of influences are highly uncertain. One key factor is the effect that CAVs will have on public perception of mobility. For many decades, cars have been used to make a statement about individual personalities and values, and often to flaunt wealth. Moreover, automakers are strongly motivated to maintain the current emotional connection of consumers to their cars [40,118], unless they adopt new business models. Public perception of shared and automated driving versus private, human driving will affect the extent to which people are willing to give up private vehicles in favor of CAVs, how car manufacturers develop and market CAVs, tax and insurance policies, and infrastructure investments. Given that CAVs are not yet commercially available, assessing public opinion and consumer choice on market penetration is challenging [77,110].

A number of surveys and questionnaires have quantified early public perception of various CAV technologies. Bansal et al. surveyed Texas families and found that more than 80% of respondents would increase vehicle utilization under a CAV paradigm [143]. König and Neumayr provided empirical evidence on mental barriers and resistance towards CAVs, and suggested that people are ready and interested in riding with CAVs but not willing to buy one

[88]. Kyriakidis et al. surveyed 5,000 people on their acceptance of, concerns about, and willingness to buy partially, highly, and fully automated vehicles. Results indicate that respondents who are willing to pay more for fully automated vehicles are likely to have higher annual VMT and utilization rates [79]. Wadud et al. and Anderson et al. stated that the utilization of privately-owned CAVs and induced travel demand are expected to have game-changing influence on their energy consumption and environmental impacts [10,13].

A significant negative externality of CAVs will be reduction in demand for human labor in services such as taxis, trucking, and delivery, thus potentially unemployment for many service drivers. But CAVs are expected to generate new and high-quality jobs in hardware/software technologies, and in fleet management and services.

Behavioral response and travel pattern shift: The convenience, accessibility, and lower travel cost of CAVs may shift travel patterns and induce higher travel demand, mainly due to travel behavior changes. Automated driving would allow people to participate in other pursuits during their trips, lowering the perceived cost of travel and increasing acceptable commute distance and time [56,76,80]. People may prefer SAVs and SAEVs to public transit if costs are comparable, since the former options provide door-to-door service. Similarly, for short trips, people may substitute CAVs for other—often more sustainable and active—modes such as walking or cycling. It is also possible that travelers consider re-chaining their trip needs (shopping, recreational, commute, errands, etc.) once they have access to CAV technology. Overall, CAVs have the potential to replace not only private vehicles but many other types of transportation.

CAVs could also unlock additional travel demand from people who have unmet travel needs and previously cannot or choose not to drive (e.g., the elderly, the young, unlicensed individuals, and people with driving-restrictive medical conditions or disabilities). CAVs can provide door-to-door mobility service for these populations that is cheaper and more convenient than current options like paratransit or taxis. Expanded mobility for currently underserved population is highly desired from an equity and ethical standpoint, but is likely to increase trip frequency—especially in suburban, vehicle-dependent areas [56]. Harper et al. estimated that the increase in travel demand from travel-restricted population could be as much as an additional 14% VMT (equivalent to 295 billion miles) per year in the U.S. [78].

Increased travel demand associated with CAVs represents a type of "rebound effect." In the energy economics, rebound effects describe the percentage of energy savings from a new, energy-efficient technology that are offset by increased use of that technology [144]. Similarly, efficiency gains from CAV technology at the vehicle-level may induce additional travel demand and consequently offset environmental benefits at the society level. Such rebound effects can cause discrepancies between predicted and realized net impacts of CAVs and other transportation innovations [145].

For CAVs, the rebound effect is one of the mechanisms connecting different system levels. Milakis et al. presented a ripple model to conceptualize rebound effects in societal aspects of automated driving [66]. Wadud et al. used a simple approach to employ rebound effects from generalized cost of travel as a multiplier of CAV travel activity by simulating a range of literature-driven travel elasticities [10]. In short, it is widely accepted that rebound effects could offset environmental benefits of CAVs, but there is significant uncertainty about the extent. Considering the importance of this issue for the environment as well as for transportation and infrastructure planning, additional effort to model and quantify CAV-related rebound effects is urgently needed.

Shared consumption: Public opinion on private vehicle use and social norms over vehicle ownership may change along with the introduction of shared mobility in the transportation sector [37,146]. CAVs can help change public perception of shared consumption by facilitating and promoting shared mobility [147]. The millennial generation has already shown different transportation preferences and opinions compared to prior generations [143,146,147]. This shift might be extended to other types of goods and services. In a society where shared consumption is mainstream, desire for product ownership will be reduced, which will reduce environmental impacts associated with product life cycles. CAV-facilitated shared mobility can support this change from a technological perspective, but questions remain as to adoption behaviors and public acceptance. The literature does not yet show what future travelers will want from their transportation systems.

Transformation of other sectors: Widespread deployment of CAVs may also influence other transportation industries such as aviation and rail. Given the lower cost of CAV travel, certain groups of users may choose to take longer trips using road transportation rather than aviation or rail. This is environmentally significant, as aviation and rail tend to have lower marginal energy use and emissions on a per-passenger-mile-traveled basis compared to low- or single-occupancy vehicles [22]. Both intercity rail (56.1 passenger-miles per gasoline-gallon equivalent (GGE)) and airlines (50.0 passenger-miles per GGE) have higher energy efficiency compared to passenger vehicles (38.9 passenger-miles per GGE) [148]. LaMondia et al. studied the impact of CAVs on long-distance travel choices by analyzing travel surveys, and concluded that CAVs could displace 25-35% of demand for air travel for trips of 500 miles or more [149]. The environmental impact of this shift could be mitigated if intercity CAV travels were mostly through larger shared vehicles such as autonomous buses.

CAVs are also likely to affect a variety of transport-intensive sectors and services. For instance, CAVs could serve as mobile overnight sleeping compartments, decreasing demand for hotels for long-distance trips [126]. Sectors that heavily utilize freight transportation—online retail, the food industry [87], etc.—will likely benefit from the emergence of CAVs. The environmental impacts of CAV adoption and utilization in these sectors are likely significant, but little is known [87]. More research is needed to measure these broader impacts and inform relevant policymaking.

Workforce impacts: Vehicle automation will render many jobs obsolete, specifically in labor-intensive transportation services such as freight trucking, public transit, and taxi driving [66,80]. The U.S. Department of Commerce estimates that 15.5 million U.S. workers are employed in occupations that could be affected by the introduction of automated vehicles [150]. Unemployment has attendant economic and social consequences. These include altered consumption patterns (usually moving toward less sustainable commodities and services) as well as adverse physical and mental health effects [83]. Both these consequences have environmental relevance as consumption pattern changes drive changes in supply chain and associated environmental impacts. It should be noted that CAV-related job losses will occur gradually in most cases. For instance, early automated trucks will still require human drivers to assist with loading and unloading, navigation, fueling, and maintenance. Over time, though, retraining the workforce and alternative job opportunities will be needed to ensure sustainable CAV adoption and mitigate adverse outcomes [87]. One option is to help workers in transportation-related jobs transition to sectors that are likely to expand as CAV penetration grows. These sectors include but not limited to hardware and software development, fleet management, and concierge services.

2.2.5. Summary of Environmental Impacts of CAVs

This review shows that due to the complexity and interdependence of higher levels of interactions, the uncertainty of CAV-related environmental impacts increases as the impact scope broadens. Most studies related to energy and environmental impacts of CAVs have tried to identify effect bounds and speculate on system-level impacts. Collectively, these studies confirm that CAV technology has the potential to deliver large environmental benefits, but realizing this potential highly depends on deployment strategies and consumer behavior. The greatest energy and environmental impacts will not stem from CAV technology directly, but from CAV-facilitated transformations at all system levels.

At the vehicle level, CAV technology can significantly enhance efficiency. Considerable fuel savings and emission reduction can be achieved through CAV design oriented towards energy efficiency. Studies reviewed in this paper report vehicle-level fuel savings ranging between 2% and 25% and occasionally as high as 40%. Integrating CAV technology and vehicle electrification can considerably improve the economics and attractiveness of transportation decarbonization. Higher CAV penetration could further alleviate negative environmental impacts of road transportation through large-scale, connected eco-driving. However, the net effect of CAV technology on energy consumption and emissions in the long term remains uncertain and depends on other levels of interactions with the environment.

At the transportation system level, CAV-related environmental benefits derive from optimization of fleet operations, improved traffic behavior, more efficient vehicle utilization, and the provision of shared mobility services. Specifically, shared mobility and CAV technology have significant mutual reinforcing effects.

At the urban system level, CAVs could reshape cities by changing land-use patterns and transportation infrastructure needs. For instance, street lighting and traffic signals could become less necessary or obsolete under a CAV paradigm, resulting in energy savings. However, CAVs could encourage urban sprawl and shifting to peripheral zones with longer commutes. CAVs also require communications with large-scale datacenters, which are generally energy intensive. At the same time, CAVs can facilitate integration of EVs and charging infrastructure into power grids. These urban-level mechanisms might not deliver significant net environmental benefits without high penetration of CAV technology.

While long-term net environmental impacts of CAVs at the vehicle, transportation system, and urban system levels seem promisingly positive, the lower cost of travel and induced demand at the society level is likely to encourage greater vehicle utilization and VMT. Most studies reviewed in this paper assume current travel patterns, vehicle ownership models, and vehicle utilization without considering realistic behavioral changes resulted from increased CAV penetration. Society-level impacts of CAVs will undoubtedly be profound, but significant uncertainties exist about behavioral changes, making it very difficult to project the actual energy and environmental impacts.

The synergetic effects of vehicle automation, electrification, right-sizing, and shared mobility are likely to be more significant than any one isolated mechanism. Hence these synergetic effects should be the focus of future research efforts. Fulton et al. projected that the combination of these technologies could cut global energy use by more than 70% and reduce CO_2 emissions from urban passengers by more than 80% by 2050 [85]. They further estimated that the combination of these technologies could reduce costs of vehicles, infrastructure, and operations in the transportation sector by more than 40%, achieving savings approaching $5 trillion annually compared to the business-as-usual case.

In order to ensure truly sustainable uptake and adoption of CAV technology, transportation systems must be more energy efficient, facilitate emissions reduction, mitigate local air pollution, and address public health concerns. At the same time, strategic development and deployment of CAV technology are necessary to control overall travel demand and congestion.

2.3. Priority Research Needs

Based on this review of the literature, I recommend the following four principles for improving research on the energy, environmental, and sustainability implications of CAVs:

I. **Where possible, transition to empirical, data-based analysis of CAV impacts and revisit assumptions**. The novelty of CAV technology and lack of data means that analysis of CAV impacts has, to date, been largely speculative and qualitative. Moreover, many analyses are based on oversimplified or unrealistic assumptions. Researchers should strive to increase the rigor of CAV studies as more data and higher fidelity models become available.

II. **Improve models by more accurately characterizing CAV impacts and better capturing uncertainty.** Most analyses have assumed the mechanisms by which CAVs impact the environment are independent of one another. This assumption frequently leads to underestimation or overestimation of aggregate impacts. Furthermore, models should better reflect the true nature of CAV impacts. For instance, many studies fail to distinguish between general trends of energy efficiency improvement in vehicles and additional benefits that are solely enabled by CAV attributes. It is also necessary to quantify the upper and lower bounds of impacts and incorporate these bounds into models to better capture and characterize uncertainty.

III. **Place more effort on understanding the effects of different CAV technologies and market scenarios on consumer behavior and travel patterns.** Although improvements in CAV efficiency at the vehicle-level should not be overlooked, the largest environmental impacts are likely to depend on consumer behavior and travel patterns: i.e., when, where, how often, and how much consumers travel with CAVs.

IV. **Integrate analysis and modeling across different system levels.** There is a need for deeper investigation on how mechanisms at each level reinforce and/or undermine each other. Figure 2-3 illustrates interactions and linkages across the four system levels identified in this review that are likely to have substantial energy, environmental, and sustainability implications. The trade-offs between interactions and linkages are largely unexplored and merit further research.

I also recommend prioritizing research on four specific topics: CAV design and testing, development of CAV-specific models and tools, investigation of behavioral phenomena associated with CAV sharing and adoption, and assessment of policy needs and opportunities. Each of these is discussed in further detail below.

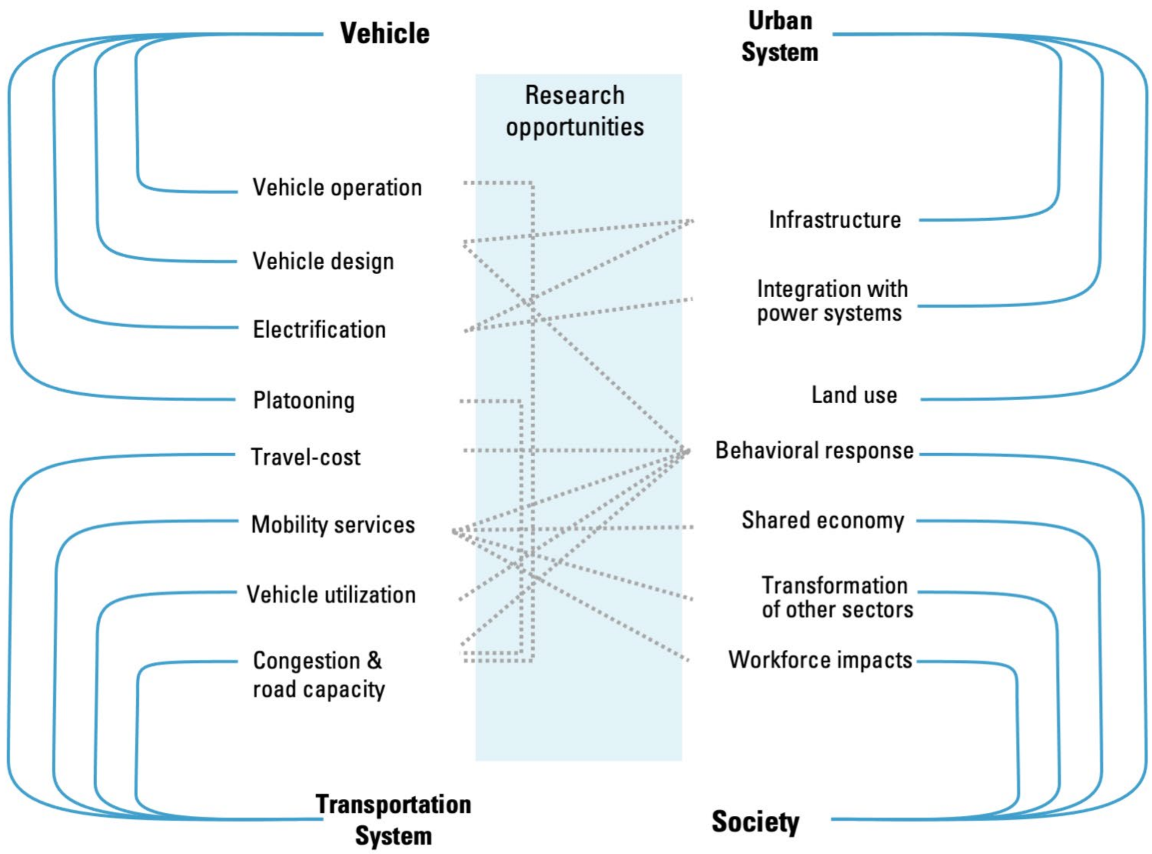

Figure 2-3. Interactions and linkages between system levels that entail energy, environmental, and sustainability impacts.

2.3.1. CAV Design and Testing

The evolution of vehicle design is a major source of uncertainty for the environmental performance of CAVs. There is a gap in the literature regarding which factors should drive the vehicle design optimization and decision-making protocols that will affect CAV-related energy consumption and emissions. Conventional life-cycle assessment (LCA) can be used to characterize the first-order impacts of various design protocols and provide insights that can improve sustainability of early CAV designs. However, for more radical and complex designs (including vehicle right-sizing and safety-enabled light-weighting), more sophisticated sustainability assessments are needed. Studies should be conducted to characterize environmental benefits of different CAV designs under different real-world scenarios and particularly under different levels of societal CAV acceptance.

Another priority should be quantifying energy efficiency improvements actually achieved by early commercial designs. Proving grounds and test facilities are needed to demonstrate that theoretical CAV efficiencies can be practically achieved. Providing researchers with real-world data from On-Board Diagnostics (of current prototypes can help identify best practices and designs. Results can then be used to improve real-world development and deployment. Considerations need to be given in carrying out such research to avoid infringing on consumer privacy or compromise intellectual property.

2.3.2. CAV-Specific Models and Tools

CAVs will have impacts on and be affected by land use, demand, demographic changes, economic factors, fueling infrastructure, and local policies, among other factors. CAV-related changes in demand for and supply of mobility services will change loads placed on transportation networks. For instance, CAVs could improve freeway traffic flows by enabling shorter following distances between vehicles but deteriorate road congestion and effective capacity by inducing more travel. Moreover, current vehicle-choice models are ill-suited to incorporate numerous consumer preference variables relevant to CAV adoption. Moreover, CAVs are not yet integrated into major transportation and energy models—such as those used by the U.S. DOT, EPA, EIA, and the Intergovernmental Panel on Climate Change—for estimating future travel demand, energy use, and environmental consequences. In most existing assessment studies, various measures that can reduce demand for travel and/or vehicle usage and improve driving performance have been identified. However, CAVs most likely entail considerable yet uncertain rebound effects, making current predictions of future transportation demand unreliable [21]. Integrated assessment models and research support tools that incorporate environmental effects of system-level CAV attributes for various market penetrations of CAVs should be developed to enable higher-quality projections of future travel trends.

2.3.3. Behavioral Studies

Scant effort has been dedicated to analyzing how consumer preference for CAV technology, vehicle ownership, and ride-sharing might evolve. This is important given that the net environmental impacts of CAVs are highly dependent on the degree to which CAVs are shared versus privately owned. Pooling and shared mobility services alleviate most adverse environmental effects of CAV technology. However, social norms may lead people to avoid sharing transportation with strangers, especially if cost differences are marginal. Research is needed to identify the factors that will affect these choices. There is a particular need to examine mixed private/shared CAV scenarios, since most studies conducted to date examine scenarios in which CAVs are either fully private or fully shared.

Further investigation is also needed into how readily consumers will adopt CAVs. Real-world data can be obtained from surveys and tests. However, surveys are probably less useful due to the novelty of CAV technology, since most respondents will not be able to provide an informed response. Novel approaches are needed to investigate if and under what circumstances people will accept CAVs and how they will use them. Creative techniques such as virtual and augmented reality might be useful in this regard. More extensive engagement—i.e., participants work with researchers to understand possible technology options and more deeply explore scenarios—could also provide deeper insight into how people actually perceive CAV technology.

2.3.4. Policy Needs and Opportunities

Governments are already playing an active role in supporting technological development of CAVs. Emphasis has been placed on safety, equity, and mobility, while scant attention has been paid to environmental implications. For example, a bipartisan group of U.S. senators recently released a set of principles for self-driving vehicle legislation as part of the American Vision for Safer Transportation through Advancement of Revolutionary Technologies (AV START) Act. These principles do not mention energy, efficiency, or emissions at all [151]. This omission is problematic, given large environmental opportunities—and risks—associated with CAV technology.

Historically, the majority of environmental policies for the transportation sector have focused on regulating tailpipe emissions. Since CAVs are likely to be more efficient and generate lower levels of emissions than conventional vehicles, limiting emissions on a per-vehicle basis is less important than considering potential environmental impacts of CAVs on a broader scale. CAVs may induce travel demand that offsets—or even eliminates—improvements in per-vehicle efficiency and emissions. It is important to develop policies that address this concern. CAVs also provide new opportunities for governance. Vehicle connectivity enables environmental policies such as mileage charges, regulation of unoccupied travel, and dynamic emission reporting [152]. Such policies have advantages. For instance, VMT taxation is seen as less regressive—hence more equitable—and more economically efficient than fuel taxes [153].

However, collecting accurate spatial and time-of-day vehicle use may raise privacy concerns and is politically difficult to implement.

In addition to exploring CAV-specific policy options, policymakers should consider establishing CAV policy frameworks that can be adapted based on how the market and technology evolves. Several possible use cases of CAVs that would have significant external costs are not discouraged by current policy, and the most beneficial use cases are not incentivized. For example, large, personally owned, inefficient CAVs could serve the owner at significant cost to the system by driving “selfishly” (for instance cruising streets empty instead of paying for parking) and underpaying for impacts on infrastructure. It remains to be seen whether this use case will manifest in reality. But implementing mechanisms—such as dynamically pricing CAV use on a per-mile basis in congested areas or at peak times—for addressing undesired outcomes will be far easier now than once CAVs are already on the road.

Chapter 3. Induced Travel and Energy Rebound of Connected and Automated Vehicles

3.1. Introduction

Connected and automated vehicle (CAV) technology is expected to be an indispensable but disruptive factor in the transportation sector, transforming the mobility paradigm, transportation markets, and travelers' behavior in the coming decades. It will likely increase transportation safety to an unprecedented level [154], enhance mobility, provide a higher level of comfort and convenience for travelers, and reduce the cost of driving for individuals, all of which will be welfare-improving for society. At the same time, vehicle connectivity and automation will inevitably and significantly change energy demand in the transportation sector. The extent of these changes is still largely unclear [9,22,155] and yet will have major consequences for energy supply and the environment alike.

Several characteristics of CAV[1] technology will influence energy consumption, including improvements in route optimization, eco-driving, crash avoidance, and vehicle right-sizing, among others [9]. Many of these improvements will push energy use downwards; however, some will very likely work in the opposing direction. Chief among the factors that will exert upward pressure on energy demand is the marginal cost of driving, which is expected to drop

[1] CAVs are also referred to as "autonomous", "self-driving", or "driverless" vehicles interchangeably in the literature, though these are not the same. For a disambiguation of definitions, refer to [9].

significantly with CAV technology. Higher fuel economy of CAVs [9,10,156] will cause the per-mile fuel cost of travel to drop. This, in turn, will induce additional travel that partially offsets the fuel savings of energy efficiency – commonly referred to as a "rebound effect"[2]. In addition, increased comfort and reduced attention requirements[3] will cause the per-mile *travel time cost* to drop [157], inducing even more additional travel [9,10,13,87].

The key parameter dictating the magnitude of travel demand induced through these channels is the elasticity of travel demand with respect to the price of travel [158–161]. The overwhelming majority of existing studies on the energy impact of more efficient vehicle technologies focus exclusively on the fuel-cost component of the price of travel [162–168]. Consequently, such studies are unlikely to have external validity in the context of vehicle automation, which will intimately affect both fuel cost *and* time cost. While recent research on the energy use impacts of vehicle automation does consider the impact of time cost changes (e.g., Wadud et al. [10]), it tends to borrow fuel and time cost elasticities that are estimated elsewhere, in isolation from each other, and without the aim of developing CAV-specific predictions. Most studies focus on how changes in mobility – especially changes in the vehicle-level energy efficiency of CAVs – affect energy use, *holding travel demand constant* (e.g., [19,23,65,169]). The assumption of fixed demand almost certainly leads to overestimation of the environmental benefits of this technology [9].

In this paper, the most recent empirical microdata available is used to estimate the elasticity of travel demand with respect to the marginal fuel and time costs of travel in a single, unified

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[2] The rebound effect can refer to the general phenomenon of increased driving after a rise in fuel economy, or it can be mathematically defined as the percent change in miles traveled caused by a one-percent change in fuel economy (or, relatedly, a one-percent change in fuel costs). The empirical investigation of micro-level rebound usually utilizes regression-based approaches with cross-sectional, time series, or panel data [162,167].

[3] This is viewed as a likely feature of high levels of automation (level 3 and above) [154].

framework. Approach presented here adapts standard microeconomic modeling and statistical techniques to account for the value of time in elasticity estimation. I first specify a theoretical model of consumer utility maximization from vehicle-miles traveled (VMT) and other goods, subject to time and income constraints. The model illustrates how the opportunity cost of time spent traveling and the fuel cost of travel affect the privately-optimal choice of VMT. From it, I derive an estimating equation for the combined, fuel- and time-inclusive price elasticity of VMT. I fit several specifications of this equation using household-level vehicle and travel data from the 2017 United States (U.S.) National Household Travel Survey (NHTS) [106] as well as predictions of travel time cost based on reported income. The resulting empirically-derived elasticity estimates allow forecasting the changes in travel demand induced by CAV technology, as well as the associated energy rebound effects.

This study produces three key findings. First, the central estimate of the combined, fuel- and time-inclusive price elasticity of demand for VMT is -0.39. This is significantly larger than the -0.06 to -0.28 range found in existing studies of the fuel price elasticity of demand [165–168] and significantly smaller than the -1.0 to -2.3 range found in studies of demand elasticity with respect to the generalized cost of travel[4], the latter of which is cited in prior work on CAV-induced travel demand [10,22]. Replicating the procedure with 2009 NHTS data yields a similar central estimate of -0.45. The results highlight the importance of accounting for the opportunity cost of time in travel demand elasticity estimation and suggest that existing predictions of CAV-induced travel may not be based on relevant travel demand parameter values.

[4] In transportation economics, "generalized cost" refers to the sum of monetary and non-monetary costs of a trip. For instance, the generalized cost of private vehicle travel includes total cost of ownership (TCO, including capital, fixed, and operation costs) and monetized passenger travel time [161].

Second, travel demand elasticities exhibit significant heterogeneity that inform future forecasting methodology and policy discussions. I find that households respond very differently, on average, to fuel price changes versus time cost changes. The preferred estimate of the fuel price elasticity is -0.1, while this preferred estimate of the time cost elasticity is -0.4. Moreover, all of my elasticity estimates vary significantly with income. I find that richer households have less elastic demand with respect to fuel costs but more elastic demand with respect to time costs. The aggregate, fuel- and time-inclusive price elasticity of VMT rises with income; for example, the average elasticity of the upper three groups is 64% larger than that of the bottom group. In other words, my estimated model predicts that relatively richer households will increase their travel relatively more in response to automation and thus stand to experience greater welfare gains.

Third, the aggregate, CAV-induced reduction in energy use may be quite small or even negative. In this model, the magnitude of this reduction depends on (a) elasticities of demand with respect to the price of travel, (b) projected increases in fuel economy of CAVs, and (c) projected decreases in travel time cost with CAVs. The estimates of (a) are used to simulate induced VMT for different combinations of (b) and (c). The range of possible impacts of CAVs on VMT, and thus energy consumption, is wide. However, backfire – a net rise in energy consumption – is a distinct possibility, because high-income households have large elasticities of demand and also high baseline energy use. This, in turn, implies the possibility of net rises in local and global air pollution.

Ultimately, the energy and environmental impacts of CAV technology will depend on not just changes in the marginal cost of travel, but also the capital cost of an automated vehicle, the safety benefits of automation, and changes in ride- and vehicle-sharing, among other aspects of the mobility transition. The very non-marginal nature of the upcoming mobility transition presents steep challenges to researchers who seek to provide rigorous predictions of future travel behavior and energy use. My contribution is to use the most recent microdata available in the United States to develop empirical estimates of a key parameter governing travel behavior, and to leverage these estimates to provide a glimpse of the possible energy impacts of vehicle connectivity and automation.

3.2. A Model of Private Vehicle Driving Decisions

Conceptually, vehicle ownership and driving decisions are a function of many factors: vehicle capital cost, the marginal cost of VMT (including fuel, time, and depreciation), and fixed costs of insurance and maintenance – collectively referred to as the total cost of ownership (TCO) Conceptually, vehicle ownership and driving decisions are a function of many factors: vehicle capital cost, the running costs of VMT (including fuel, time, maintenance, and depreciation), and fixed costs of insurance, registration fees and tolls – collectively referred to as the total cost of ownership (TCO) [94], the perceived cost of in-vehicle time, the utility an individual derives from travel, which depends on the goods and services obtained through travel, vehicle attributes, and individual preferences; and constraints such as income and time. In keeping with an extensive literature on empirical rebound effects (see, for example [162,166,170]), I focus this analysis specifically on the *marginal cost* of VMT conditional on vehicle choice. Marginal fuel and time costs are economically important and technologically relevant: together, they make up the majority of the variable cost of travel (19% and 45%, respectively [171]), and they are both projected to drop significantly with the diffusion of CAV technology [9,94,118,172]. Moreover, available data on these fuel and time costs (as well as

VMT itself) allow us to develop empirically grounded forecasts of CAVs' potential impact on energy use even when CAVs themselves have not yet been deployed commercially.

I begin by modeling VMT as a choice made by a utility-maximizing household, given constraints on income and time. Similar models exist in the energy rebound effect literature, but these do not include a time constraint [144,162,164], because energy efficiency improvements alone do not generally affect the use of time spent in a vehicle. In contrast, vehicle automation will decrease the opportunity cost of time through reduced in-vehicle attention requirements, which has the potential to alter driving decisions considerably. To capture this change, Linn's model of VMT choice [165] is adapted by adding a second constraint on time, following seminal economic theory on the allocation of time by Becker [173].

Consider a household that derives utility (U) from vehicle miles traveled (VMT) and consumption of a numeraire good (y), which proxies for all other goods in the economy. The household chooses levels of these variables subject to its available income and time as well as the monetary and time costs of VMT and y. The maximization problem is written as follows:

$$\max_{VMT,y} \mathrm{U}(VMT, y) \tag{3-1}$$

such that:

$$P_f VMT + y \leq W \tag{3-2}$$

$$T_{vmt} + T_y + T_w \leq T \tag{3-3}$$

In Equation (3-2), P_f is the per-mile fuel cost of VMT, while the price of y is normalized to one; W is household income. In Equation (3-3), T_{vmt} is total travel time, T_y is the consumption time of good y, T_w is time spent on wage work, and T is total available time. Total income W is the product of T_w and earned wage ($\widetilde{w}$): $W = T_w\widetilde{w}$. Similarly, $T_{vmt} = t_{vmt}VMT$ and $T_y = t_y y$, where t_{vmt} and t_y are the time input required per unit consumption of the two goods.

In equilibrium, the two budget constraints will be binding. I rewrite Equation (3-3) as

$$T_w = T - t_{vmt}VMT - t_y y \tag{3-4}$$

and substitute this expression into Equation (3-2) to yield a single budget constraint:

$$(P_f + t_{vmt}\widetilde{w})VMT + (1 + t_y\widetilde{w})y = T\widetilde{w} \tag{3-5}$$

This single constraint follows from the fact that time can be converted to money through wage work. In other words, the opportunity cost of time spent on consumption is the income one forgoes in order to consume. Equation (3-5) expresses time in dollars: $t_{vmt}\widetilde{w}$ is the dollar value of time spent on VMT, $t_y\widetilde{w}$ is the analogous value for y, and $T\widetilde{w}$ is the income one would have if all available time was devoted to work. The household spends its total "achievable" income either directly through expenditure on goods or indirectly by using time at consumption instead of work.

To derive an estimable equation for VMT choice, an explicit utility function should be specified. The household's true utility function is unknowable; I thus follow Linn [165] – whose goal is to estimate the energy rebound effect for passenger vehicles – and define utility as follows:

$$U(VMT, y) = -(VMT \cdot \xi)^{\alpha} + y \tag{3-6}$$

where $\alpha < 0$ is a utility parameter and ξ is vehicle quality which is known to the household but unobserved by the econometrician. Utility therefore increases in VMT and vehicle quality. The chosen functional form is part of a class of utility functions that produce a constant price elasticity of demand, as shown below. While constant demand response is a special case and unlikely to hold in reality, it is nonetheless useful here to clearly demonstrate how fuel and time costs affect VMT demand.

The optimum choice of VMT and y satisfies the first-order condition:

$$\frac{\partial U}{\partial VMT} = -\alpha\xi(VMT \cdot \xi)^{\alpha-1} + \frac{\partial y}{\partial VMT} = 0 \tag{3-7}$$

Using the budget constraint Equation (3-5), y can be expressed as a function of VMT and parameters. Substituting this expression into Equation (3-7), rearranging terms, and taking the logarithm of both sides yield:

$$\begin{aligned}\log(VMT) = &\left[\frac{1}{1-\alpha}\log(-\alpha) + \frac{\alpha}{1-\alpha}\log(\xi) + \frac{1}{1-\alpha}\log\left(1 + t_y\widetilde{w}\right)\right] \\ &- \frac{1}{1-\alpha}\log(\pi_{vmt})\end{aligned} \tag{3-8}$$

where $\pi_{vmt} = P_f + P_t = P_f + t_{vmt}\widetilde{w}$ is defined as the time-inclusive marginal cost (or price) of travel. Since $\alpha < 0$, Equation (3-8) implies that VMT decreases with higher π_{vmt}. The log-log form of this equation makes the coefficient on π_{vmt}, $(\frac{-1}{1-\alpha})$, interpretable as a first-order approximation of the elasticity of VMT with respect to π_{vmt}. Denoting this elasticity by ε_{vmt} and collecting the first three terms of Equation (3-8) results in:

$$\log(VMT) = \varepsilon_{vmt}\log(\pi_{vmt}) + constant \tag{3-9}$$

With data on VMT, fuel economy, gasoline prices, and travel time cost, it is possible to fit this equation and estimate the key parameter of interest, ε_{vmt}.

3.3. Data and Empirical Strategy

3.3.1. Data

I obtain data on the price and quantity of VMT from the National Household Travel Survey (NHTS) [106]. This representative nationwide survey is conducted by the Federal Highway Administration (FHWA) in order to assist policymakers and transportation planners in understanding travel behavior and how it changes over time. My main source is the 2017 round of the NHTS, but I test the robustness of the results to use of the 2009 round as well. In both of these surveys, households submit day-long travel logs which include VMT and time spent driving for each vehicle driven. FHWA then imputes annual totals from these daily numbers using weight adjustments. Respondents also report the make and model of each vehicle, as well as the price of retail gasoline on the day of reporting. In addition to providing these vehicle data, the NHTS records several socioeconomic and demographic characteristics of households. The full sample includes 129,696 observations; the analysis sample consists of the 114,923 households with non-missing values for key analysis variables.[5] In all analyses, sampling weights provided in the NHTS is used, equal to the reciprocal of selection probability to make the sample nationally representative.[6]

Table 3-1 summarizes the household-level NHTS variables on which are drawn to construct this analysis. I tabulate means and standard deviations, both overall and within each of five specific income groups. While before-tax household income is reported in eleven distinct

[5] I remove the 3.1% of households with unreported income and an additional 8.4% who report zero VMT, no vehicle ownership, a vehicle model from before 1984 (which is not included in the EPA testing data), or unknown vehicle make and model.

[6] Analysis without weights would yield internally valid estimates of the parameters of interest but would not be nationally representative.

intervals in the 2017 NHTS, I follow Wadud [94] and collapse intervals into five income groups with roughly the same number of households. Sample-average annual VMT is 16,254 miles and rises monotonically from the first (i.e., lowest) income group to the fifth (highest); the latter group drives more than 2.5 times as many miles as the former. Annual driving time follows a similar pattern but drops slightly from the fourth income group to the fifth. Reported gas prices rise monotonically in income group but only differ by about five cents per gallon from the first income group to the fifth. Average fuel economy, weighted by miles traveled in each one of a household's vehicles, exhibits an inverse U-shaped relationship with income group.

Table 3-1. Summary statistics for 2017 NHTS (non-exhaustive list of variables)

Variable	U.S. Average	1st Income Group	2nd Income Group	3rd Income Group	4th Income Group	5th Income Group
Income Interval	-	Up to $24,999	$25,000 to $49,999	$50,000 to $74,999	$75,000 to $124,999	Over $125,000
Average Income†	$70,237	$19,447	$40,976	$64,563	$106,173	$180,674
Annual VMT (Miles)	16,254 (20,166)	8,592 (14,447)	14,146 (17,818)	17,580 (20,528)	20,589 (21,879)	22,055 (22,870)
Annual Driving Time (Hours)	482.18 (496.11)	269.73 (302.21)	434.27 (455.73)	521.69 (537.89)	615.38 (622.23)	601.67 (598.75)
Reported Gas Price ($/gallon)	2.392 (0.2066)	2.3747 (0.2018)	2.384 (0.2026)	2.3902 (0.2061)	2.4013 (0.2076)	2.4225 (0.212)
Weighted Average Fuel Economy (MPG)▿	23.69 (10.99)	23.11 (10.41)	24.90 (12.21)	25.30 (11.10)	24.41 (10.95)	23.16 (13.11)
Household Size (Persons)	2.514 (1.380)	2.146 (1.451)	2.273 (1.325)	2.532 (1.363)	2.776 (1.324)	2.987 (1.233)
Count of Adults	1.925 (0.821)	1.623 (0.843)	1.804 (0.807)	1.959 (0.799)	2.101 (0.767)	2.215 (0.733)
Count of Drivers	1.762 (0.882)	1.205 (0.852)	1.623 (0.790)	1.842 (0.804)	2.049 (0.796)	2.210 (0.783)
Count of Vehicles	1.935 (1.255)	1.130 (0.970)	1.727 (1.067)	2.078 (1.169)	2.357 (1.237)	2.545 (1.306)
Indicator for urban area (1 = urban; 0 = rural)	0.808 (0.378)	0.834 (0.363)	0.817 (0.385)	0.801 (0.394)	0.818 (0.385)	0.857 (0.348)
Census Tract Population Density (Persons per square mile)	5,647 (7,345)	6,314 (7,816)	5,388 (6,897)	5,340 (7,180)	5,273 (7,084)	6,005 (7,772)
Census Tract Housing Density (House per square mile)	3,042 (5,465)	3,386 (5,529)	2,850 (4,978)	2,809 (5,115)	2,812 (5,369)	3,452 (6,461)
N	114,923	22,959	25,793	21,45	26,005	19,531

Standard deviations are reported in parentheses. All observations are weighted using the sample weights provided in the NHTS.

† Average income within income group is calculated from the 2016 Consumer Expenditure Survey.

▿ Fuel economy is derived from EPA Fuel Economy Testing Data [174] for vehicles.

To produce a fuel price of VMT (P_f in dollars per mile) for each household, its reported fuel price per gallon is multiplied by its weighted average fuel economy:

$$P_f = \frac{\phi}{\sum_{i=1}^{n} VMT_j} \sum_{j=1}^{n} \frac{VMT_j}{MPG_j} \tag{3-10}$$

where n is the number of vehicles that a household uses, VMT_j and MPG_j are vehicle miles traveled and fuel economy (miles per gallon) of the jth vehicle, respectively, and ϕ is the price of gasoline (dollars per gallon). Unlike the 2009 NHTS, the 2017 NHTS does not itself report vehicle fuel economy; I thus obtain combined MPG (45% city, 55% highway) from EPA Fuel Economy Testing Data [174] for all vehicles in this sample.[7]

The time component of the marginal cost of travel (P_t), which referred to as travel time cost (TTC), is not directly observable in NHTS data, nor in any other dataset of which I am aware. To overcome this data problem, I follow the economics literature and the U.S. Department of Transportation's (US DOT) 2016 guidelines for Revised Value of Travel Time [175] and parameterize TTC as a function of wage. The NHTS only reports an annual income bracket for each household; I calculate the "equivalent" hourly wage of each household by dividing the average income in a household's bracket, taken from the 2016 Consumer Expenditure Survey, by 2,080 working hours in a year. Like Chen et al., I then categorize all survey-reported trips as either "work-related" or "non-work", the latter of which includes shopping, family/personal errands, school/church visits, social/recreational trips, among others [71]. The work-related trips are valued at 100% of hourly wage and non-work trips at 50% of hourly wage, following U.S. DOT guidelines [175].[8] Finally, I compute a weighted average of these trip values using time shares of each trip type as weights:

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[7] Although, the EPA fuel efficiency data is known to overstate of fuel economy of vehicles, it is the most comprehensive dataset available.

[8] In the Appendix A, I show results of a robustness check in which I use alternative definitions of travel time cost.

$$P_t = \frac{\left(\gamma_W\,\widehat{w} + \frac{1}{2}\gamma_{NW}\widehat{w}\right) \times \sum T_{vmt}}{\sum VMT} \tag{3-11}$$

Here, γ_W is the share of total travel time devoted to work-related trips, γ_{NW} is the corresponding share for non-work trips, $\widehat{w}$ is imputed hourly wage, and $\sum T_{vmt}$ is the total time spent on all trips. While my focus is on the travel time cost per mile, also the time cost per hour is plotted in Figure A-1. In the sample, the average time cost per hour of travel is 19.56 $/h, which is comparable to the Value of Travel Time recommended by U.S. DOT (18 $/h) [175].

Figure 3-1 displays fuel, time, and aggregate marginal costs by income group. The aggregate marginal cost of VMT (π_{vmt}) rises steeply and monotonically with income group, as does the time cost component (P_t). The fuel component (P_f) shows a shallow U-shaped relationship with income group. The time cost generally dominates the fuel cost, consistent with previous research that highlights the relative importance of travel time cost [94,157,172]. In the sample, both time cost and aggregate cost per mile rise faster than linearly in income group.[9] In fact, the top income group has nearly seven times the travel time cost as the bottom income group and more than three times the aggregate marginal cost of travel.

[9] This is a result of defining time costs as proportional to income, as well as the non-linear relationship between median income and the chosen income grouping.

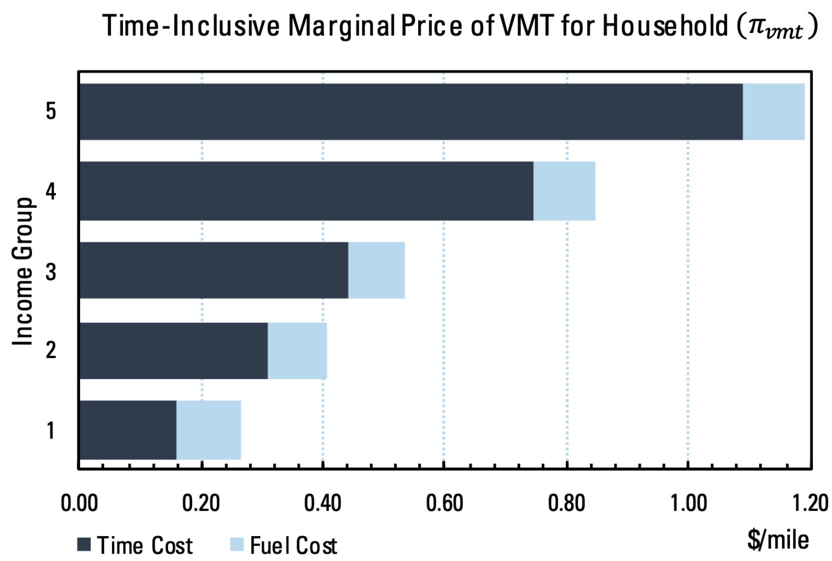

Figure 3-1. Marginal price of one vehicle mile traveled (VMT) by income group for the average household in each income group. Equations 10 and 11 are used to derive fuel cost and time cost per mile of driving.

3.3.2. Empirical Estimation

Using the above data, I fit various specifications of Equation (3-9) to estimate the price elasticity of demand for VMT. I choose four closely-related econometric models:

Model 1: $$\log(VMT_i) = \beta_0 + \beta_1 \log(P_{f,i}) + \gamma\vec{X}_i + \omega_i$$ **(3-12)**

Model 2: $$\log(VMT_i) = \beta_0 + \beta_2 \log(P_{t,i}) + \gamma\vec{X}_i + \omega_i$$ **(3-13)**

Model 3: $$\log(VMT_i) = \beta_0 + \beta_1 \log(P_{f,i}) + \beta_2 \log(P_{t,i}) + \gamma\vec{X}_i + \omega_i$$ **(3-14)**

Model 4: $$\log(VMT_i) = \beta_0 + \beta_3 \log(\pi_{vmt,i}) + \gamma\vec{X}_i + \omega_i$$ **(3-15)**

The subscript i indexes a household. VMT_i, $P_{f,i}$, $P_{t,i}$, and $\pi_{vmt,i}$ are as described in Section 2. $\vec{X}_i$ is a vector of household characteristics taken directly from the NHTS. One subset of this vector pertains to household members and includes household size, number of adults and drivers, indicators for respondent's race, and indicators for a household's age distribution.[10] A second subset contains socioeconomic measures including indicators for income group and homeownership as well as a count of a household's vehicles. A third pertains to location and includes census block group population density and housing density, indicators for urban (versus rural) area and metropolitan statistical area (MSA), MSA size, and indicators for values of a categorical variable defined by census division, whether or not a MSA has a population above one million, and whether or not an MSA has a subway system. A fourth, and final, subset includes indicators for survey month of year and day of week. I choose these control variables to match Linn and Su [165,166] as closely as possible. Lastly, ω_i is an error term that captures the effect of unobserved drivers of VMT.

I estimate each model via Generalized Least Squares regression, using the sampling weights provided by the NHTS. Standard errors are clustered by MSA, to allow for correlation of individual errors within each MSA. The log-log functional form has three virtues: it is motivated directly by the model in Section 2; it gives the coefficient on $\log(\pi_{vmt,i})$ the interpretation of the price elasticity of demand for VMT; and, in this specific empirical context, it produces model residuals that are normally distributed, implying that heteroscedasticity is of minimal concern.

Model 1 specifies VMT to be a function of only the fuel component of VMT price (i.e., not the corresponding time component). This specification is typical in the economics literature on energy efficiency rebound and yields an estimate of VMT elasticity with respect to the fuel price of VMT ($\hat{\beta}_1 = \hat{\varepsilon}_f$). However, it is susceptible to omitted variable bias if the omitted time component of price is correlated with the included fuel component. Model 2 is the time-cost

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[10] Indicators for a household's age distribution include, for instance, "two or more adults, youngest child 16-21".

analog of Model 1; it yields a VMT elasticity with respect to the time cost of VMT ($\hat{\beta}_2 = \hat{\varepsilon}_t$) and suffers from the same risk of omitted variable bias. Models 3 and 4 mitigate this risk by including the costs of both fuel and time as explanatory variables. Model 3 allows for joint estimation of the fuel-price and time-cost elasticities, $\hat{\varepsilon}_f$ and $\hat{\varepsilon}_t$. Parameter estimates from this model can be compared to those of Models 1 and 2 to quantify the bias of the latter.

Model 4 is the specification of VMT that follows directly and exactly from the economic model of VMT choice in Section 2. Fitting this model yields an estimate of the average combined, fuel- and time-inclusive price elasticity of VMT, $\hat{\varepsilon}_{vmt}$. This combined elasticity is related to $\hat{\varepsilon}_f$ and $\hat{\varepsilon}_t$ but not necessarily a linear function of the two. If $\hat{\varepsilon}_f \neq \hat{\varepsilon}_t$, then $\hat{\varepsilon}_{vmt}$ will depend intrinsically on the relative magnitudes of changes in P_f and P_t. In the special case in which P_f and P_t change by the same proportion, $\hat{\varepsilon}_{vmt} = \hat{\varepsilon}_f + \hat{\varepsilon}_t$; but in the general case where cost changes are not equal in proportion, $\hat{\varepsilon}_{vmt}$ may be larger or smaller than the sum of $\hat{\varepsilon}_f$ and $\hat{\varepsilon}_t$.

Income plays an especially important role in the determination of travel behavior and therefore transportation equity. As my theoretical model shows, VMT demand is affected by income through both the income budget constraint (i.e., money available to pay for VMT) and the time budget constraint (i.e., the opportunity cost of time, which depends on wage). As such, I break out my estimation of Models 1-4 by income group, interacting price variables with indicators for income group[11]. In all cases, the interaction of price with the lowest income-group

[11] The primary objective in this paper is to estimate average elasticities, both overall and within income group. For applications that benefit from more disaggregated predictions, machine learning and artificial intelligence methods may provide significant gains in precision. For instance, these methods are increasingly being used to predict household-level electricity demand as a function of observable characteristics [259–261].

indicator is omitted, so that the point estimate on the (un-interacted) price level is interpretable as the elasticity corresponding to this bottom group.

3.3.3. Scope and Limitations

The theoretical model and empirical strategy here are well-suited to leverage household-level driving data to estimate demand elasticities, but they abstract from several qualitatively important aspects of driving decisions. First, I do not model the capital decision of vehicle purchase. A static, two-period economic model with a first stage capturing vehicle purchase would show that buying a new car tightens the budget constraint and thus pushes VMT downwards [144,176]. This, in turn, would suggest that my elasticity estimates will be biased upwards. In a dynamic model, on the other hand, a forward-looking consumer might not adjust VMT in response to the (planned and expected) expense of a new car. More generally, the upfront cost of CAV use will depend on future innovation in CAV production technology as well as the prevalence of shared CAV modes. In any case, since I estimate elasticities by comparing changes in marginal costs, the external validity of these estimates rises as the upfront cost of CAV use decreases.

Also note that the measurement of costs includes fuel and time but not depreciation, maintenance, insurance, or congestion. The omission of depreciation, maintenance, and insurance costs is motivated by a lack of data on these cost components and little consensus on the changes likely to occur with CAV technology diffusion along these dimensions. Note, however, that bias from omission of these variables is only a risk insofar as changes in depreciation and insurance costs are correlated with changes in fuel and time costs. Congestion is similarly unobservable in the data and difficult to forecast in a CAV-dominant mobility paradigm. Every additional VMT comes with an external congestion cost to other drivers that is not measure. At low levels of CAV penetration, congestion costs may be negligible, but at higher levels, and with large associated reductions in the marginal cost of travel, congestion may be an important check on induced travel [177].

Finally, the travel time cost measure is imputed from reported income data. It is thus subject to significant measurement error as well as a risk of omitted variable bias. This imputation, which follows a long literature in economics and transportation research that links opportunity costs to wage, is the best one can do to estimate the opportunity cost of time spent traveling. Measurement error biases estimates towards zero; on the other hand, if households that drive more also value time more for reasons other than income, the omission of such explanatory factors might bias estimates away from zero. It is for this latter reason that I include a large vector of control variables in regression. Ultimately, I make no strong claim on the statistical precision of these estimates; rather, I argue that this exercise illustrates the sizeable role that time cost plays in current travel decisions and will play in a future with driverless vehicles.

3.4. Estimates of Price Elasticity of Demand for VMT

Table 3-2 displays the estimates of the sample-wide elasticity of demand for VMT with respect to different components of VMT price. The point estimate obtained from Model 1 implies a fuel price elasticity of approximately -0.14; that is, a one percent rise (drop) in the fuel price per VMT is associated with a 0.14 percent drop (rise) in VMT itself. This magnitude is well within the range provided in the existing literature [162,165–168] , which includes estimates as low as -0.06 [166,167] and as high as -0.28 [168]. Model 2, meanwhile, yields a corresponding point estimate of approximately -0.45 for the time cost elasticity. While this is significantly larger than the fuel price elasticity estimate, such a large difference is consistent with the findings of the travel demand literature [158,159,161,178]. There are few existing estimates of the elasticity of VMT with respect to travel time cost, and there is no consensus on its magnitude.

The estimates from Models 1 and 2 are susceptible to omitted variable bias, because each omits one of the two key components of the marginal cost of travel. In fact, P_f and P_t are positively correlated in the data (the Pearson correlation coefficient is 0.37), which implies that the estimates from Models 1 and 2 are biased upwards. The results from Model 3 confirm this: the jointly estimated fuel and time price elasticities are approximately -0.10 and -0.40, respectively, and both are smaller than their separately-estimated analogs.[12] Together, the results using Models 1-3 suggest that existing estimates of travel demand elasticities may be systematically biased upwards. There are no studies that jointly consider fuel prices and the opportunity cost of time in empirical measurement of elasticities. This is primarily due to a lack of available data on the value of time [157], which is a challenge for us just as much as any other researchers. While households' true valuations of time is unknown, there is broad consensus that the opportunity cost of travel rises with income [157]. As long as the fuel price of VMT rises in income, as it does in this case, omitting one cost component or the other will produce upward bias in elasticity estimates.

[12] A neoclassical economic model would yield the prediction that $\hat{\varepsilon}_f = \hat{\varepsilon}_t$. The fact that this is not the case in this context suggests the possibility that some behavioral-economic phenomenon causes households to respond differently to a change in fuel cost than a dollar-equivalent change in time cost.

Table 3-2. Results of elasticity estimation (main explanatory variables) for different models

	Model 1	**Model 2**	**Model 3**	**Model 4**
$\hat{\varepsilon}_f$	-0.1408*** (0.028)	-	-0.0989*** (0.017)	-
$\hat{\varepsilon}_t$	-	-0.4486*** (0.042)	-0.4007*** (0.048)	-
$\hat{\varepsilon}_{vmt}$	-	-	-	-0.3920*** (0.049)
Pseudo R^2	0.227	0.261	0.272	0.240

The dependent variable is $\log(VMT)$. Each column reports a separate regression. All regressions include fixed effects and control variables described in Section 3.2. Observations are weighted by the household sample weights. Asterisks denote 1 (***), 5 (**), and 10 (*) percent significance levels.

Model 4, like Model 3, accounts for both the fuel price and the time price; however, it parameterizes demand to depend only on the (log) sum of the two, rather than each individually. Using this model, I estimate a combined elasticity of demand ($\hat{\varepsilon}_{vmt}$) of approximately -0.39. Since $\hat{\varepsilon}_f$ and $\hat{\varepsilon}_t$ from Model 3 are markedly different, there is no special reason to believe that $\hat{\varepsilon}_{vmt}$ is equal to the sum of $\hat{\varepsilon}_f$ and $\hat{\varepsilon}_t$. Rather, the relationship between these three parameters depends on the empirical distribution of prices in this particular context. In this case, the time channel dominates the fuel channel, as $\hat{\varepsilon}_{vmt}$ is approximately the same as $\hat{\varepsilon}_t$. To us, this comparison exercise underscores the importance of using separate fuel and time price elasticities in travel demand forecasts. The combined price elasticity estimate is internally valid, but it is unlikely to be externally valid to scenarios in which the relative prices and price changes pertaining to fuel and time are different.

The estimated combined VMT elasticity of -0.39 differs significantly from other estimates in the existing literature. This discrepancy illustrates the importance of empirical analysis in the calibration of demand response. Elasticities of travel demand are a key input into any forecast of

CAV travel and energy use; one must be careful in applying estimates from one context to another, different context. Using existing fuel price elasticity estimates – which are 25-85% lower than the combined elasticity [162,165–168] – to predict energy rebound would almost certainly underestimate the impact of vehicle automation on energy use. On the other hand, using previously published estimates of VMT elasticity with respect to generalized travel costs – which are 60-400% higher [10,22] than here – would very likely *overestimate* the energy use impact of CAVs.

It is not just the type of price change (fuel- or time-specific) that dictates the size of the demand response; it is also household wealth that matters. Table 3 displays the results of estimating modified versions of Models 3 and 4 that allow for differences in demand response across the wealth spectrum. Panel A contains the individual fuel and time price elasticities, while Panel B contains the combined price elasticities. Figure 3-2 shows the same results graphically. There is significant heterogeneity in all three parameter estimates across income groups.

Panel A of Table 3, which reports results from Model 3, show that the gap between $\hat{\varepsilon}_f$ and $\hat{\varepsilon}_t$ in the overall sample persists within each income group as well. Panel B of Table 3, which reports results from Model 4, reveals the relationships between wealth and demand response to specific components of VMT price. The absolute-value fuel price elasticity drops in wealth until the last income group; in contrast, the absolute-value time cost elasticity *rises* monotonically in wealth. These findings imply that richer households have less elastic demand than poorer ones with respect to fuel price changes and more elastic demand with respect to time cost changes. I do not attempt to explain these findings here, but I note that both positive and negative relationships between demand elasticity and wealth have been found in the existing economics literature [167,179–181]. On the one hand, wealthier households may engage in more discretionary travel than poorer ones, and for that reason their demand for VMT may be more elastic to price. On the other hand, wealthier households are also generally less price-sensitive than poorer ones, and this may make their demand less elastic. The results using Model 4 (Table 3-3, Panel B) reveal that, on aggregate, wealthier households in the context have relatively more elastic demand for VMT. For all four models, the signs and relative magnitudes of estimated coefficients on control variables are consistent with both economic intuition and the findings of previous studies utilizing similar approaches and datasets [165,166].

Table 3-3. Elasticity estimates by income group

Income Group	**1st Income Group**	**2nd Income Group**	**3rd Income Group**	**4th Income Group**	**5th Income Group**
			Panel A: Model 3		
$\hat{\varepsilon}_f$	-0.153***	-0.131***	-0.097***	-0.092***	-0.109***
	(0.026)	(0.012)	(0.019)	(0.015)	(0.017)
$\hat{\varepsilon}_t$	-0.290***	-0.403***	-0.446***	-0.463***	-0.474***
	(0.063)	(0.055)	(0.049)	(0.038)	(0.048)
			Panel B: Model 4		
$\hat{\varepsilon}_{vmt}$	-0.256***	-0.351***	-0.401***	-0.444***	-0.421***
	(0.048)	(0.052)	(0.051)	(0.037)	(0.042)

The dependent variable is $\log(VMT)$. Both regressions include fixed effects and control variables described in Section 3.2. Observations are weighted by the household sample weights. Asterisks denote 1 (***), 5 (**), and 10 (*) percent significance levels. The pseudo R^2 of regression for Panel A is 0.272 and for Panel B is 0.240.

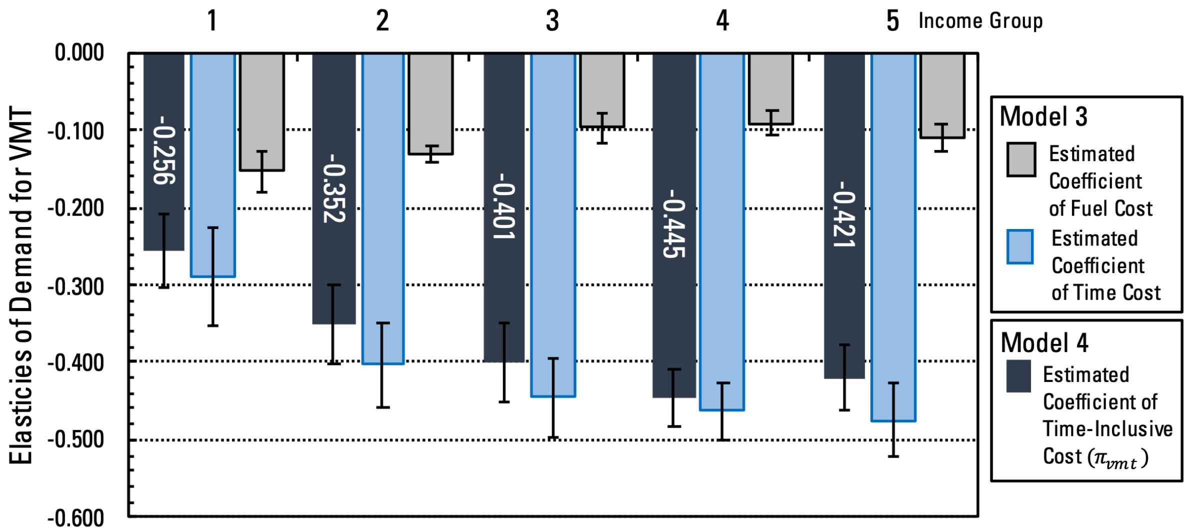

Figure 3-2. Estimated elasticities of demand with respect to $\boldsymbol{P_t}$ and $\boldsymbol{P_f}$ (from Model 3) and $\boldsymbol{\pi_{vmt}}$ (from Model 4). Clustered standard errors are shown as error bars. Standard errors are clustered by MSA, and observations are weighted by the household sample weights.

I conduct two sets of robustness checks to assess the sensitivity of the results to key modeling decisions. First, I compare results of using the 2017 NHTS to those of using the 2009 NHTS while maintaining the same definitions and parameterizations wherever possible.[13] Table A-1 displays the findings, including sample-wide and income-group specific estimates. The absolute magnitudes of all three sample-wide elasticity estimates are modestly larger in 2009 than in 2017, as highlighted in Column 7. Across income groups, trends in $\hat{\varepsilon}_t$ and $\hat{\varepsilon}_{vmt}$ are consistent in both the 2009 data and the 2017 data, while $\hat{\varepsilon}_f$ exhibits more of a U-shaped relationship with income in the 2009 data. Some variation in estimates across the two survey rounds is expected, since baseline income, fuel prices, and fuel economy are not constant over time. In fact, 2009 is notably defined by the onset of the Great Recession. The fact that 2009

[13] Household income groupings in the raw 2009 NHTS do not exactly match those in the 2017 NHTS. I aggregate income groups in the 2009 data to match those of the 2017 data as closely as possible.

elasticity estimates are qualitatively similar to the main, 2017-based estimates lend credence to the empirical strategy and results.

In the second robustness check, I test how the definition of time cost affects estimation results. Two alternative definitions of travel time cost are employed: first, that it is equal to 100% of hourly wage for all trips; and second, that it is equal to 50% of hourly wage for all trips (Figure A-2). I report the results in Table A-2. Mechanically, the first of these definitions causes estimated time and combined price elasticities to fall relative to the preferred estimates, while the second causes estimated elasticities to rise. The former effect is much more pronounced than the latter, perhaps because the high proportion of non-work trips in the data makes the preferred estimates much more similar to alternative definition 2. Meanwhile, trends in all three elasticity parameter estimates (not shown for fuel prices) across income groups are robust. While the alternative definitions rely on reported income just as much as the preferred estimate, this robustness check does imply that the qualitative findings are not solely an artifact of defining work and non-work trips differently.[14]

3.5. Forecasting CAV-Induced Travel and Energy Use

One way to predict the travel and energy impacts of CAVs is by estimating the demand response to changes in energy efficiency and travel time cost that may occur as a result of CAV technology. The two primary inputs to such an analysis are travel demand elasticities and price changes. These estimates from Section 4 are used for the former and a range of estimates based

[14] Several robustness checks are additionally conducted to assess the sensitivity of results to model specification and parametrization. All results are within a reasonable range of the main estimates.

on the existing CAV literature for the latter. While it is widely understood that automation and connectivity will enable a range of fuel-saving practices at the vehicle level, estimates of the magnitude of associated fuel and time cost changes are rare and largely speculative. Studies collectively suggest 5% to 20% energy efficiency improvement in CAVs compared to conventional counterparts, mainly due to optimal driving cycle, eco-routing, congestion reduction, and improving vehicle electrification[15] attributes [9,10,22,23,155,177].

Reductions in TTC for CAVs relative to conventional cars are predicted to come mainly from decreased attention demands and driving-related stresses [10], the resulting increase in opportunities to engage in alternative in-vehicle activities[16] [56,182], and increases in travel speeds (through improved safety and traffic flow) [80]. Comparing previous studies of TTC in rail travel versus vehicle travel, Wadud estimates that the switch from conventional to CAVs will yield a 25-60% reduction in TTC [94]. The recent survey results of Correia et al. show that a CAV with an office interior could reduce travel time cost by 26% compared to a conventional car [183]. 60% is consistently accepted as the upper bound of possible TTC reductions in the literature [10,22,56,65,80,118], since in-vehicle attention requirements cannot be completely eliminated.[17]

In this forecasting exercise, I increase fuel economy (MPG) and travel time cost (p_t) by X and Y, respectively, where $X \in [0.05{,}0.2]$ (or 5-20%) and $Y \in [0{,}0.6]$ (or 0-60%). The direct outcome of interest is the travel demand induced by CAV cost changes as a percentage of the

[15] While the effect of vehicle electrification on net energy consumption is similar to fuel economy improvement, it could have a much different impact on vehicle tailpipe emissions as well as upstream emissions from electricity generation.

[16] Such activities include, for example, watching movies, sleeping, eating, working, checking emails, browsing web and social media.

[17] Some studies argue that increased productivity while riding with CAVs is not guaranteed. Apprehension [262] or motion sickness may limit the ability of passengers to engage in other activities or raise the disutility of travel [88,182]. Short average trip times may not provide sufficient time for sustained productivity or sleep [262].

pre-CAV "business as usual (BAU)" ($\delta = \frac{VMT_{CAV}}{VMT_{BAU}} - 1$). The fitted regression function from Model 3 is used to generate VMT predictions for any cost conditions: $\widehat{VMT} = e^{\widehat{\beta}_0} p_f^{\hat{\varepsilon}_f} p_t^{\hat{\varepsilon}_t}$. Substituting the expression for $\widehat{VMT}$ into the equation for δ, rewriting $p_f = \phi/MPG$, and assuming gasoline price ϕ is fixed, I obtain:

$$\delta = \left(\frac{MPG_{BAU}}{MPG_{CAV}}\right)^{\hat{\varepsilon}_f} \left(\frac{p_{t_{CAV}}}{p_{t_{BAU}}}\right)^{\hat{\varepsilon}_t} - 1 \tag{3-16}$$

Finally, I re-express CAV values as functions of BAU using X and Y and simplify to yield

$$\delta = \left(\frac{1}{1+X}\right)^{\hat{\varepsilon}_f} (Y)^{\hat{\varepsilon}_t} - 1 \tag{3-17}$$

I compute δ overall (using elasticities from Column 3 in Table 3-2) and for each income group (using elasticities from Columns 1-5 in Table 3-3), iterating over values of X and Y in increments of 0.05.

In principle, elasticity estimates from any of the four empirical models (Equations 3-12 to 3-15) could be used to forecast induced travel. Using Model 3 estimates is preferred in this case because they strongly suggest that demand response depends on the specific source of price changes (fuel vs. time). Models 1 and 2 consider only one source or the other and are thus relatively more susceptible to omitted variable bias. Model 4 accounts for both fuel cost and time cost, but it does not allow the elasticity of demand to vary with the relative sizes of fuel and time cost changes.[18] Consider any two different $\{X, Y\}$ pairs that, on aggregate, produce the same proportional change in p_t: Model 3's results strongly suggest that these two pairs produce

[18] The Model-4 equivalent equation to Equation 3-16 is $\delta = \left(\frac{\pi_{vmt_{CAV}}}{\pi_{vmt_{BAU}}}\right)^{\hat{\varepsilon}_{vmt}} - 1$.

different VMT demand response; using Model 4 would force them to yield the same response. Motivated by this discrepancy, I show forecasting results based on Model 3 here and those based on Model 4 in Appendix A.

Figure 3-3 depicts the results in the form of heat maps. The x-axis indicates the fuel economy improvement, while the y-axis indicates the time cost reduction. Color depth measures the induced travel demand δ in percentage terms. Two patterns are readily observable. First, the magnitude of induced travel rises monotonically with increases in either X or Y, consistent with negative price elasticities of demand. For the average household in the 2017 NHTS, the range of simulated price changes produces a minimum forecast of 2% induced travel and a maximum of 47%. Second, induced travel rises with income group for any given (X, Y) pair, consistent with larger absolute-value time cost elasticities among richer households that dominate smaller absolute-value fuel price elasticities. In the lowest income group, the average household is forecast to increase VMT by 1-35%, while the corresponding range is 3-58% in the highest income group.

The dashed lines in Figure 3-3 connect forecasted induced travel to forecasted energy use. In particular, they indicate combinations of (X, Y) that yield zero net change in energy use. Such an exact offsetting is possible because, even as fuel and time price drops induced travel, energy efficiency reduces the energy required per unit of travel. The slopes of the dashed lines therefore denote the rate at which time costs need to drop in order to fully offset the energy savings from an additional percentage rise in fuel economy. For instance, Figure 3-3 indicates that, in the sample-average household, a 20% rise in fuel economy would lead to net energy savings unless travel time cost drops by 38% or more. In each heat map, the area below and to the right of the dashed line is characterized by net decreases in energy use from the simulated changes, while the area above and to the left of the dashed line is characterized by net increases, i.e., what is known in the literature as "backfire" [144].

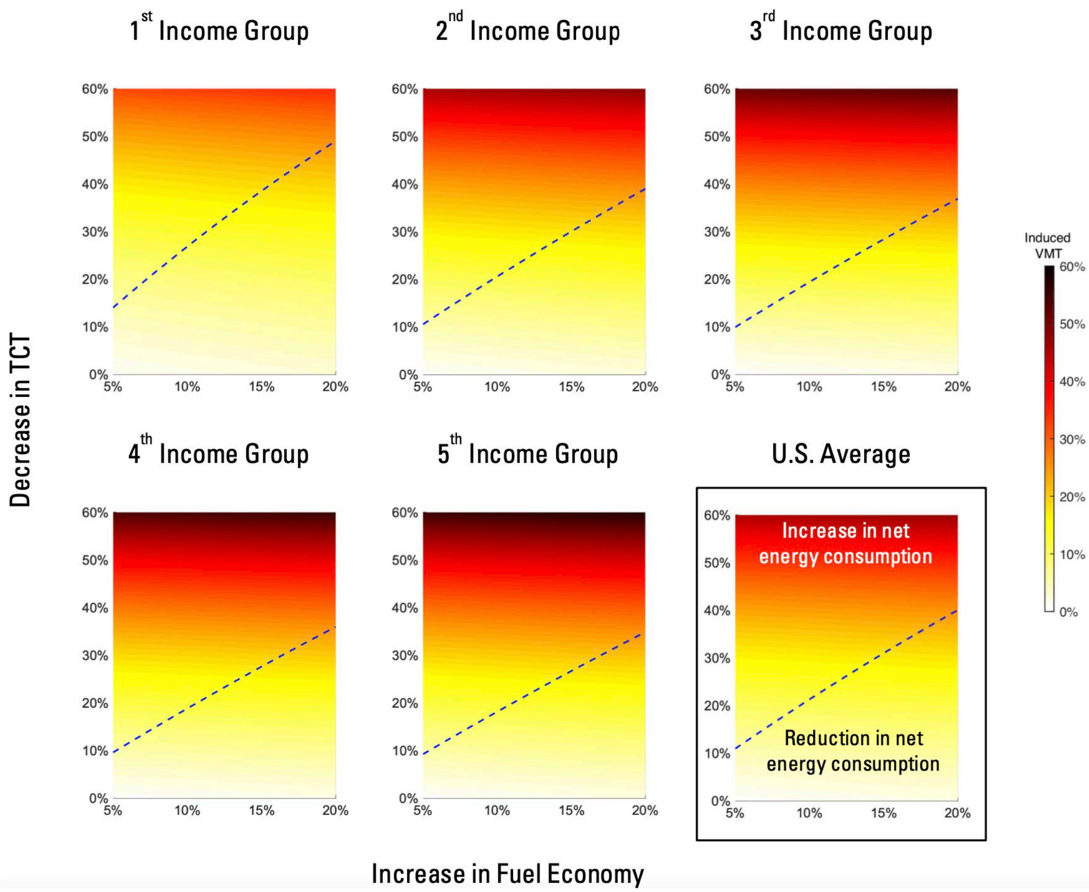

Figure 3-3. Simulation of induced travel to fuel economy improvement and reduction in TTC for CAVs, and the impact on net energy consumption.
Any point above dashed curves represents the case of backfire (increase in net energy consumption despite increase in fuel economy).

It is apparent, both overall and in each specific income group, that a wide range of CAV cost changes can produce backfire. Of course, not all combinations of (X, Y) are equally likely to occur. I therefore do not argue that backfire is "likely" to occur at any specific levels of X and Y. The empirical analysis nevertheless suggests the possibility of net energy increases from changes which are well within the ranges predicted in the CAV literature. Furthermore, backfire is increasingly likely in higher income groups. This trend follows naturally from two empirical facts about relatively richer households in the 2017 NHTS: (1) a greater proportion of their imputed total travel costs come from time rather than fuel; and (2) they have more elastic demand with respect to time costs. I predict that the energy savings from a 20% rise in fuel economy can be offset by a 50% drop in travel time cost in the lowest income group; in the highest income group, however, only a 32% drop in time costs is needed.[19]

There are other existing studies of the travel demand changes stemming from CAV technology. The methods and results of some of these are highlighted in Table 3-4. In the prior literature, higher VMT in CAVs is attributed not just to higher passenger travel but also to, variously, new user groups [78], empty vehicle travel (i.e., unoccupied VMT) [99,184], and the possibility of shifts in mode choice and urban sprawl [22,71,143]. New user groups include minors and elderly and medically infirmed individuals who *may begin* traveling with the availability of CAVs. Empty vehicle travel refers to VMT with no passengers, such as what might occur in a private CAV before or after passenger drop-off or in a shared CAV dispatched to pick up the next passenger. Mode choice shift includes substitution of CAV use for public transit, and urban sprawl refers to the possibility of changes to residential location choice due to CAV availability. This work focuses entirely on induced travel among existing drivers and yields estimates of overall VMT change in the range of 2 to 47 percent.

[19] Figure A-3 depicts the simulation results from use of Model 4. Overall induced travel demand is lower at any $\{X, Y\}$, and the slope of the dashed line changes more dramatically with income group. Otherwise, the patterns are the same.

Table 3-4. Literature estimate of changes in VMT due to CAV technology (list is non-exhaustive).

Study	Method	Estimate of VMT change	Sources of VMT change
Childress et al. [56]	Activity-based model for Puget Sound region	-30% to +20%	Changes in driving cost through value of travel time, road capacity, and parking cost
Fagnant and Kockelman [80]	Scenario-based analysis based on assumptions	+10 to +20%	Induced travel demand
Harper et al. [78]	Demand wedge analysis based on 2009 NHTS data	Upper bound: +14%	New demand from underserved travelers including elderly, young age, and travel-restricted with medical condition
Wadud et al. [10]	Literature-driven elasticity of VMT	+4% to +60%	Reduced generalized cost of driving
Stephens et al. [22]	Assumption based on multiplicative factors for travel demand	+20% to +160%	Easier travel due to traffic flow, crash avoidance, reduced cost of driving
Zhang et al. [99]	Activity-based model of Atlanta, GA area	+30% (per reduced vehicle)	Unoccupied relocation of private CAVs for meeting travel needs of household with reduced vehicle ownership
Harb et al. [184]	Naturalistic experiment, survey, and interview when providing chauffeur as a proxy for CAVs	+4% to +341% with central estimates of 83% increase	Travel pattern shift, longer and more frequent travels, unoccupied VMT (for a small sample size)
This Study	Estimation of VMT elasticity with respect to fuel- and time-inclusive marginal price of private vehicle driving using 2017 NHTS data	+2% to 47%	Reduced marginal cost of driving and heterogeneous response of different income groups (purpose: forecasting energy consumption impacts)

3.6. Conclusions

The aim of this study is to shed light on the possible travel and energy impacts of CAVs. To that end, I use microeconomic modeling, applied econometric techniques, and the most recent data available on household travel behavior to estimate average travel demand elasticities with respect to the price of fuel and travel time. These elasticity estimates are then leveraged in a forecast of CAV-induced travel under a range of different realized changes to fuel economy and per-mile time costs.

I estimate an average elasticity of VMT demand with respect to the combined, fuel- and time-inclusive price per mile of -0.4. Allowing for heterogeneity in VMT elasticity by price channel (fuel vs. time) and income, I find that demand response to price increases is larger through the time channel (with an elasticity of -0.4) than through the fuel channel (with an elasticity of -0.1). I also find that richer households are more sensitive to the overall price of travel as well as the time cost.

Applying these fuel and time cost elasticities in the forecasting exercise, I find a large range of possible travel and energy impacts of CAV diffusion. A number of plausible scenarios for fuel economy and time cost changes are characterized by backfire, or a net rise in energy use. Backfire is more likely in higher income quantiles, where relatively less of a time cost reduction is required to offset the energy savings from fuel economy improvements. On average, a 38% reduction in time cost fully offsets a 20% fuel economy improvement enabled by CAVs.

The results strongly suggest that travel demand will rise as a behavioral response to the diffusion of CAVs. Some of this rise will come from shifts away from other transportation modes, including public transit, cycling, and walking. Some will come from additional travel – such as new passenger trips, empty trips in between passenger travel, travel pattern change, breaking of pooled trips into several lower occupancy trips, and longer and more frequent trips necessitated by shifting home locations to peripheral zones. Regardless, this induced travel will pose a stiff challenge to policy goals for reductions in energy use, traffic congestion, and local and global air pollution.

The proper government response to CAV market penetration is not obvious. There is no "silver bullet" that can achieve all goals efficiently and equitably, and policies aimed at meeting some of these goals may make it more difficult to meet others. For instance, while it is natural to view the results as evidence that even greater fuel efficiency is needed, this study also underscores the limitations of vehicle energy efficiency improvements: they provide incentive to drive more, which offsets some environmental benefits and increases congestion. Taxation – another commonly cited policy tool for internalizing the negative externalities of driving – is also imperfect. Taxes are viewed by many as a more economically efficient policy instrument, but they are also sometimes viewed as regressive, because poorer households generally devote a greater proportion of their total budget to energy than richer ones. Vehicle connectivity may, on the one hand, actually enhance the cost-effectiveness of taxation in the transportation sector by offering the potential to tax VMT instead of (or in addition to) to fuel use.[20] On the other hand, the fact that wealthier households have more elastic demand than poorer ones in this context increases the risk of regressive welfare impacts of taxation.[21] Above all, policymakers should prioritize incentives for high-occupancy pooling, ride-sharing, and minimizing empty trips, as these have the potential for large reductions in fuel use at low cost to well-being.

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[20] This is seen as desirable because, while fuel use is highly correlated with greenhouse gas emissions, it is much more weakly correlated with local air pollution, congestion, and accident risk (see, e.g., [263]).

[21] The relationship between demand elasticity and income is an important input into distributional welfare analysis; see [264,265]).

This analysis expresses induced travel and rebound in percentage terms, but it is instructive to consider the absolute magnitude of prospective changes in travel and energy due to CAVs. For instance, an assumed 15% average improvement in fuel economy is expected to save 10.56 billion gallons of gasoline equivalent (GGE) annually (26.4 billion USD), from a current consumption level of 88.85 billion GGE in light-duty vehicles. However, that number should be viewed as a best-case scenario. CAVs with the same 15% fuel economy advantage would very likely induce travel that would offset some of those savings. Based on this estimate, at 100% market penetration, CAVs may result in anywhere between the aforementioned 10.56 billion GGE annual decrease and a 15.26 billion GGE (17.2%, or 38.15 billion USD) annual *increase*.

While the present study uses U.S. data to quantify the energy rebound caused by CAV penetration, the methodology that I develop here is general and can be applied to other regions of the world, where travel is less heavily reliant on private vehicles. Future research should also aim to compare the broader social benefits of CAV travel with their social costs, considering the value and frequency of driving and all the externalities that it produces. Finally, there remains a large degree of uncertainty in the attributes, costs, and benefits of connected and automated vehicles, which in turn makes it difficult to forecast and react to future travel and energy behaviors. Even at this early stage of CAV technology maturity, however, it is vital to consider the potential of CAVs to induce significant new travel and energy use.

Chapter 4. Widespread Range Suitability and Cost Competitiveness of Electric Vehicles for Ride-hailing Drivers

4.1. Introduction

Transportation Network Companies (TNCs) or ride-hailing services [41] have brought about a new paradigm in personal travel that is rapidly reshaping the transportation sector. Ride-hailing platforms such as Lyft, Uber, and DiDi provide on-demand mobility services that complement and compete with personal vehicle ownership and transit use, changing urban travel patterns and the associated energy and environmental impacts. TNCs account for a small yet rapidly growing share of transportation miles [46] and have likely raised energy use and emissions by substituting for public transit, increasing "deadhead" miles, and inducing new travel demand [24,31,38,51,54]. The Union of Concerned Scientists (UCS), for example, finds that the average ride-hailing trip produces an estimated 69% more greenhouse gas (GHG) emissions than the trip it replaces [185]. California Air Resources Board estimates that the 2018 TNC vehicle fleet emitted 301 $CO_{2\text{-}eq}$ per passenger-mile travelled (PMT), approximately 50 percent higher than the statewide passenger vehicle fleet average of 203 $CO_{2\text{-}eq}$/PMT [186]. In 2018, California became the first U.S. state to regulate GHG emissions by TNCs, through the California Clean Miles Standard and Incentive Program (Senate Bill (SB) 1014).

Fleet electrification is widely viewed as a solution to the problem of large and increasing transportation-sector emissions, through the substitution of low- or zero-carbon electricity for emissions-intensive automotive fuels [26,32,36,187,188]. Consistent with this notion, Lyft recently announced a commitment to transition to 100% electric vehicles (EVs) on its platform by 2030 [189]. A few months later, Uber announced the same electrification goal for its U.S. platform as well as a similar goal of full electrification internationally by 2040 [190]. A number of factors, however, are thought to constrain this transition. As of 2019, fewer than 0.5% of active TNC vehicles were estimated to be electric [191]. The upfront cost of an EV is currently higher than that of an internal combustion engine vehicle (ICEV), which elicits questions about the cost competitiveness of EVs. Ride-hailing drivers predominantly self-identify as low income and as a member of minority groups [192], which suggests the possibility that financing constraints limit EV uptake. In addition, EV batteries must be charged periodically, which, given the relative sparseness of the U.S. charging station network may induce "range anxiety" among some would-be EV users. Furthermore, the need to regularly charge an EV is an example of how the experience itself of owning and operating an EV differs from that of an ICEV. Relatedly, current limitations on the size or other non-price attributes of EVs may be a disincentive to their take-up (Supplementary Note B-1 provides more details on EVs).

In this study, the ability of currently available battery electric vehicle (BEV) models is investigated to meet the range needs of ride-hailing drivers and compete with ICEV and hybrid vehicles on total cost of ownership. A large, novel dataset is used for this study: the universe of 2019 rides and drivers on the Lyft platform. The absolute count of active drivers represented in this study remains the proprietary information of Lyft Inc. The analysis results is reported based on the percentage of driver cohorts to comply with the data use agreement. For context, Schaller (2018) estimates that there were nearly 4.2 million active ride-hailing drivers in the U.S. working on Lyft and Uber platforms in 2018, whose approximate market shares were 40% and 60%, respectively [43].

A few previous studies have shed light on BEV range and cost considerations in specific contexts and for specific driver types. Tu et al. study range needs and vehicle operation costs in a week's worth of GPS trajectory data for nearly 140,000 ride-hailing drivers on the DiDi platform in Beijing [193]. Bauer et al. simulate ride-hailing patterns in New York and San Francisco using agent-based modeling and find evidence that BEVs can provide the same level of service at lower cost than ICEVs [194]. Pavlenko et al. estimate the total costs of EV ownership for several "representative" driver profiles [195]. This work expands on these previous studies by providing a more comprehensive, empirical picture of BEV range suitability and cost considerations than has been previously possible (Supplementary Note B-2 provides a more detailed review of literature).

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

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

4.2. Materials and Methods

4.2.1. Data

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

4.2.2. Driver Cohorts

I create mutually exclusive "cohorts" of drivers exhibiting similar travel patterns using an unsupervised learning algorithm. I compare the performance of k-means, k-medoids, and hierarchical clustering and choose the k-means method with k=4 for the main analysis [196] (Supplementary Note B-3 provides more details on the driver clustering). The clustering variables are number of active days, daily number of rides, daily total VMT, daily occupied VMT, and daily shift hours; all variables are standardized before clustering. Based on the relative attributes of each cohort, I use the following cohort names: Ultra-High Mileage (UHM); High-Frequency High-Mileage (HFHM); Low-Frequency High-Mileage (LFHM); and Low-Frequency Low-Mileage (LFLM) (Figure B-1). Table B-1 includes summary statistics for key variables by cohort.

4.2.3. Total Cost of Ownership (TCO) Model

I build a TCO model to calculate average annual ownership cost of vehicles of different types, total mileages, and commitment periods. New (2020) and pre-owned (2017) ICEVs, HEVs, and BEVs are considered; consistent with Pavlenko et al., plug-in hybrid electric vehicles are excluded, since they often operate similar to non-plug-in hybrid models and are challenged by relatively high fueling and maintenance costs and higher upfront costs [195]. For each vehicle type, I choose one representative vehicle model to evaluate. For ICEVs, and HEVs, the Toyota Camry LE and Toyota Prius are chosen, respectively; these are currently the best-selling vehicles of their type overall as well as the most common vehicles of their type on the Lyft platform [197]. For new and pre-owned BEV250, the Chevy Bolt is chosen, which is the most common BEV among ride-hailing drivers (the best-selling BEV overall is currently the Tesla Model 3)

[197]. For pre-owned BEV100, the Nissan Leaf is chosen, which is again the best-selling EV of its range on the used market [198].

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

$$AATCO_{CP}^{ICEV\ or\ HEV} = \frac{D_{CP}}{CP} + \frac{1}{CP}\sum_{i=1}^{CP}\left(\frac{I + \left(\frac{G_s}{MPG} + \phi(.)\right) \times (M_{TNC} + M_P)}{(1+r)^{i-1}}\right) \quad \textbf{(4-1)}$$

$$AATCO_{CP}^{BEV} = \frac{D_{CP}}{CP} + \frac{1}{CP}\sum_{i=1}^{CP}\left(\frac{I + \left(LCOC_s \times \varphi + \phi(.)\right) \times (M_{TNC} + M_P)}{(1+r)^{i-1}}\right) \quad \textbf{(4-2)}$$

$AATCO_{CP}^{ICEV\ or\ HEV}$ and $AATCO_{CP}^{BEV}$ are average annual total cost of ownership for ICEV or HEV and BEV, respectively. D_{CP} is the depreciation over the commitment period as described below. CP is the commitment period in years (3 or 5 years). i denotes year index and r is the discount rate (5%). I is the annual insurance cost. G_s is the 2019 average gas price ($/gallon) in state s where the vehicle operates and, analogously, $LCOC_s$ is the levelized cost of electricity ($/kWh) for BEV charging in state s as estimated in Borlaug et al [199] (Table B-5). MPG is the vehicle fuel economy (miles per gallon) and φ is the BEV energy efficiency (kWh/mile). $\phi(.)$ is the mileage weighted service and maintenance cost ($/mile) as described below. M_{TNC} is the annual mileage observed on the Lyft platform and M_P is the annual mileage for personal use of vehicle, which I assume to be 7300 miles per year [106]. I exclude taxes, registration costs, and fees given their high variability and that they do not contribute substantially to the comparative TCO (they are very similar among ICEVs, HEVs, and BEVs. This exclusion may slightly disadvantage BEVs, since in some regions BEVs receive discounts on registration and fees.

4.2.4. Depreciation

Depreciation depends on both mileage and vehicle age. Vehicles depreciate much faster at the beginning of their lifespan; the depreciation curve flattens in later years (of ownership). Prior research has shown that BEV cost-competitiveness increases in total mileage and commitment period in part because of a depreciation curve with a steeper head and flatter tail [200–202].

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

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

4.2.5. Insurance

Lyft provides drivers with insurance for *P1*, *P2* and *P3* segments of their mileage (dispatched and passenger on-board), but *P0* and personal mileage is paid by the driver. Several studies have attempted to estimate the TCO components of ride-hailing vehicles inclusive of insurance cost. The most widely used estimates come from Zoepf et al., who survey drivers about operating cost and provide a distribution of cost estimate (median combined cost of $0.13 per mile for maintenance, repair, and insurance) but do not break down by the components [203]. Henao and Marshall estimate annual insurance costs to be $1,500 [204]. Parrot and Reich estimate commercial insurance costs for ride-hailing drivers in New York City of $0.14/mile, which is higher than the national average. I opt for the American Automobile Association's estimate, with the assumption that insurance rate is not a function of mileage [205] as presented in Table B-4. This estimation of annual insurance costs yields a median per-mile cost of $0.067/mile for ICEV based on the annual mileage of all drivers, which is slightly higher than Zoepf et al.'s survey estimates when accounting for service and maintenance (S&M) costs. Insurance cost is slightly lower for HEVs and BEVs relative to ICEVs as well as pre-owned models relative to new ones.

4.3. Service & Maintenance Costs

It is widely believed that service and maintenance (S&M) of BEVs are far less expensive than those of ICEV and HEV on average, given fewer parts that need routine maintenance. Reliable life cycle maintenance data from EVs are rare and usually reported in the form of a single estimate regardless of vehicle age and mileage [200]. Here, I develop a model which benefits from mileage-specific S&M costs for the whole lifecycle of a vehicle.

In the TCO model, $\phi(.)$ is a dynamic function which returns a mileage-weighted average S&M cost per mile for each vehicle technology based on a driver's annual mileage (observed and personal) and ownership commitment period. $\phi(.)$ is calculated based on the mileage-specific S&M costs for the lifecycle of vehicles represented in Figure B-6. I assume that the useful life of a BEV is 200,000 miles and that of an ICEV or HEV is 150,000 miles [206]. For fair comparison, I augment an upfit cost of 2.04 ¢/mile after 150,000 miles for ICE and HEV, as suggested in [206]. Ranges of estimated S&M costs for different combinations of vehicle type, new vs. pre-owned, and commitment period length are shown in Figure B-7.

4.3.1. Fuel and Electricity Costs

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

For gas price (G_s), I use the EIA 2019 average estimate in the driver's state, which includes taxes and is based on the weighted sales volume of three grades of gas, as shown in Table B-5[207]. National average gas price in 2019 is $2.763/gal with median of $2.625/gal. The levelized cost of charging (LCOC) for BEV charging is adopted from a recent study from NREL [199] and matched by driver's state ($LCOC_s$). Baseline estimates of LCOC for each state are presented in Table B-5, which shows a national average of 0.150 $/kWh (exclusively charging at DCFC stations increases the national LCOC to 0.18 $/kWh, while the price falls to 0.11 $/kWh for drivers who only charged their BEV using a dedicated household outlet.). For simplicity, I assume G_s and $LCOC_s$ do not change over the ownership commitment period.

4.4. Range Suitability of BEVs for Ride-hailing Drivers

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

To aid in the presentation and interpretation of results in this large dataset, I use unsupervised learning algorithms to identify distinct cohorts of drivers with shared travel patterns (Methods). This procedure results in four cohorts: Ultra-High Mileage (UHM); High-Frequency High-Mileage (HFHM); Low-Frequency High-Mileage (LFHM); and Low-Frequency

Low-Mileage (LFLM) (Figure B-1). These cohorts account for 9%, 14%, 31%, and 46% of all drivers, respectively. I report characteristics and summary statistics of relevant variables in the dataset in Table B-1 and Figure B-2.

Observing the distance traveled on the job every day by every driver on the Lyft platform makes it possible to characterize the suitability of electric vehicles to meet daily range needs as well as the total cost of BEV (versus ICEV) ownership. Other attributes certainly matter as well in the vehicle purchase decision [34,35,208,209]; however, the fact that ride-hailing driving is primarily done to earn money suggests that such drivers are likely to weigh range suitability and cost of ownership heavily in vehicle choice. Consistent with this notion, a recent survey finds that ride-hailing drivers rank BEV range limitation and economics as their top reasons for not choosing BEVs [197].

I use several definitions of BEV range suitability. The primary definition is the ability of a BEV to meet a driver's daily vehicle-miles traveled (VMT) needs on 95% of days in the year (or, alternatively, fewer than 5% of her active days have total VMT higher than BEV range). I additionally characterize suitability according to 90% and 99% thresholds. To illustrate the pitfalls of focusing on *average* behavior, I also show the results of defining suitability as meeting a driver's average daily VMT need. Throughout the analysis, I assume that BEVs have an energy efficiency of 0.28 kWh/mile and 88% usable battery capacity on average [193]. Furthermore, I subtract 30 miles from the technical BEV range as a buffer to allow for VMT for personal use (the U.S. average VMT for non-work was 20 miles per day in 2017 [106]). In the base specification, I assume that a BEV's State of Charge (SoC) is 100% at the beginning of the day and no charging occurs during the day. I conduct sensitivity analyses in which initial SoC is incomplete or partial mid-day charging is possible.

Figure 4-1 presents cumulative distributions of range suitability with respect to BEV battery size. In Panel A, I plot full-sample distributions for each of the four definitions of suitability; in Panel B, I reprint the full-sample distribution for the preferred definition alongside analogous distributions for the Low-Frequency Low-Mileage (LFLM) and Ultra-High Mileage (UHM) cohorts. Panel A shows that, for the great majority of drivers, their range needs are met on most or all days of ride-hailing activity. For example, a BEV250 satisfies 95% or more days of driving needs for 86.2% of all non-EV drivers on Lyft's platform in 2019. The corresponding number for the 90% and 99% thresholds are 92.4% and 74.7%, respectively. For context, there are currently several BEV250s on the market, including the Chevy Bolt, Tesla Model 3, Ford Mustang Mach E, and Kia Niro.

Three other facts are apparent from Figure 4-1. First, assessment of range suitability using average behavior is misleading. According to Panel A, a 200-mile battery meets nearly every driver's average daily need – but at the same time, I calculate that such a battery size *fails* to meet a driver's needs on 48 days of the year, on average. Second, the marginal suitability effect of battery size decreases at higher battery sizes in the full set of drivers (Panel A). The right tail of ride-hailing driver activity is long: a battery size of 300 miles would be 99% range-suitable for 86.7% of drivers, but to provide the same level of suitability to nearly *all* (99.9%) drivers, a size of 590 miles would be needed. Third, there are wide differences in range suitability across the driver distribution. According to Panel B, a BEV250 is suitable for all LFLM drivers but only a quarter of UHM drivers.

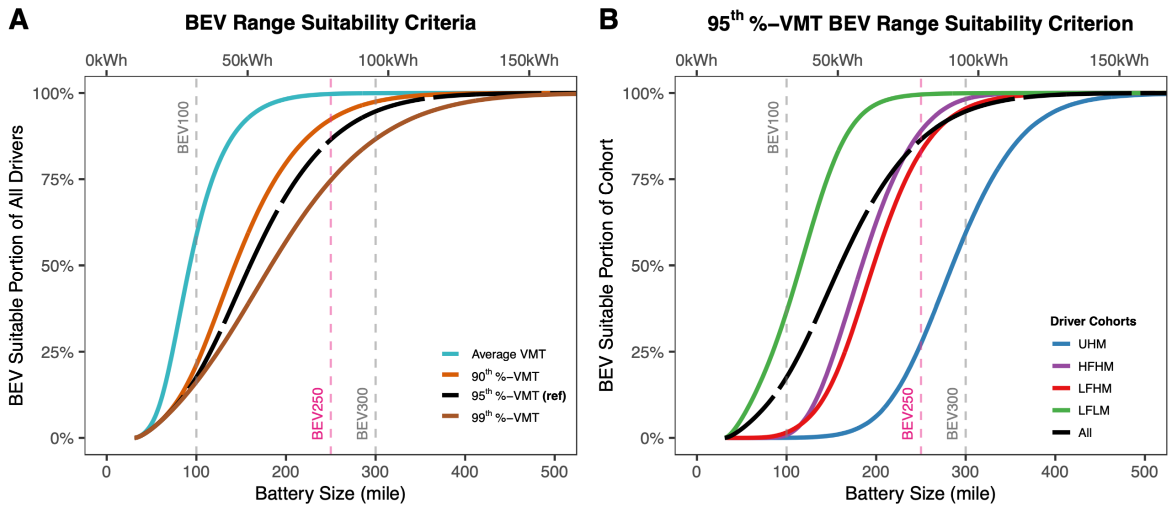

Figure 4-1. (A) BEV range suitability for all drivers on the platform based on battery size (mile and kWh capacity) under different suitability criteria.
95th%-VMT BEV suitability indicates that the BEV range meets the daily VMT needs of a driver on 95% of her active days. 90th% and 99th% suitability criteria are analogous. "Average VMT" suitability indicates that daily VMT needs are met on a driver's average day. (B) BEV suitability with the 95th%-VMT metric overall and for specific cohorts (see text for cohort definitions).

Note two additional analyses that shed light on the sensitivity of range suitability to assumptions about BEV charging. First, I replicate the prior calculation while assuming that each driver takes advantage of a 30-minute daily partial charging via a 30kW DC Fast Charger (DCFC), which is equivalent to a 90-mile range increase. There is an opportunity cost of mid-day charging, but the magnitude of this cost depends on the counterfactual activity of drivers. A recent survey of 732 BEV drivers on the Uber platform shows that a significant portion of drivers do engage in mid-day charging, with a mix of public level 2 chargers and DCFCs [197]. With 30-minute daily partial charging, the preferred estimate of BEV250 suitability increases from 86.2% to 97.7% of drivers (Figure B-5).

Second, I investigate the extent to which observed days of ride-hailing activity can be met with less-than-complete States of Charge (SoCs), in acknowledgment of the fact that not all drivers are able to charge their vehicle to 100% before starting the day. I run a stochastic simulation with 10,000 iterations: in each iteration, I draw a random initial SoC uniformly distributed between 20-100% for each of the all active driver-days and count the number of driver-days whose VMT can be met with BEVs of different battery size (otherwise I use the same assumptions as in the Figure 4-1 analysis). Figure 4-2 plots the empirical distribution (across the 10,000 iterations) of the percentage of driver-days with VMT less than the range of a BEV250 (or BEV100). The figure shows that, on average, 82% of all driver-days can be completed with a BEV250, while 40% can be completed with a BEV100. For the LFLM driver cohort, meanwhile, a BEV100 is sufficient for the completion of 71% of driver-days. These findings are consistent with a prior study which finds that, relying only on night-time charging, a BEV with just under a 100-mile battery size could meet the travel demand of 87% of vehicle-days in the U.S. based on the 2009 National Household Travel Survey (NHTS) [210]. More generally, the simulation exercise suggests that the high degree of BEV suitability implied by the main results is not overly sensitive to the assumption of 100% SoC.

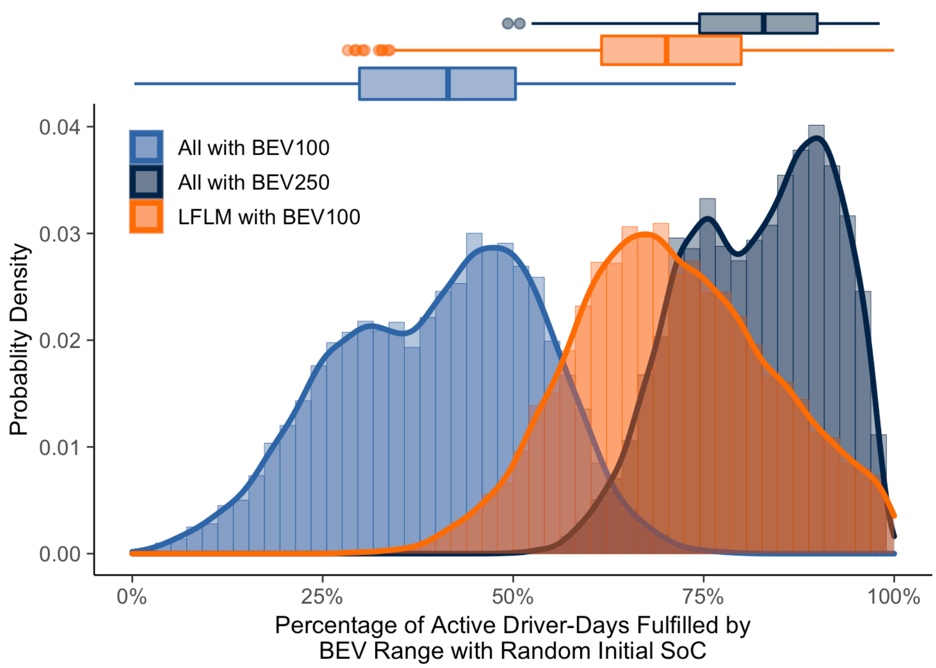

Figure 4-2. Sensitivity of BEV suitability to initial State of Charge (SoC) based on stochastic simulation with 10,000 iterations.

Initial SoC is uniformly distributed between 20-100%, and all other procedural details are the same as in Figure 4-1. The average percentage of active days completed by BEV250 (BEV100) is 82% (40%). The simulation of specifically the LFLM driver cohort shows 71% of active days can be fulfilled with BEV100.

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

4.5. Total Cost of Ownership of BEVs

I utilize a Total Cost of Ownership (TCO) approach to model vehicle cost over the commitment period. TCO modeling is a standard tool in transportation economics for comparing different technologies on the grounds of cost [201]. In the analysis, TCO depends on the annualized fixed costs of capital and insurance, the marginal costs of service and maintenance (S&M) and fuel, and the levelized cost of electricity charging (LCOC). I estimate costs for a representative ICEV, HEV, and BEV model on the market at each battery range (Methods). LCOC reflects the average cost of charging given the monetized opportunity cost in level of access to charging infrastructure as well as electricity cost calculated at the state level [199]. I exclude taxes, registration costs, and other fees, which are very similar for ICEVs, hybrid electric vehicles (HEVs), and BEVs (this exclusion may slightly disadvantage BEVs in TCO comparisons, because there are rebates on such fees for BEVs in some states). I apply a 5% discount rate on expenses beyond the purchase year. A variety of state and federal government subsidies are available to most EV buyers, including, most prominently, a federal tax credit for

EV purchases that is currently capped at $7,500. To model the effect of these subsidies on TCO, I incorporate a rebate of varying sizes on all new BEV purchases in the analysis.

I begin by estimating TCO for different vehicle types, annual VMT, and commitment periods. I consider both new and used BEVs (of varying battery sizes), HEVs, and ICEVs. I vary annual VMT from 10,000 to 40,000. Following evidence on the average ownership commitment period among TNC drivers [204,211], I evaluate TCO over commitment periods of three and five years (a longer ownership commitment period would favor BEVs). I then divide TCO by total VMT over the ownership commitment period to obtain a "levelized cost" of ownership in dollars per mile.

Figure 4-3 illustrates the per-mile TCO of new and pre-owned vehicles for different annual mileages and commitment periods. With an annual VMT of 10,000 – which is close to the annual average mileage of a personal vehicle in the U.S. – a new pre-subsidy BEV250 costs nearly 27% more than a new ICEV for three years of ownership. However, as annual mileage and commitment period increase, BEV250 becomes increasingly cost-effective. 20,000 VMT per year is sufficient to make a pre-subsidy BEV250 cost less per mile than an ICEV with a five-year commitment period; 30,000 VMT is sufficient to do so for both commitment period lengths. Meanwhile, with a $10,000 purchase subsidy, which is roughly consistent with the combined value of current federal and state incentives for many BEV models, a new BEV250 consistently costs far less than a new ICEV. For example, with a modest annual VMT of 10,000, a five-year commitment period, and a $10,000 subsidy, a BEV250 costs nearly 29% less than ICEV. An HEV also consistently costs less than an ICEV and competes with BEV250 depending on mileage, commitment period, and subsidy level. The cost estimates are consistent with those of Borlaug et al. [199] and Palmer et al. [201] but slightly larger in magnitude due to the shorter ownership commitment periods I use here. Several market research entities also report $6,000-$10,000 lifetime savings for BEVs compared to ICEVs, and even larger savings for pre-owned BEVs [202,212].

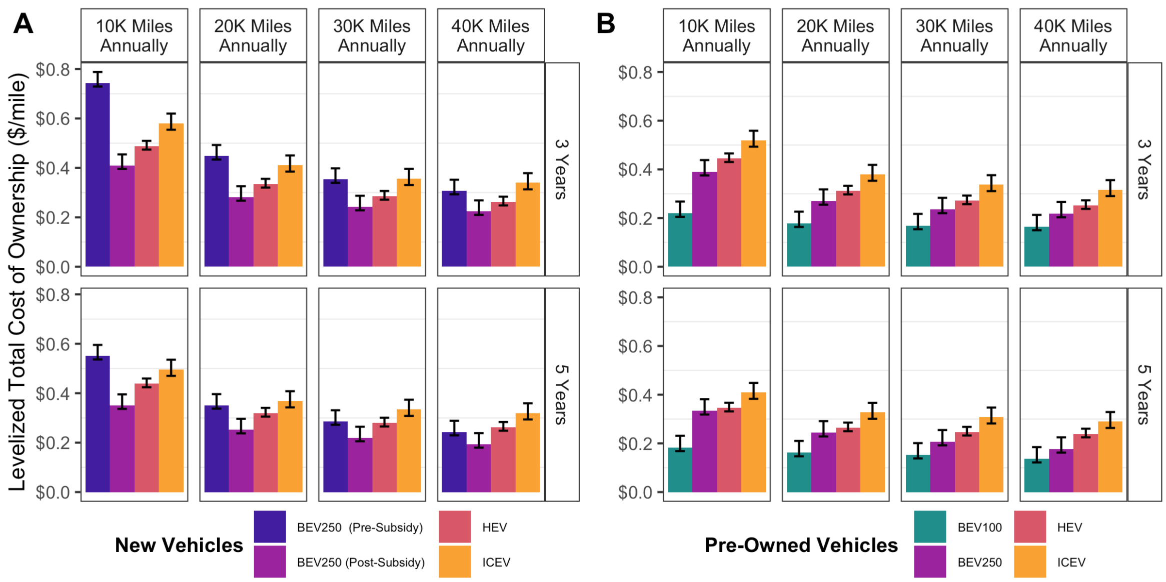

Figure 4-3. Levelized (per mile) total cost of (A) new and (B) pre-owned vehicles for different annual mileages and commitment periods.
The error bars represent the highest and lowest estimates with respect to variation of fuel and LCOC in different states. Per-mile cost includes depreciation, insurance, fuel/electricity, and S&M costs

Notably, pre-owned BEVs cost less than pre-owned HEVs and ICEVs regardless of mileage and ownership commitment period, even without the aid of any purchase subsidy (for which pre-owned BEVs are ineligible). For instance, a pre-owned BEV100 (e.g., a Nissan Leaf) appears to be a very cost-effective option for those drivers whose daily VMT needs are met by a battery size of 100 miles. This represents a significant portion of drivers in the LFLM cohort and implies that, at currently observed vehicle prices, switching to a pre-owned BEV100 could significantly reduce total vehicle costs for many. The main reason why pre-owned BEVs have a greater relative cost advantage than new ones is that BEVs are currently considered semi-luxury vehicles; this induces a steep depreciation curve at the beginning of vehicle use and a flatter curve than those of ICEVs and HEVs from the third to fifth year of ownership [202].

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

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

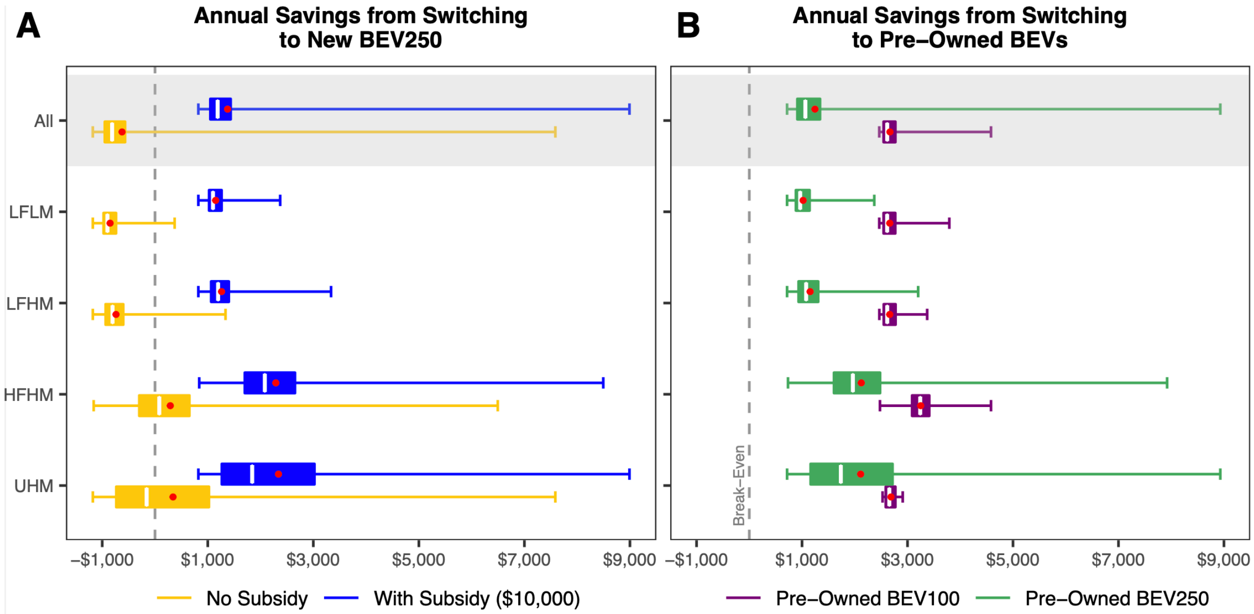

Figure 4-4. The range and distribution of annual savings from ICEV to BEV for BEV-suitable drivers. (A) From new ICEV to BEV250 with and without purchase subsidies, under a 5-year commitment period. (B) From pre-owned ICEV to pre-owned BEV250 and pre-owned BEV100, under a 3-year commitment period. The red dots show the average annual savings for the whole population in the cohort.

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

The purchase subsidy available to a potential BEV buyer is clearly very impactful in bringing BEVs to cost parity with ICEVs: a new BEV250 is projected to be range-suitable and cost-saving for 8.6% of drivers on the Lyft platform with no subsidy and 86.2% of drivers with a $10,000 subsidy. Given the magnitude of this effect, as well as uncertainty and geographic variation in what the subsidy level will be going forward, it is instructive to investigate how TCO moves with the subsidy level between $0 and $10,000. Figure 4-5 displays precisely this relationship, overall and in each cohort, again under a five-year commitment period (Figure B-12 repeats the experiment for a three-year commitment period). The average driver breaks even by switching to a new BEV250 with a subsidy of $3,200, though the right-skewed VMT distribution of ride-hailing drivers means only 26.5% of drivers actually break even at this subsidy level. However, a subsidy of $5,700 is enough to cause all range-suitable drivers to at least break even on the switch. The curves in Figure 4-5 are capped below 100% (except in the case of the LFLM cohort) only because there are drivers in each cohort for whom a BEV250 does not provide suitable range. An equivalent reduction in vehicle purchase price due to battery cost cut has the same effect. The re-designed 2022 Chevrolet Bolt is projected to cost $5,500 less than the prior model [213]; the analysis implies that this price reduction brings nearly all range-suitable drivers to the break-even point on switching without any additional subsidy.

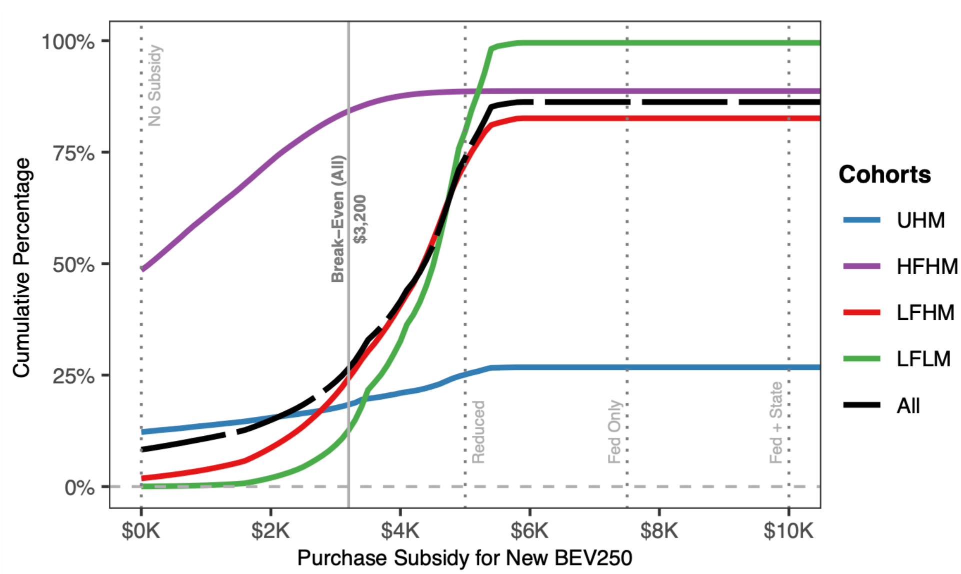

Figure 4-5. Percentage of drivers in each cohort that both find a BEV250 range-suitable and break even under a 5-year ownership commitment, as a function of subsidy level.

Curves that plateau below 100% have drivers for whom a BEV250 does not have suitable range. An average driver breaks even with a minimum of $3,200 purchase subsidy. Vertical lines indicate certain specific levels of subsidy. *Fed + State*: current level ($10,000) for majority of states; *Fed Only*: $7500 federal tax credit; *Reduced*: a scenario where tax rebate is reduced to $5,000.

4.6. Discussion and Policy Implications

Overall, the analysis suggests that range and total cost should not be seen as constraints on significant BEV take-up in the ride-hailing sector. I estimate that approximately 86% of drivers on the Lyft platform in 2019 could switch to a BEV250 – of which several models are currently on the market – without having to curtail their mileage on more than 5% of their active days. When I relax the assumption of 100% initial state of charge (SoC), the median percentage of driver-days (across 10,000 simulations) for which a BEV250 meets the suitability criterion remains high at 83%. Some of these drivers – in particular, high-mileage ones – are projected to save money by driving a new BEV250 even without a purchase subsidy. *All* range-suitable drivers are projected to at least break even with a subsidy of $5,700; the average savings at this subsidy level is $511 per year. Given that the federal tax credit program for EV purchase is expiring, maintaining this level of subsidy is crucial to making new BEVs cost-effective for the majority of ride-hailing drivers. Meanwhile, pre-owned BEVs offer significant savings and may be particularly attractive to those drivers who don't value the "luxury" attribute of new BEVs.

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

Subsidies, too, could be targeted to good effect, to the extent that this is feasible. Not every driver needs the same subsidy level to be incentivized to switch. Moreover, while EVs are competitive with ICEVs on *total* cost grounds, their higher upfront cost may prevent some financially constrained drivers (including those with low income, credit score, or tax appetite, or facing other barriers to financing mechanisms) from making the switch. Subsidies targeted and tailored to such drivers could help reduce this barrier. More generally, the revelation (and communication) of widespread range suitability and cost competitiveness should free up TNCs and other entities in the transportation sector to prioritize other potential barriers to EV take-up. For instance, rather than investing in further range expansion of BEVs, companies and policymakers may more productively invest in charging technology and infrastructure to harness the battery sizes that are already suitable for most drivers.

This work, its meaning, and its limitations suggest several avenues for future research on the electrification of cars on TNC platforms. First, discrepancies between perceived and actual range suitability and cost of ownership of BEVs point to the value of research on changing perceptions about such vehicles. Second, this study uses standard assumptions in the literature about access to charging infrastructure; accurately depicting current and projected access at a high resolution would improve future analyses of range suitability and total cost of ownership. Third, a TNC-wide transition to BEVs would very likely induce changes in purchase price (among other attributes), and future work to understand EV supply and demand dynamics could shed light on such changes. Finally, ride-hailing drivers predominantly self-identify as low-income and as members of a minority group [192]; research centering equity in the EV transition and policy design is paramount.

Chapter 5. Trip-level Sharing Behavior in Ride-hailing

5.1. Introduction

Transportation Network Companies (TNCs) are rapidly transforming the urban and personal transportation. The increase in the adoption of ride-hailing (or ridesourcing) services such as Uber and Lyft can be attributed to the ease of access using a smartphone application along with a higher availability compared to the regulated, traditional taxi services [42–44]. Ride-hailing services offer flexible, efficient, and convenient mobility, promoted as a remedy for private vehicle dependency, traffic congestion, high parking costs, and environmental pollution. However, recent evidence reveals that the unintended consequences of ride-hailing services may outweigh some benefits by undermining public transportation [48,49], taking away from more sustainable transportation modes [38,50], increasing vehicle ownership, vehicle-miles-traveled (VMT) and large levels of deadheading miles [43,51–53,214], and leading to aggravated congestion in urban areas [54]. In large US ride-hailing markets, including metropolitan areas of Chicago, San Francisco, Washington, and Boston, it is estimated that 7-13% of total traffic in core counties is attributed to TNCs, while they serve only 2-3% of regional trips [46].

Ride sharing or pooling, in which a rider shares all or portion of the trip with other passengers, has the potential to mitigate negative impacts of solo ride-hailing by consolidating VMT from multiple trips, which are spatially and temporally suitable for matching. The rate of sharing is a key factor in determining the sustainability of ride-hailing compared to other transportation alternatives, especially for future autonomous on-demand mobility services

[9,39,55]. For instance, a recent study found sharing a ride-hailing trip reduces GHG emissions by 10% to 47% [185]. Despite advantages of ride sharing (services such as UberPool and LyftShare), the portion of shared trips relative to solo trips in ride-hailing is still small [215]. In California, an average ride-hailing trip has 1.54 passengers, while an average household vehicle trip has 1.68 passengers [186]. Both city governments and TNCs are therefore trying to understand underlying factors of riders' willingness to share (WTS) their trips and factors of successful sharing. Nonetheless, lack of access to empirical data hinders better understanding of sharing behavior in ride-hailing trips. Currently, the vast majority of literature relies on revealed and stated preference surveys to understand ride-hailing adoption and usage [50,216–218]. To address the data availability challenge and better understand and regulate ride-hailing, many cities, including Chicago, implemented data mandates for active TNCs [219].

Chicago is one of the largest ride-hailing markets in the US, where ride-hailing make up about 3% of the total regional VMT [46]. The publicly available ride-hailing data from the City of Chicago has provided an unprecedented opportunity for empirical understanding of ride-hailing demand patterns [220,221], relationship with transit services [222], and neighborhood characteristics [223]. Since it has a unique feature of observing which trips were requested to be shared, recent studies with this data attempted to understand the determinants of WTS [224–226]. The results of these studies reveal key factors affecting WTS, but only focusing on the aggregate level between origin-destination (O-D) pairs of census tracts. The WTS for individual trips, however, remains largely unknown. In addition, what factors determining the actual success of sharing once a rider requests to share the trip are also rarely studied. Understanding the trip-level determinants of WTS and sharing success is important for city governments and

TNCs to design effective policies to encourage sharing in ride-hailing and improve the sustainability of urban transportation.

Building on the prior work, I examine this novel dataset of all ride-hailing trips in the city of Chicago [227] in 2019 to explore the factors affecting trip-level WTS (willingness of the rider to request a shared trip) and sharing success. By designing robust and generalizable ensemble machine learning (ML) prediction models, I find that the travel impedance variables (trip cost, length, duration) collectively contribute to 95% and 91% of the predictive power in determining the WTS of a trip and whether the trip that is requested to share is successfully shared or not, respectively. Specifically, for a dollar increase in the per-mile cost, I find about 58% reduction in the odds of a trip being requested to share. Unlike prior studies that found other variables (socioeconomic, demographic, built environment, spatial and temporal attribute, and transit supply variables) have high predictive power in determining the *portion* of trips requested to share between O-D pairs of census tracts, I find those variables do not entail predictive power in determining the WTS of individual trips. The results imply that pricing signals have a higher potential to encourage riders to share their rides. I also find that longer but less expensive requested-to-share trips are more likely to be successfully shared with another ride.

The reminder of the article is organized as follows. Section 2 reviews the literature and recent findings on factors that influence willingness to share the ride-hailing trips. Section 3 describes the dataset used in this study and provides an exploratory analysis of sharing behavior in ride-hailing trips in Chicago. Section 4 looks at the declining time-trend of trip sharing and attempts to understand the factors that influenced this decline, using a regression analysis. Section 5 describes the machine learning approach for prediction of willingness to share and successful sharing of ride-haling trips, and section 6 reports the results. Finally, section 7 provides a detailed discussion, draws conclusions on the findings, and explains major limitations of data and modeling approach used in this study that could thwart the inference. The findings shed light on sharing behavior in ride-hailing trips and can help TNCs, urban planners, and policymakers to devise better strategies and targeted pricing mechanisms to increase sharing in ride-hailing. While sharing is currently suspended in most markets because of COVID-19, incentives can regain and improve the WTS of TNC users in the post-pandemic period, thereby helping avoid unintended congestion and environmental impacts from ride-hailing.

5.2. Factors Associated with Willingness to Share

An extensive body of travel behavior literature is dedicated to understanding the theoretical aspects as well as stated and releveled preference for sharing the ride and sharing for ride-hailing. These studies predominantly use surveys combined with the neoclassical econometric models to understand the preference for using ride-hailing services in general, as well as investigating the factors that contribute to riders opting for a shared ride-hail trip [38,50,228]. A majority of these stated-preference studies suggest that employed, educated, urban residents living in high density, walkable neighborhoods are more likely to share rides and use ride-hailing in general than those hailing rides from predominately non-white, older, or low-income neighborhoods. They also state that underlying discomfort with sharing a ride with strangers and increase of travel time are among major barriers of sharing [217,228–231]. Shared rides can take longer than private ride-hailing trips due to time and mileage penalties associated with detours for pickups and drop-offs of the matched rides [232]. Therefore, such trips might not be a viable option when traveling to time-sensitive appointments (work, doctor's visit, airport, etc.) or for riders who place a high value on travel time. With shared rides costing less than regular trips, individuals would have to weigh the cost savings against increased travel times, as well as discomfort (if any) in traveling with strangers.

Converging evidence from revealed preference and empirical data from sharing behavior is scarce, and in some cases contradictory to the previous understanding. Using trip data in Los Angeles, Brown found riders living in low-income dense areas make higher proportion of shared trip, and 10% of riders make 94% of shared trips [233]. Young et al. found that higher demand and longer trip distances significantly improve matching propensity for shared ride-hailing trips in Toronto [232]. Leveraging the same Chicago dataset used in this study, Hou et al. and Xu et al. took a similar approach to study the ratio of shared trips to total trips between O-D pairs (binned by pickup and drop-off census tracts) as a regression-based ML problem [224,226]. They found that that socio-demographic variables as well as pickup/drop-off in airport census tracts have the highest predictive power, but both reported relatively large unexplained variance and high sensitivity to outlier observations. Dean and Kockelman employed a more nuanced econometric approach to model the count and ratio of shared ride trips. They found the spatial accessibility variables and underlying socioeconomic characteristics of the origin zones significantly influence the proportion and count of shared ride-hailing trips [225]. All these studies reveal the association of requested-to-share trips with explanatory variables. However, there is less empirical evidence on the factors that influence successfully shared trips, which are a subset of requested-to-share trips.

5.3. Ride-hailing Trip Data and Exploratory Analysis

The City of Chicago has had a data sharing mandate in place for all active TNCs (Lyft, Uber, and Via) since November 2018, as a part of compliance and operation licensing framework. I use the city's person-trip level database, which records, most importantly, when and where a ride (that is, person-trip) happens and whether the rider (a) "requested to share" the ride and (b) successfully shared the ride. The raw data for this study is available from the City of Chicago data portal [227]. This spatiotemporal data is at the trip level and contains trip attributes including ID, start/end timestamps, duration, distance, pickup/drop-off census tracts, fare, additional charges, tip, and trip total cost. Every trip record has an indictor to show whether the rider requested sharing (i.e., whether the rider is willing to take a potential shared trip). Each trip also has a binary indictor to show whether they were successfully shared or not. For simplicity, I henceforth define the trips that are requested (or authorized) to share as "requested-to-share trips" and the subset of requested-to-share trips that are successfully shared as "shared trips". The City of Chicago has had a data sharing mandate in place for all active TNCs (Lyft, Uber, and Via) since November 2018, as a part of compliance and operation licensing framework. I use the city's person-trip level database, which records, most importantly, when and where a ride (that is, person-trip) happens and whether the rider (a) "requested to share" the ride and (b) successfully shared the ride.

The City of Chicago has applied de-identification and aggregation techniques to reduce the risk of linking individuals' trip data to their identities. This includes aggregating the pickup and drop-off locations at the census tract level[22], rounding the trip-start and trip-end times to the nearest 15 minutes, and rounding the fares and tips to the nearest $2.50 and $1.00, respectively. Nearly 16.5% of trips suffer from missing pickup and/or drop-off census tracts, 77% of which

[22] Although the pickup and drop-off locations are suppressed to the centers of census tracts, the trip distance and duration have not been impacted by the de-identification process and represent the real mileage and real time interval (in seconds) of the trip, respectively.

represent the trips that requested sharing. The data provider cites privacy concerns in masking these values. However, the de-identification process may have impacted the data quality. Specifically, rounding the fares may induce bias in the inference.

For this study, I focus on data from the entire year of 2019 (111.85 million trip records before cleaning). Since the pickup and drop-off are reported at the census tracts, I can augment many explanatory variables from auxiliary datasets at the census tract level. I derive spatial and temporal attributes of trips from the main Chicago dataset. I also append the trip data with three sets of variables from auxiliary datasets: 1) socioeconomic and demographics variables from American Community Survey (ACS) [234] and Chicago Metropolitan Agency for Planning (CMAP); 2) built environment variables from ACS, CMAP, Longitudinal Employer-Household Dynamics (LEHD) [235], and Google Map API; and 3) transit supply variables from General Transit Feed Specification (GTFS). The census tract level data from auxiliary datasets is provided in the Supporting Information.

The data requires significant cleaning effort as well as dealing with significant portion of missing data. For the procedure for data cleaning and imputation of missing values, I first remove all incorrect observations which can be characterized as inconceivable trips.[23] To protect the privacy, the pickup and/or drop-off of some trips are masked (missing). The majority of missingness is from the requested-to-share trips and census tracts in outskirts. Since this missingness is not at random, simply removing those observations changes the distribution of requested-to-share trips relative to all trips and also hinders their spatial variance. This could bias

[23] The likely inconceivable trips include trips with total trip duration less than 1 minute and longer than 5 hours; trips less total distance traveled than 0.25 miles and greater than 300 miles; trips with total fare equal to zero (fares are already rounded); trips with extreme speeds (below 0.2 mph and above 80 mph - an auxiliary variable from trip distance and trip duration). I removed all these trips from the dataset.

the analysis and thus, I follow an imputation strategy to overcome the non-random missingness. I first attempt to infer the pickup or drop-off tracts from the pickup or drop-off community code if it is not missing. The City of Chicago has 77 community areas and within each community area there are multiple census tracts. I group the dataset by community area and impute missing census tracts within each community area by trip-density weighted ranking of the non-missing census tracts in that group. This imputation reduces missing values to 5.8% but may induce a modest bias in the estimation (note that Xu et al., 2021 used a comparable strategy for imputation). The data also includes some trips outside the boundaries of the City of Chicago (Cook County). I also remove census tracts outside of the City of Chicago based on the 2010 census boundaries (801 census tracts). After the cleaning and imputation processes, 12.1% of trips were removed, bringing down the total number of observations to 96,268,064 trip records for all 12 months in 2019 covering over 470 million miles.

I observe that from over 96 million trips in 2019, on average, only 19.6% of trips were requested-to-share trips and less than 70% of those were successfully matched with another ride, thus only 13.8% of trips were shared. Figure 5-1 provides a detailed exploratory analysis of the data, showing spatial and temporal variation of requested-to-share and shared trips. The average portion of shared requested trips and successfully shared trips based on hour of the day and day of the week has a relatively similar pattern to trip demand with some distinct differences. The peak hours of demand for TNCs in Chicago are 7AM-9AM and 5PM-7PM weekdays, 10AM-12AM and 5PM-7PM on weekends. As shown in Figure 5-1A, the average share of requested-to-share trips increases during the weekday peak demand hours, likely due to the fact that commuter trips during these hours are more likely to share [228]. It also peaks at midnight reaching over 25% except for Friday and Saturday. The share of shared trips follows a similar pattern, which is expected as more requested trips naturally yield more shared trips. However, the portion of successfully shared trips drops precipitously after the midnight, despite the portion of requested-to-share trips remains relatively high. This drop is likely due to lower supply of ride-hailing vehicle overnight.

Figure 5-1B shows the share of trips and requested-to-share trips in different origin and destination areas including downtown, airport, economically disconnected areas (EDA), and other census tracts. Chicago has two major airports, and the downtown zone consists of 30 census tracts. EDA consists of 489 tracts with higher than regional average concentrations of low-income households and minorities (Chicago Metropolitan Agency for Planning). I observe that in these areas the rate of requested-to-share trips is significantly higher than the rest of the city. Among those, nearly 40% of EDA-to-EDA trips are requested to be shared (twice the city-wide average). Looking at the average spatial variation, as shown in Figure 5-2, I can observe that the downtown and airport trips are associated with a low average rates of shared requested trips and successfully shared trips, while census tracts associated with lower income residents and higher percentage of African American residents (majority in EDA) have higher level of requested-to-share and shared trips.

Figure 5-3 shows the trend of requested-to-share trips versus solo-trips in EDA and non-EDA. Trips with either or both pickup and drop-off in 489 EDA census tracts are labeled as EDA trips. The rate of requested-to-share trips in EDA is twice as non-EDA trips. EAD trips are consistently longer and more expansive for both solo and requested-to-share trips compared to non-EDA trips. Figure C-2 and Figure C-3 show the kernel density distribution of key variables for requested-to-share and successfully shared trips. The distributions of the total cost, distance, duration, and per-mile cost of requested-to-share and solo trips, as well as successfully shared and unmatched subset of requested-to-share trips, significantly overlap, despite that the mean differences are statistically significant (mainly due to very large sample size). Due to frequent surge pricing that TNCs impose on trips (for instance, when vehicle supply is lower than trip demand), the cost per mile or time of a requested-to-share trip could be higher than a solo one from the same pick-up and drop-off, depending on the time of the day and many other demand factors that are not observable.

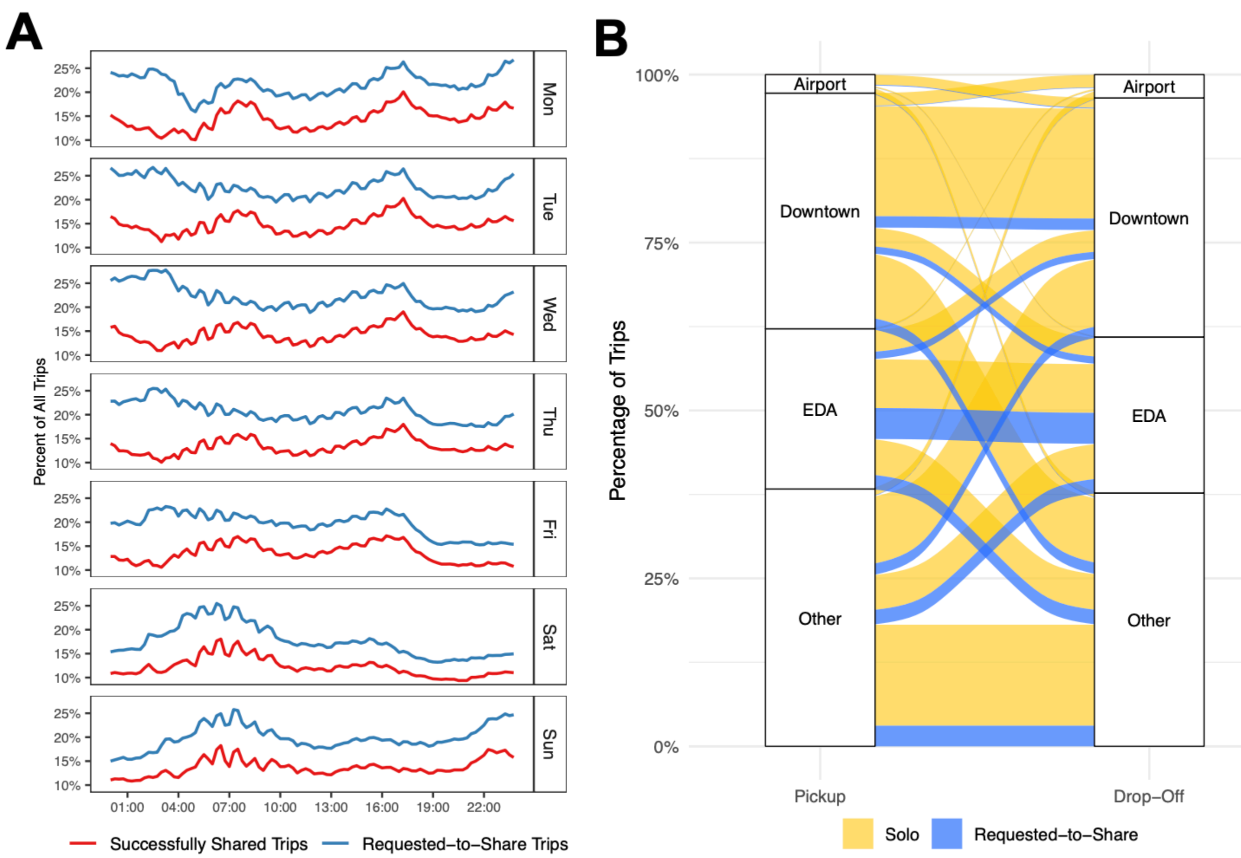

Figure 5-1. Exploratory analysis of requested-to-share trips and successfully shared trips. (A) Day of the week and time of day average rates of requested-to-share and successfully shared trips (15-minute window average). (B) Flow of trips between downtown, airport, economically disconnected areas (EDAs) and other census tracts of Chicago as pickup and drop-off points. The portion of requested-to-share trips is show in blue.

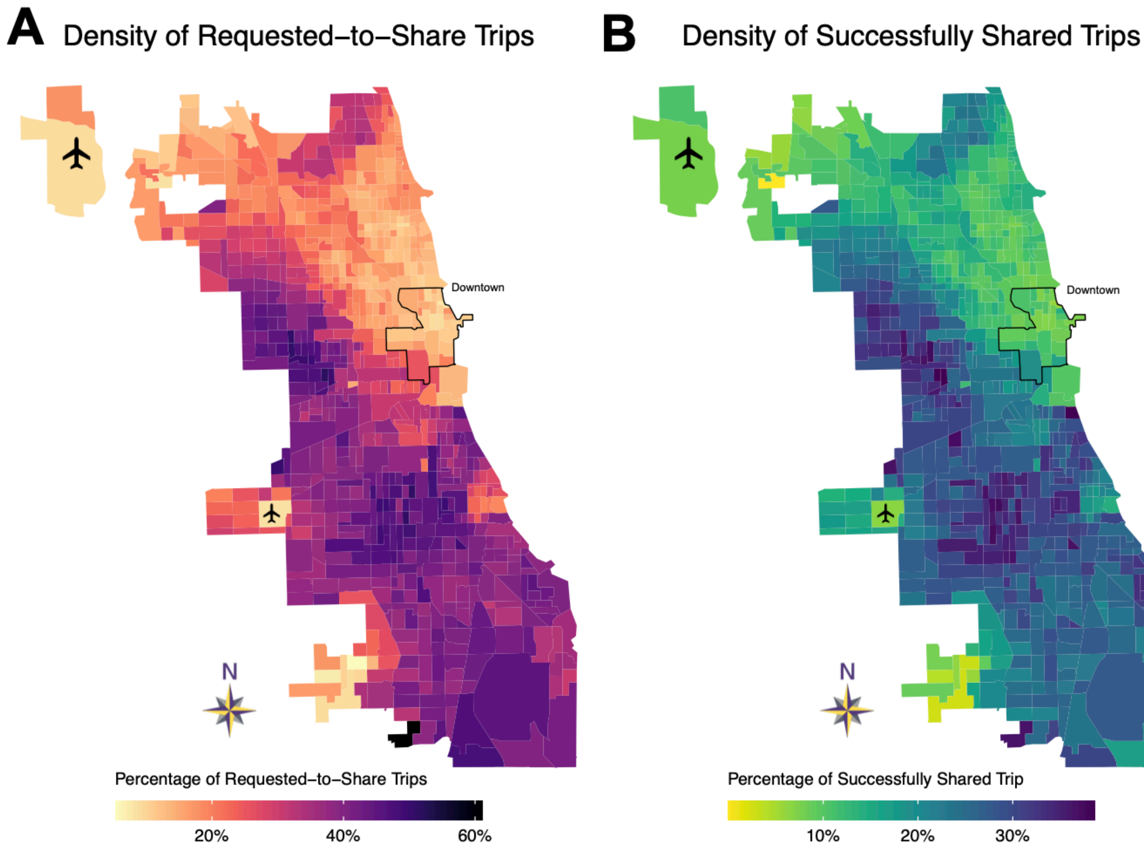

Figure 5-2. Density of requested-to-share and successfully shared trips by the pickup census tract. The downtown area is shown in black line. There densities with the drop-off census tract are highly correlated with those of pickup census tract.

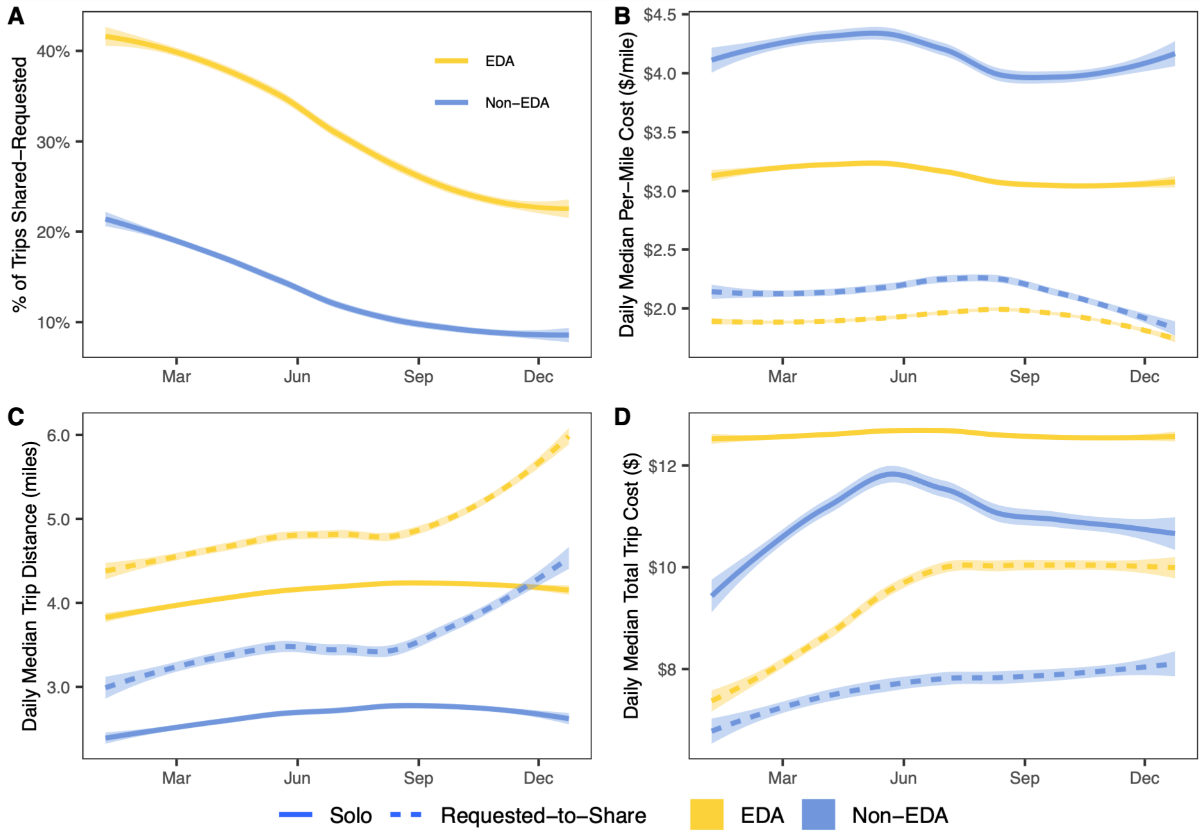

Figure 5-3. The smoothed trend of requested-to-share trips versus solo-trips in EDA and non-EDA. (A) The percentage of requested-to-share trips among all trips; (B) Daily median per-mile cost of the trip; (C) Daily median trip distance, (D) Daily median total cost of the trip.

5.4. Trends of Sharing in Chicago's Ride-hailing Trips

Figure 5-4A shows that riders' WTS declined throughout the year 2019, confirmed by a Mann-Kendall test showing monotonic downward trend of the portion of requested-to-share trips (□ = -0.89, $P < 10^{-4}$) which decreased from 27.0% in January to 12.8% in December. However, the trip volume and mileage have remained statistically unchanged in this period. The portion of shared trips closely follows the same trend with a shift, indicating a relative stable rate of successful sharing—67-71% of requested trips were successfully shared throughout the year. Intuitively, a lower demand for requested-to-share trips would further reduce the successful sharing, since the matching algorithm would have fewer potential rides to choose/match with.

This counterintuitive observation here, where the rate of successful sharing remained stable, may be explained by an unobserved systematic factor. For instance, the matching algorithms continuously maintain a metric by design such as successful matching rate.

As show in Figure 5-4B, the continuous decline of WTS may be because the increasing cost of requested-to-share trips over time. Specifically, the median cost of a requested-to-share trip increased substantially in 2019, while the median cost of solo trips remained relatively stable throughout the year. The reduced incentive to share the ride due to higher cost might explain why more travelers opted for solo rides over time. However, the per-mile cost of the requested-to-share and solo trips (dotted lines) was relatively stable with median of $1.99/mile and $3.76/mile, respectively. The per-mile cost of requested-to-share trip even decreased in the second half of 2019 while the per-trip cost continued to increase. This indicates that riders' WTS for longer trips increased over time while that for shorter ones declined (Figure C-1).

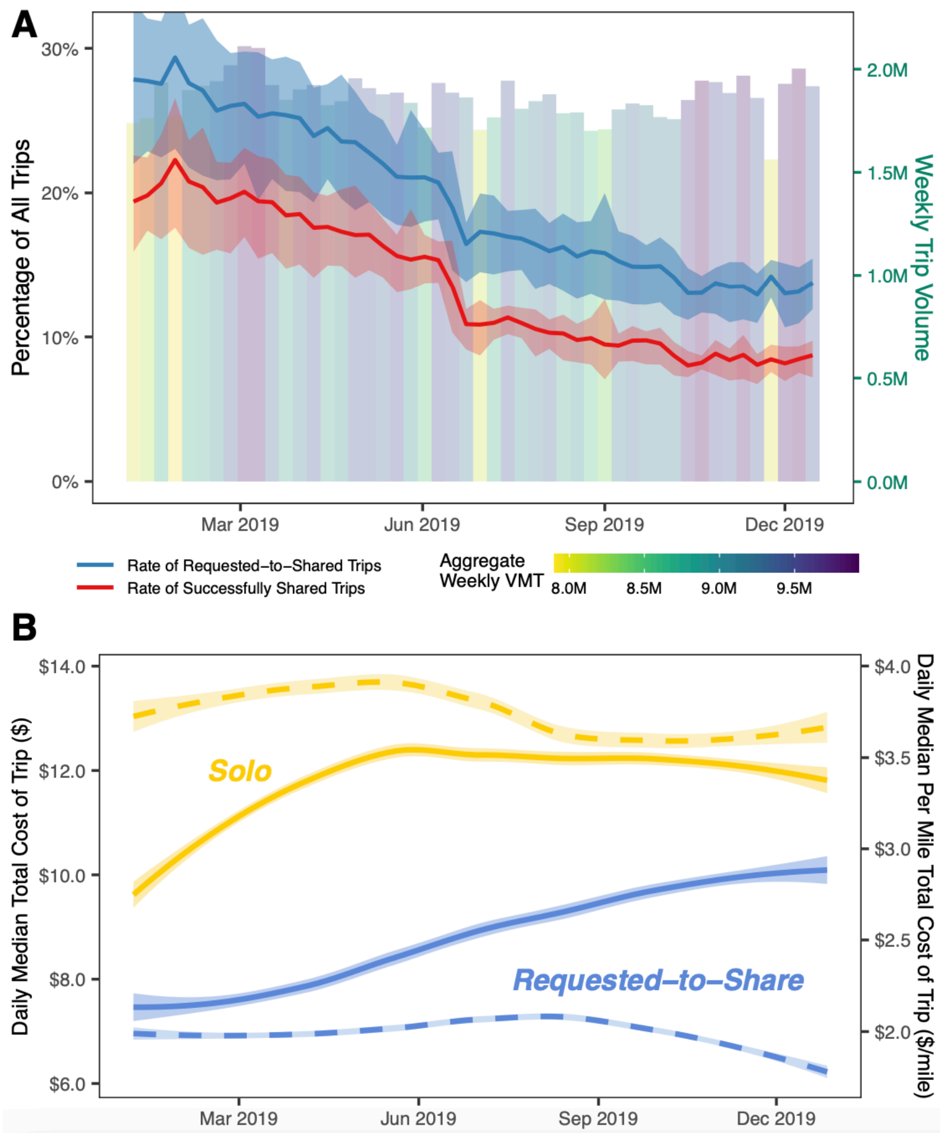

Figure 5-4. Trend of sharing behavior in Chicago in 2019.
(A) Weekly average rates of requested-to-share rides, successful sharing, weekly trip volume and aggregate VMT. Ribbons show daily variations. (B) The solid lines represent the smoothed daily median cost of requested-to-share trips and solo trips (left y-axis). The dashed lines represent the smoothed daily median per-mile cost of requested-to-share trips and solo trips (right y-axis).

To understand how trip attributes might lead to the decline of WTS over time, I run a logistic regression where the covariates are interacted with time (week of the year) as a continuous variable. This estimator explicitly examines the marginal effect of time by adjusting the response with the main effects. A general form of $logit(P) = \beta_0 + \beta X + \beta' X \times week + \varepsilon$ is employed where P is the probability of requesting a shared ride, $logit(P)$ representing the natural log transformation of odds, X is a vector of trip characteristics, and ε is the error term. In this specification, $\beta + \beta' week$ represents the time-varying marginal effect of a covariate. I take a random stratified sample of 100,000 trip observations from the dataset to fit the model. Since trips are collapsed at the pickup and drop-off census tract levels, there is a possibility of correlation within the tract clusters. Thus, I cluster-adjust the standard errors within each pickup census tract to account for correlated unobserved components in outcomes for trips within tracts.

As shown in Table 5-1, all main effects are statistically significant. As expected, a unitary increase in time (week) reduces the WTS by 4% (more precisely, the odds of a trip being requested to share). Unitary increase in per-mile cost of the trip reduces the odds of WTS by 58%. Having one or both legs of the trip in the downtown area reduces the WTS, and a trip that started or ended in EDAs increases the WTS. While the main effects are important determinants of WTS, the decline of WTS over time can be explained by the estimated coefficients for time interaction terms. The per-mile cost and trip distance both have positive signs when interacted with time. Given that higher per-mile cost and longer distance without time interactions reduce the odds of WTS with statistical significance, the preference of riders to share shorter rides declined over time and a greater number of shorter trips were requested solo. The interactions of time with downtown and EDA indicators are not significant.

Table 5-1. Logistic regression results to understand the time trend of sharing behavior

Covariate	Parameter estimates		Odds ratio		
	Parameter	Clu. Std. Err.	Estimate	LB (95% CI)	UB (95% CI)
Main Effects					
Week of year	-0.0448***	0.006	0.9561	0.9441	0.9683
Per-mile cost	-0.8614***	0.0411	0.4225	0.3898	0.4580
Trip distance	-0.2019***	0.0133	0.8171	0.7959	0.8389
Downtown indicator	-0.3381***	0.0497	0.7131	0.6469	0.7860
EDA indictor	0.3077***	0.0516	1.3603	1.2294	1.5051
Time Interactions					
Week × Per-mile cost	0.0039**	0.0014	1.0039	1.0012	1.0067
Week × Trip distance	0.0032***	0.0003	1.0032	1.0025	1.0038
Week × Downtown Ind.	-0.0021	0.0013	0.9979	0.9953	1.0006
Week × EDA Ind.	0.0016	0.0014	1.0016	0.9986	1.0045
Constant	3.4182***	0.2078			

Notes:

- Solo trip is a base category and parameters are estimated for requested-to-share trip.
- Sample size: 100,000; Loglikelihood: -77937.86; Pseudo R-square: 0.188; AIC: 78,058.
- LB (95% CI) and UB (95% CI) imply lower and upper bounds of 95% confidence interval.
- Standard errors are clustered by pickup census tract (Clu. Std. Err.). All variables in the final model have variance inflation factor (*VIF) < 10*.
- Asterisks denote 1 (***), 5 (**), and 10 (*) percent significance levels.
- EDA indicator denotes whether the trip had a leg in economically disconnected areas (EDA).
- Other variables included in the regression are indictors for whether the trips had a leg in white majority (negative***) census tract, black majority census tract (positive***), airport (negative***), and normalized median income of pickup tract (negative***). The first three variables are also interacted with week, but the coefficients are not statistically significant at any level.

5.5. Predicting Willingness to Share and Successful Sharing

To predict the probabilities of a trip being requested to be shared and a requested-to-share trip being successfully shared, I use several ensemble ML methods and compare the performance. The goal of ensemble learning is to combine decisions or predictions of several weak classifiers to build non-parametric and interpretable predictive models to improve prediction, generalizability, and robustness over a single classifier [237]. I utilize Python-based Scikit-Learn implementation of Adaptive Boosting or AdaBoost (Ada) [238], Gradient Boosting

(GB) [239], and Random Forests (RF) [240]. In addition to their ability to capture nonlinear relationships, these ensemble models deal well with both numerical and categorical variables and are robust to such issues as feature multi-collinearity, imbalanced datasets, and the existence of outliers and missing values [237]. The attributes of selected ensemble classifiers are particularly valuable given the characteristics of the dataset. The interpretability of models enables us to understand the relationship between the input variables and the prediction. The framework of the classification is depicted in Figure 5-5.

After data preparation, building and training the model involved several steps: hyperparameter tuning, feature selection, model validation, calibration, and interpretation. These steps are explained in Appendix. The performance of models on the test set is evaluated using area under the receiver operating characteristic curve (ROC-AUC), prediction accuracy, precision, and recall as described in the performance metrics section. Informed by the literature and the exploratory analysis, I choose six categories of explanatory variables from the main dataset and auxiliary data sources to explain sharing behavior. The travel impedance variables and spatial and temporal attributes of trips are at the trip level. The socioeconomic, demographic, built environment, and transit supply variables are at the census tract level according to pickup and drop-off locations. Each trip is described by 45 explanatory variables (features), as shown in Figure 5-5. The variables of interest (target response) are binary and reflect whether the trip is requested to be shared and whether a requested-to-share trip is successfully shared. The level of correlation between binary targets and selected features are shown in Figure C-4 and Figure C-5. I only select explanatory variables which have a variance inflation factor (VIF) score below the threshold of 10, in order to avoid multicollinearity issues in the ML process [237].

Using learning curves with different sample sizes of input data (Figure C-6), I find that with 8,000 data points the models fully saturate. Thus, to reduce training time, I use a randomly chosen stratified sample with 8,000 observations. Although it is a small fraction of the entire dataset of 96 million trip records, feeding the models with more data does not improve the performance anymore. As a robustness check and to quantify the performance uncertainty, I repeat the entire learning process with 100 bootstrapped random samples size of 8,000 from the entire dataset. Note that the random sampling procedure does not substitute the imputation procedure that was explained before. Removing the observations with non-random missingness of pickup and/or drop-off is not appropriate since it changes the distributional balance of the data and biases these models.

I split the stratified random learning sample of 8,000 trips to 75% training and cross-validation, and 25% testing (hold-out-sample). All models are evaluated using suitable performance metrics for classification, including accuracy, precision, and recall on the testing set. The accuracy is the proportion of correct predictions. The precision evaluates the fraction of correct classified instances among the ones classified as positive, and the recall (sensitivity) quantifies the number of correct positive predictions made out of all positive predictions that could have been made. I evaluate the overall performance of a classifier by the area under the receiver operating characteristic curve (AUC-ROC).

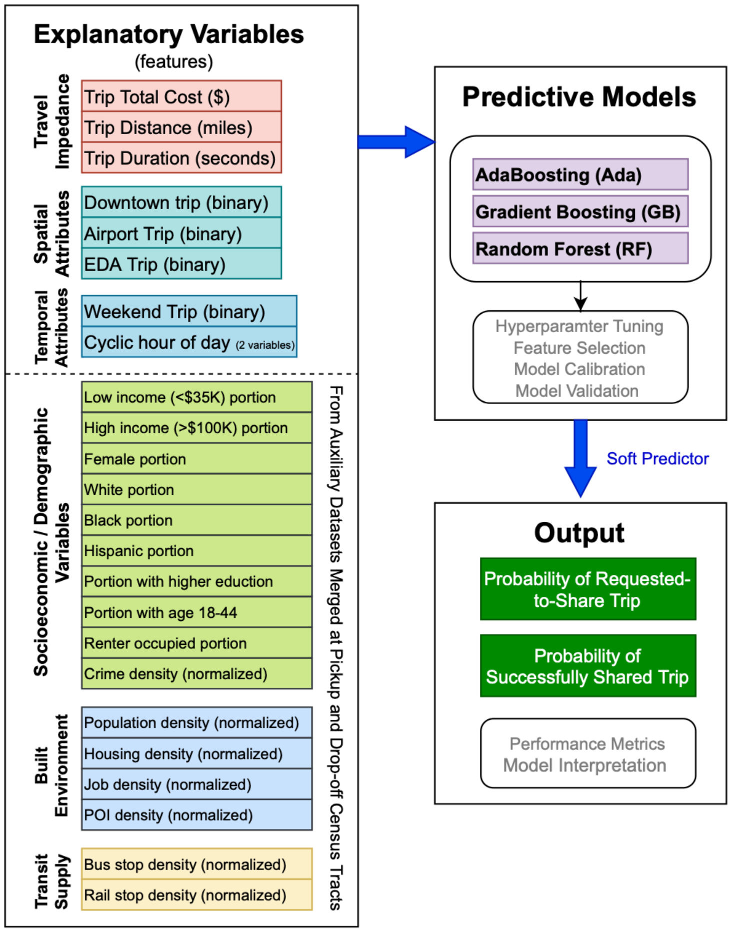

Figure 5-5. ML framework to predict requested-to-share trips and successfully shared trips.

5.6. Results

The learning process reveals the variables with the highest predictive power. I measure the predictive power of a variable by iterative measuring of how model performance decreases when a variable is permutated [240]. I prefer permutation feature importance to impurity-based measures given its robustness to inflating the importance of numerical features, which may overfit the model. I find the travel impedance variables (trip cost, distance, and duration) have the highest predictive powers for both WTS and sharing success. Figure 5-6A shows that for the requested-to-share trip prediction, the trip cost has the highest predictive power in all three models (Ada, RF, GB) and the three travel impedance variables collectively represent 89%-95% of predictive power of models. For prediction of successful sharing, Figure 5-6B reveals that the travel duration entails the highest relative variable importance. Other variables including socioeconomic, demographic, spatial and temporal attribute, built environment, and transit supply variables at the origin and destination census tract of the trip show trivial predictive power compared to the travel impedance variables.

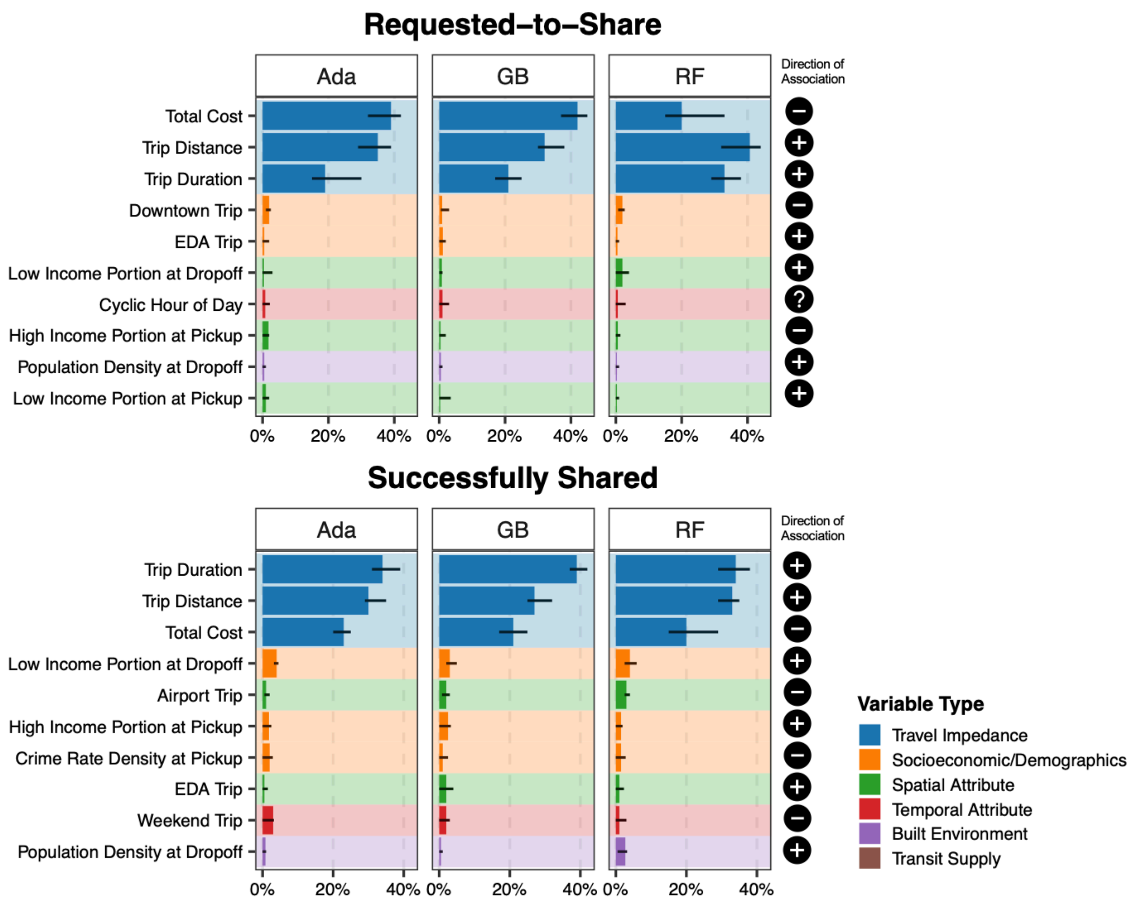

Figure 5-6. Normalized relative predictive power of variables based on permutation feature importance. Only top ten variables with the highest median predictive power are shown. The direction of association for each variable is determined using partial dependence analysis.

I use the results of permutation feature importance to choose the top ten relevant variables for the training and fine-tuning the classifiers. Irrelevant features simply add noise to the training data and affect the classification accuracy [237]. For example, adding noisy features such as transit supply variables increases the classification error. After hyperparameter tuning, the performance of Ada, RF, and GB classifiers are evaluated using several metrics. To show the overall performance of different classifiers for prediction of requested-to-share trips and successfully shared trips, ROC curves are illustrated in Figure 5-7. Specifically, the Ada and GB models outperform the RF model for predication of requested-to-share trips even after significant hyperparameter tuning of the RF model. However, all three classifiers have a comparable performance in predicting successful sharing. I find that the shard-requested predictive models show higher performance than successful-sharing predictive models. This is likely due to more stochastic nature of successful matching affected by availability of nearby trips, traffic conditions, and the performance of TNC dispatch algorithms.

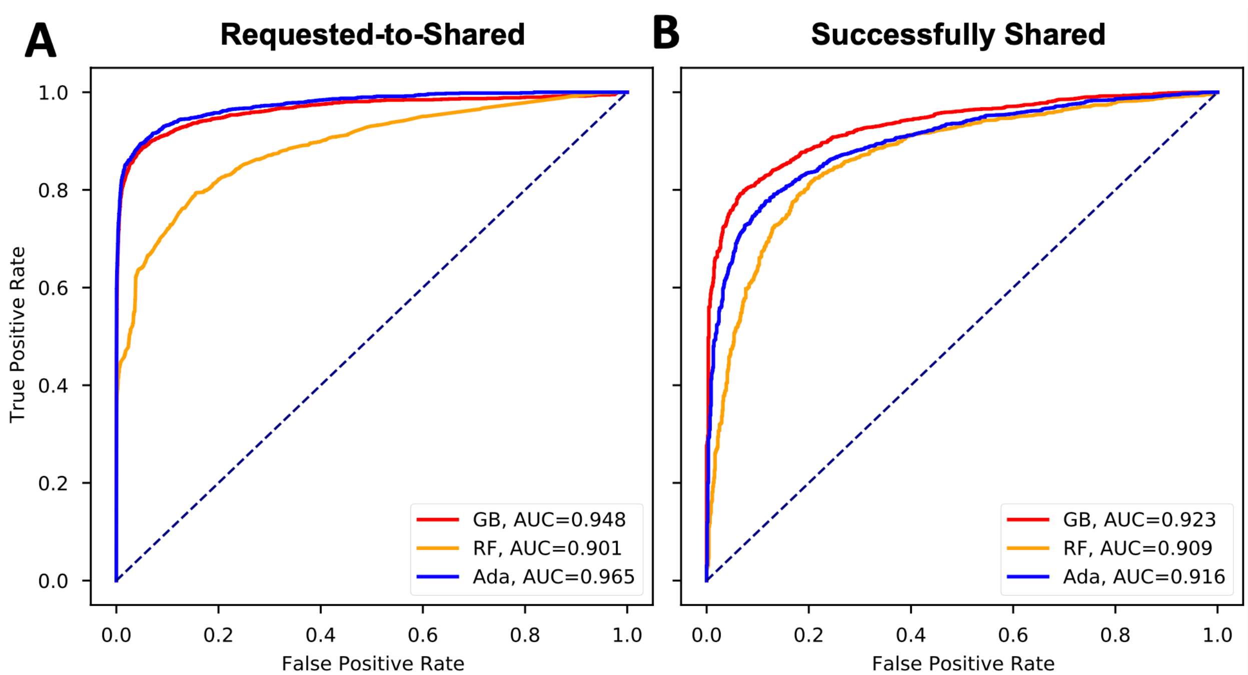

Figure 5-7. Performance of ML models in prediction
(A) requested-to-share trips and (B) successfully shared trips. The area under the receiver operating characteristic (AUC-ROC) curve is equivalent to the probability that the model will rank a randomly chosen positive instance higher than a randomly chosen negative instance. The higher the AUC, the better a classification model. The diagonal line represents the baseline null classifier.

Table 5-2 provides more details on the performance metrics of final optimized classifiers. Since recall and precision are more important than accuracy in this problem, I specifically tune the classifiers' hyperparameters to maximize recall instead of accuracy. In this process, the RF model trades off a significant improvement in recall and precision to a slight decline in accuracy compared to the untuned model. This is mainly due to aggressive overfitting nature of the RF method before tuning (Figure C-6). The Ada model shows superior classification performance with the highest recall rate for predicting requested-to-share trips while maintaining over 96% accuracy. For prediction of successfully shared trips, all three models are reasonably accurate, but the GB model maintains a slightly higher edge in other performance metrics.

Table 5-2. Performance of hyperparameter-tuned models on the test set.
The percentage performance improvement compared to the untuned model on the validation set is shown in parentheses.

Models	***Prediction of Requested-to-Share***			***Prediction of Successfully Shared***		
	Accuracy	***Precision***	***Recall***	***Accuracy***	***Precision***	***Recall***
Random Forest	0.92 (-1%)	0.93 (-2%)	0.74 (+4%)	0.89 (-1%)	0.91 (-1%)	0.91 (+3)
Ada-Boosting	0.96 (+3%)	0.94 (-1%)	0.82 (+6%)	0.90 (0%)	0.92 (+1)	0.90 (+1%)
Gradient Boosting	0.95 (+1%)	0.94 (0%)	0.80 (+4%)	0.91 (+1%)	0.91 (+2%)	0.92 (+1%)

To assess the relationship between the target responses of models (WTS and probability of sharing success) and selected explanatory variables, I use partial dependence plots (PDP). They intuitively show the marginal effect that specific features have on the predicted outcome of a model [239,241]. The PDPs for top three variables are shown in Figure C-7 and Figure C-8, capturing the highly nonlinear relationship with the target responses. The direction of associations reveals that longer trip distance and duration increase both requested-to-share and shared probabilities, but higher cost reduces the probability. The joint dependency of trip cost and distance also signifies a high level of nonlinearity, which cannot be capture by a simple per-mile cost variable. I also tested several other scenarios for model specifications such as substituting trip duration and cost by per-mile cost, removing trip duration, which is correlated with trip distance. However, the performance of all alternative scenarios was inferior to the preferred classifiers. Moreover, other tested classification models including logistic regression and support vector machine do not reach an acceptable recall likely because the relationship between high importance features cannot be explained as linear.

To ensure robustness of the model, I repeat the entire learning process for all candidate models using 100 bootstrapped random samples size of 8,000 from the whole dataset. To quantify the uncertainty in performance metrics, I measure accuracy, precision, and recall on the test sets. As Figure 5-8 shows, on average, the Ada model outperforms other models in all metrics for prediction of requested-to-share trips and GB has a slight edge for prediction of successfully shared trips. Overall, the narrow bounds of distributions of performance metrics ensures robustness to sampling and the training process in the classifications.

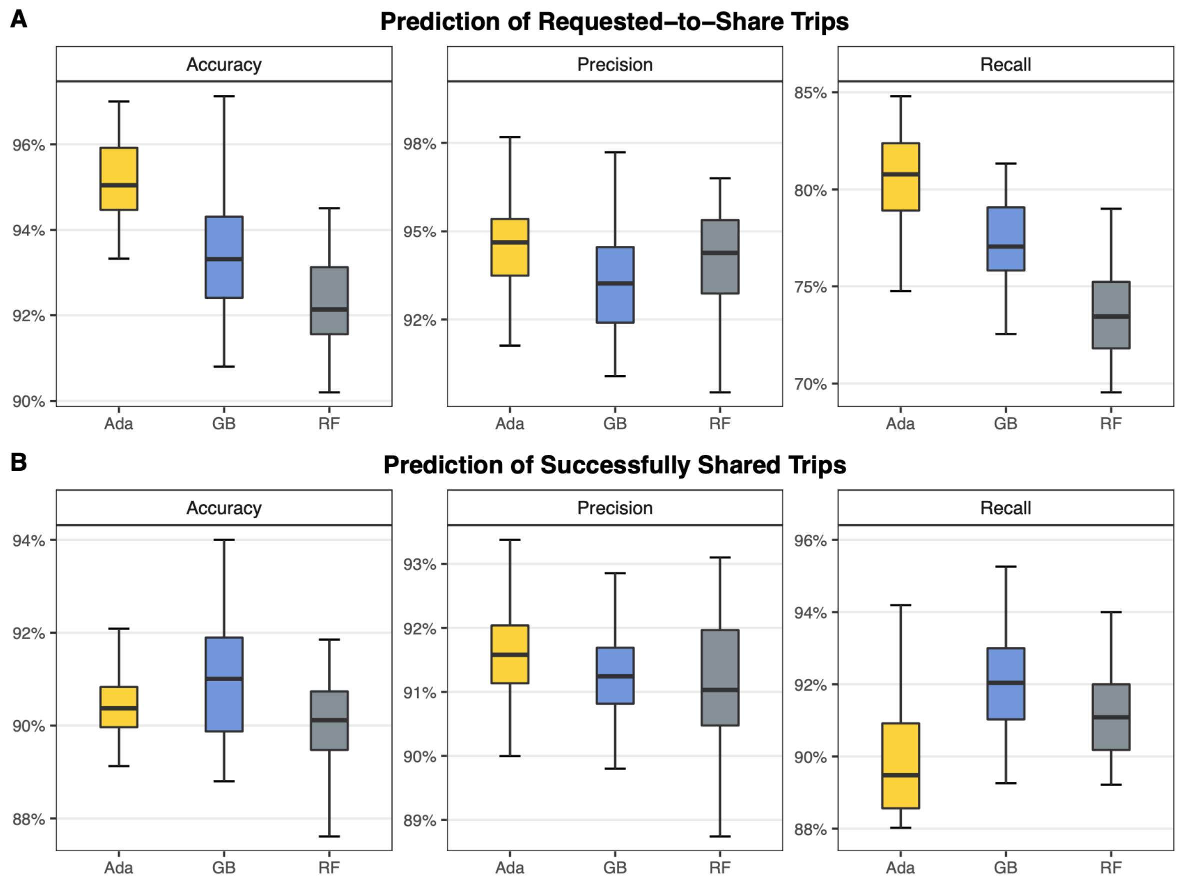

Figure 5-8. Distribution of model performance metrics over 100 bootstrapped random samples size of 8,000 from the entire dataset.

5.7. Discussion and Conclusions

In this study, I investigate sharing behavior in ride-hailing trips in Chicago. I show that WTS and successfully shared trips in Chicago halved throughout 2019 with a strictly declining trend, while the rate of successful matching, as well as trip volume and VMT, have been stable. A regression analysis reveals that a gradual increase in per-mile cost of the trip over time has been the major factor in the decline of WTS, especially for shorter trips which were likely substituted by solo trips. Using ensemble ML methods, I find that travel impedance variables (trip cost, distance, and duration) have the highest predictive power in predicting the propensity to share. Longer but less expensive requested-to-share trips are more likely to be successfully shared with another ride. A wide range of explanatory variables at the pickup and drop-off of trips, including socioeconomic, demographic, spatial and temporal attributes, built environment, and transit supply variables are loosely correlated with WTS and successful sharing, but do not bear significant predictive power (although the characteristics of all census tracts along the trip route could matter as well, I have not studied them here). WTS in EDAs (low incomes and high concentration of minorities) is nearly double that of non-EDAs. However, as shown in Figure 5-3, since the EDA trips are longer and more expensive, lower price of shared trips has become a stronger factor encouraging riders to opt for sharing. In EDAs, the transit supply is also poor, suggesting that the convenience of door-to-door mobility combined with lower price of shared trips may be replacing active and public transit trips and come at the expense of expanding infrastructure and/or services to those areas [222]. This is consistent with Schaller (2021) which found sharing in ride-hailing is most popular in lieu of public transit and attracts passengers from existing shared modes [215]. Some studies, however, argue that ride-hailing and sharing to transit hubs have increased transit ridership [242].

Since travel impedance variables best explain sharing behavior compared to other variables, pricing signals have the highest potential to encourage riders to substitute solo rides with sharing. Thus, policymakers and TNCs can more efficiently allocate sharing incentives to increase the penetration of sharing and reduce congestion and environmental externalities of ride-hailing. Recognizing this, on January 6, 2020, the City of Chicago initiated a new congestion fee policy for ride-hailing trips with differential pricing for shared trips in the downtown area [243]. The new policy increased the congestion tax on shared trips in the downtown congestion zone by 74% (0$.72/trip to $1.25/trip), but more than quadrupled the congestion tax on solo ride-hailing trips ($0.72/trip to $3/trip). Future research may assess the impacts of this new policy on sharing behavior.

In essence, the *trip-level* classification problem here is comparable to Hou et al. [224] and Xu et al. [226] in which the aggregate ratio of requested-to-share trips between O-D pairs at the census tract level is predicted as a regression-based problem. These studies attempted to identify the factors that are associated with WTS. They found high mean squared error in prediction as well as high sensitivity of models to inclusion of O-D pairs with few connecting trips (outliers). Since travel impedance variables show little variance in O-D pair analysis aggregated at the census tract level, their predictive power is limited. The classification models demonstrate high level of accuracy and robustness in direct prediction of shard-requested and successfully shared trips with the highest predictive powers in travel impedance variables. The association of factors with WTS does not necessarily guarantee causality. For instance, it is identified that the higher portion of black population or lower income in the pickup or drop-off census tracts are associated with greater WTS [224,226]. However, cost, distance, and duration of trips are also higher in lower income and black-majority areas (EDAs) in Chicago (Figure 5-3). Thus, a casual inference without constructing a structural model is likely unreliable.

There are several inherent limitations in the Chicago data as well as the approach of examining the sharing behavior and making inference. First and foremost, the Chicago dataset does not divulge details on characteristics of riders and trips. The choice of solo and shared for the rider is largely a function of fare difference between alternatives when the rider requests a ride. The data does not reveal the cost difference between alternatives choices and only report the final state of the trip. Rounding the fare to nearest $2.5 is a source of unknown bias in the inference, which prior studies have also acknowledged [224–226]. Secondly, since the trips are anonymized, I cannot attribute the pattern to individual riders with specific sociodemographic attributes to identify the determinants of WTS. The data does not reveal wait time for requested-to-share rides versus solo rides, which is among the most important factors for WTS of individual trips. The suppression of pickup and drop-off locations to the census tracts creates large bias. The data does not carry any information on individual ridership characteristics, which hinders higher resolution identification of sharing preferences (for instance, the number of people in each requested ride or a unique id for each rider to assess the individual sharing behavior over multiple trips). Thus, the findings cannot be generalized to human behavior in facing a choice and should not be interpreted as a choice experiment. Rather, the findings underscore the predictive power of trip-level attributes, which can still be leveraged to answer important questions associated with propensity for ride sharing. Finally, the sharing behavior after COVID-19 will likely change significantly. Since March 16, 2020, no shared ride was offered in Chicago, and it will likely continue for a foreseeable future. Thus, it is important to revisit the data once shared rides are offered again and assess the post-pandemic behavior and how preference has changed.

Chapter 6. Impacts of Congestion Pricing on Sharing Behavior in Ride-hailing Trips

6.1. Introduction

In the age of transportation network companies (TNCs), ridesharing – that is, the combining of two or more individual trips entirely or partly into one trip served by a single vehicle – is an important potential lever for reducing negative externalities from energy use. There has been much interest in the question of what effects TNCs have had on vehicle miles traveled, emissions, and congestion. While electrification can reduce the emissions intensity of ride-hailing services [19,187], it does not address the congestion externality [51,54,244,245]. Ridesharing, in contrast, can reduce both emissions [185] *and* congestion [215], by raising the efficiency of energy use for travel. It is thus a key part of TNCs' claim to being sustainable [9,39].

Despite this, little is known about how attainable the vision of widespread ridesharing truly is. Ridesharing is currently only offered by TNCs in an urban subset of the U.S. Scattered data show recent rates of TNC ridesharing in a selection of cities to be in the range of 13-36% [215,233]. A few recent studies build predictive models of "willingness to share" and identify its key predictors [224–226]. TNCs and municipal governments have both experimented with incentives for ridesharing like fare discounts and driver subsidies [215,246], but there is no published evidence on the impacts of such incentives.

In this paper, I provide some of the first empirical evidence of the effect of price incentives on ridesharing. I study a unique policy change in the city of Chicago, which in January 2020 implemented a congestion pricing scheme for TNC rides, differentiated by whether a ride is private or shared. This policy is a direct response to perceived impacts of TNCs on congestion and public transit ridership [247], and the first of its kind as an effective "tax" on private ride-hailing. While the fee is applied to all TNC rides, the fee is relatively higher for private rides, and also relatively higher for rides to or from the downtown "zone" during peak hours (6AM-10PM). I leverage these differences in policy "treatment", in conjunction with trip-level TNC data from the city of Chicago, to show how ride-hailing activity in the city has responded to a rise in the relative price of a private ride.

Total TNC ridership (measured as person-trips) in Chicago is roughly flat during the period of observation (July 2019 to February 2020) [248]. Total *shared* person-trips, on the other hand, drops steadily over time but jumps noticeably in the week the policy takes effect. Using difference-in-differences (DD) and triple-differences (DDD) regression. I estimate that a $1.15 rise in the relative price of a private ride is associated with a 2.4 percent rise in willingness to share (which I measure as a rider's authorization of a shared TNC ride). I find no evidence that total person-trips dropped as a result of higher prices, which implies that the short-run effect of the policy has been to induce some substitution from private to shared rides. The back-of-the-envelope estimate is that the $1.15 rise in the relative price of a private ride reduced VMT by roughly 4,000 miles per week, and that the full policy effect (including price increases in the neighborhoods and off-peak periods) may be closer to a reduction of 8,000 miles per week.

Price incentives for ridesharing thus appear to have some empirical backing as a policy for reducing externalities from urban energy use. However, while their effect here is statistically significant, it is of relatively modest magnitude. The evidence here thus does not, on its own, suggest that strong price incentives would be adequate to induce a major shift towards ridesharing. I emphasize that the results speak only to short-run effects; the COVID-19 pandemic dramatically changed travel behavior around March 2020, so I only observe two months of post-policy outcomes (which themselves may have been affected by the pandemic). Moreover, the results pertain specifically to the price changes observed in the Chicago sample, so the effects of further price changes in Chicago are unknown, and so are the effects of similar price changes occurring in different cities, where demand for ride-hailing may differ. I view the results as evidence that price incentives can induce at least modest increases in ridesharing. However, given the trajectory of transportation emissions and urban congestion in the United States, I believe a much more widespread switch to ridesharing is needed to make private vehicle travel sustainable. More research is needed to assess the broader potential for policy and innovation to induce this sort of norm shift.

6.2. The Chicago Congestion Fee System

Chicago is one of the largest ride-hailing markets in the US, where Uber, Lyft, and Via together dispatch nearly 300,000 rides per day [227] and ride-hailing makes up about 3% of the total regional VMT [46]. Between 2015 and 2018, the annual number of TNC trips grew by 271 percent, with half of all TNC trips citywide beginning or ending in the downtown area [247]. In November 2019, the City approved a new congestion fee policy for ride-hailing services. The new policy went in effect starting January 6, 2020, and is currently the highest ride-hailing tax in the nation, expected to raise $40 million per year [249].

The policy did three things: first, it changed the price of all TNC rides in the city; second, it raised the price of all rides in the “congestion zone” [243], that is, the downtown area during weekday peak hours (6AM-10PM); third, it raised the prices of private rides more than those of shared rides. shows the geographic coverage of the congestion zone versus “the neighborhoods”. Table 6-1 details the fee structure for TNC rides before and after the congestion fee went into effect.

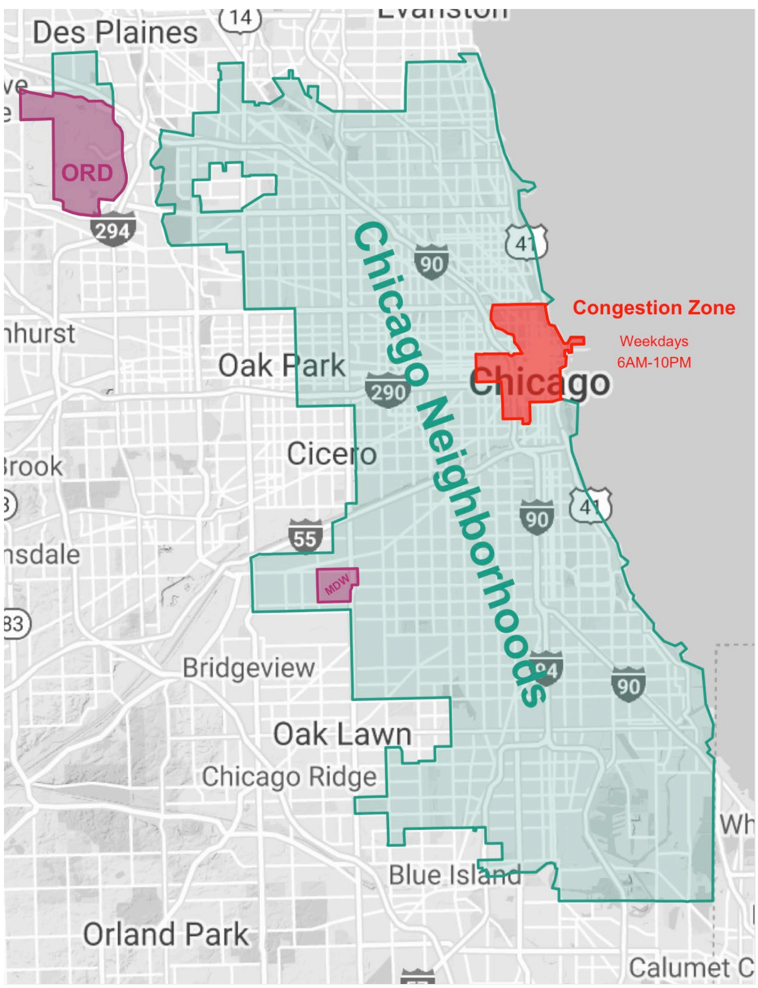

Figure 6-1. The City of Chicago and the boundary of the downtown, airports, and neighborhoods. The City of Chicago designated the Congestion Zone as the boundary of downtown area during weekdays 6AM to 10PM. Any trip with pickup or drop-off in the congestion zone is assessed a higher tax.

Table 6-1. Ride-hailing fees before and after the congestion policy took effect

	Post-Policy (1/6/2020 –present)		**Pre-Policy (1/1/2019 –1/5/2020)**
	Solo	**Pooled**	**All**
Downtown Peak Time **(Congestion Zone)**	\$3.00/trip	\$1.25/trip	\$0.72/trip
Downtown Off-Peak	\$1.25/trip	\$0.65/trip	\$0.72/trip
Neighborhoods	\$1.25/trip	\$0.65/trip	\$0.72/trip
Airports – Congestion Zone	\$8.00/trip	\$6.25/trip	\$5.72/trip
Airports – Neighborhoods	\$6.25/trip	\$5.65/trip	\$5.72/trip

† All taxes and fees include \$0.10/trip Access fee and \$0.02/trip administration fee.

Since all areas of Chicago are "treated" with price changes, there is no natural control group with which to estimate an aggregate policy impact on ride-hailing outcomes. However, differences in treatment across time of day and area of the city make it possible to compare the effect of relatively larger price changes to the effect of relatively smaller ones. In particular, the relative price of a private ride in the "congestion zone" (downtown, peak time) rose more than in all other "zones" listed in Table 6-1. I thus compare ride-hailing over time and across these zones, using the difference-in-differences (DD) method. The primary zonal comparison is between downtown peak periods and downtown off-peak periods, but I also consider the triple-difference using pre-post, downtown-neighborhoods, and peak-off peak differences. Further, I compare estimated effects in areas classified as "economically disconnected areas" (EDAs) versus those in areas that are not. The Chicago Metropolitan Agency for Planning defines EDAs as areas that have higher than regional average concentrations of low-income households and minority or limited English proficiency population, resulting in lower economic mobility [236].

6.3. Materials and Methods

The raw data for this study are available from the City of Chicago data portal [227]. These spatiotemporal data are at the trip level and contain trip attributes including ID, start/end timestamps, duration, distance, pickup/drop-off census tracts, fare, additional charges, tip, and trip total cost. Every trip record has an indicator to show whether the rider requested sharing (that is, whether the rider is willing to take a shared trip). A requested-to-share trip does not necessarily translate to a successfully shared trip, and may end up solo, but the rider secures the trip cost regardless of matching with another rider or not. For this study, I focus on data from July 1, 2019 to March 8, 2020 (75.73 million trip records before cleaning). This range spans six months prior to enactment of the new congestion policy and two months following it, before all shared trips were suspended on March 11, 2020 due to the COVID-19 pandemic (the data show a significant reduction in demand beginning March 9, 2020). The data provider has taken several steps to protect the privacy of riders and drivers (Supplementary Note); de-identification has resulted in missingness of some characteristics for many trips. Supplementary Note explains the procedure for data cleaning and imputation of missing values. 14.6% of trip records are removed as part of the cleaning process, bringing down the total number of observations to 64,663,012 trips for the period of study.

I transform the trip-level data so that each observation is an origin-destination (O-D) census tract pair in a specific week during a specific time-period (peak or off-peak). This dataset contains 9,525,426 unique observations. For each tract-pair week time-period, I count total trips, total shared trips, and the proportion of all trips (a) requested to be shared and (b) successfully shared. Table D-1 summarizes the key variables in this sample.

Our preferred, "downtown" difference-in-differences (DD) estimation model uses only the observations from the downtown area and is given by Equation (6-1):

$$Y_{itp} = \beta_0 + \beta_1 Post \times Peak_{itp} + \theta_t + \varphi_{ip} + \varepsilon_{itp} \tag{6-1}$$

Here, Y_{itp} is percentage requested to be shared ("willingness to share"), percentage successfully shared, or total trips, all corresponding to tract-pair i, in week t, in time-period p. $Post \times Peak_{itp}$ is a binary variable equaling one if an observation is from a week after the policy change as well as from the peak time-period. θ_t and φ_{ip} are week and tract-pair time-period fixed effects, respectively; these two vectors together control for "single differences" across space and over time. I cluster standard errors at the week level (there are 36 weeks in the data and thus 36 clusters; as a robustness check, I cluster standard errors at the week time-period level in Panel A of Table D-2). For regressions with percent shared as the outcome variable, I weight observations by total trips (regressions with total trips as outcome variable do not use weights, and Panel B of Table D-2 omits weights entirely as a robustness check).

I also estimate a triple-differences (DDD) model, given below by Equation (6-2):

$$Y_{itp} = \beta_0 + \beta_1 Post \times Peak_{itp} + \beta_2 Downtown \times Peak_{itp} + \beta_3 Downtown \times Post_{itp} + \beta_4 Downtown \times Post \times Peak_{itp} + \theta_t + \varphi_{ip} + \varepsilon_{itp} \tag{6-2}$$

Here, $Downtown \times Peak_{itp}$ and $Downtown \times Post_{itp}$ are binary interaction terms analogous to $Post \times Peak_{itp}$. β_4, the coefficient on $Downtown \times Post \times Peak_{itp}$, is the DDD coefficient of interest. I employ the same clustering and weighting strategies as with Equation (6-1).

Finally, I use the "downtown DD" specification given by Equation 1 to compare the policy effect in Economically Distressed Areas (EDAs, as defined by the City of Chicago) against the effect elsewhere. I define a binary variable EDA_{itp} that equals one if a tract-pair has either origin or destination in an EDA. I then estimate Equation 1 separately for the EDA subsample and the non-EDA subsample. Further, I estimate Equation 1 with the full sample but augmenting the equation with interaction terms $Post \times EDA_{itp}$, $Peak \times EDA_{itp}$, and $Post \times Peak \times EDA_{itp}$ – the last of which provides an estimate of the differential policy impact in EDAs vs. non-EDAs.

6.4. Impact of the Policy on Ridesharing

The City of Chicago has had a data sharing mandate in place for TNCs since February 2019 [227] (and other cities have done the same [219]). I use the city's person-trip level database, which records, most importantly, when and where a ride (that is, person-trip) happens and whether the rider (a) "requested to share" the ride and (b) successfully shared the ride (see Table D-1 for summary statistics on the key variables). Figure 6-2 shows how total TNC person-trips and total shared (requested) TNC person-trips evolved from July 2019 to February 2020. Both counts show a precipitous, short-lived drop at the end of December 2019 – this is due to the significant drops in demand for as well as supply of TNC rides during the Christmas period. Otherwise, the visual trends look different: total person-trips do not discernibly rise or fall over time; total *shared* trips drop steadily over time, including after the congestion policy took effect, but this downward trend is interrupted by a noticeable jump in the first week of the policy.

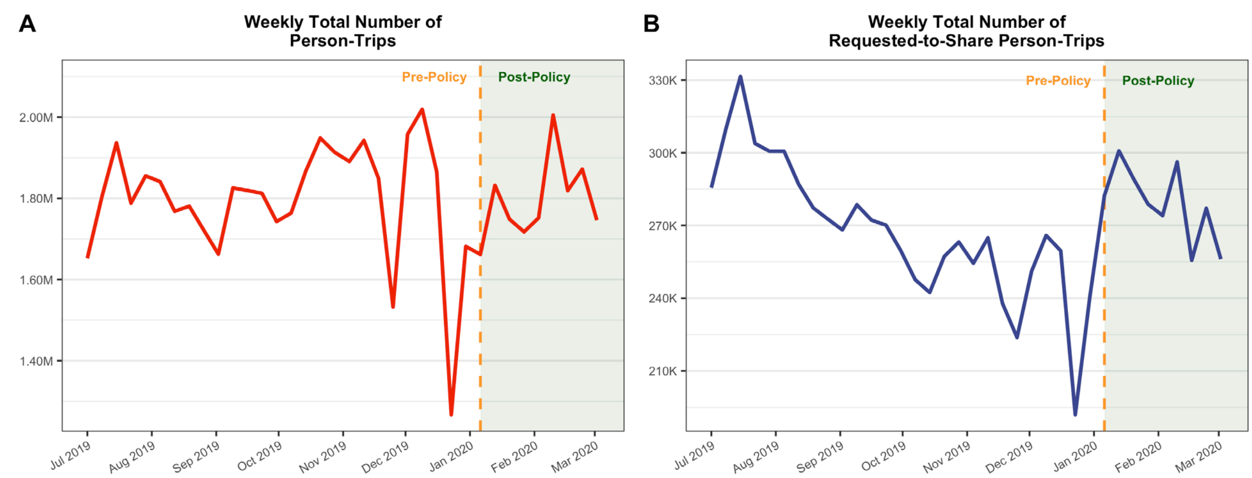

Figure 6-2. (A) Weekly total number of person-trips citywide over time; (B) Weekly total number of requested-to-share person-trips citywide over time

With total and shared counts, I can compute a willingness to share (WTS) measure as the percentage of person-trips in a week-zone that were requested to be shared. In Figure 6-3, I compare WTS over time in the downtown area during peak hours (i.e., the "congestion zone") versus the downtown area in off-peak hours. Prior to the congestion fee policy taking effect, all (non-airport) rides to or from the downtown area are subject to the same 72-cent fee, regardless of timing and number of vehicle occupants. After the policy's imposition, private rides in the downtown area are subject to a higher fee than shared ones: during off-peak hours, a private ride comes with a \$1.25 fee, while a shared ride comes with a \$0.65 fee; during peak hours, the private-ride fee is \$3,00, while the shared-ride fee is \$1.25. Thus, both time periods are "treated" with a rise in the relative price of a private ride, but the rise is larger in the peak period (\$3.00 - \$1.25 = \$1.75) than in the off-peak period (\$1.25 - \$0.65 = \$0.60).

Figure 6-3 provides compelling evidence that the downtown off-peak times is a viable control group for downtown peak. Panel A shows consistently parallel trends in WTS: both lines drop steadily over time from July through December 2019, with weekly changes of very similar magnitudes. WTS jumps suddenly in both periods concurrently with the policy change, and then resumes a downward trend in both periods. The strongly similar time trends in WTS throughout the pre-policy period imply that the analogous difference-in-differences regression would yield a credible estimate of short-run impact. Panel B of Figure 6-3 makes this case more directly, by plotting the cross-period difference (normalized to zero in the first week of the sample) in WTS over time. The difference hovers near zero for the duration of the pre-period, never deviating more than one percentage point. In the week of the policy's start, however, the difference jumps to 2.3 percentage points, and it remains elevated with a mean of 2.6 percentage points throughout January and February. Figure D-1 shows similar results using the "percentage successfully shared" outcome variable.

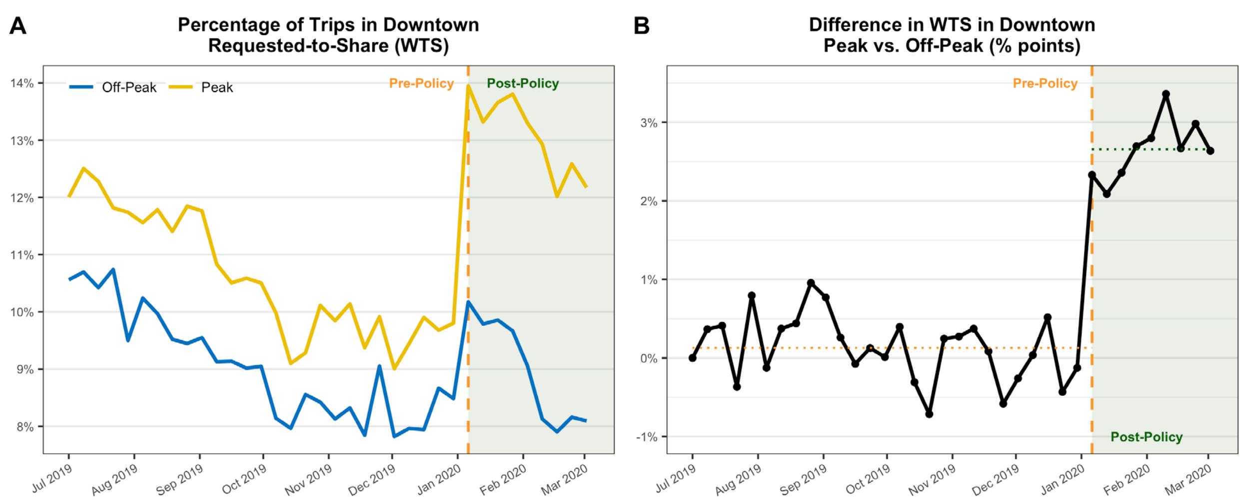

Figure 6-3. (A) WTS in downtown during peak versus off-peak; (B) Difference in WTS in downtown during peak versus off-peak, with the difference in the first week being normalized to zero.

Figure 6-4 shows analogous trends using total person-trips as the outcome variable of interest. In contrast to Figure 6-3, however, Figure 6-4 reveals no discernible change in the cross-period difference in ride-hailing behavior. There are sizeable drops in trips taken in both periods during the week of Christmas, but the post-policy difference is not noticeably distinguishable from that of the pre-period. Put together, Figure 6-3 and Figure 6-4 provide suggestive evidence that the policy change has affected propensity to share a ride but not overall ride-hailing person-trips taken. Figure D-2 and Figure D-3 show analogous results to Figure 6-3 and Figure 6-4 using the peak-period DD comparison of downtown versus neighborhoods, before versus after the policy change. These figures show non-parallel trends downtown and in neighborhoods, so I do not rely on them for estimation.

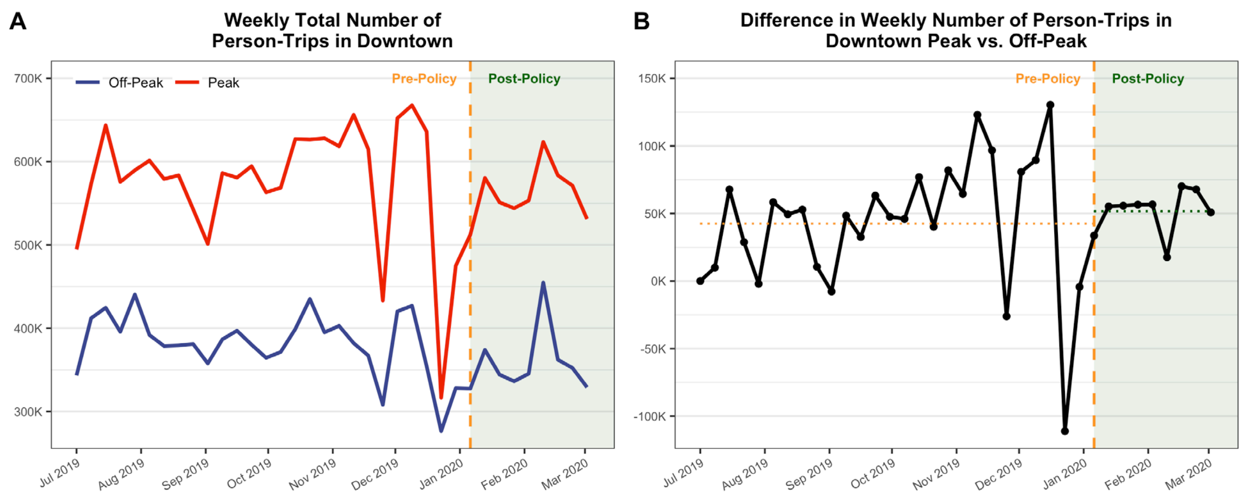

Figure 6-4. (A) Weekly total number of person-trips in downtown; (B) Difference in weekly number of person-trips in downtown during peak versus off-peak, with the difference in the first week being normalized to zero.

In Table 6-2, I present the point estimates of the impacts implied by Figure 6-3 and Figure 6-4. I show results using three different outcome variables: percent requested to share; percent successfully shared; and total person-trips. I estimate the DD model comparing downtown peak to downtown off-peak before and after the policy start; and I additionally estimate the analogous triple-differences model, where the third difference is downtown vs. neighborhoods (Table D-2 shows robustness checks that adjust standard-error clustering and regression weighting). The coefficients shown can be interpreted as the predictive effect of the rise in the relative price of a private ride induced by the policy. The congestion zone is associated with a $1.15 rise in this price; Table 6-2 shows that this is associated with a 2.4-2.5 percentage-point rise in willingness to share (columns 1 and 2). This, in turn, translates into a slightly smaller impact on the percentage *successfully* shared – roughly two percentage points (columns 3 and 4). These estimates are significant at the one percent level. The estimates of the effect on total person-trips are, in contrast, small and statistically indistinguishable from zero (columns 5 and 6).

Table 6-2. Difference-in-differences estimates of policy effects

	% requested to share		**% successfully shared**		**Total person-trips**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Estimated effect	2.38***	2.47***	2.06***	1.99***	0.32	0.04
	(0.17)	(0.17)	(0.17)	(0.13)	(0.41)	(0.40)
Downtown DD	X		X		X	
DDD		X		X		X
N	1,639,450	6,815,103	1,639,450	6,815,103	1,990,102	9,372,058

Notes: The dependent variable is percent of person-trips requested to be shared (columns 1-2), percent of person-trips successfully shared (columns 3-4), or the total number of person-trips (columns 5-6). "Downtown DD" denotes the difference-in-differences (DD) estimate comparing downtown peak-period ride-hailing to downtown off-peak period ride-hailing, before and after the policy change. "DDD" denotes the triple-differences specification, where the differences are peak vs. off-peak, downtown vs. neighborhoods, and pre vs. post. In all specifications, an observation is uniquely identified by its origin-destination pair of census tracts $\boldsymbol{i}$ in week $\boldsymbol{t}$ during period $\boldsymbol{p}$ (peak or off-peak). All regressions weight observations by total person-trips. See Methods for precise estimating equations.

The aforementioned table and figures speak to the average effect of the policy among rides to and/or from the downtown area, but there may be differences in responsiveness to the price change across space. For example, if income is positively correlated with demand inelasticity, then I might expect to see a larger shift to ridesharing among the relatively poor. I test this hypothesis in Figure 5, by comparing rides starting and/or ending in an EDAs to those that do not. The plotted data points are week-specific peak / off-peak differences in willingness to share, analogous to Panel B of Figure 6-3. I see relatively stead peak / off-peak differences in both groups (EDA and non-EDA) prior to the policy start, followed by similar jumps in the WTS differential of approximately two to three percentage points. These trends show no visual evidence of a greater ridesharing response in EDAs. Via difference-in-differences regression, I estimate that the price change is associated with a 2.38 percentage-point rise in WTS among non-EDA ride and a 2.54 percentage-point rise in EDA rides. The difference is small in magnitude and statistically insignificant (I present these results in Table D-3).

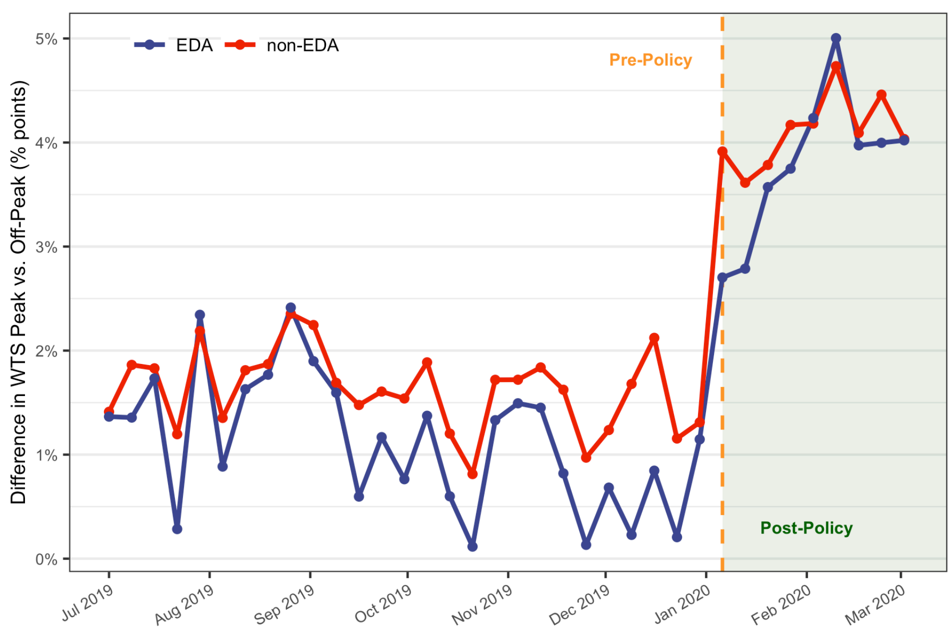

Figure 6-5. WTS in EDA versus non-EDA trips.
The difference is small in magnitude and statistically insignificant, indicating that there is no greater ridesharing response in EDAs versus non-EDAs.

6.5. Discussion

Despite the importance of ridesharing to transportation network companies' sustainability claims, willingness to share rides has empirically been low and there is no direct evidence on what works to change that. I attempt to fill this void by estimating the effect of an increase in the relative price of private ride-hailing, in the context of Chicago's landmark TNC congestion fee policy. The main results are that raising this price is, in fact, associated with increased willingness to share (and successful sharing as well), but it does not, in Chicago's context, reduce total person-trips.

As Table 6-2 shows, the downtown-area DD model finds a significant predictive effect of the relative-price change on the percentage of rides requested to be shared and successively shared. Trends in the peak and off-peak periods downtown appear to be parallel prior to the policy change (Figure 6-3), suggesting the possibility of a causal interpretation. The estimated effect sizes are very similar when I add a third difference (downtown versus neighborhoods) to the identification strategy. They also hold for the slightly different DD comparison between downtown and neighborhoods, though I do not rely on these results because of non-parallel pre-policy trends in the outcome variable. Finally, the estimates are robust to both an alternative level of standard error clustering and the exclusion of regression weights (Table D-2).

Note two primary limitations to the interpretation of the analysis. First, the estimates can only be accurately described as capturing *short-run* impacts. The new fees took effect on January 6th, 2020, and I observe TNC ridership for the following eight weeks – after this point, the intensification of the COVID-19 pandemic caused TNC ridership to plummet. It is thus unclear whether the magnitude of the estimate (a 2.4 percentage-point increase in WTS) would have held in the longer run (that is, in the absence of the pandemic).

Second, the estimates do not speak to the *full* impact of the congestion fee policy change. Rather, they pertain specifically to the additional impact of the congestion-zone price change relative to the price change elsewhere. I do not attempt to estimate the full impact of the policy change because all areas of the city are "treated" with a change in prices, and thus there is no credible control group with which to identify the full impact. Instead, I focus on the "marginal" effect of the congestion-zone price changes (relative to the price changes elsewhere). While this is incomplete with respect to the full congestion fee policy, it nonetheless captures a meaningful change – a rise of $1.15 – in the price of a private ride relative to a shared one. It thus sheds light on the potential for price incentives to induce more ridesharing. Note, however, that Figure 6-3 Panel A does provide suggestive, time-series evidence of larger aggregate policy impacts: WTS rises suddenly in both the peak *and* off-peak periods in the week of the policy change.

I believe the findings are the first empirical evidence on the impact of price incentives to rideshare. They provide reason to believe that raising the price of private TNC rides (and/or reducing the price of shared rides) is a viable strategy for reduction of energy use, emissions, and congestion. However, the estimated effect size of the $1.15 rise in the relative price of a private ride is modest: a 2.2 percentage-point increase in the proportion of rides successfully shared (with no reduction in overall person-trips). To put this in more context, I make a back-of-the-envelope calculation of the vehicle miles traveled (VMT) saved from this effect. Assuming that half of each person-trip is actually shared [215] and using observed person-trips totals and average trip length (in miles), I estimate that the relative price change in the Chicago Congestion Zone avoided 4,034 vehicle miles traveled (VMT) per week, or 32,272 miles over the course of the eight-week period of the observation. While the full policy impact is likely larger than the effect I estimate here, 4,000 miles avoided per week is a mere sliver of total weekly ride-hailing VMT – approximately 0.04 percent. I thus believe that modest policy interventions in the TNC market are unlikely to lead to a meaningful shift in willingness to share rides. Aggressive price incentives, as well as a change in perceptions about private vehicle travel, are likely necessary (but perhaps not sufficient) for a future with widespread ridesharing.

Chapter 7. Conclusions and Future Directions

Emerging technologies in transportation, including vehicle automation, electrification, and shared mobility are increasingly gaining attention in academia, industry, and government, especially as environmental and social impacts of transportation sector are becoming mainstream in the infrastructure overhaul. Drawing from various disciplines, including data science and econometric modeling, this dissertation sheds light on how these emerging technologies impact travel pattern, energy use, and economics of mobility and leverages the synergies that improve transportation system efficiency, sustainability, and social equity. Overall, robust understanding of energy, environmental, and sustainability impacts of emerging mobility technologies depends on the evolution of technologies, behavioral responses, market dynamics, and regulatory and policy considerations.

In particular, Chapter 2 demonstrates that due to the complexity and interdependence of higher levels of interactions, the uncertainty of CAV-related environmental impacts increases as the impact scope broadens. The greatest energy and environmental impacts will not stem from CAV technology directly, but from CAV-facilitated transformations at all system levels. Results from Chapter 3 suggest that travel demand will rise as a behavioral response to the diffusion of CAVs. Some of this rise will come from shifts away from other transportation modes, including public transit, cycling, and walking. Some will come from additional travel – such as new passenger trips, empty trips in between passenger travel, travel pattern change, breaking of pooled trips into several lower occupancy trips, and longer and more frequent trips necessitated by shifting home locations to peripheral zones. Regardless, this induced travel will pose a stiff challenge to policy goals for reductions in energy use, traffic congestion, and local and global air pollution.

Chapter 4 focuses on the nexus of electrification and shared mobility and suggests that range and total cost should not be seen as constraints on significant BEV take-up in the ride-hailing sector. The effective communication of widespread range suitability and cost competitiveness to different stakeholders should free up TNCs and other entities in the transportation sector to prioritize other potential barriers to EV take-up. Chapter 5 investigates sharing behavior in ride-hailing trips and shows that WTS and shared trips in Chicago halved throughout 2019 with a strictly declining trend while the successful matching rate, as well as trip volume and VMT, has been stable. Using ensemble ML methods, I find that travel impedance variables (trip cost, distance, and duration) have the highest predictive power in predicting the propensity to share. Results from Chapter 6 provide empirical evidence that raising the price of private TNC rides (and/or reducing the price of shared rides) is a viable strategy for reduction of energy use, emissions, and congestion. However, for the Chicago case, the estimated effect size of the $1.15 rise in the relative price of a private ride is modest: a 2.2 percentage-point increase in the proportion of rides successfully shared (with no reduction in overall person-trips).

Despite the rapid developments in this research space in the past few years, there are some significant gaps in understanding the true impacts of emerging mobility technologies. In particular, the novelty of CAV technology (and ambiguity of its nature to the public) hinders the ability to model the behavioral response to adoption of this technology [250]. The state of understanding from behavioral response is based on unrealistic representation of the technology to survey responders who have never experienced this technology, or oversimplified assumption for agent-based and optimization studies. As more companies test their technology on public roads and more people experience automated features in their cars and become familiar with the technology, the acceptance of CAV technology and willingness to adopt them will change. Future research should continue to design studies and collect data to identify the dynamic nature of CAV adoption, and monitor the evolution of responses over time, for different groups, as a function of social or formal information sources, and across cultures.

As identified in Chapter 3, an outstanding question in the behavioral response and consequent environmental impacts of the CAV technology is whether (and to what degree) CAVs will be largely privately owned or operated by the mobility companies, and users pay per use. Limited research has attempted to answer this question using survey results with respondents in geographically constrained regions [251]. Furthermore, while the reduction in value of time is a key driver and a large assumption for changes in travel-related behaviors in response to CAVs, not enough attention has been devoted to this research question. Various studies estimated that value of time for shared automated vehicles generally stands between typical transit and private driving. More effort needs to be put into collecting stated preference data from surveys and revealed preference data from field experiments to quantify changes in value of time and how it differs by mode, demographic, and trip purpose for a more accurate integration of these changes into simulation studies. Addressing the change in residential location decisions in response to adoption of CAV technology is another priority area of research.

The impacts of CAVs on modality and mode choice have been receiving more attention in the past couple of years. Additional research is required to understand the driving forces that will shift people away from auto-dependency and into sharing and multimodality. Future research can also explore more robust answers to different sociodemographic groups from cultures with higher dependency on vehicle ownership. CAVs could also exacerbate existing social inequalities if government agencies do not implement the appropriate policies to encourage CAV deployment strategies that consider traditionally under-served populations. Future research could identify the equity implications of these technologies on different sociodemographic profiles and evaluate how regulatory requirements for CAVs could affect access, congestion, and environmental sustainability. As an effort to address this, I attempted to determine the distributional impact of using CAVs for private ownership or on-demand mobility for different socioeconomic groups. I utilized a dual stage choice model for mobility choice, called multiple discrete-continuous extreme-value (MDCEV) model. This model can be used when one is interested in both a discrete outcome and a continuous outcome, particularly when the choices are made jointly. The continuous choice of mileage depends on the prior discrete choice of mobility mode, and the discrete choice of mobility mode is made recognizing the expected levels of the continuous choice (mileage) that will follow. While MDCEV estimation was a very promising approach for joint modeling of modality choice and demand, as well as their equity implications, I faced major identification issues due to limited behavioral attributes of NHTS data, and hence excluded this analysis from the dissertation. I suggest continuing this line of research line with better data sources, due to its theoretical significance and applicability.

Among the three emerging mobility technologies, electrification has received greatest attention in academic research. EVs can provide a number of benefits, including addressing reliance on fossil fuels, improving local air quality, reducing GHG emissions, and improving driving experience. Vehicle electrification aligns with broader electrification and decarbonization trends and integrates synergistically with other emerging technologies of automation and mobility-as-a-service. The effective integration of EVs into power systems presents numerous complementary opportunities for enhancement of the efficiency and economics of both fleets and power grid, with EVs capable of supporting power-system planning. I suggest more research on investments in charging infrastructure, consumer education (especially for low-income and marginalized drivers including ride-hailing drivers), CAV-facilitated grid integration, and the role of electrification in mobility-as-a-service businesses.

Despite developments on understanding of pooling behavior and shared mobility service, with the ongoing COVID-19 pandemic, it is an open question how views of health and safety of shared and pooled services are evolving. Questions on the critical service-levels, including cost, waiting time, travel time, or the flexibility that shared services offer, remain unanswered and addressing them will enable decision-makers to develop informed policies to guide these emerging technologies.

Forecasting the future, including technology adoption, remains a daunting task. Nevertheless, I remain hopeful that the regulatory, societal, behavioral, and business-model barriers associated with the emerging mobility technologies can be addressed over time to support a faster transition toward cleaner, more efficient, equitable, and affordable mobility solutions for all. To conclude, the emerging mobility technologies have the potential to transform our lives, and understanding their implications is key in realizing their benefits and minimizing associated costs. Inclusion of all relevant factors to maximize environmental and social benefits and minimize adverse consequences is critical for the development of these transformational transportation technology that do not only enhance the transportation system safety and efficiency but also save the environment.

Appendices

Appendix A. Supporting Information for Chapter 3

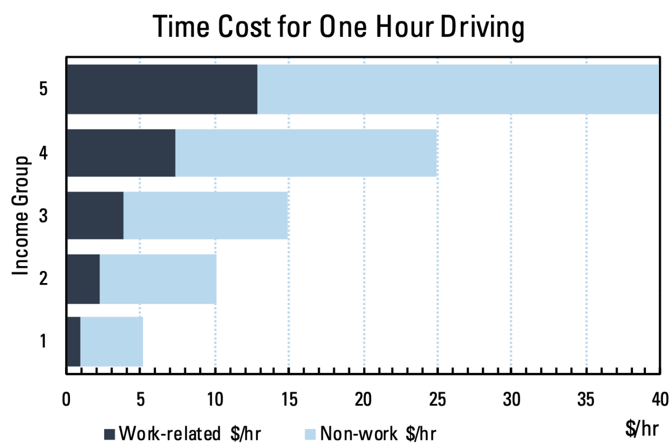

Figure A-1. Travel time cost of one hour of driving, for the average household in each income group.

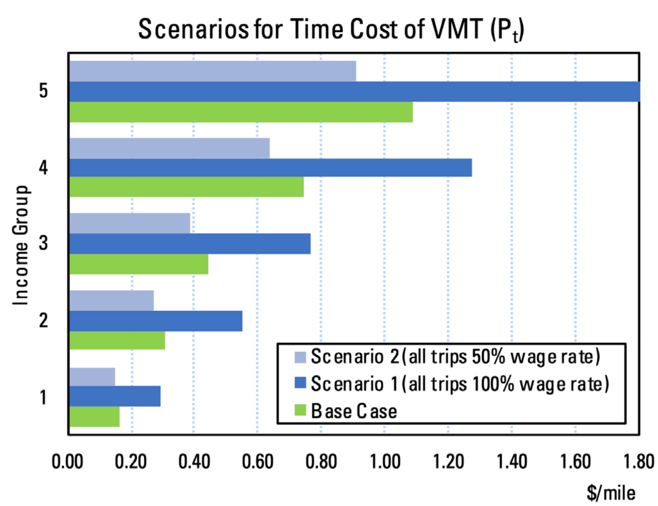

Figure A-2. Scenarios designed for different definitions of TTC.
'Base Case' assigns 100% hourly wage to work trips and 50% hourly wage to non-work trips. 'Scenario 1' assigns 100% hourly wage to all trips while 'Scenario 2' assigns 50% hourly wage to all trips.

Table A-1. Estimation result of 2009 NHTS

Income Group	**1st Income Group**	**2nd Income Group**	**3rd Income Group**	**4th Income Group**	**5th Income Group**	**U.S. Average**	**% difference of average with average of 2017 NHTS**
			Panel A: **Model 3**				
$\hat{\varepsilon}_f$	-0.161*** (0.027)	-0.119*** (0.014)	-0.101*** (0.016)	-0.137*** (0.020)	-0.140*** (0.022)	-0.128*** (0.022)	29.4%
$\hat{\varepsilon}_t$	-0.353*** (0.055)	-0.444*** (0.049)	-0.498*** (0.051)	-0.518*** (0.039)	-0.552*** (-0.051)	-0.501*** (0.055)	25.1%
			Panel B: **Model 4**				
$\hat{\varepsilon}_{vmt}$	-0.291*** (0.050)	-0.394*** (0.048)	-0.459*** (0.037)	-0.488*** (0.049)	-0.513*** (0.054)	-0.451*** (0.051)	15.0%

Dependent variable is $\log(VMT)$. Asterisks denote 1 (***), 5 (**), and 10 (*) percent significance levels, based on p-value. Clustered standard errors are reported in parentheses. Regressions include all controls and fixed effects described in the main text. Standard errors are clustered by MSA, and observations are weighted by household sampling weights. The dollar value is unadjusted between 2017 and 2009. The sample size for both models is 134,482. The pseudo R^2 of the regression is 0.213 in Panel A and 0.198 in Panel B.

Table A-2. Results of robustness check with respect to the definition of TTC

Income Group	**1st Income Group**	**2nd Income Group**	**3rd Income Group**	**4th Income Group**	**5th Income Group**	**U.S. Average**
			Panel A: **Scenario 1**			
$\hat{\varepsilon}_{vmt}$ **(Model 4)**	-0.140*** (0.026)	-0.197*** (0.029)	-0.230*** (0.028)	-0.261*** (0.022)	-0.251*** (0.028)	-0.225*** (0.028)
$\hat{\varepsilon}_t$ **(Model 3)**	-0.159*** (0.034)	-0.226*** (0.031)	-0.256*** (0.028)	-0.272*** (0.022)	-0.283*** (0.029)	-0.229*** (0.027)
			Panel B: **Scenario 2**			
$\hat{\varepsilon}_{vmt}$ **(Model 4)**	-0.283*** (0.053)	-0.373*** (0.055)	-0.432*** (0.051)	-0.481*** (0.040)	-0.460*** (0.046)	-0.422*** (0.053)
$\hat{\varepsilon}_t$ **(Model 3)**	-0.318*** (0.069)	-0.552*** (0.062)	-0.511*** (0.056)	-0.543*** (0.045)	-0.566*** (0.057)	-0.459*** (0.055)

Figure A-3. Heat maps of induced travel using Model 4.
All points above dashed curves are characterized by backfire in net energy consumption.

Appendix B. Supporting Information for Chapter 4

Supplementary Note B-1: Electric vehicles in the transportation sector.

Transportation is currently the largest contributor to greenhouse gas (GHG) emissions among the U.S. economic sectors [2] and the fastest-growing source of GHG emissions and energy consumption globally [3]. Improving the energy efficiency of transportation and reducing the associated GHG emissions are crucial to meeting the Paris Agreement 2°C goal. Electric vehicles (EVs) not only entail higher energy efficiency compared to internal combustion engine vehicle (ICEVs), but also can concentrate emissions from point sources of tailpipes to power plants for more efficient and effective emission control and, most importantly, help renewable energy integration [26]. However, transportation electrification is challenging due to decentralized operation, policy conflicts, infrastructure insufficiency, and consumers' lack of awareness, interest, and confidence, among other factors [36]. Recent studies have shown even aggressive adoption of EVs cannot alone meet the net zero emission economy targets [31,32]. The market penetration of battery electric vehicles (BEVs) is currently hindered by their high cost, arguably short driving ranges, long charging time, and limited charging infrastructure [33,34]. The extent to which BEVs can be accepted by consumers depends on individual travel patterns (travel time, trip length, parking duration, etc.), BEV characteristics (driving range, charging rates, etc.), charging infrastructure access, economics, and a host of psychological factors [35].

Supplementary Note B-2: Literature review of EVs for ride-hailing drivers.

Limited research has shown the potential for adoption of EVs among ride-hailing drivers. However, these conclusions were drawn largely based on using limited unrepresentative data, simulation, or proxy data such as data from taxi operations, because data from real-world ride-hailing operations are scarce. Chief among which is a new study suggested that electrifying a ride-hailing vehicle offers triple the emission reduction compared to switching a personal ICEV vehicle to BEV in California [187]. UCS suggested that ride-hailing with BEVs can reduce GHG emissions by 39% per passenger-trip compared to private ICEVs [185]. Tu et al. used GPS trajectories from 144,867 ride-hailing drivers in Beijing over one week to quantified that up to 55% of total distance driven by the ride-hailing drivers can be met by 200-mile range BEV and ubiquitous home chargers (1.7 kW) [193]. Yu et al. found that environmental benefits of electrifying ride-hailing can be further enhanced with clean electricity generation [252]. Studies from the International Council on Clean Transportation found that hybrid electric vehicle (HEV) is the least expensive option for ride-hailing drivers on per-mile cost basis and BEV will reach cost parity with ICEV by 2023-2025 even without subsidies [195,253]. Bauer et al. showed that BEVs can provide equivalent ride-hailing services to ICEVs at lower cost and the cost of charging infrastructure is not a significant barrier to ride-hailing electrification [194].

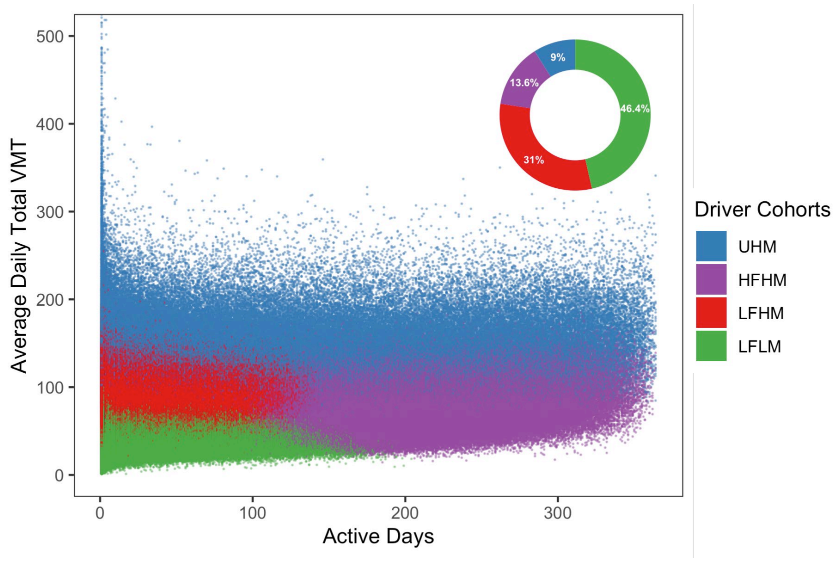

Figure B-1 Near optimal and externally valid driver cohorts.
UHM: Ultra High Mileage; *HFHM*: High Frequency High Mileage; *LFHM*: Low Frequency High Mileage; *LFLM*: Low Frequency Low Mileage.

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

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

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

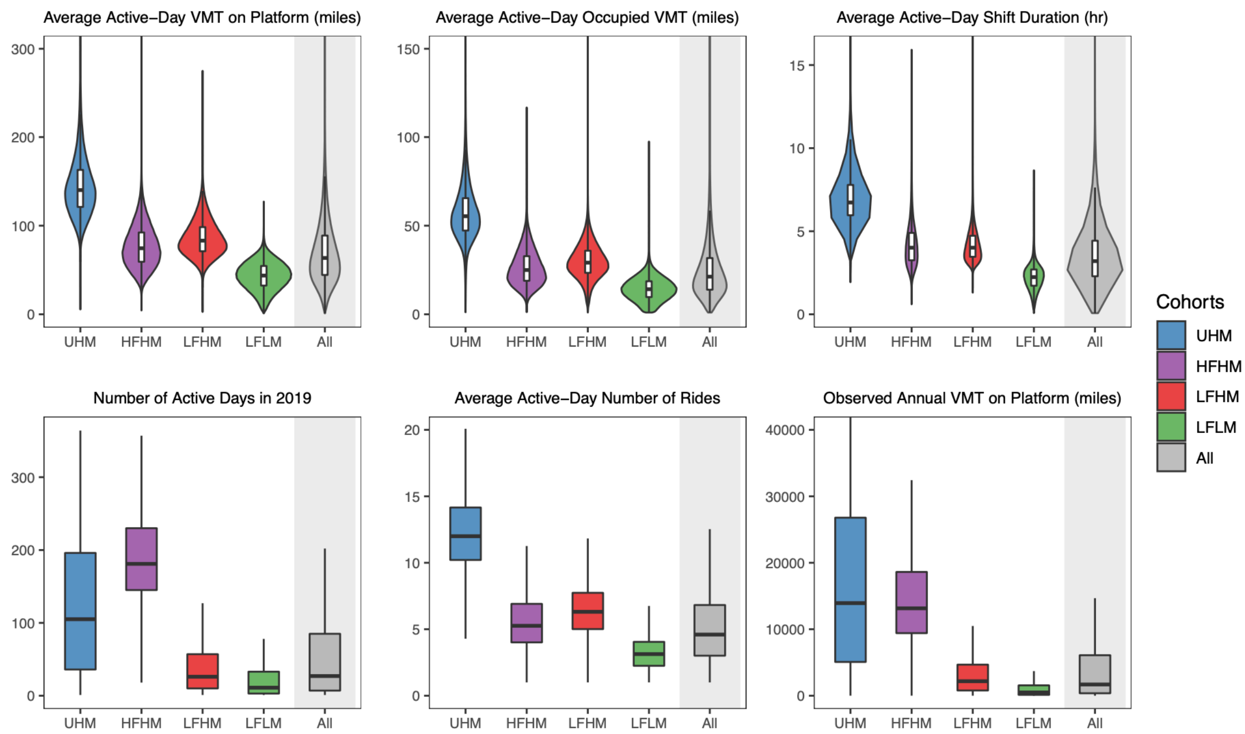

Figure B-2. Distributions of selected variables in the dataset for all drivers and by cohort. The gray shade represents the distribution of variable for all drivers, regardless of cohort.

Supplementary Note B-3: Driver clustering.

Based on computational efficiency and superior clustering power, I choose k-mean clustering, which minimizes within-cluster variances (squared Euclidean distances) of the aforementioned variables. Finally, several verification methods are used for checking the optimality of clusters (Figure B-3). Both Elbow method and Silhouette width method suggest only two optimal clusters on selected variables and then marginal decrease in optimality with higher number of clusters (Figure B-4). I use expert knowledge on average characteristics of resultant clusters to choose the near-optimal yet externally valid set of driver clusters. While the analysis is conducted at the individual driver level, some results are also reported on the cohort basis to provide a roadmap for identifying the ideal cohort of drivers for electrification efforts.

Note that these cohorts based on the clustering method are not absolute, and drivers on the boundary of cohorts have travel patterns similar to those of either cohort.

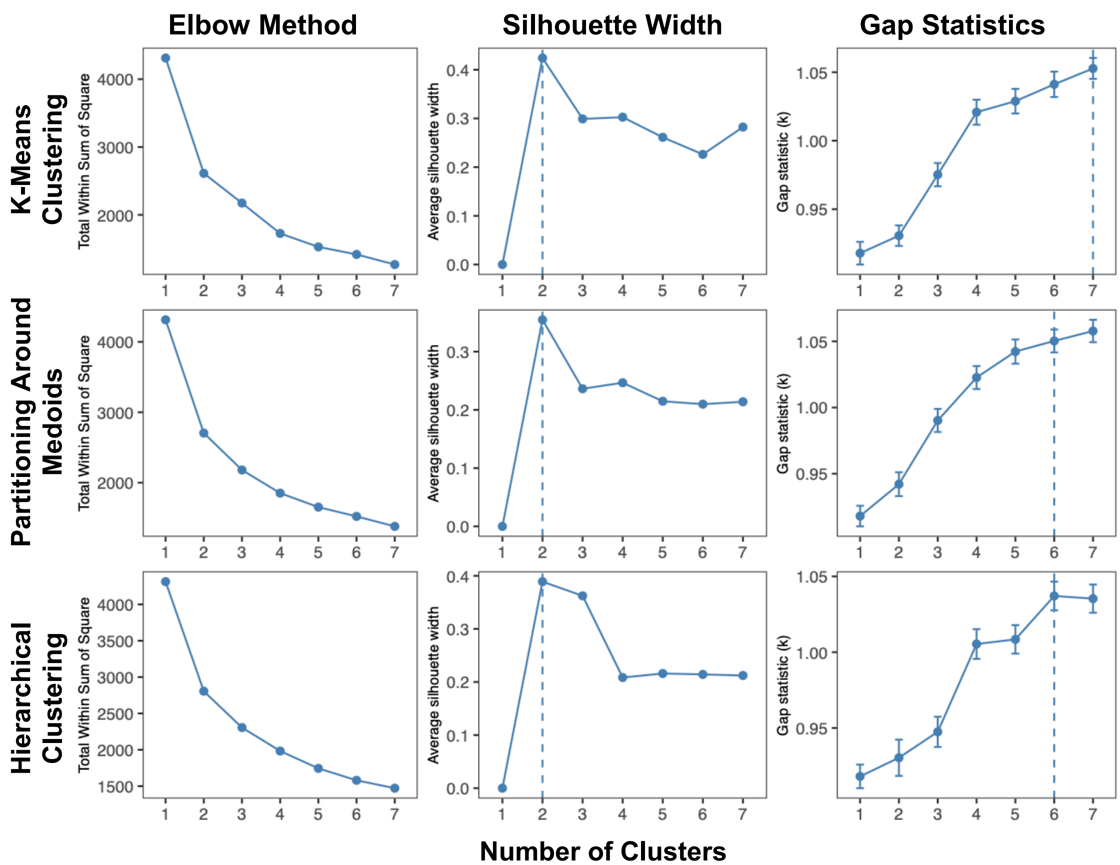

Figure B-3. The performance of other unsupervised ML methods tested for defining the driver cohorts. Both Elbow method and Silhouette Width result in only two optimal clusters for all three algorithms. I use expert knowledge to choose four clusters as externally valid cohort without significantly losing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

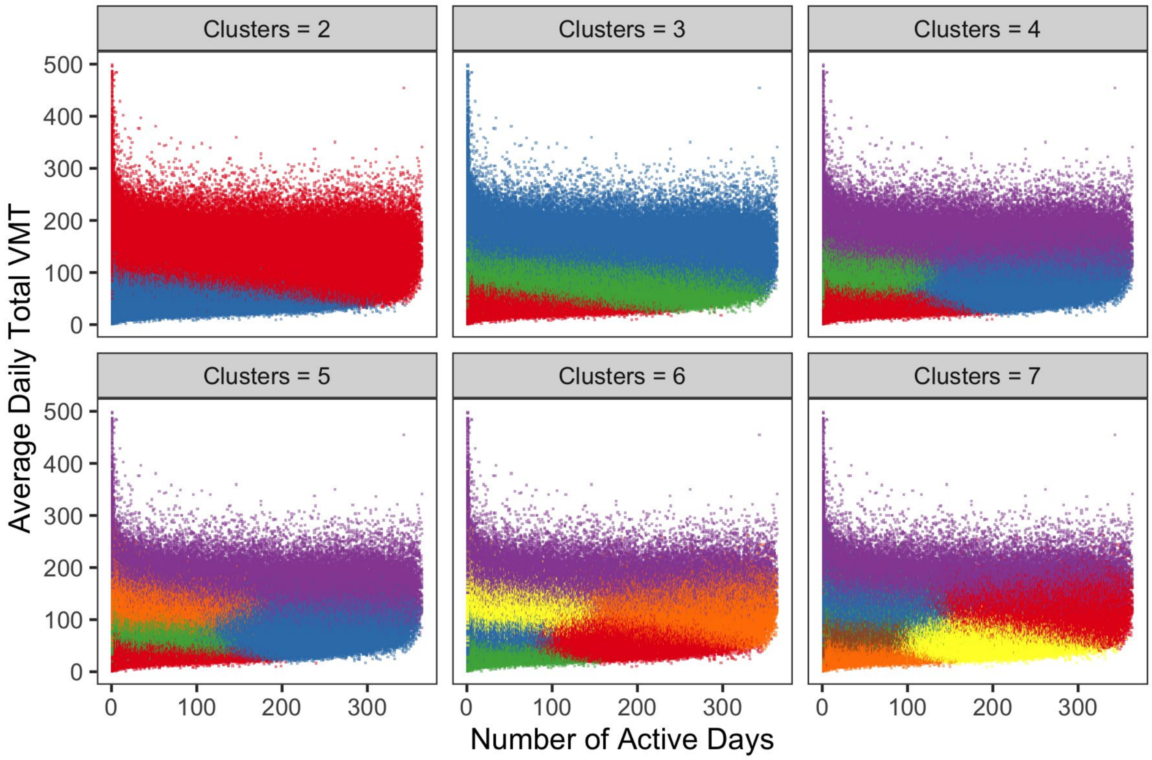

Figure B-4. Results of different number of clusters on K-means clustering of cohorts on two variables. 4-cluster appears to have more external validity than others. The Greater number of clusters than 4 makes further cuts on low frequency low mileage drivers and does not improve the external validity.

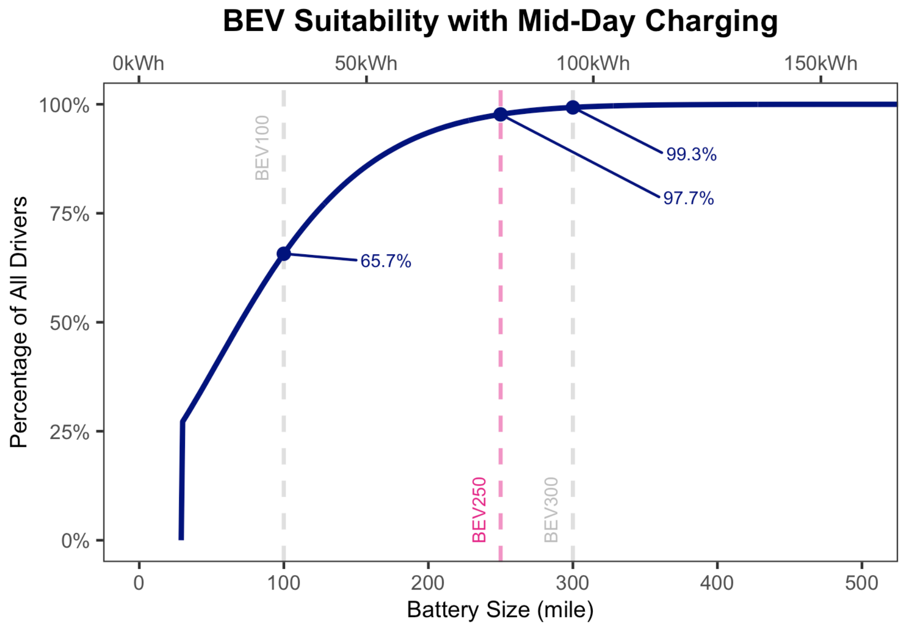

Figure B-5. 95th%-VMT BEV Suitability with midday 30-minute charging at 30 kW DCFC. I use the full sample of drivers on the Lyft platform.

Table B-2. The residual value ($\boldsymbol{VRV}$) of new vehicles at the end of ownership commitment period from alg.com. The residual value is expressed as the percentage of MSRP.

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

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

Table B-3. The residual value ($\boldsymbol{VRV}$) of pre-owned vehicles at the end of ownership commitment period from alg.com

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

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

Table B-4. Estimated annual insurance costs ($\boldsymbol{I}$) for new and pre-owned vehicles.
I assume the insurance rate is not a function of mileage, following the methodology of AAA.

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

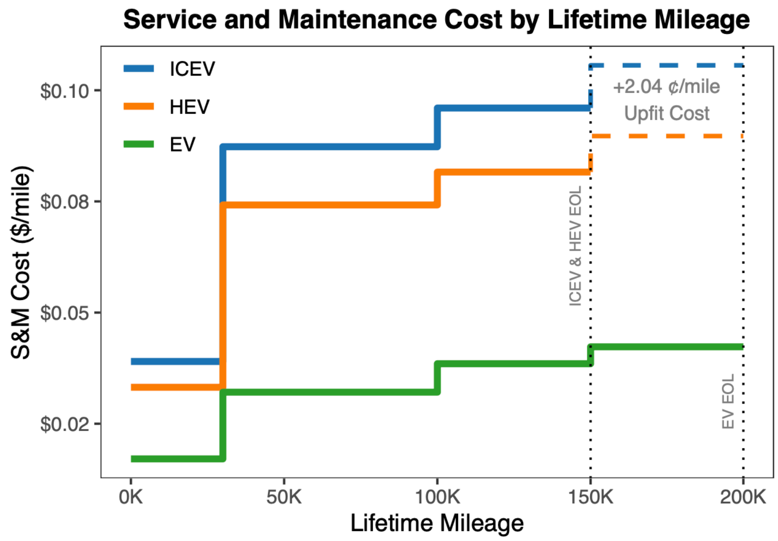

Figure B-6. Service & Maintenance (S&M) costs per mile for different vehicle types.
I assume that ICEV and HEV reach the end of their life (EOL) at 150,000 miles, while BEV reaches EOL at 200,000 miles. An upfit cost of $0.0204/mile is assumed for any mileage after 150,000 miles for ICEVs and HEVs. No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

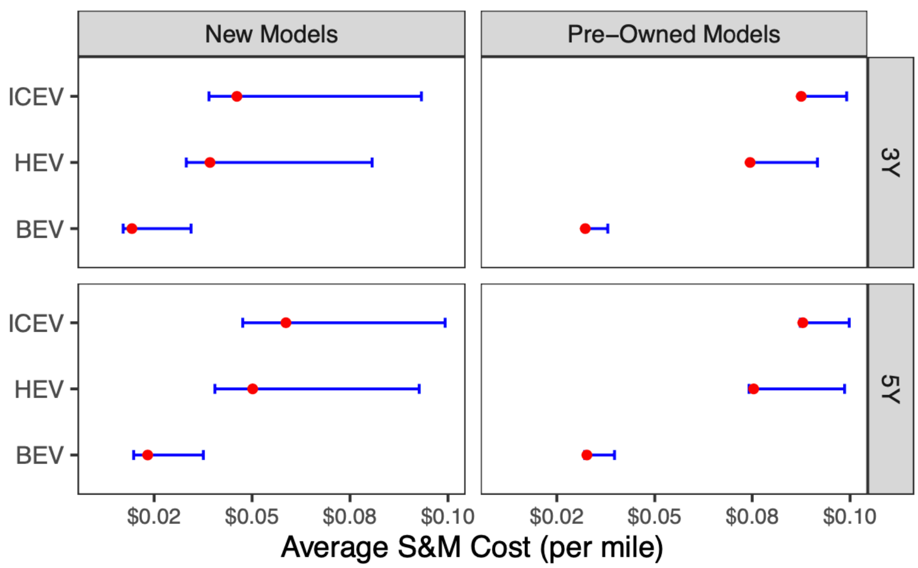

Figure B-7. Range of mileage-weighted average S&M costs per mile for all drivers by model type, new vs. pre-owned, and commitment period length.
The mileage-weighted average S&M cost additionally depends on annual mileage. Red points denote averages and whiskers show minimum and maximum.

Table B-5. 2019 average gas price and LCOC by state.
Gas price includes taxes and is based on the weighted sales volume of three grades of gas, as calculated by the U.S. Energy Information Administration [207]. The national average gas price in 2019 is $2.763/gal, and the median is $2.625/gal. LCOC is based on the central estimate of Borlaug et al. for each state [199].

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

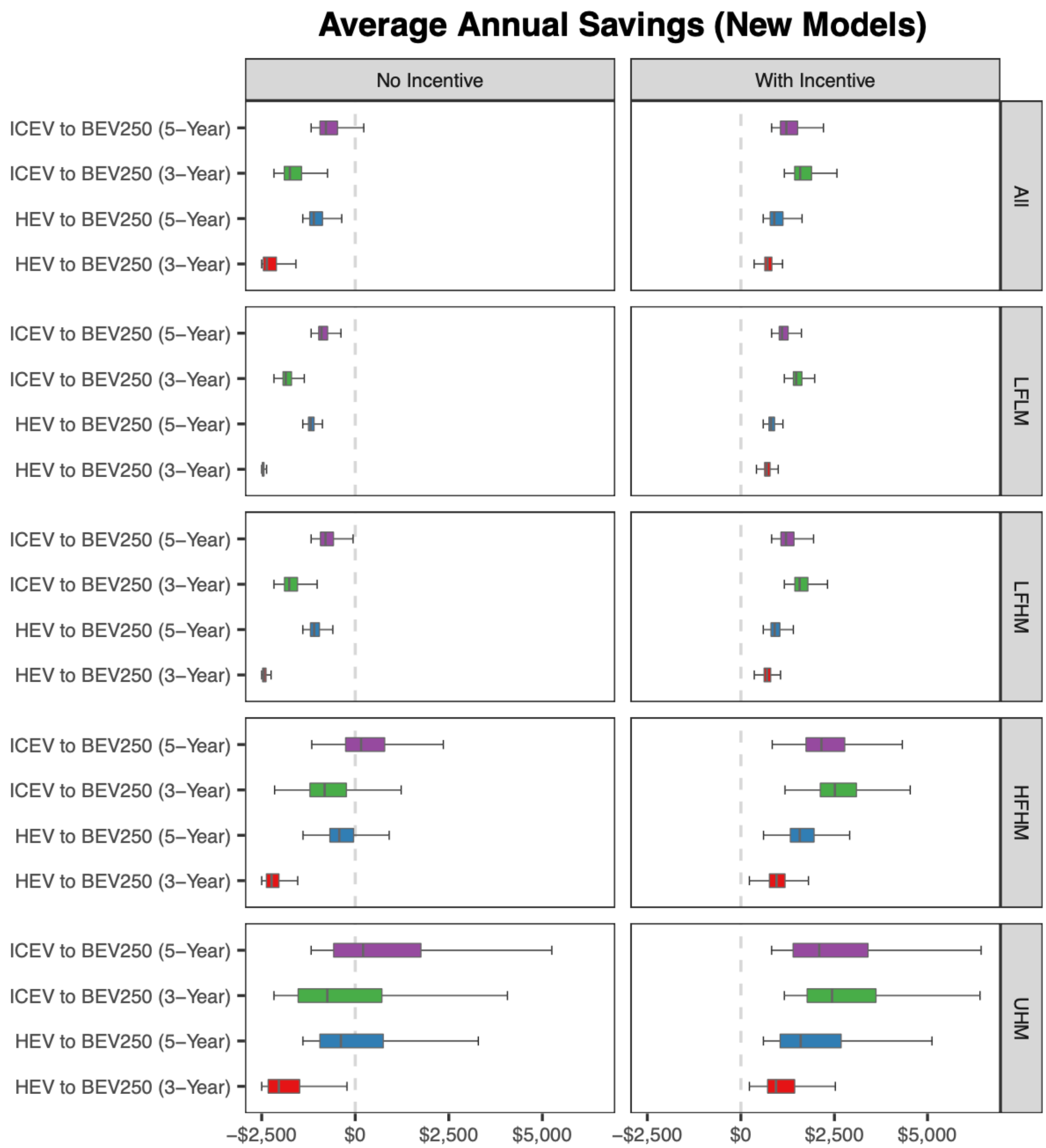

Figure B-8. Distribution of average annual savings from switching to *new* BEVs under various scenarios. The range for all drivers is shown regardless of whether they are BEV suitable or not. Columns show with and without purchase subsidy and rows show the distribution for the cohorts. The boxes describe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

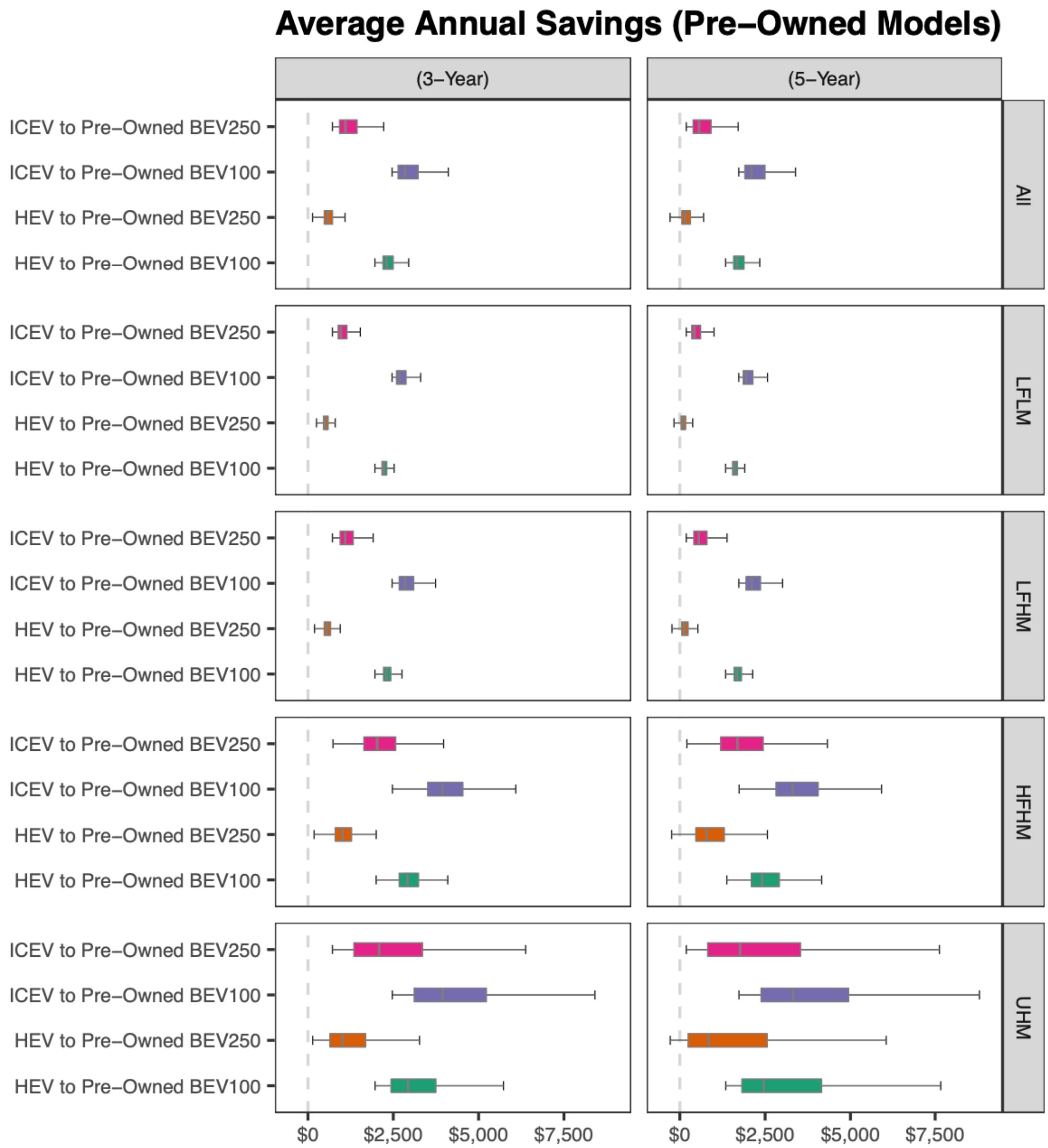

Figure B-9. Distribution of average annual savings from switching to *pre-preowned* BEVs under various scenarios. The range for all drivers is shown regardless of whether they are BEV suitable or not. Columns show the average savings 3- and 5-year commitment period and rows show the distribution for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

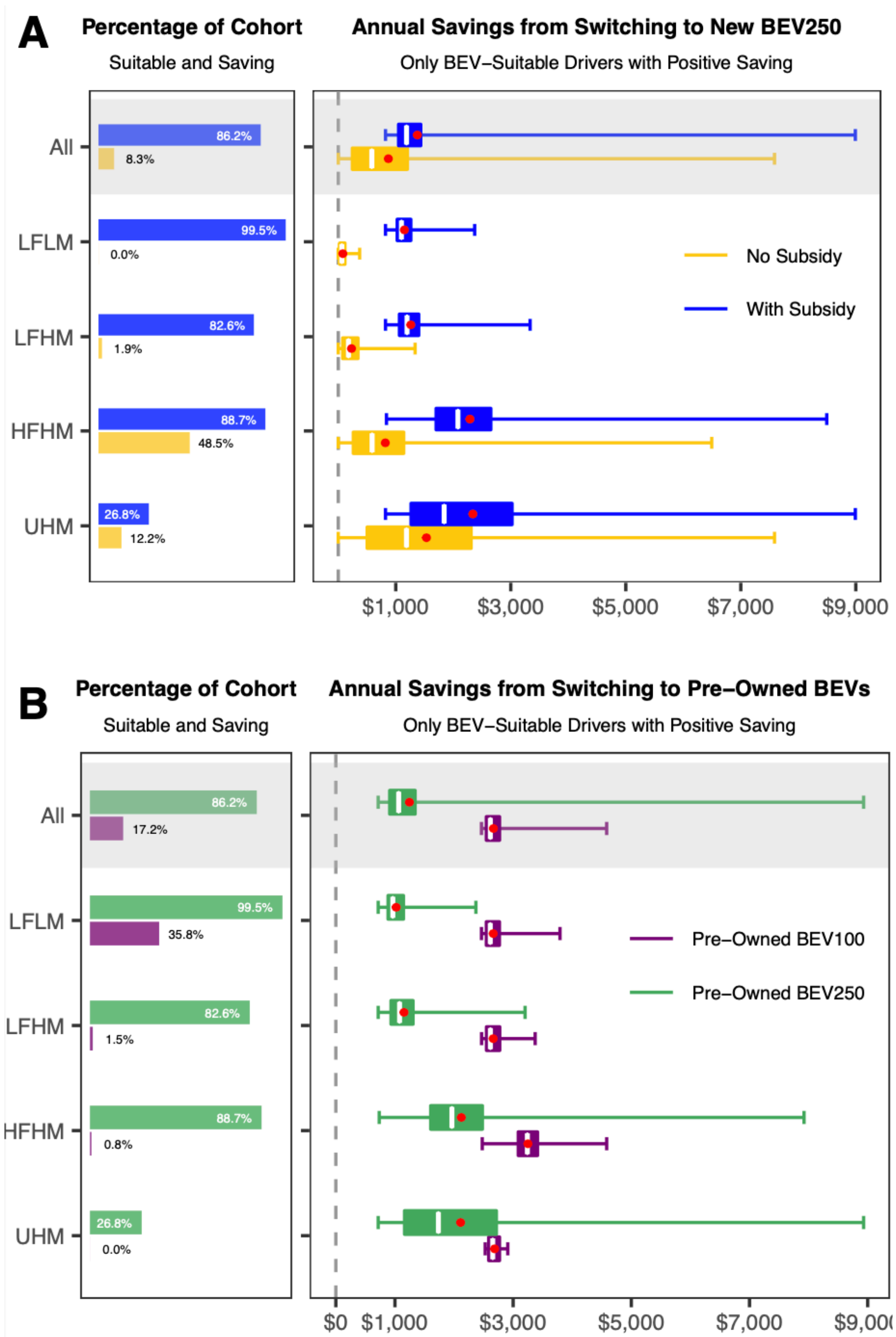

Figure B-10. The range and distribution of annual saving from ICEV to BEV for BEV-suitable drivers with positive savings

(A) From new ICEV to BEV250 with and without purchase subsidies under 5-year commitment period. (B) From pre-owned ICEV to pre-owned BEV250 and pre-owned BEV100 under 3-year commitment period. The red points show the average annual savings. The boxes describe 25th percentiles (left hinge), medians (white line), and 75th percentiles (right hinge) and whiskers describe absolute minimum and maximum.

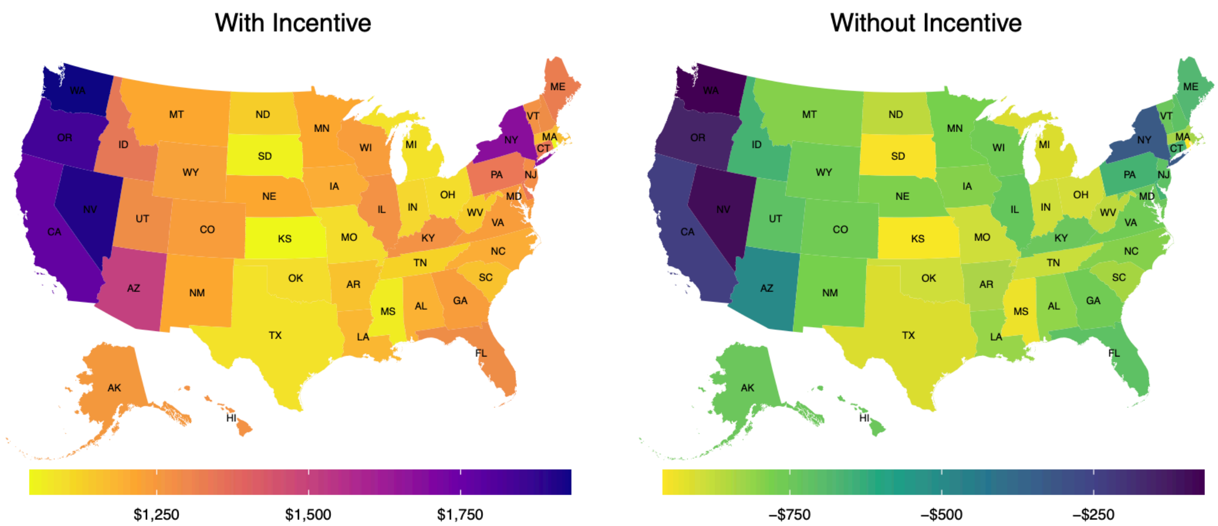

Figure B-11. State-level average annual savings from new ICEV to new BEV250 with and without purchase subsidies under 5-year commitment period.

Supplementary Note B-4: State-level average annual savings from new ICEV to new BEV250.

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

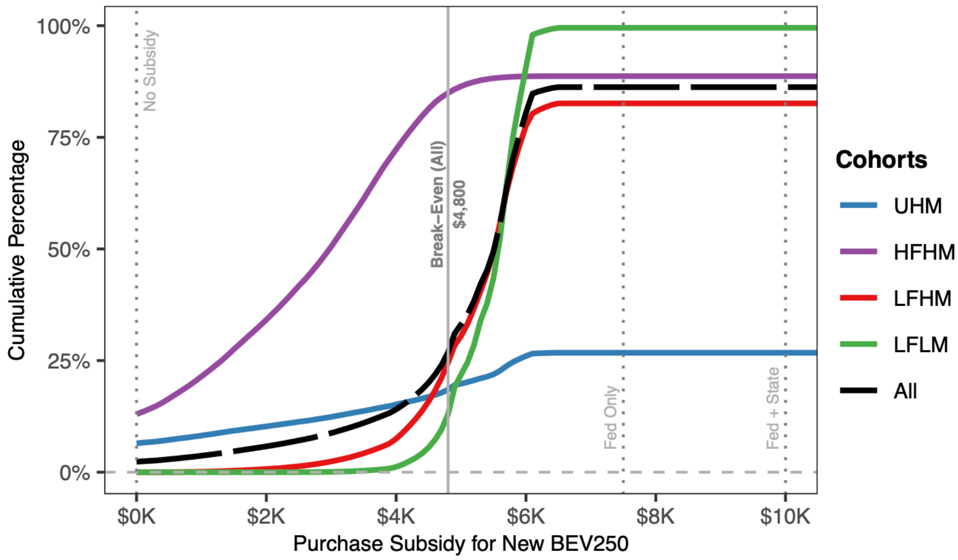

Figure B-12. Percentage of drivers in each cohort that both find a BEV250 range-suitable and break even under a 3-year ownership commitment, as a function of subsidy level.
Curves that plateau below 100% have drivers for whom a BEV250 does not have suitable range. An average driver breaks even with a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

Table B-6. Implications of electrification of all drivers who are BEV250-suitable and save from switching.

	All	UHM	HFHM	LFHM	LFLM
Annual Oil Consumption Savings (Million Barrels of Oil)	1422.6	70.9	380.5	387.9	583.3
Annual Avoided Tailpipe GHG Emissions (Million Metric Tons of $CO_{2\text{-}eq}$)	5.72	0.85	1.52	1.55	2.34
Annual Avoided Life-Cycle GHG Emissions (Million Metric Tons of $CO_{2\text{-}eq}$)	4.30	0.22	1.18	1.16	1.74
Annual Electricity Consumption (TWh)	4.86	0.24	1.30	1.33	1.99

Supplementary Note B-5: Sustainability implications.

The emissions conversion from gasoline to CO_2 is based on EPA measurements of 8,887 $grCO_{2\text{-eq}}$ per gallon of gas and the fuel economy of replaced ICEV (27 miles per gallon). For the life-cycle GHG emissions I use BEV energy efficiency, data from state-level average emission factor of electricity generation from NREL's Cambium dataset [254] and per-mile vehicle cradle-to-grave emissions (including vehicle manufacturing and battery production and end of life) for ICEV and BEV. The estimate of state-level marginal emission factor of electricity generation is for year 2020 based on short-run mid-case scenario of NREL's Regional Energy Deployment System [254]. The U.S. average marginal emission factor of electricity generation is 365.16 grCO2-eq/kWh but varies greatly among the states. As a point of comparison, the estimate of California's marginal emission factor for electricity generation is 192 grCO2-eq/kWh which is slightly higher than the estimate of Jenn [187] (186 grCO2-eq/kWh). I use a central estimate of 43 grCO2-eq/mile for ICEV and a conversative estimate of 144 grCO2-eq/mile for BEV including battery production for cradle-to-grave emissions excluding the use phase. Note that Cox et al., Hoekstra et al. and Elgowainy et al. estimate a range of 85-162 grCO2-eq/mile for BEV as use-phase excluded cradle-to-grave emissions [206,255,256].

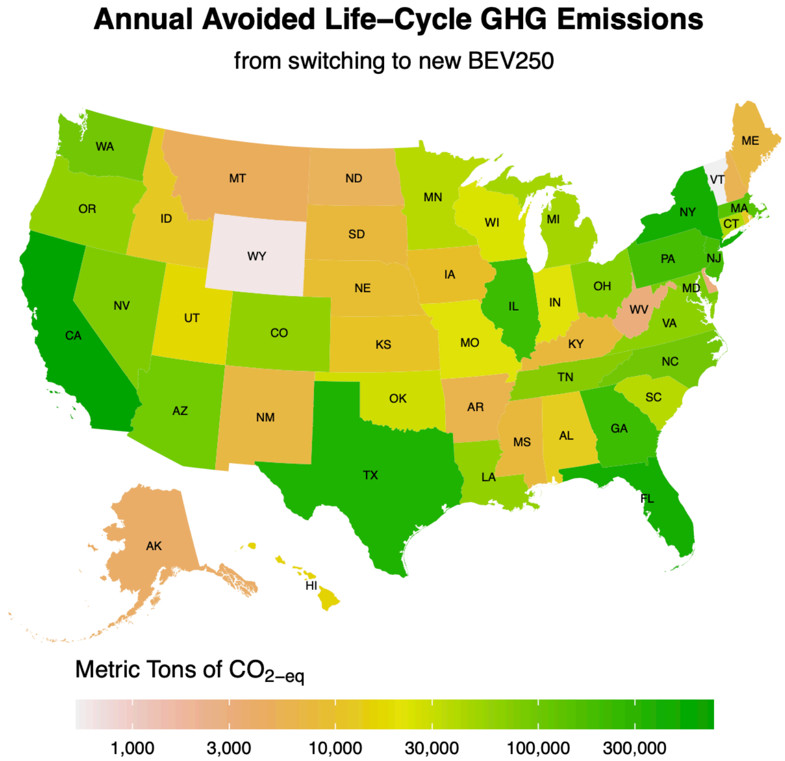

Figure B-13. Annual avoided life-cycle GHG emissions from switching to new BEV250 across different states.

Appendix C. Supporting Information for Chapter 5

Supplementary Note C-1: Model training procedure.

Hyperparameter tuning. To ensure the model performance and address the potential risk of overfitting, the models' hyperparameters are tuned. The regularization in the training process excludes the patterns that are unimportant for the prediction and do not generalize beyond the training set. These hyperparameters included core parameters and learning control parameters (e.g., learning rate and, number of trees, and maximum tree depth; see Table C-1 for all hyperparameters tuned).

Since I deal with unbalanced classifications (i.e., nearly 20% requested-to-share versus 80% solo trips and 70% successfully shared versus 30% unmatched trips), I maximize recall as the objective of hyperparameter tuning instead of prediction accuracy. The best set of parameters enables the model to generalize from the training set to the test set while maintaining the highest intended performance. I use randomized grid search for implementation of hyperparameter tuning to reduce the training time.

Table C-1. Hyperparameter tuning results using 5-fold cross-validation.

Hyperparameter	**Prediction of Requested-to-share**			**Prediction of Successfully Shared**		
	Ada	***GB***	***RF***	***Ada***	***GB***	***RF***
Number of Trees (number of estimators)	100	100	50	100	100	150
Max Depth	-	7	5	-	5	5
Number of Features	10	5	8	8	8	5
Learning Rate	0.5	0.1	-	1	0.7	-
Criterion	-	friedman_mse	gini	-	friedman_mse	entropy

Feature selection. Before confirming the final list of features to be included in the models, I perform feature selection, to identify the variables most relevant to the prediction and removing those that do not contribute to, or reduce, the predictive power of the model [240]. An incorrect generalization from an unintended property of the training set is called overfitting. The feature selection process is implemented trough permutation feature importance (Scikit-learn), which reports the relative importance of all variables as shown in Figure 5-6 (normalized for comparison and only top 10 are shown). I exclude the variables that have an average impact on the prediction less than 0.5% when the variable value is randomly shuffled. This ensures that the 10 variables included in the final models (as listed in Figure 5-6) are all stable and important for the prediction.

Model validation. *I* validate models, a process to test the performance of the tuned and trained model on data different from the training set, that is, a validation set. This ensures that the models do not overfit, and performs well not only on the training set, but also out-of-sample. I use k-fold cross-validation, in which the data are split into k folds and the model is fitted k times, each time with a different fold chosen as a test set with the rest performing as a training set. I chose k = 5 here.

Model calibration. The classification models return the probability of binary class (soft predictor). The probabilistic prediction made by the model are calibrated using the sigmoid approach [258]. Calibration is essential for retrieving unbiased probability estimates from the model. The output of a well-calibrated model can be directly interpreted as an estimate of probability.

Performance metrics. Accuracy, precision, and recall are compiled to assess the performance of models from different perspectives. All measures can be calculated from TP (true positives), TN (true negatives), FP (false positives), and FN (false negatives) of the confusion matrix. The accuracy is the proportion of correct predictions ($\frac{TP+TN}{n}$), the precision evaluates the fraction of correct classified instances among the ones classified as positive ($\frac{TP}{TP+FP}$), and the recall (sensitivity) quantifies the number of correct positive predictions made out of all positive predictions that could have been made ($\frac{TP}{TP+FN}$). For imbalanced classifications such as this problem, recall and precision are more important performance measures than accuracy. Unlike precision that only comments on the correct positive predictions out of all positive predictions, recall provides an indication of missed positive predictions [237] and hence is a better metric for classification of requested-to-share and shared trips. The overall performance of a classifier can be evaluated by the area under the receiver operating characteristic curve (ROC-AUC), which is equivalent to the probability that the model will rank a randomly chosen positive instance higher than a randomly chosen negative instance [237]. Higher AUC reflects higher predictive performance of a model.

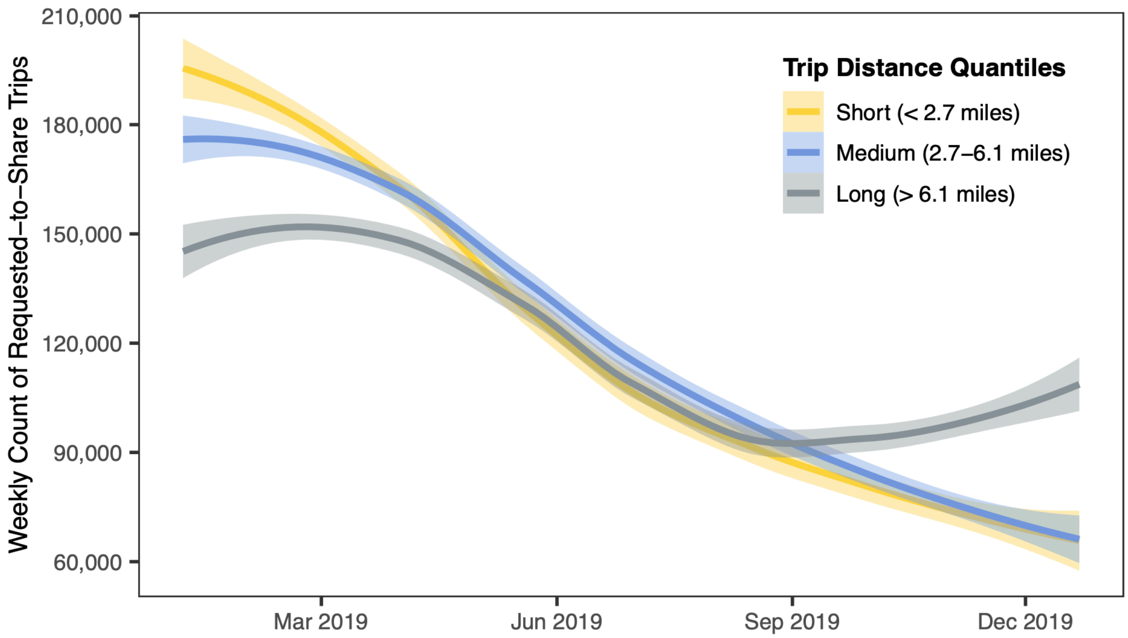

Figure C-1. Smoothed trend of requested-to-share trip by trip distance.
The requested-to-share trips are divided to three equally sized quantiles: 0-33.4 percentile: short (less than 2.7 miles); 33.4-66.7 percentile: medium (2.7-6.1 miles); and 66.7-100 percentile: long (above 6.1 miles. Over time, the frequency of short and medium trips drops more long ones. Since the volume of trips did not statistically changed over time, it implies that the preference for shorter trips shifted to solo.

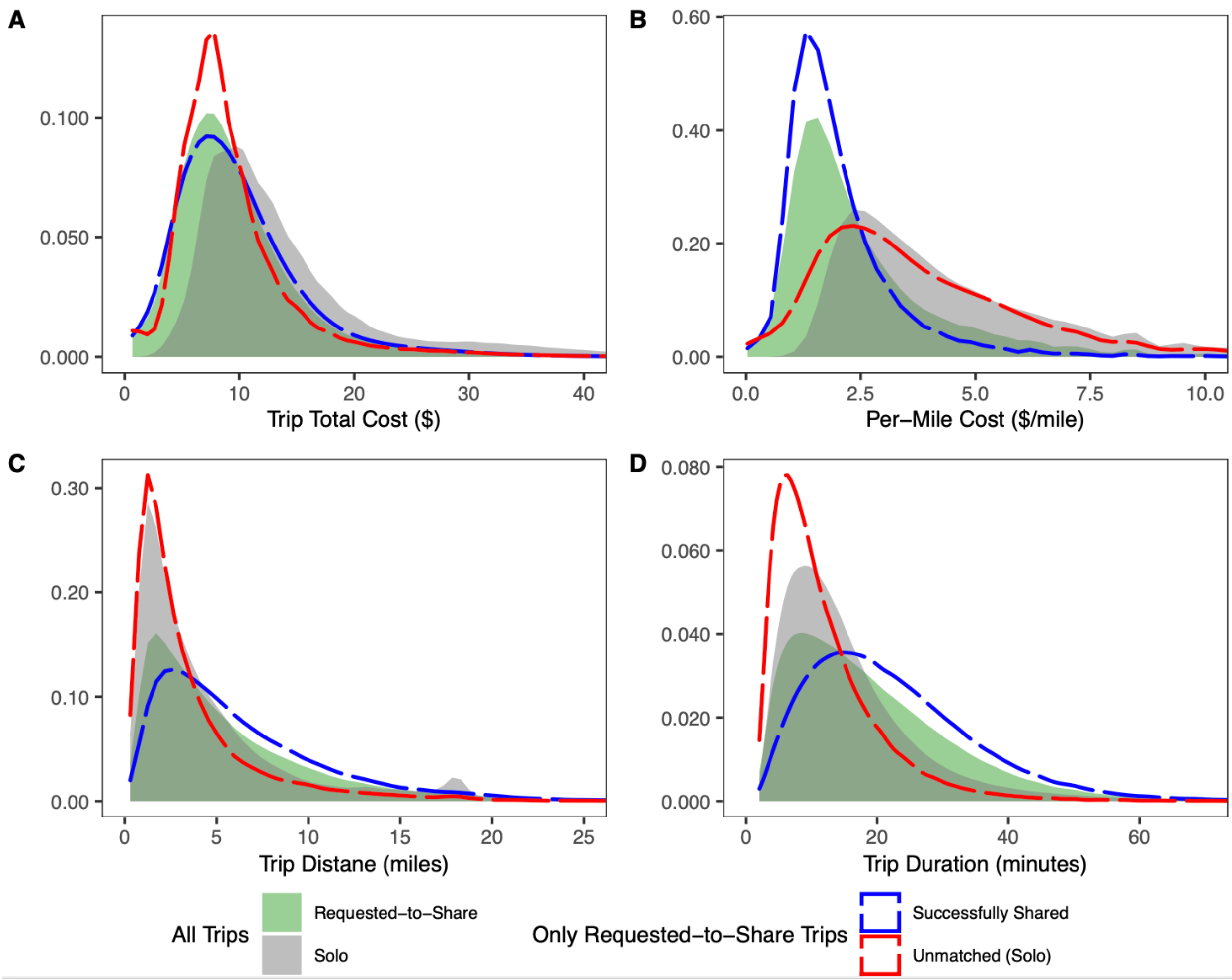

Figure C-2. Kernel density distribution of key variables for requested-to-share trips, solo trips, shared trips, and unmatched requested-to-share trips.
(A) trip total cost; (B) trip per-mile cost; (C) trip distance; (D) trip duration.

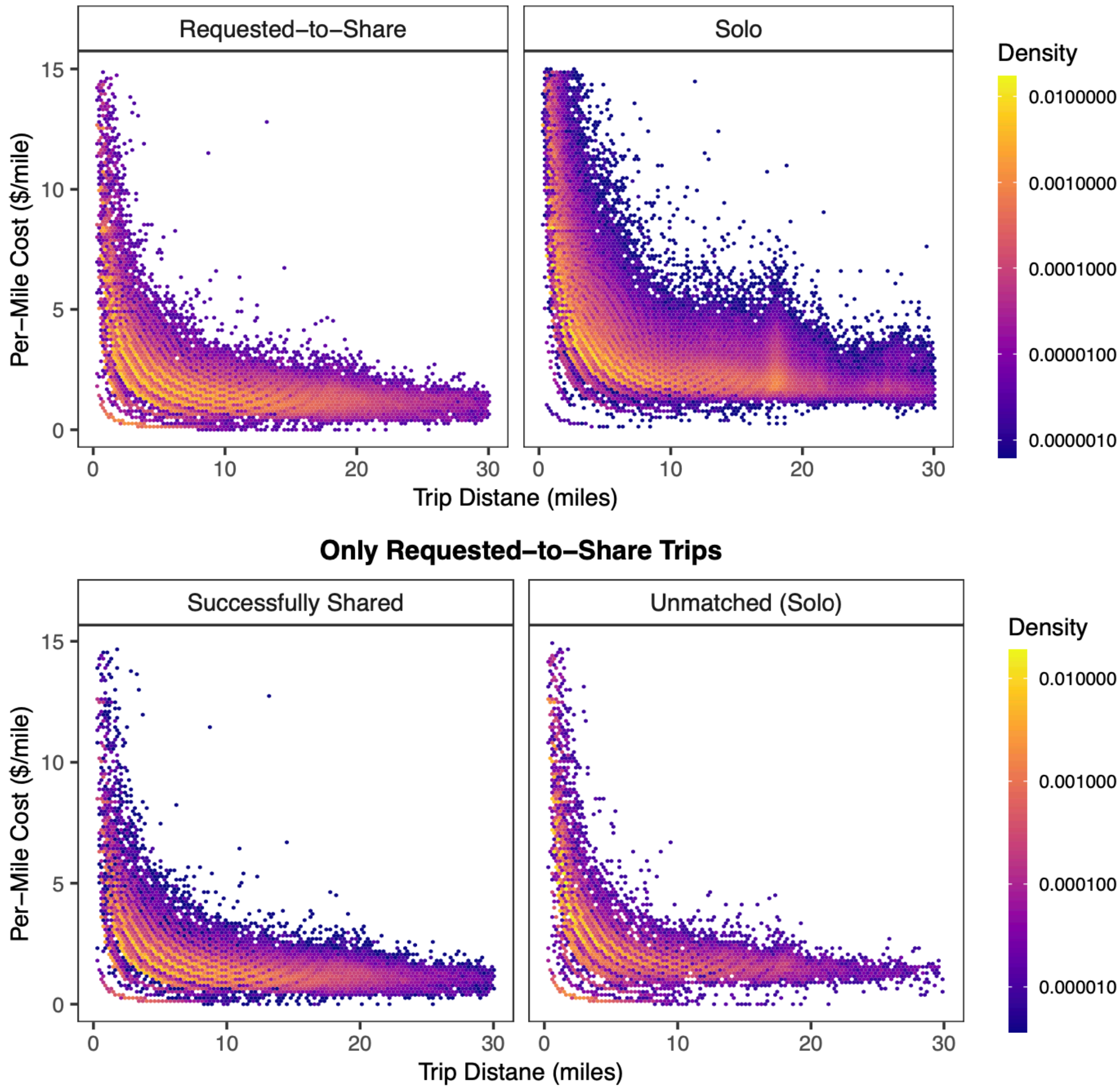

Figure C-3. Joint density distribution of trip distance and per-mile cost for requested-to-share trips, solo trips, shared trips, and unmatched requested-to-share trips.

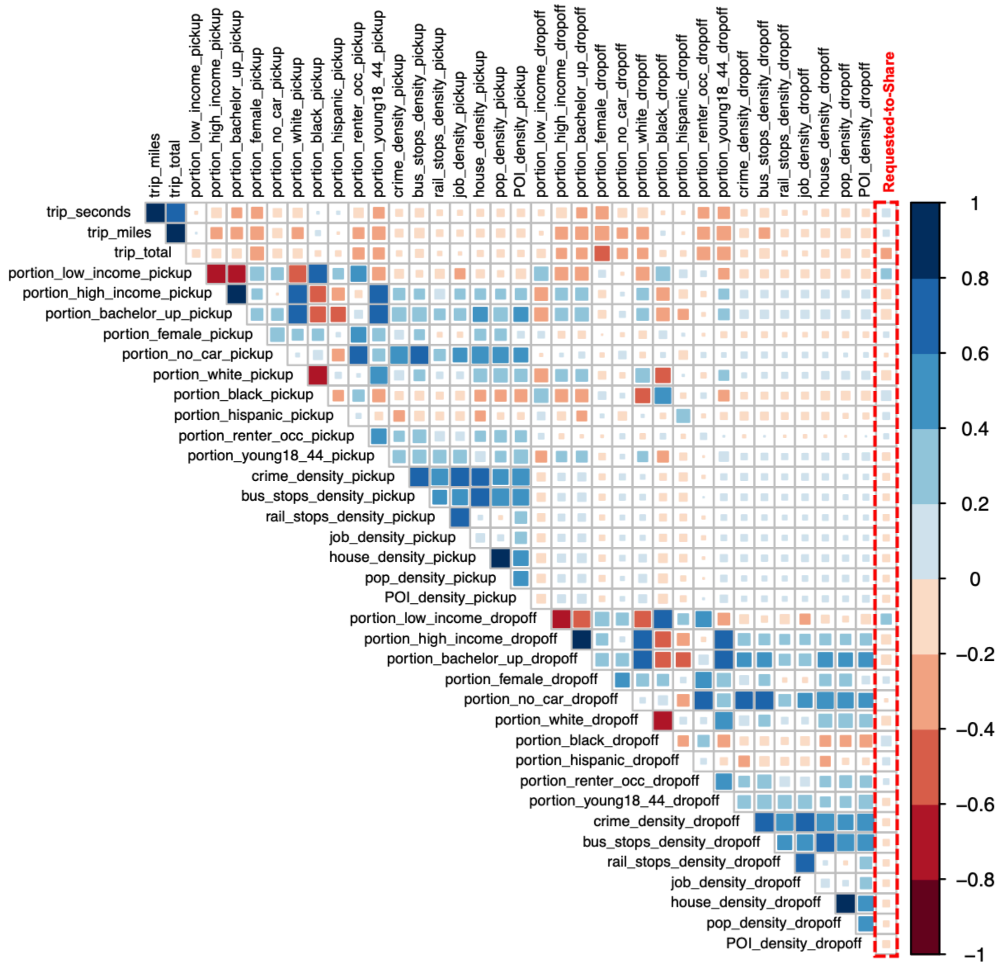

Figure C-4. Correlation matrix between target response and explanatory variables. The target response is whether the trip is requested to be shared.

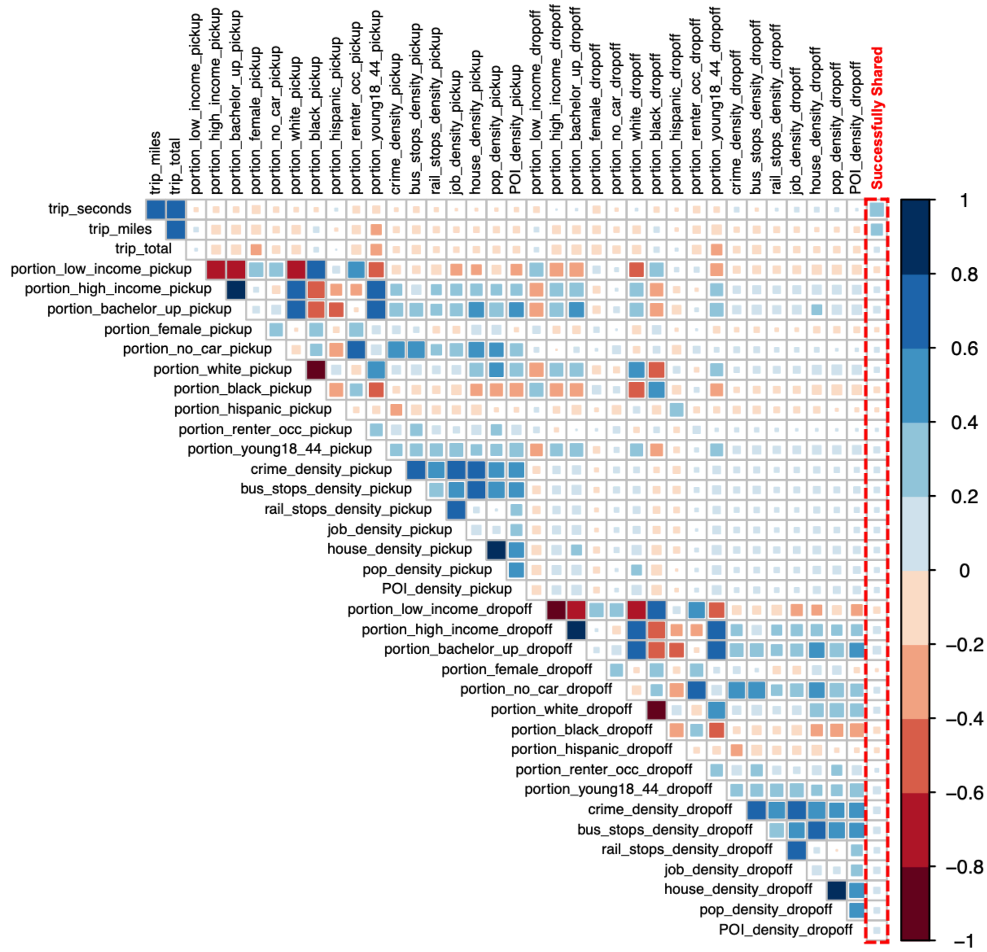

Figure C-5. Correlation matrix between target response and explanatory variables.
The target response is whether a requested-to-share trip is successfully shared or not.

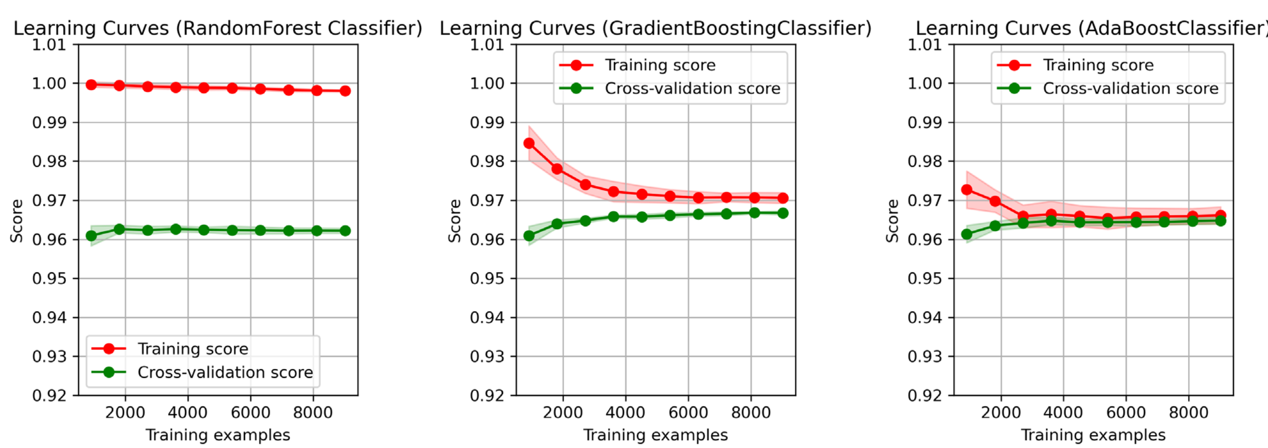

Figure C-6. Learning curves with 5-fold cross validation for RF, GB, and Ada classifiers.
A training sample of 6000 trips (8000 trips including test set) saturates all models with sufficient amount of data.

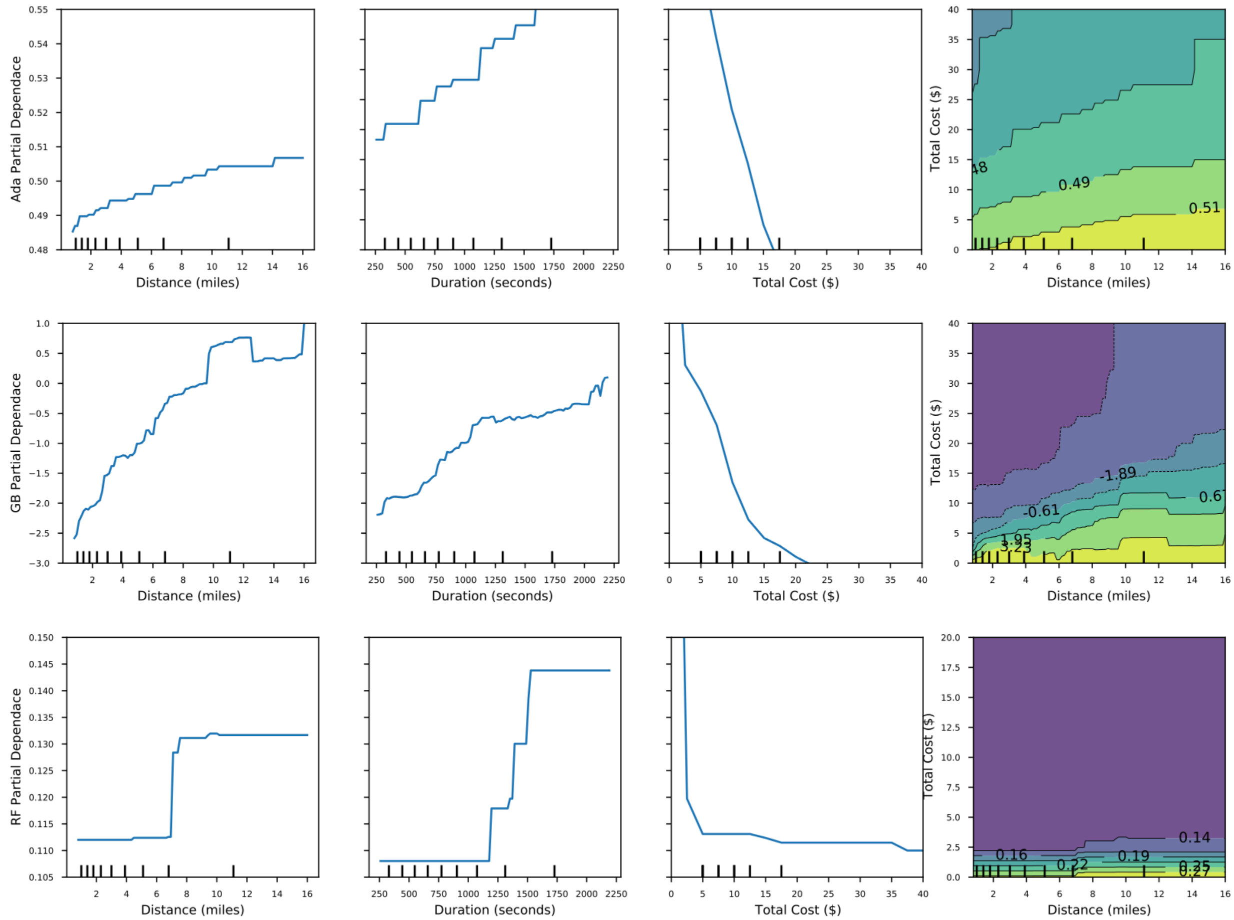

Figure C-7. Partial dependence plots for three classification models of requested-to-share trips. Top three variables with highest permutation feature importance are shown. The partial dependence shows high nonlinearity between the target response and explanatory variables.

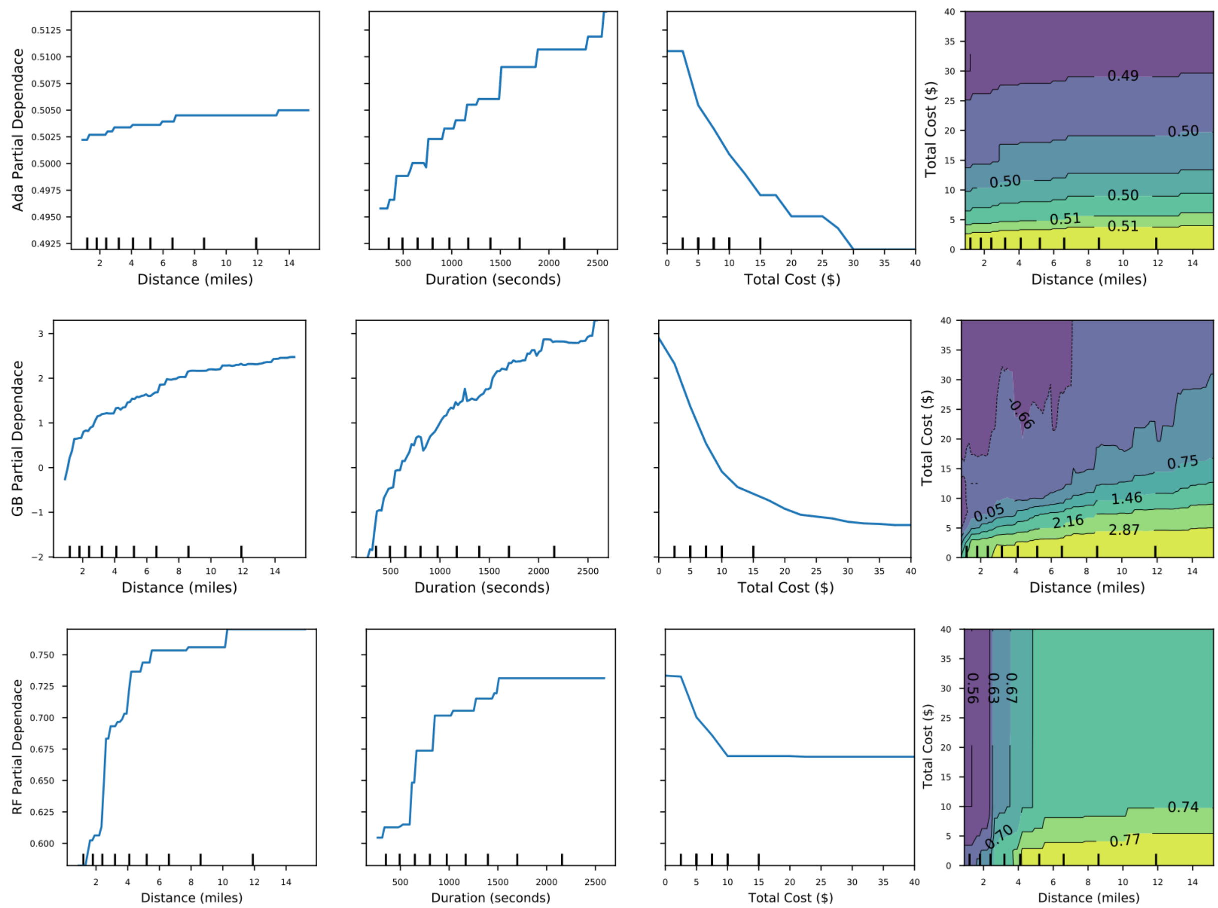

Figure C-8. Partial dependence plots for three classification models of successfully shared trips. Top three variables with highest permutation feature importance are shown. The partial dependence shows high nonlinearity between the target response and explanatory variables.

Appendix D. Supporting Information for Chapter 6

Supplementary Note D-1: Data privacy and de-identification

The City of Chicago has applied de-identification techniques to reduce the risk of linking individuals' trip data to their identities. This includes reporting pickup and drop-off locations disaggregated only to the census tract level, rounding the trip-start and trip-end times to the nearest 15 minutes, and rounding the fares and tips to the nearest \$2.50 and \$1.00, respectively. Nearly 16.5% of trips suffer from missing pickup and/or drop-off census tracts, 77% of which are trips that requested sharing. The data provider cites privacy concerns in masking these values.

Supplementary Note D-2: Data cleaning and imputation procedures

I first remove all observations with attributes inconsistent with the logic of travel:

- Trips with total trip duration less than 1 minutes and longer than 5 hours.
- Trips less total distance traveled than 0.25 miles and greater than 300 miles.
- Trips with total fare equal to zero (fares are already rounded).
- Trips with extreme speeds (below 0.2 mph and above 80 mph - an auxiliary variable from trip distance and trip duration).
- Trips which were successfully shared but did not authorized to share.

For the trips with missing pickup or drop-off census tracts as described in Supplementary Note , given that the majority are requested-to-share trips and removing those biases our analysis, we follow an imputation strategy. We first attempt to infer the pickup or drop-off tracts from the pickup or drop-off community code, if it is not missing. The City of Chicago has 77 community areas, and within each community area there are multiple census tracts. We group the dataset by community area and impute missing census tracts within each community area by trip-density weighted ranking of the non-missing census tracts in that group. This imputation reduces missing values to 5.8% but may induce a modest bias in our estimation. The data includes some trips outside the boundaries of the City of Chicago (Cook County). We also remove census tracts outside of the City of Chicago based on the 2010 census boundaries (801 census tracts).

Table D-1. Summary statistics for selected variables

	Mean	St. Dev.	Min	Max
Downtown (0/1)	0.21	0.41	0	1
Post (0/1)	0.26	0.44	0	1
Peak (0/1)	0.5	0.5	0	1
Person-trips	6.79	39.01	0	4163
Person-trips requested to be shared	1.02	5.42	0	810
Person-trips successfully shared	0.64	2.98	0	322
Willingness to share (%)	15.61	30.6	0	100
Successfully shared (%)	10.72	26.04	0	100
Economically distressed area (0/1)	0.68	0.47	0	1
(N=9,525,426)				

Notes: An observation is a tract-pair week time-period (peak vs. off-peak). Source: City of Chicago.

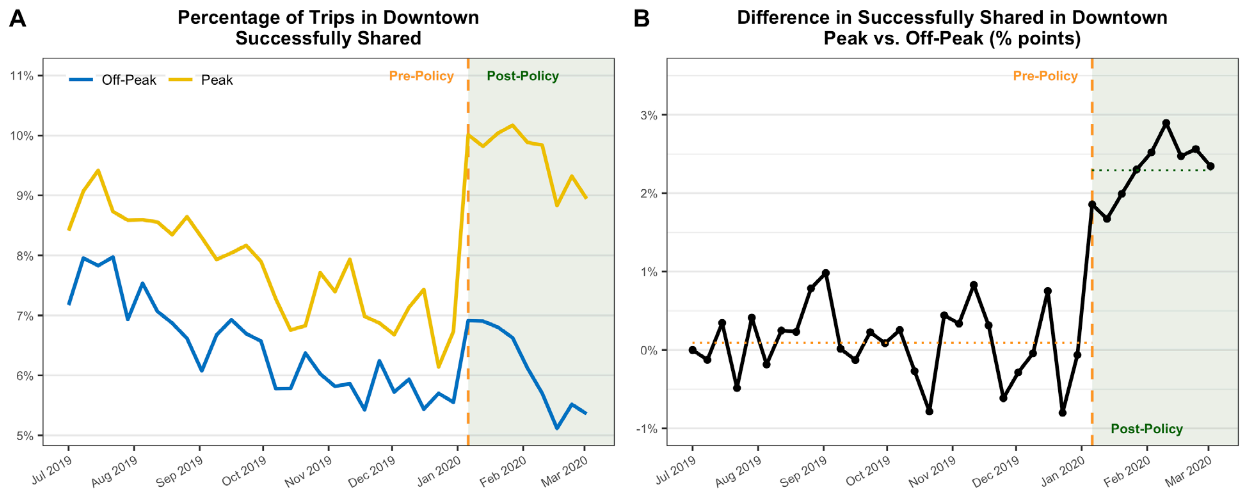

Figure D-1. (A) Weekly percentage successfully shared in the peak period, downtown versus neighborhoods; (B) The weekly difference in peak-period percentage successfully shared between downtown and neighborhoods, with the difference in the first week being normalized to zero.

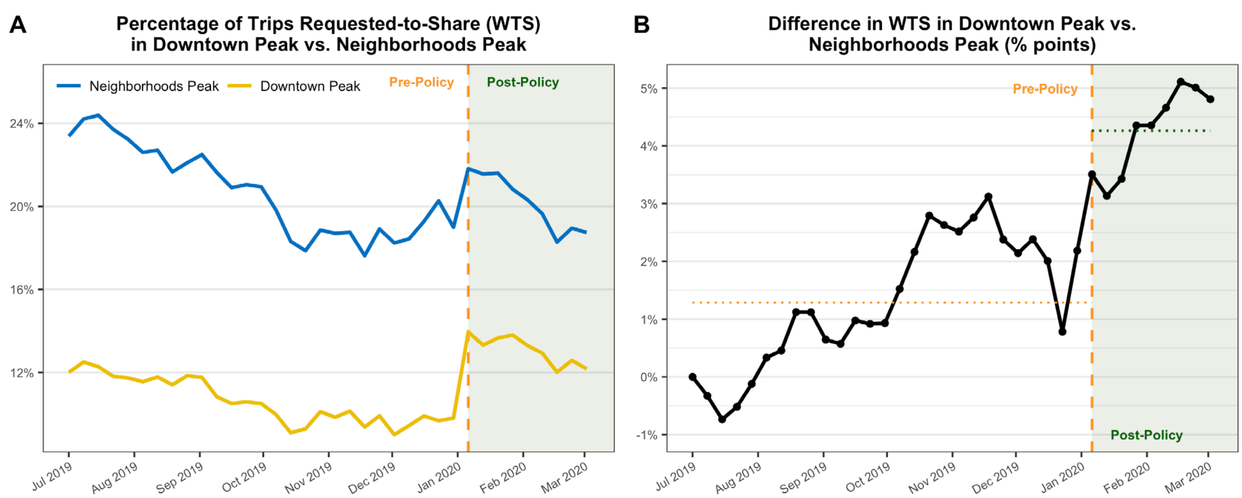

Figure D-2. (A) Weekly willingness to share (WTS; %) in the peak period, downtown versus neighborhoods; (B) The weekly difference in peak-period WTS between downtown and neighborhoods, with the difference in the first week being normalized to zero.

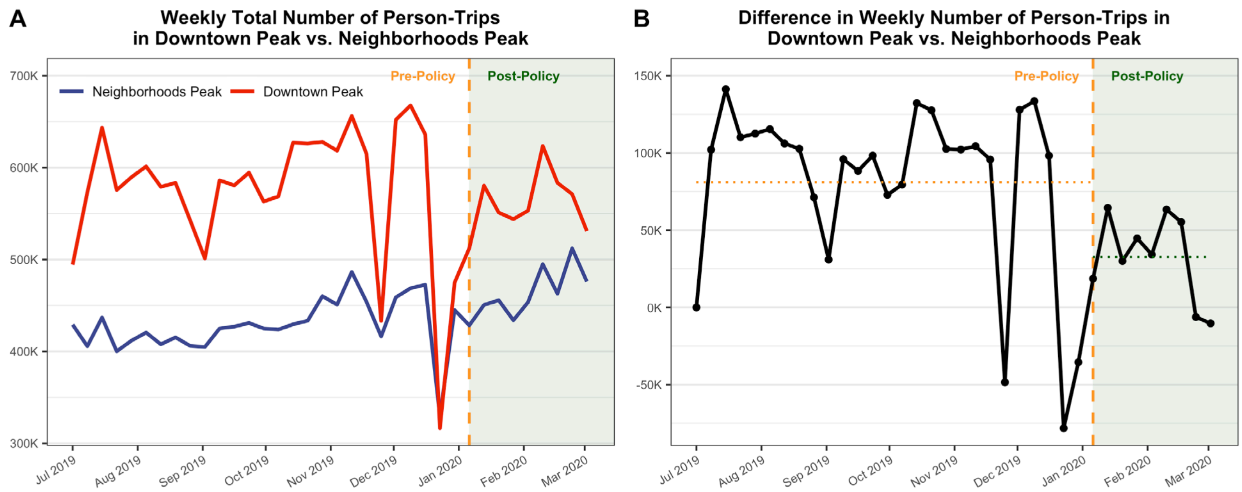

Figure D-3. (A) Weekly total person-trips in the peak period, downtown versus neighborhoods; (B) The weekly difference in peak-period person-trips between downtown and neighborhoods, with the difference in the first week being normalized to zero.

Table D-2. Robustness checks on DD and DDD estimates

	% requested to share		% successfully shared		Total person-trips	
	(1)	(2)			(5)	(6)
Panel A. Clustering by week-period						
Estimated effect	2.38***	2.47***	2.06***	1.99***	0.32	0.04
	(0.12)	(0.49)	(0.12)	(0.29)	(0.29)	(0.79)
Downtown DD	X		X		X	
DDD		X		X		X
N	1,639,450	6,815,103	1,639,450	6,815,103	1,990,102	9,372,058
Panel B. No weights						
Estimated effect	2.39***	1.84***	2.13***	1.75***	0.32	0.04
	(0.20)	(0.20)	(0.20)	(0.16)	(0.41)	(0.40)
Downtown DD	X		X		X	
DDD		X		X		X
N	1,990,102	9,372,058	1,990,102	9,372,058	1,990,102	9,372,058

Notes: In all specifications, an observation is uniquely identified by its origin-destination pair of census tracts $\boldsymbol{i}$ in week $\boldsymbol{t}$ during period $\boldsymbol{p}$ (peak or off-peak). The dependent variable is percent of person-trips requested to be shared (columns 1-2), percent of person-trips successfully shared (columns 3-4), or the total number of person-trips (columns 5-6). Panel A depicts results from the same specifications as in Table 6-2 except for changing the level of standard error clustering to week-period (where period is either peak or off-peak). Panel B depicts results from the same specifications as in Table 6-2 except for the exclusion of regression weights. "Downtown DD" denotes the difference-in-differences (DD) estimate comparing downtown peak-period ride-hailing to downtown off-peak period ride-hailing, before and after the policy change. "DDD" denotes the triple-differences specification, where the differences are peak vs. off-peak, downtown vs. neighborhoods, and pre vs. post.

Table D-3. Estimated policy effects by economic disconnected status

	Overall (1)	**EDA=1** (2)	**EDA=0** (3)	**Interaction** (4)
Panel A. Willingness to share (%)				
Post x Peak (0/1)	2.38***	2.54***	2.34***	2.33***
	(0.17)	(0.30)	(0.15)	(0.15)
Post x Peak x EDA (0/1)				0.28
				(0.18)
N	1,639,450	830,075	809,375	1,639,450
Panel B. Total person-trips				
Post x Peak (0/1)	0.32	0.28***	0.36	0.36
	(0.41)	(0.09)	(0.80)	(0.80)
Post x Peak x EDA (0/1)				-0.07
				(0.73)
N	1,990,102	1,089,582	900,520	1,990,102

Notes: An observation is a tract-pair week time-period (peak or off-peak). All regressions are based on the downtown difference-in-differences (DD) strategy. "Overall" refers to the full-sample DD and is identical to column 1 of Table 6-2. "EDA=1" refers to the subsample of observations with origin and/or destination in an "economically disconnected area" (EDA) as defined by the Chicago Metropolitan Agency for Planning [236]. "EDA=0" refers to the subsample with neither origin nor destination in an EDA. "Interaction" refers to the full-sample regression with an interaction term between the "Post x Peak" dummy and an EDA dummy (as well as interactions between EDA and Post and EDA and Peak).

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