Long-Term Transportation Electricity Use: Estimates and Policy Observations

> By Peter Fox-Penner* Will Gorman[@] Jennifer Hatch[#]

Boston University Institute for Sustainable Energy 595 Commonwealth Ave Boston, MA 02215

PRELIMINARY DRAFT

COMMENTS WELCOME

Preface

This is a very long and somewhat detailed literature review and discussion. Its purpose is to stimulate further discussion, research, and policy formulation and give the power industry some idea of what might be coming in the way of EV sales growth. Due to the paper's length, most readers will want to read only the executive summary or selected parts. Depending on reviewer feedback, the paper may remain in its present form, become a book, or be divided into smaller articles for review at journals.

^{*}Professor of the Practice, Questrom School of Business at Boston University; Director, Boston University Institute for Sustainable Energy, <u>pfoxp@bu.edu</u>

[@]Ph.D. Program, Energy and Resources Group, University of California, Berkley, Ca. [#]Research Fellow, Boston University Institute for Sustainable Energy, <u>hatchj@bu.edu</u> – Corresponding Author

Abstract

In this paper we model three layers of transportation disruption – first electrification, then autonomy, and finally sharing and pooling – in order to project transportation electricity demand to 2050. In addition, we consider three "wild cards" that have the potential to influence LDV travel in especially unpredictable ways. Using an expanded kaya identity framework, we model vehicle stock, energy intensity, and vehicle miles traveled, progressively considering the effects of each of these three disruptions. We find that energy use from light duty vehicle (LDV) transport will likely be in the 570 TWh to 1140 TWh range, 13% to 26%, respectively, of total electricity demand in 2050.

Acknowledgements

This paper would not be possible without the extensive input, advice, and deep expertise of several thought leaders in the realm of electric and automated vehicles and transit futures. In alphabetical order, the authors would like to thank:

Heidi Bishop, Austin Brown, Kristopher Carter, Christos Cassandras, Stacey Davis, John Dulac, Reid Ewing, Ryan Falconer, Alison Felix, Tyler Folsom, Lewis Fulton, Marianne Gray, Jeff Gonder, John Helveston, Robert Herendeen, Alejandro Henao, Ryan Hledik, Josh Johnson, Henry Kelly, Kyeil Kim, Kara Kockelman, Ken Laberteaux, Ryan Laemel, Amory Lovins, Andy Lubershane, Roger Lueken, Greg Rucks, Susan Shaheen, James Schulte, Dan Sperling, Joshua Sperling, Tom Stephens, Jerry Weiland, Jurgen Weiss, and Johanna Zmud for their guidance in writing various segments of this paper. We would also like to extend an enormous thanks to Bai Li and Xuehui Sophia Xiong for their research assistance. In addition to general assistance, Xuehui Sophia Xiong examined emissions factors and Bai Li prepared the EV energy intensity projections through 2050.

We gratefully acknowledge financial support from the Hewlett Foundation, the Energy Foundation, and Boston University.

Author Disclosures

In addition to his Boston University duties, Peter Fox-Penner serves as chief strategy officer for Energy Impact Partners, which owns interests in storage and EV infrastructure firms, among others. In addition, he is on the Advisory Board of EOS Energy Storage. Jennifer Hatch and Will Gorman have no financial interests in the transport or power sectors.

Table of Contents

Pr	efa	ace	i
Al	osti	ract	ii
A	ckn	nowledgements	iii
Αı	uth	nor Disclosures	iii
Τa	ble	e of Contents	iv
Li	st c	of Acronyms, Abbreviations, and Initializations	vi
E۶	ec	cutive Summary	I
I.		Introduction and Overview	13
	A.	Introduction and Purpose	13
	Β.	Relevant Prior Work	17
II.		Research Approach	21
	A.	The Kaya Identity Framework	21
	Β.	Modeling the Three Main Disruptions By Layer	24
	C.	Similar Efforts	30
	•	Conventional Ownership Scenarios Stage Results	31
	A.	EV Projections under conventional ownership	31
	Β.	VMT Assumptions	40
	C.	Electric Vehicle Energy Intensity Projections	43
	D.	. Conventional Ownership Pre-Autonomy Results	47
IV	•	The Impact of Autonomous Vehicles	50
	A.	Initial Assumptions and Overview	50
	Β.	Timing and Narratives	50
	C.	VMT Changes from Autonomy	57
	D.	. The Effect of AVs on Electric Intensity	67
		Categorizing AV EI Effects	67
		Traffic Smoothing	70
		Better Intersection Management	73
		Faster Travel	73
		Platooning	74
		Rightsizing, Performance Reductions, and Weight Reduction	75
		Onboard Electronics and Appliances	77

Electric_Transport_Draft _10_5_17

	The Net Future Energy Intensity of AEVs	78				
V. Pooling, Sharing and Seamless Mobility Networks						
Α	. Introduction	80				
В	Non-Pooled Dynamic Ridesourcing	84				
C	. Traditional Carpooling	90				
D	0. Car-sharing and VMTs	91				
E.	. Pre-Autonomy Pooled Dynamic Ridesharing or Ridesplitting	94				
F.	. Seamless Mobility Systems	98				
VI.	"Wild Card" Factors	102				
Α	. Infrastructure and Road Pricing	102				
В	Possible RUC Designs and Levels	106				
C	Electronic Substitutes for Travel	111				
D	 The Built Environment and VMT 	114				
E.	. Conclusion	119				
VII.	Results and Observations	120				
А	. Exploring the Range of Outcomes Via Scenarios	120				
В	. Main Scenario Results	125				
C	. Factor Analysis and Sensitivity Calculations	128				
D	0. Concluding Observations	132				
Bibli	iography	136				

Appendices, workpapers, and a copy of the excel model are posted online at: http://www.bu.edu/ise/what-we-are-working-on/.

List of Acronyms, Abbreviations, and Initializations

AEV	Autonomous electric vehicle
AET	Autonomous electric taxis
AV	Autonomous vehicle
BEV	Battery-Electric vehicle
BSUV	Battery SUV
CSUV	Conventional SUV
CV	Conventional car
DRS	Dynamic Ridesharing Services
EI	Electric intensity (kWh/mile)
EAV	Electric autonomous vehicle
EHV	Electric hybrid vehicle
EV	Electric vehicle
GDP	Gross domestic product
GHG	Greenhouse gas
GWh	Gigawatt hour
HDV	Heavy-duty vehicle
HEV	Hybrid electric vehicle
ICE	Internal combustion engine
kWh	kilowatt-hour
LDV	Light-duty vehicle
MPG	Miles per gallon
PHEV	Plug-in hybrid electric vehicle
PHSUV	Plug-in hybrid SUV
PM	Passenger-mile
SAV	Shared autonomous vehicle
SBEV	Shared battery electric vehicle
SBSUV	Shared battery SUV
SPHEV	Shared plug-in hybrid electric vehicle
SPHSUV	Shared plug-in hybrid SUV
TWh	Terawatt hours
WT/mile	watt hour/mile
UI	use intensity, same as EI when referring to electric vehicles
VMT	vehicle miles traveled

Executive Summary

The transportation sector is now facing trifecta disruptions of electrification, sharing, and autonomy – disruptions known in some transport circles as the "Three Revolutions." Together, these disruptions are expected to have profound impacts across developed world economies, from the auto industry, to the labor force, to family lifestyles and more. In an attempt to explore a small corner of impact from these revolutions, this paper attempts to quantify the electricity needed to power light duty passenger electric fleets.

In contrast to many other works on the subject, our focus is on the aggregate national electrical energy needed to power the light-duty vehicle fleet between now and 2050. From the standpoint of climate policy the electric energy we need is the single most important indicator of our need for carbon free power. As we stick to this specific focus we do not analyze or discuss many other important aspects of the growth of electric transport on electric utilities, including charging patterns or methods, integrating EV demand response, or energy sourcing. We also do not produce new forecasts of EV and AV sales or the underlying costs of owning and operating vehicles over time.

We review and rely on several industry forecasts to create our own EV scenarios. Our work can be viewed as attempting to improve upon, or at least add usefully to, the handful of studies that examine long-term transport power demand. The studies we reference and rely upon can be referenced in part II.A – Prior Work.

Research Approach

Transport energy and emissions are often forecasted by (1) estimating the vehicle-miles that will be traveled (VMT), using well-established models benchmarked from prior changes in travel on these modes over decades; and (2) multiplying VMT times the energy use per vehicle-mile which can be forecasted by analyzing current efficiencies, fuel economy rules, fleet composition shifts, and similar factors. To address difficulties in depending upon aggregate VMT forecasts, in our work we use a conceptual framework based on an expanded kaya identity, and then apply the framework in the three "layers" and further adjustments as explained below. The disaggregated kaya identity we use is:

$$\sum_{i} \left[v_{i,t} \cdot \kappa_{i,t} \cdot en_{i,t} \right] = \Phi_{l,t}$$

Where the stock in year t of EVs of a motorized vehicle type i is denoted by $\kappa_{i,t}$; v_{it} is the average miles travelled by that vehicle type in year t; and en_{it} is the average power use of the vehicle type i per mile travelled during year t.

One obvious deficiency with our approach is that VMT, mode share, and electric intensity are all interdependent. Every decision to take a trip is a function of the underlying drivers of travel and the mode choices for each chosen trip – time cost, money cost, and other costs and benefits for each mode option. This interdependence operates differently in the short-run and the long-run. In the short run, the choice of travel mode is approximately fixed by the state of technology, existing infrastructure and vehicle stocks, and current arrangements such as transit schedules and the accessibility of EV chargers. In the long-run, every one of these trip choice determinants changes in a path-dependent manner. Moreover, in the long-run the choice is nested, first in a choice of own/share a vehicle by type and then whether to use that vehicle for a trip.

We break through this deep interdependence using a very simple and inelegant approach. We first posit a baseline in which none of the Three Revolutions occurs. In this baseline scenario, we generally adopt the view of Litman, Circella, et al, and the Federal Highway Administration that per-capita LDV travel by Americans has hit its peak and is likely to decline, but for the potential effects of the Three Revolutions. The effect of the Three Revolutions is then factored into our implicit baseline in three "layers" of calculations.

The first layer is electrification, an interim scenario in which the only major change is the availability of EVs as an alternative to CVs, i.e. without changes in ownership models, autonomy, shared modes, or any urban design changes not already embedded in conventional forecasts. The next layer of our calculation modifies this interim case to reflect the onset of autonomous vehicles. As many researchers are predicting, AVs will have many complex effects on travel demand, amounting on net to a significant and perhaps very large increase in VMT. Conversely, AVs will reportedly enable savings in EI through network and vehicle management approaches not available to conventional vehicles, and (much later, we think) energy-reducing changes to the vehicles themselves. In this layer, we first survey AV penetration predictions and adopt an AV penetration base case and a second, more aggressive

2 Electric_Transport_Draft _10_5_17 sensitivity case. In the final layer, we add the potential impacts of the new pooled and shared modes, including integrated multimodal systems, also called mobility-as-a-service, among other ideas. The figure below illustrates our conceptual approach.



Figure 1: Conceptual Approach

Conventional Ownership

For our analysis, we begin with forecasts from industry groups that have projected electric vehicle sales, with or without visible adjustments for the growth of autonomous driving or new ownership models. After examining several commercial projections, we assume that EV adoption follows a similar technology adoption curve described by Everett Rogers's Diffusion of Innovations theory.

Electric vehicle sales, though, do not represent the actual stock of electric vehicles in a given year that would consume electricity. Rather, electricity consumption would be driven by the total number of vehicles on the road, which is affected by car retirements as well as sales. To inform our estimate of electric vehicle stock, we rely on the survival rates for conventional cars and light trucks provided by the

> 3 Electric_Transport_Draft _10_5_17

Oak Ridge National Laboratory's Transportation Energy Data Book (Oad Ridge National Lab, 2016). Details of our assumptions and estimations can be found in section III.A – EV Projections Under Conventional Ownership.

The figure below shows the stock of electric LDVs in our high and low cases.





We next estimate how many miles each conventionally-owned vehicle in our stock will drive annually, using 2015 Idaho National Labs survey data for BEVs and PHEVs. The eVMT values for both PHEVs and BEVs, though, are noticeably lower than the average VMTs of ICE LDVs today. For ICE cars in 2015, the average annual VMT was 11,327 miles and for SUVs it was 11,855 miles. Current models of electric vehicles often do not have the same drive range as the ICE equivalent vehicle due to the limitations of current battery technology. However, we expect the annual miles driven using electricity to increase as battery technology continues to improve and battery ranges increase. In order to capture the effect of battery improvement for the future years of our analysis, we fit a curve to projected battery energy density increases and use the percent increase over time to gross up the total electric vehicle miles for both PHEVs and BEVs.

We then use the annual VMT for ICE vehicles as the baseline distance the average electric car owner would drive in a year under conventional ownership prior to autonomy. In other words, in this scenario we linearly trend annual eVMTs for PHEVs and BEVs from their current average levels to the average VMT of conventional vehicles in 2015 as reported by the FHWA. Details of our methodology can be found in section III.B – VMT Assumptions.

Even if we assume the ownership model will not change, as we assume for the base layer, EVs are likely to become steadily more energy-efficient over time. We therefore estimate trends in energy efficiency improvements based on well-established theories of the returns to R&D and manufacturing learning curves.

The combination of these assumptions represents the three main inputs to the kaya identity formulation. Our EV projections, eVMT estimates, and expected vehicle energy intensities are multiplied by each other to calculate our conventional ownership base case (or stage one) electricity consumption projections, shown in the table below:

Table 3: Conventional Ownership Results

				Total	Fleet			
		Total	Portion	Number	Average	Fleet		Total
		Number of	Stock	of AV in	eVMT/	Average	Total	TWh EV
Case	Year	EV in Service	Electric	Service	Vehicle	Efficiency	TWh	Bump
			(%)		(per yr)	(kWh/mile)	(TWh)	(TWh)
	2015	406,076	0.2%	0	7,179	0.32	0.9	0.9
	2025	17,086,996	6.6%	0	10,075	0.34	59.0	59.0
Base High	2030	52,378,548	19.7%	0	10,734	0.33	187.9	194.0
	2040	166,919,164	59.6%	0	11,039	0.32	593.0	651.9
	2050	251,742,035	85.4%	0	11,231	0.31	886.2	973.8
	2015	406,076	0.2%	0	7,179	0.32	0.9	0.9
	2025	7,063,273	2.7%	0	10,061	0.34	24.3	24.3
Base Low	2030	20,532,231	7.7%	0	10,729	0.33	73.6	76.0
	2040	81,511,381	29.1%	0	11,049	0.32	289.2	317.9
	2050	145,941,420	49.5%	0	11,236	0.31	511.7	562.3

Overall, we project 2050 electricity demand of 890 TWh and 510 TWh in our high and low cases, respectively. These figures represent roughly 23 and 13% of the current electricity demand of 3900 TWh and 20 and 11%, respectively, of EIA's projected 2050 electricity consumption of 4,500 TWh.

Impact of Autonomous Vehicles

Next, we examine the power impacts of commercially available, fully-self-driving ("autonomous") lightduty vehicles. We oversimplify by treating the transition to AVs as a bright line before and after Level 4 or 5 AVs sold and allowed to be used with relatively few restrictions. Our projections show the national totals, increasing as the number of areas and vehicles sold both rise.

There is a cacophony of opinions as to when and how the autonomy revolution will occur – not to mention its implications for travel, the economy, and our built environment. On one end stand highly optimistic writers such as Aribib and Seba, who predict that AVs will handle 95% of all passenger-miles by 2030, all but ending individual auto ownership. At the other extreme, researchers such as Litman (Litman, 2017) and Nieuwenhuijsen (Niewenhuijsen, 2015) predict that 100% level 5 autonomy in the fleet will not occur until 2070 or later. Beyond differences in numerical outcomes, some of these estimates come with somewhat concrete scenarios or narratives as to how the AV market will unfold with respect to regulatory approval, cost reduction, consumer choice shifts, and urban infrastructure changes.

Amongst all these considerations the work we find most convincing is Lavasani, Jin, and Du's (Lavasani, Jin, & Du, 2016) estimates of Bass or "S-curves" using parameters selected by comparing AVs to other types of technologies, similar and dissimilar, for which there are full adoption histories. The results of LJD's base estimate, is that cumulative AV sales rise from 1.3 MM in 2030, five years after introduction, to 70 MM by 2045 and saturation (i.e. no further growth in AV sales) by 2060. We also create estimates of electricity use for the A&S scenario, which we consider a highly aggressive upper bound on AV use. If nothing else, this allows us to estimate a range of possible outcomes.

There is widespread agreement that vehicle autonomy will trigger significant changes in the travel patterns of many Americans (along with changes in EI, explored later). Some of these changes will reduce VMT, while others are expected to increase it significantly. These effects include increased road capacity as AVs travel smoothly at close intervals, lower time cost for drivers as driving time is freed for leisure or work activities, and increased access as children, the elderly, and disabled use autonomy to increase mobility – the results of these effects are outlined in the table below.

Table 4: VMT Effect of Automated Vehicles

	Lo	w	High		
					Later Modified
EV on AV VMT Effect	impact	Timing	Impact	Timing	for Sharing
Road Capacity Effect	0		+5%		no
Lower Time Cost for Driver		per		Linear Phase in 2040-	
(Intra- and Intercity)	+ 15%	vehicle	+20%	2050	no
		per			
Increased Access	+ 8%	vehicle	+15%	per vehicle	yes
Total	+23%		+50%	per vehicle	yes

AVs similarly have significant effects on the energy intensity used per mile of any given vehicle type. These effects include: traffic smoothing due to their ability to immediately see and respond to traffic conditions; better intersection management to reduce starts and stops and therefore reduce energy use; faster travel which will increase EI as AVs travel at higher speeds; platooning, which will reduce air resistance; and rightsizing, where smaller and lighter vehicles will be available because safety features of conventional vehicles will no longer be necessary. The net EI of AVs is summarized in the table below:

Table 5: El Effect of Automated Vehicles

Effect	Impact	Timing		
Traffic Smoothing	-15%	50% reduction in technology		
		improvements in EI for the first		
		10 years, then linear phase- in		
		from 2035		
Intersection Management	-4%	Linear phase-in for urban EVs		
		starting in 2035 and fully		
		implemented by 2055		
Higher Average Speed	+8%	Linear phase-in from 2030-2035		
Platooning	-2.5%	Linear phase-in from 2030-2035		
Rightsizing/Weight Reduction	-50%	Phased in linearly at 1% per year		
		or 1.5% per year starting in 2040		

Pooling, sharing, and seamless

We next add a third layer to our electric power forecasts, the impacts of many shared and pooled modes and businesses including various forms of what are being called "mobility networks." We examine literature surrounding non-pooled dynamic ridesourcing, traditional carpooling, car-sharing, and pooled dynamic ridesharing or ridesplitting, and in the end conclude that these three phenomena, while extremely important for the ways in which our transportation system may operate in the future, will likely not significantly change total electricity demand from transport, which is the goal of this paper. Our review of the literature can be found in sections V.A – V.D.

Seamless mobility systems, which integrate public transport with "last mile" taxi services, could shift enough transportation away from individual LDVs to have a small impact, and we conduct a simple calculation to bound the power implications of a concerted public policy push towards SMSs. The result of this calculation (found in Section V.E – Seamless Mobility Systems) is a potential 2% drop in electricity demand.

Wild Card factors

Finally, we consider "wildcard factors" – a handful of factors that will influence future LDV travel in especially unpredictable ways. We look at (1) Road Infrastructure Costs, including AV-specific infrastructure, and the manner in which LDV travelers will or will not pay for it; (2) telecommuting, e-commerce, and other electronic substitutes for personal or business travel; and (3) redesign of urban areas to reduce the need to travel.

The three "wild cards" we have surveyed have generally done a poor job of living up to their label. Of the three, we have concluded that electronic travel substitutes are unlikely to result in VMT differences not already captured in the range of outcomes in the three layers of modeling above. Our review also indicates that urban design will, at most, add 2% on top of our existing scenarios. As urban redesign is largely policy-driven, not an exogenous factor, our non-policy scenarios amount to a prediction that the most likely outcomes exclude a significant policy shift that could, if adopted, reduce travel.

Charges for the use of infrastructure in a manner that affects driving is also a true wild card. It is far beyond our ability to predict how the U.S. federal government and the states will cope with the deterioration of existing roads and the need for infrastructure to service AVs. Even today, well before the advent of AV-specific infrastructure, these questions push the U.S. Congress and many states to the political breaking point. About all that can be said of this wild card is that it, too, presents almost entirely downside risk to transport power demand. Today, no LDV pays anywhere near its full share of the cost of roadway infrastructure; total infrastructure funding is far short of funding needs; and as yet electric vehicles pay even less than gasoline cars.

We believe we can get a rough, order-of-magnitude range by examining two simple pricing scenarios: a flat 2.2 2017 cents per mile charge and a larger 2.4 cents per mile (\$.60/gal @ 25 mpg) escalating to double its level in real terms by 2050.

Snapshot results of the effect on VMT in the year 2050 can be expressed in a 4x4 matrix, below:

Table 6: Road Pricing Reductions in VMT

	35 Elasticity	2 Elasticity
High Base El		
.048\$ RP	-42%	-24%
Policy Case El		
.022\$ RP	-17%	-10%

The result is a 10% to 42% reduction in VMT in the year 2050 when the full effects of our four VMT fee scenarios are applied. However, we use only the -.2 elasticity for our two base scenarios.

Results and Observations

The authors of the hundreds of pieces of research we have relied upon have each made dozens of assumptions underlying their work. As we have compiled this research we have made dozens more. Were we to catalog these comprehensively, we would end up with a huge list and an infeasibly large number of possible scenarios and sensitivity runs that could be examined.

However, over the course of our research a handful of assumptions stand out as particularly important, either because they describe an important fork in the development path for U.S. passenger transport or because they have relatively strong and direct effects of LDV power use. A full summary of these variables is included in chapter VII. In brief, they encompass: 1) projections for vehicle sales and adoption, changes in VMT from EV price signals and AV technological improvements, gains in energy efficiency from both EV and AV evolutions (EI), and potential road pricing and policy signals.

The table below summarizes LDV transport power demand from our calculations for the milestone years between now and 2050. As the table shows, 2050 LDV power use is approximately 1140 TWh and 570 TWh, in the High Base and Policy Cases, respectively. As these cases are intended to approximate upper and lower likely boundaries, the results are surprisingly close together. Whereas the earlier literature surveys described in Chapter II of the report found upper and lower bounds differing by as much as a factor of ten, our calculations suggest that the difference between our likely boundary cases is only about 600 TWh, 15 percent of today's power use. If our calculations have any value, we have a pretty good idea of the power we'll need thirty years from now so long as EVs take off on roughly the high sales trajectory we forecast and no black swan events cause a serious rupture in American driving habits.

Case	Year	Total Number of EV in Service	Portion Stock Electric (%)	Total Number of AV in Service	Fleet Average eVMT / Vehicle (per yr)	Fleet Average Efficiency (kWh/mile)	Total TWh (TWh)
	2015	406,076	0.2%	0	7,179	0.32	1
	2025	16,890,719	6.5%	0	9,087	0.34	53
Base	2030	52,379,566	19.7%	3,182,833	10,290	0.35	187
High	2040	166,979,970	59.6%	65,615,683	13,420	0.33	742
	2050	252,371,537	85.6%	180,263,265	16,927	0.27	1140
	_						
	2015	406,076	0.2%	0	7,179	0.32	1
	2025	17,086,996	6.6%	0	8,508	0.31	45
Policy	2030	52,378,548	19.7%	196,278	8,826	0.30	140
Case	2040	166,928,240	59.6%	17,786,550	8,865	0.29	435
	2050	251,932,162	85.5%	128,559,496	10,038	0.23	570

Electricity Consumption Summary

Section VII.C dives further into sensitivity analyses and scenario decomposition, and lead us to the same overall conclusion. It is beyond both our means and expertise to provide anything approaching a complete discussion of the implications of our findings for energy, transport, or climate policy. Instead, we provide a small set of policy observations that speak mainly to the focus of our analysis, namely the intersection of transport changes and the power industry. Beyond electrification of LDVs per se, the policy approaches to reducing carbon seem to divide into these categories:

- (A) shift drivers and later, single occupants of AVs -- out of SOVs and into either pooled rides or, much better, integrated multimodal on-demand mobility systems, via any number of policy tools;
- (B) encourage or require electric LDVs to become more efficient more quickly than otherwise, much as CAFE and ZEV standards have forced ICE fleet efficiency gains; or

(C) Harvest the vehicle and system efficiency improvements theoretically offered by AVs as soon as possible after they are introduced.

From the policy standpoint, the autonomous vehicle revolution is exceedingly complex. This is an area where much more work is needed. We need much better data on the realistic changes we will need to make to our road and communications infrastructure to accommodate AVs at each penetration level, and how these changes can be staged so they need not be completely redone as the AV fleet grows. We also need better data on how these vehicles will co-exist with conventionally-driven cars and trucks and how efficiency and safety improvements can be accelerated in the presence of mixed fleets. Finally, there is almost no data on how much the infrastructure changes for AVs will cost, much less on how we will finance them.

With the possible exception of the latter, enormous amounts of research are now underway. When we have some of these answers we will have the ability to make somewhat better estimates of the impacts of autonomous vehicles on future power demand.

I.Introduction and Overview

A. INTRODUCTION AND PURPOSE

The transportation sector is now facing the same disruptions that have upended many other sectors of the economy. Platform and car-sharing companies such as Uber and Zipcar are threatening the vehicle ownership model that has stood for a century. Electric vehicles are the fastest-growing segment of the industry, with more than 40 models for sale in the U.S. today. And aided by a new generation of families who prefer "walkable urbanism," the design of urban areas to reduce the need for car travel has moved from the fringes to the core of much city planning.¹

Transportation is also undergoing shift from human-piloted to driverless or autonomous vehicles (AVs). (Some researchers stress the difference between connected and unconnected AVs; we assume that all AVs are connected, but do not use the acronym CAV.) Most experts agree that AV technology will be commercially available by the mid-2020s and commonplace in the 2030s. This technology is predicted to unleash dramatic changes in the ways personal and freight vehicles are used, transport safety, urban design, and transport energy use. Importantly, we employ the gross simplification that all AVs are electric, intentionally biasing our power demand upward.

The trifecta disruptions of electrification, sharing, and autonomy have become known in some transport circles as the "Three Revolutions."² Together, the three are expected to have profound impacts across developed world economies, from the auto industry, to the labor force, to family lifestyles and more.³

At the same time, the need for reducing greenhouse gases from transportation is as much beyond dispute as is the science of climate change itself. In 2016, U.S. GHG emissions from transport for the first time became the largest single component of total U.S. GHG emissions.⁴ In many states and cities, including our home city of Boston, transport emissions now exceed the less-carbon intensive use of electricity for

¹ (Leinberger, The Option of Urbanism: Investing in a New American Dream., 2008)

² (Sperling, 2017)

³ (Barclays, 2015); (Clements & Kockelman, Economic Effects of Automated Vehicles, 2017) (Albright and Stonebridge Group, 2016)

⁴ (U.S. Energy Information Administration, 2017)

buildings and industry. As the locus of climate action shifts to states and cities – especially in Trump's post-Paris U.S. – putting transport emissions on a firm trajectory to mid-century zero is clearly of the utmost importance.

In the U.S., all these disruptions and imperatives for change are occurring against a backdrop of modest economic and population growth, increasing e-commerce and automation, increased urbanization and continued sprawl, and an increasingly congested and deteriorating travel infrastructure. The latest national assessment of U.S. transportation notes that the network quality of U.S. roads is rated 16th in the world and likely to slide further unless transport investment increases substantially.⁵

The purpose of this paper is to examine one important outcome from all of these forces: the electricity needed to power passenger electric fleets and the implications for greenhouse gas emissions (equivalently, carbon, CO2, or GHGs for short). The amount of electricity used along this path will obviously be a function of billions of individual trip and vehicle purchase decisions, all influenced in turn by myriad economic, demographic, policy, and technological factors. Our goal is to establish *realistic bounds* on the aggregate increase in electricity required to power all electric transport between now and 2050. Our hope is that a carefully structured set of assumptions and calculations can reduce a problem of unfathomable complexity into a set of scenarios realistic enough to guide policies regarding climate change and the electric power industry.⁶

In contrast to many other works on the subject, our focus is on the aggregate national electrical energy needed to power the light-duty vehicle (LDV) fleet between now and 2050. From the standpoint of climate policy the electric energy we need is the single most important indicator of our need for carbon free power (We intentionally but inaccurately use the terms power and energy interchangeably in this work, referring in both cases to electrical energy and/or the full industrial system that makes and delivers it). Sales of electric energy are also one of the most immediate and intuitive measures of the growth potential for both the supply and delivery segments of the power sector. These growth prospects, in turn, critically inform the possibilities for change in the business and regulatory structure of the industry.

⁵ (U.S. Department of Transportation) P.3

⁶ Importantly, we ignore the potential for hydrogen as a transport fuel source; we plan to include it in subsequent work.

As we stick to this specific focus we do not analyze or discuss many other important aspects of the growth of electric transport on electric utilities. For example, we do not examine the patterns or methods of vehicle charging, so we reach no conclusions on the size or character of the electric delivery infrastructure needed to power the EV fleet. We likewise do not examine the very important potential for managing EV charging by integrating EVs into their local distribution system as one of many distributed energy resources.⁷ Finally, we do not focus on the degree to which electricity in any given year will come from carbon-free sources nor the changes required in the power system to integrate renewables and storage and provide zero-carbon power as soon as possible -- certainly by mid-century. These are all topics of widespread, important research; our work is simply intended to add a realistic aggregate size range to the discussion.

We stress at the outset that this report is not a new EV or AV forecast based on original work – quite the reverse. It is rather a synthesis of hundreds of original studies, blog posts, industry reports, and other sources that range from peer-reviewed work to opinions reported in newspaper articles. Our modeling is essentially an accounting framework that provides a way of deconstructing the deeply interconnected issues of fleet electrification, autonomy, new business models, and other factors into subparts we think we have been able to analyze and interrelate. In no way does this remove a constant need to choose from among many unprovable assumptions and opinions, and nearly every number in this paper fits this description.

Consistent with this, it is not our purpose to produce new forecasts of EV and AV sales or the underlying costs of owning and operating conventional, electric, and autonomous vehicles over time. Certainly any economically-derived forecast of vehicle sales must be based on a long-term view of the capital and operating costs of vehicle alternatives, unless the forecast is for a period in which policy mandates require a single vehicle type (e.g. bans on further conventional vehicle sales). However, for the sake of transparency, the general view we have formed of the underlying comparative cost drivers are as follows:

• The purchase cost premium for non-autonomous BEVs will diminish to smaller and smaller levels and be inconsequential by the 2030s;

⁷ Similarly, we do not treat electric vehicle charging infrastructure as part of the transport infrastructure, though if we were to be analytically strict we easily could. Instead we assume throughout that this infrastructure is amply supplied by electric utilities and third parties, and that the costs of this infrastructure are collected through electric power prices.

- Autonomous vehicles will have a purchase price premium that also erodes, though over a longer period, as reflected in the AV forecast we use below;
- U.S. electricity prices will vary between roughly constant in real terms through 2050 and growing at most one percent real a year in some years and locations; and
- Gasoline and diesel prices will vary between constant and declining real prices as conventionallyfueled vehicles lose market share.

Most of the forecasts we review and employ do not make their comparable cost assumptions transparent; regardless, we have no doubt that our views may not align entirely with those adopted by the researchers whose work we rely on. In those cases, it is fair to say that our work embodies implicit or explicit internal inconsistencies.

Our work examines light-duty vehicles, separated between autos and light trucks as much as possible. The obvious reason is that LDVs account for 90% of motor vehicle travel⁸ in the United States; of this, urban mass transit is about one percent of person-miles.⁹ In subsequent work we plan to add estimates of freight and transit electric use, as well as addressing electric use for new transport infrastructure, to attempt at arriving at total U.S. transport electric use.

This work is largely a review of various highly uncertain forecasts, trends, and policy outcomes. Our selection of any of these parameters is inherently judgmental, biased by our own priors and experience. While exercising this judgment, we have attempted to use a consistent philosophy of assumption selection. For all parameters examined, this philosophy is to search for upper and lower limits that correspond to our subjective judgment that it is (subjectively) 70-80% likely that the eventual true parameter is within these two limits. In other words, we are not trying to find true upper and lower bounds, but rather our subjective view of the approximate center of a multidimensional probability space.

Mechanically, we implement this in a very simple fashion. For the parameters we find significant, we adopt high and low values. Occasionally we adopt a third value as a sensitivity case, or treat either the

⁸ (Federal Highway Association, 2017)

⁹ As (Polzin, 2006) p. 26 notes, if all urban mass transit in the U.S. disappeared overnight, the impact on VMT would be less than two percent.

high or low value as the "base" value. This is a simplistic way of saying that we assume the probability distribution is not a bell-shaped curve with symmetric high and low values, but rather an asymmetric curve weighted towards the base value we adopt.

After adopting many of these values, we assemble them into two main scenarios labeled High Base and Policy. The High Base scenario attempts to assemble a consistent set of parameters that together reach (judgmentally) perhaps 85% of the way towards the highest level of power use we believe will occur in 2050. The Policy case does the same thing in the other direction, implementing policies atop negative outcomes that yield a comparable level of low demand. In short, our goal is to isolate – perhaps *guess* is a more accurate verb -- a span of power demand that contains most of the overall probability of the 2050 demand for LDV power.

B. RELEVANT PRIOR WORK

Many researchers have looked at electricity use for light duty EVs, often in combination with general forecasts of EV adoption and broader questions of transport energy use during a disruptive period. Most of these estimates are either very short term in nature or for a specific metropolitan area – both of which are valuable and interesting, but difficult to generalize. Forecasts of metropolitan area EV use are exemplified by Gucwa¹⁰ for the San Francisco area, Zhao and Kockelman¹¹ for Austin, Texas, and Childress, et al¹² for Portland, OR. Of the long term forecasts, the enormous changes engulfing the sector typically give rise to a scenario approach, where transport energy use varies by such a wide margin that it is difficult to extract much in the way of policy or planning guidance.¹³ Nonetheless, we review and rely on several industry EV forecasts to create our own EV scenarios.

There are many good examples of *short-term* transport power forecasts. Goldman Sachs¹⁴ (GS) recently estimated that EVs would add 0.5% to electricity demand by 2025, half of an estimated 1% total annual electric sales growth per year during this period. Morgan Stanley¹⁵ estimated that EVs will add 0.1% to

¹⁰ (Gucwa, 2014)

¹¹ (Zhao & Kockelman, Anticipating the Regional Impacts of Connected and Automated Vehicle Travel in Austin, Texas, 2017)

¹² (Childress, Nichols, Charlton, & Coe, 2015)

¹³ See, for example, (World Energy Council, 2011)

¹⁴ (Kooroshy, Ibbotson, Lee, Bingham, & Simons, 2015); (Kooroshy, et al., 2016)

¹⁵ (Morgan Stanley 2016)

Electric_Transport_Draft _10_5_17

average electric sales growth rates through 2025. Although it is difficult to gain long-term insights from these forecasts, the GS paper suggests the interesting (and somewhat contrarian) view that the rate of change in the total stock of EVs will not foreseeably rise above 4% per year, a rate that increases power demand about 1% per year.¹⁶ Interestingly, our results bear this out (for LDVs), and it remains true all the way to 2050.

In the academic literature, both Brown, Gonder, and Repac (BGR)¹⁷ and MacKenzie, Wadud, and Leiby (MWL)¹⁸ estimate long-term energy use – but only by scenario. BGR's three scenarios span long-term outcomes from -95% to +173% of current energy use -- an extraordinarily large range of outcomes. MWL's four scenarios cover an only slightly smaller expanse; from -40% of current energy to about +140%. Stephens, et al¹⁹ derives the widest estimates of all, partly because their purpose is explicitly to search for upper and lower bounds. Expressed as gallons of gasoline, their scenarios range from 37 to 303 billion gallons of gasoline per year, a factor of ten difference. Although these papers are extremely valuable in many ways, and we draw on them extensively in our work, their conclusions cover too wide a range to guide many policy decisions.

A handful of studies do examine long-term transport power demand; our work can be viewed as attempting to improve on, or at least add usefully to, these studies. One such study is the Electric Power Research Institute Natural Resources Defense Council (EPRI/NRDC)²⁰ environmental assessment of electric transport. This three-volume work predicts 450 TWh of LDV electric demand in 2050, a figure not far from one of our cases. A second expansive study of transportation by Bank of America/Merrill Lynch (BAML) also predicts a 7.5%-27% increase in U.S. electric demand by 2050.²¹ Another estimate comes from the Brattle Group's recent report on Electrification,²² which estimates a rough bound of 2,100 TWh of power use if all U.S. vehicle transport is electrified, a 56% increase over 2015 sales.

¹⁶ (Kooroshy, Ibbotson, Lee, Bingham, & Simons, 2015), p.1, 6

¹⁷ (Brown, Gonder, & Repac, 2014)

¹⁸ (MacKenzie, Wadud, & Leiby, 2014)

¹⁹ (Stevens, et al., 2016)

²⁰ Electric Power Research Institute and Natural Resources Defense Council. Environmental Assessment of a Full Electric Transportation Portfolio, Volume 2: Greenhouse Gas Emissions (2015)

²¹ (Bank of America Merrill Lynch, 2017) (p. 231)

²² (Weiss, Hledik, Hagerty, & Gorman, 2016)

Electric_Transport_Draft _10_5_17

Alternatively, essentially every estimate of 2050 EV fleets can be transformed into a power use prediction, as we do later in this paper. Using this approach, Bank of America/Merrill Lynch Research shows 2050 electricity percentage increase forecasts spanning a more conventional range, from +7.5% to +27.3% of base 2050 electric demand, at 25%, and 100% of EV penetration, respectively.²³ Relative to current U.S. power demand, this represents about 290 to 1,000 TWh. While these numbers seem plausible, and well within the ability of the industry to accommodate, they are also derived more or less from parametric scenarios of EV penetration rather than explicit EV forecasts by BAML (which are, themselves, scenario-driven).

Similarly, Bloomberg New Energy Finance (BNEF) recently predicted that 50% of 2040 U.S. auto sales will be EVs, a little below one-sixth of global sales in that year. Total global power demand, for EVs, per BNEF, was 1800TWh. If we assume US vehicles are twice as energy-intensive as the global average, U.S. EV power use will be 600 TWh in 2040.²⁴ As a final example, the Rocky Mountain Institute, predicts 50% electrification of the U.S. fleet by 2050.²⁵ A second RMI report links this prediction to approximately 600 TWh greater power demand in a "fast growth" scenario.²⁶ Table I-1 summarizes these predictions.

Table I-1

	, , , , , , , , , , , , , , , , , , , ,			
Source	Nature of Estimate	Nature of Estimate Year		
BNEF (2017)	Electric LDV fleet tranlated to	2040	~600	
	power demand			
BMI (2016)	Modeled power demand,	2050	600	
(1010)	LDV only	2050	000	
Waiss at al (2016)	All ground transport 100%	2050	2100	
Weiss, et al (2010)	electrified	2050	2100	
EPRI/NRDC (2015)	Modeled electric LDV use	2050	450	
	LDV use; approach	2050	+7.5% to +27.3%	
BAIVIL (2017)	unspecified	2050	of 2050 demand	

Estimates of U.S. Transport Power Use, 2040-50

One reason why these estimates are difficult to grasp is that so many changes are hitting the sector at once. Electrification and battery improvements are proceeding faster than most past predictions. Self-driving cars, which many believe will revolutionize transportation in a variety of unpredictable ways, are

²³ (Bank of America Merrill Lynch, 2017), p. 231

²⁴ (BNEF, 2017)

²⁵ (Walker & Johnson, 2016)

²⁶ (Walker & Johnson, 2016) p. 19

also improving quickly. Mature countries like the U.S. are also experiencing declines in driving and license rates as millennials express a preference for walkable urbanism. New transport network firms have rocketed up to become major providers in only a decade. Information technologies and ecommerce continues to grow. Adding up the long-term effect of these changes on power use seems impossible, but we attempt it nonetheless.

II. <u>Research Approach</u>

A. THE KAYA IDENTITY FRAMEWORK

Transport energy and emissions are often forecasted by (1) estimating the vehicle-miles that will be traveled (VMT), using well-established models benchmarked from prior changes in travel on these modes over decades; and (2) multiplying VMT times the energy use per vehicle-mile, which can be forecasted by analyzing current efficiencies, fuel economy rules, fleet composition shifts, and technical change.²⁷ VMT are either forecast in the aggregate using reduced-form econometric equations or from vehicle forecasts. This relationship, known as a Kaya identity²⁸, is often written in its aggregate form as:

$$v \cdot en = \Phi_l$$
 (1)

Where total VMT is denoted by v, average energy intensity in kilowatt-hours per mile is denoted by en, and $_{ql}$ is the total energy use for LDV transport. Obviously, this approach is useful when models predicting aggregate total travel are stable enough to perform well over long forecast periods and fleetwide average energy intensity can also be projected with confidence.

Unfortunately, essentially none of the conditions that make this aggregate approach easy hold today. Traditional forecasts of aggregate VMT began losing accuracy following the Great Recession of 2008, well before the sharing and autonomy disruptions had much of an effect. Autonomy is expected to greatly disrupt these forecasts, possibly along with new preferences for walkable urbanism, ridesharing, and other changes. At present, most econometrically-derived models of VMT can't be expected to reflect new forms of demand for travel from AVs, nor do they capture VMT changes from shared ownership and related changes in urban design.²⁹ Driverless personal and freight vehicles are so different that they constitute essentially new, never-before-experienced transport modes. In the words of several experts,

²⁷ Carbon emissions follow trivially from energy use using accepted emissions factors per unit of fuel. There are also many other types of models that forecast transport energy use using agent-based models, energy and emissions-focused simulation models, and others. We organize the discussion around Kaya Identity approaches, but survey and cite many results from other types of models herein.

²⁸ (Kaya, 1990)

²⁹ See Workpaper A and (Litman, 2016) for a brief discussion of aggregate VMT models.

"AVs have the potential to interact with each other, the transportation infrastructure and the built environment in such complex ways that it is likely to take years of dedicated research to have a detailed assessment of the possible impacts of the future system."³⁰ Without useful aggregate VMT forecasts, we have nothing by which to multiply the estimated efficiency of these vehicles to come up with estimated energy use or emissions. Furthermore, aggregate VMT forecasts do not allow us to determine the extent of EV penetration, which is obviously the centerpiece of electricity forecasts. Fleetwide energy intensity is also much harder to predict as many new modes and models enter the picture in the next 30 years.

There is nothing close to a silver bullet to address these difficulties, but we gain a little tractability with a conceptual framework based on an expanded identity of the following form, and then applying the framework in the three "layers" and further adjustments as explained below. The disaggregated kaya identity we use is:

$$\sum_{i} \left[v_{i,t} \cdot \kappa_{i,t} \cdot en_{i,t} \right] = \Phi_{l,t}$$
⁽²⁾

Where the stock in year t of EVs of a motorized vehicle type i is denoted by $\kappa_{i,t}$, v_{it} is the average miles travelled by that vehicle type in year t, and en_{it} is the average power use of the vehicle type i per mile travelled during year t, which we refer to as electric intensity or EI.

Intuitively, this expansion of the identity trades the problem of forecasting aggregate VMT and energy intensity for the problem of forecasting the number of each type of vehicle in the fleet each year, the efficiency of that vintage vehicle, and number of miles that vehicle is driven. The uncertainties and potential errors in this approach are no less gigantic, but at least they are disaggregated within a more flexible and transparent framework. For example, this framework allows us to treat electric non-autonomous and autonomous cars and light trucks all separately, adjusting use intensity for modes or submodes (such as shared or pooled vehicles) as well as allowing the composition of the fleet to migrate from one mode to another. For example, it is widely predicted that non-autonomous pooled vehicles will ultimately be replaced by so-called "robotaxis" around 2030-2035, according to most forecasts.

³⁰ (Brown, Gonder, & Repac, 2014); (Karim, 2017)

Equation (2) allows us to shift between individual and pooled AVs during this period, trend VMT per vehicle for each of these modes, and express and trend EI for each.³¹

This disaggregated form hardly obviates the need to study and then forecast each of these elements over the next several decades as they undergo disruption in the Three Revolutions. However, forecasting adoption of vehicles by mode, average VMT by vehicle/mode/vintage, and average EI by vehicle/mode/vintage unpacks the giant box of fleet-wide aggregates into elements for which there are sometimes extensive bodies of work and some basis for intuition. Although this may create a sense of false precision – there is no guarantee that N forecasted variables will have an aggregate error lower than two aggregate variables – we at least have visibility into several of the main change processes extant.

Moreover, we must recognize at the outset that the growth of all of the modes and sub-modes, their EI, and annual use will all be greatly affected, directly and indirectly, by federal, state, and local policies, as well as economics and tastes. Researchers agree that public policies will have an unusually strong impact on the pace of new mode adoption, especially for AVs. We discuss policy dependence throughout the paper, seeking a range reflecting the most likely policy outcomes. In this important sense, our results are bounded in large part by our pure judgement as to the likely ranges and impacts of many U.S. transport policies.

As discussed below, researchers are starting to come up with useful ways to estimate the changes in mode-and vehicle-specific VMT triggered by all of these factors. However, the timing of each source of VMT shift is also important and equally uncertain. All three revolutions are occurring on separate but undoubtedly interdependent timetables, yielding feedback loops between many of the major drivers. This triggers a multifaceted interdependence between all of the terms, including an indirect interdependence between VMT and the rate of AV and EV penetration. Thus, while equation (2) is arithmetically straightforward, each term is extremely difficult to forecast in isolation and the interactions between the terms are nearly impossible to capture outside of a few extremely new and somewhat specialized studies.

³¹ As we apply this framework below, we do not find it necessary to use all the degrees of freedom, but the expanded framework is nonetheless essential.

B. MODELING THE THREE MAIN DISRUPTIONS BY LAYER

As just noted, one obvious deficiency with our approach is that VMT, mode share, and electric intensity are all interdependent. Every decision to take a trip is a function of the underlying drivers of travel and the mode choices for each chosen trip – time cost, money cost, and other costs and benefits for each mode option. This marks the first simultaneity: whether one is willing to take a trip depends in part on the features of, and options for, the traverse. If the food store is one block away, frequent trips by foot substitute for weekly trips by car; if the market is one mile away, trips are less frequent and almost surely by car, taxi, or transit.

In short, the simultaneous choice of whether and how to take a trip is a function of the attributes of the travel modes available, which in turn are a function of technology and cost attributes for each mode and the nature of the route/mode choices. In turn, route choices are a complex function of the built environment between origin and destination. Dense walkable and bikeable areas enable shorter non-car trips, while distant jobs and homes in suburbs and exurbs often allow only one realistic mode and route choice involving a car. Yet the choice of where to live, work and shop are also endogenous, often shaped or even decided by transportation options.

This interdependence operates differently in the short-run and the long-run. In the short run, the choice of travel mode is approximately fixed by the state of technology, existing infrastructure and vehicle stocks, and current arrangements such as transit schedules and the accessibility of EV chargers. In the long-run, every one of these trip choice determinants changes in a path-dependent manner. Moreover, in the long-run the choice is nested, first in a choice of own/share a vehicle by type and then whether to use that vehicle for a trip.³² A future breakthrough on battery costs should lower the cost of EVs, leading to larger and cheaper fleet of shared SAVs, leading more young families to decide that they prefer to remain in dense urban neighborhoods. As demand for these neighborhoods goes up, developers and planners provide a larger and larger supply of denser, metropolitan homes and transit system provide more frequent service due to increased density. Thus, in the decades between now and 2050, one technology

³² See for example (Binny, Kockelman, & Musti, 2011) Figure 3.

breakthrough could alter the future path of urban design and the mode choices available dozens of years hence.

We break through this deep interdependence using a very simple and inelegant approach. We first posit a baseline in which none of the Three Revolutions occurs. In this baseline scenario, we generally adopt the view of Litman,³³ Circella, et al,³⁴ and the Federal Highway Administration³⁵ that per-capita LDV travel by Americans has hit its peak and is likely to decline, but for the potential effects of the Three Revolutions. The latest FHWA forecast of VMT projects 0.71%/yr growth for the next 30 years, just slightly higher than U.S. population growth (0.63%). Litman and Circella, et al. both suggest that, aside from the shocks of the Three Revolutions, long-term trends such as the aging of the American population, stabilization or even decline of workforce participation levels, and the preferences of millennials for walkable urbanism all suggest that the era of growth in per-capita U.S. travel is at an end.

The manner in which our approach reflects this baseline view is somewhat opaque. As our goal is to forecast only electric VMT (eVMT), we forecast the sales of EVs each year and multiply them by each vehicle's expected annual travel. We do not increase expected per-vehicle travel based on an exogenous trend, such as the FHWA's 0.71% increase in per-capita VMT. This is our bow to our view that pre-revolution per-capita travel is stable, if not declining. As explained in the next section, we increase per-vehicle VMT only from specific changes due to electrification, autonomy, or the advent of new shared/pooled modes. (Of course, we must also account for electricity use per mile, as explained further below).

The effect of the Three Revolutions is then factored into our implicit baseline in three "layers" of calculations. The first layer is electrification, an interim scenario in which the only major change is the availability of EVs as an alternative to CVs, i.e. without changes in ownership models, autonomy, shared modes, or any urban design changes not already embedded in our implicit baseline. We employ relatively conventional third-party forecasts of EV penetration that do not appear to reflect the full impacts of vehicle sharing or connected, autonomous vehicles. Disaggregating them by vehicle class, we create a

 ³³ (Litman, The Future Isn't What It Used to Be: Changing Trends and Their Implications for Transport Planning, 2016); (Litman, Evaluating Public Transit Benefits and Costs: Best Practices Guidebook, 2017)

³⁴ (Circella, Tiedeman, Handy, Alemi, & Mokhtarian, 2016)

³⁵ (Federal Highway Association, 2017)

Electric_Transport_Draft _10_5_17

preliminary disaggregated kaya identity and associated electricity forecast that we call our Conventional EV Ownership Interim Case.

Within this first layer we also project the composition of the EV vehicle fleet and changes in EV EI due to technological improvements in EVs themselves. At this stage, we do not incorporate AV-induced electricity shifts, such as increased travel or traffic-smoothing. Allow VMT to increase for EVs based solely on their cheaper per-mile operating costs, including their current exemption from per-mile fuel taxes.³⁶ Further, major adjustments to VMT are considered in the following two stages, reflecting travel demand impacts induced by ridesharing and autonomy.

The next layer of our calculation modifies this interim case to reflect the onset of autonomous vehicles. As many researchers are predicting, AVs will have many complex effects on travel demand, amounting on net to a significant and perhaps very large increase in VMT. Conversely, AVs will reportedly enable savings in EI through network and vehicle management approaches not available to conventional vehicles, and (much later, we think) energy-reducing changes to the vehicles themselves. In this layer, we first survey AV penetration predictions and adopt an AV penetration base case and a second, more aggressive sensitivity case. Based on the timing implied by these forecasts, we first allocate all of these AVs to the EV stock. We then manually adjust VMT for each type of EAV according to the penetration timetable and the literature on each VMT change driver. We also consider whether AEVs are likely to have significantly different EI than non-AEVs, including whether AV technology will change travel and road safety to the point where vehicles will downsize and downweight significantly and thereby use less power per mile. As we are modifying our conventional ownership case only to add in the effects of autonomy, this stage is equivalent to the currently-unpopular scenarios in which carsharing, ridesharing, and other transportation-as-a-service (TaaS) or "new mobility" models do not take hold.

In the final layer, we add the potential impacts of the new pooled and shared modes, including integrated multimodal systems, also called mobility-as-a-service, among other names. As one of our AV penetration scenarios is intended to reflect these new modes stimulating AV adoption, we consider the extent to which AVs will change the number of VMT driven by each AEV type. In kaya terms, the question here is

³⁶ In chapter seven we examine road pricing scenarios that require EVs to pay per-mile road taxes, partly offsetting these savings and resulting VMT increases.

the extent to which these new models create a different composition of the EV/AEV vehicle stocks and different annual VMT for the components of the stock.

In other words, when all the pooling, ridesharing, carsharing, and mobility-as-a-service changes are said and done, there will be a future number of passengers in a future set of vehicles each going a certain number of miles at a certain level of efficiency. The differences between our second and third layers are that, in a pooled/shared/services world, there are ideally fewer vehicles, each driving more annual miles and each with larger average occupancies. This implies more use of increasingly electrified mass transit and a faster rise of low-power, lighter intracity passenger vehicles which are more efficient than the average LDV. Complex as they are, all these changes boil down to shifts of VMT between modes (including some new ones) in the disaggregated Kaya identity and perhaps some changes in EI.

Although this description makes our analysis sound like a sophisticated adjustment of Kaya terms to reflect these effects, our actual analysis is far less advanced. After studying the literature on shared and pooled modes, and applying our own opinions on the pace of vehicle occupancy shifts due either to policy or taste, we conclude (or perhaps assume) that the net effects of this layer on electric use can be captured by a handful of simple adjustments and scenarios.

With the addition of our third layer the main part of our computational framework is complete. The scenarios emerging from this layer are intended to reflect the main impacts of all three revolutions on LDV power use through 2050. However, there are three additional issues we examine further to see whether our scenarios might be updated: travel pricing options triggered by the need to pay for transport infrastructure, the effect of communications-based substitutes for travel (e.g. telecommuting), and the effect of concerted efforts to redesign urban centers for less travel. These have the potential to change VMT and EI enough to affect power use and we do not think they are fully captured in our construction of the three main model layers. We refer to these three items as "wild cards," though in fact there is more than enough uncertainty to apply this label to any other element of our forecast.

In summary, our calculation proceeds in four layers or stages: Modeling EV adoption and travel under conventional ownership; modeling the penetration of AVs (all assumed to be EVs) and their impact on VMT by mode, also before reflecting pooled/shared/integrated mobility business models; adding in the VMT and EI effects of these shared/pooled modes and business models; and finally considering the effects

of the three wild cards: urban design, electronic substitutes for travel, and infrastructure pricing. Figure II-1 illustrates our conceptual approach.





29 Electric_Transport_Draft _10_5_17

C. SIMILAR EFFORTS

The approach we take in this paper builds upon several similar efforts. Some of these efforts would appear from their title to focus on only one of the Three Revolutions, but inevitably all three creep into the analysis. In particular, as far back as 2014, two groups of authors pioneered essentially the approach we are using under the guise of researching only the energy impacts of AVs. Brown, Gonder and Repac (2014)³⁷ reviewed, in sequence, literature estimates for all of the factors affected by autonomy that will drive electricity use up or down. They created lists of factors that would alter "use intensity" (UI), roughly translating into VMT, and energy intensity, respectively. For each of these factors, they searched the literature to reach a judgement as to what a reasonable estimate might be for the impact of that factor, taken in isolation. However, their goal was to examine fuel savings of all types, not electric demand, so their results are expressed as percentages of baseline fuel use over a specific horizon.

The second 2014 paper, Morrow, et al (2014)³⁸, performs a condensed version of the same exercise. This work revolves around two scenarios: (1) a best-case outcome where automation reduces VMTs by 40% and EI is reduced by two-thirds, yielding an 80% reduction in energy use; and (2) a worst-case scenario where VMTs increase by 40% and auto energy intensity increases by 25%. As in BGR, however, the results are in the form of percentage changes from an unspecified base case, a measure not easily translated into EV electricity use.

A third paper using this approximate approach is MacKenzie, Wadud, and Leiby (MWL, 2014)³⁹. Although styled as an investigation of the energy impact of AVs, the authors quantify – again in percentage terms versus an unspecified baseline – the effects of ridesharing as well as autonomy. Consistent with the Kaya identity adjustment approach, the authors divide their impacts between those affecting travel demand (VMT) and energy use per mile (EI). The authors pay particularly close attention to aspects of AV technologies that could change EI, such as changes in average highway speeds, and also include an interesting elasticity-based estimate of travel demand changes from AVs. As with the studies above, the raw materials are extremely valuable but the end product cannot be used to forecast electricity use.

³⁷ (Brown, Gonder, & Repac, 2014)

³⁸ (Morrow III, et al., 2014)

³⁹ (Wadud, MacKenzie, & Lieby, 2016)
An updated and expanded version of these approaches was published in 2016 by Stephens, et al.⁴⁰ In addition to updating the underlying literature review, this work explicitly incorporated ridesharing, as well as varying level of autonomy, through four scenarios: conventional, partial autonomy without sharing, full autonomy without sharing, and full autonomy with full sharing. As with our current work, the goal was to establish upper and lower bounds for LDV energy use, and in contrast to the studies above the authors estimated the change in fuel consumption (not just percentages) in each scenario. This study was highlighted in a U.S. Department of Energy paper on new mobility systems. However, the study appears to use a current-year base case and does not explicitly factor in electrification, once again making it difficult to translate directly into EV power demand.

We draw heavily on all of these works, and many other similar but more narrowly focused works, in a framework that essentially translates these results into long-term projections of electricity use.⁴¹

III. Conventional Ownership Scenarios Stage Results

In this section, we provide numerical results from the first stage of our analysis. As mentioned above, these initial scenarios do not factor in changes from the growth of autonomous vehicles or new ownership/TaaS business models. We highlight the key assumptions used in our projections of light duty vehicle (LDV) electricity consumption and provide the main takeaways. We begin by discussing our projection of electric vehicle sales and compare our projections to other industry forecasts. Then, we provide our average annual electric vehicle miles travelled (eVMT) and electric vehicle energy intensity assumptions. Finally, we discuss our results and put our first stage of results into context with the latter two stages of our analysis.

A. EV PROJECTIONS UNDER CONVENTIONAL OWNERSHIP

⁴⁰ (Stephens, Taylor, Moore, & Ward, 2016)

⁴¹ There are dozens more papers in the literature that address one or more aspects of future EV energy use, many of which are subsequently cited below. Additional studies that resemble (Brown, Gonder, & Repac, 2014) and (Stevens, et al., 2016) include (Greenblatt & Saxena, 2015) who estimate the impacts of a wide range of scenarios in which gasoline vehicles are converted into autonomous electric taxis (AETs) through 2050. Their calculations show, for example, that converting the majority of gasoline vehicles to AETs by that year would reduce GHGs by 70%-90% versus EIA's 2014 long-term baseline. However, their calculations are in the form of parametric "what if" scenarios, not projections.

Many industry groups have projected electric vehicle sales, often without any visible adjustment either for the growth of autonomous driving or for new ownership models. For our analysis, we begin with these forecasts. After examining several commercial projections, we assume that EV adoption follows a similar technology adoption curve described by Everett Rogers's Diffusion of Innovations theory.⁴² Specifically, we employ a reduced form of the Bass Diffusion Model, a widely accepted and cited quantitative generalization of the theory used to model product growth rates, for our empirical modeling.⁴³ The specific quantitative formulation is shown below.

$$S_{(t)} = m(\frac{1 - e^{-(p+q)t}}{1 + \frac{q}{p}e^{-(p+q)t}})$$
(3)

Where,

 $S_{(t)}$ = percent of total sales in year t m = final percent of total sales

- p = coefficient of innovation
- q = coefficient of imitation

t = year

Our EV sales share forecasts are most accurately viewed as extensions of two prominent industry forecasts out to the year 2050. We prepared these by first reviewing projections made by Green Tech Media (GTM, 2016), the US DOE's 2017 Annual Energy Outlook (U.S. Energy Information Agency, 2017), (EPRI & NRDC, 2015), (BNEF, 2017), and the Institute for Electric Innovation (IEI, 2017). Based on our judgement, we selected GTM's forecast as our high EV case and IEI's projection as our low case.

Because neither of these projections extend to 2050, we "backfit" a Bass curve to approximate these forecasts as far as they went. We did this by entering parameters from the published forecasts and then experimenting with the Bass p and q parameters until our curves closely fit the published forecasts. As part of this exercise, we assumed that the 2050 terminal sales shares for EVs were 90% in the high case and 58% in the low case.

The p and q parameters resulting from this exercise appear reasonable. Our p factor assumption (i.e. coefficient of innovation) is 0.0013 in our low and high case. The p factor represents how quickly a new

⁴² (Rogers, 2003)

⁴³ (Lavasani, Jin, & Du, 2016)

technology is being adopted, and our coefficient of innovation estimate is high compared to values estimated for the automobile (0.0002) and cellphone (0.00067) and about the same as the value for the internet (0.0017). However, our estimate is low compared to those calculated by Lavansani for hybrid electric vehicles (HEV, between 0.01 and 0.015). Lavansani and her co-authors argue that HEV's p factor is higher than other technologies because from a consumer perspective, HEV technology does not represent a revolutionary new approach to car ownership and operation as compared to an internal combustion engine (ICE) vehicle.⁴⁴ The fact that our estimates for the coefficient of innovation are lower than HEV estimates but higher than other disruptive technologies suggests that BEVs will require new demands from consumers regarding vehicle operation (e.g. understanding charging constraints) but are otherwise not massively different than their ICE counterparts.

On the other hand, our q factor (i.e. coefficient of imitation) estimates of 0.24 and 0.30 in our low and high cases, respectively, were lower than most comparable technologies, though higher than the value estimated for automobile adoption. Unlike the p factor, which mostly deals with a consumer's risk of technology adoption, the q factor represents a consumer's cultural and lifestyle preferences. For automobiles, the factor was estimated to be 0.09; however, the factor for the HEVs in Lavasani's study varied from 0.34 to 0.39, indicating that these technologies, once being adopted by innovators, would be adopted more quickly than our corresponding estimates for BEVs. This is consistent with a view that imitating a neighbor's purchase of an HEV is easier than imitating a BEV purchase.

Figure III.1 below shows the two sales projections we model.

^{44 (}Lavasani, Jin, & Du, 2016)

Figure III-1: Projections of Electric Vehicles



It is important to note that the data that results from our analytical formulation is returned as percent of total LDV sales ($S_{(t)}$) as projected by the U.S. Department of Energy's National Energy Modeling System. If at this point we were to incorporate the view that ridesharing services were going to vastly reduce vehicle sales, we could create multiple car ownership scenarios. Instead, we begin with projections of vehicle sales under a continuation of current ownership trends, and use these to develop sales numbers such as those in Figure III.1. EIA's estimation for vehicle growth is based on econometric modeling that uses forecasted macroeconomic indicators such as population and GDP to estimate future LDV sales.⁴⁵ Overall, they report a cumulative average growth rate of 0.4% for LDV sales through 2050 which compares to their 0.6% projected population increase.⁴⁶ Accordingly, we multiply these projected market shares by EIA's estimate of total U.S. LDV annual sales through 2050 to generate the numbers shown above in Figure III.1.

EIA's projection does not account for the paradigm shifts in the transportation sector that were introduced in the earlier sections of this report. The EIA does not take a position on transformative technology such as car sharing and vehicle automation but rather provides a picture of the business as

⁴⁵ (U.S. Energy Information Agency, 2014)

⁴⁶ (EIA, 2017)

usual world. However, since our first stage analysis does not consider the effects of technologic change, we are comfortable using the EIA figure as the basis of total annual LDV sales.

To check our work, we compared other industry projections to our own; Figure III.2 below depicts some of the key comparisons. GTM research projects a range of 2025 electric vehicle sales from 3 to 3.5 million in their base case and high case, respectively, and EV go, a leading car charging provider, projects 2025 sales between 1.2 to 2.4 million.^{47,48} Longer term and more bullish estimates from the National Resource Defense Council (NRDC), the Electric Research Power Institute (EPRI), and the Climate Policy Initiative (CPI) estimate a range of annual sales between 6 and 17 million by 2040 and BNEF projects sales slightly above 10 million by 2040.^{49,50,51} Yet other sources are less bullish on the EV market. UBS research projects less growth in sales in the near term, estimating only 600 thousand EV sales by 2025, and EEI only projects around 1 million EV sales by 2025.^{52,53} Similarly, EIA projects 1.2 million electric vehicle sales by 2025 in their reference case but then holds sales level relatively constant. By 2050, their reference case projects only 1.7 million annual sales of EVs.⁵⁴ The EIA, however, is constantly adjusting their forecasts and as stated above tends to be a poor predictor of technological revolution. Their EV projections in the 2017 Annual Energy Outlook (AEO) are double their forecast from the prior year and nearly 10 times larger than their forecast from 2014. In general, the EIA usually trails technology trends and is generally regarded as a conservative forecaster.⁵⁵

⁴⁷ (Gavrilovic, The Impact of Electric Vehicles on the Grid: Customer Adoption, Grid Load, and Outlook, 2016)

⁴⁸ Personal communications, EV Go to James Schulte, Energy Impact Partners

⁴⁹ (Alexander, 2015)

⁵⁰ (Energy Transitions Commision, 2017)

⁵¹ (BNEF, 2017)

⁵² (Dounis & Langan, 2017)

⁵³ (Cooper & Schefter, 2017)

⁵⁴ (EIA, 2017)

⁵⁵ (Cohan, 2017)





Source: ISE Analysis; GTM, EV Go, NRDC, EPRI, BNEF, EEI, and CPI

Similar to other industry projections, our projection in Figure III-2 lumps the various electric vehicle types (i.e. car/sedan, light truck/SUV, plug-in hybrid (PHEV), and battery electric vehicle (BEV)) into one broad EV category. However, each of these types will likely consume different amounts of electricity. SUVs have higher electric energy intensities than sedans due to their larger sizes, and PHEVs use a combination of electric and fossil fuel. Therefore, we break up our projections of electric vehicles into these various vehicle types.

First, to split up near-term electric sales into electric trucks and cars, we use the 2016 breakdown of 72% electric cars and 18% E-SUVs.⁵⁶ We then assume that SUV sales as a percent of total sales grows based on the bass diffusion formulation discussed above until the breakdown between E-SUV and car sales equals

⁵⁶ Inside EV website, accessed at <u>http://insideevs.com/</u> on May 2017.

the traditional ICE LDV division of sales in 2015, 56% for light trucks/SUVs.⁵⁷ We assume the same breakdown is reached for electric vehicles by 2027.⁵⁸

To break out the sales between PHEVs and BEVs, we also started with the breakdown of sales between these two types in 2016. In 2016, about half of electric vehicles purchased were PHEVs with the other half being BEVs. We assume this breakdown will continue in the near to medium term as range anxiety and attachment to gasoline driven vehicles remains. However, Bank of America and Merrill Lynch (BAML) project that by 2025, only about 30% of total electric vehicle sales will be PHEV.⁵⁹ We trend this percentage from 30% in 2025 to 10% in 2050.⁶⁰

Electric vehicle sales, though, do not represent the actual stock of electric vehicles in a given year that would consume electricity. Rather, electricity consumption would be driven by the total number of vehicles on the road, which is affected by car retirements as well as sales. To inform our estimate of electric vehicle stock, we rely on the survival rates for conventional cars and light trucks provided by the Oak Ridge National Laboratory's Transportation Energy Data Book (ORNL).⁶¹

The survival rates provided by ORNL are estimates of the percentage of gasoline vehicles, from a specific year, that remain on the road (i.e. a survival rate of 99% suggests that 1% of vehicles have been retired). The percent slowly decreases the older or more distant a particular car model is from the year it was built. For instance, the 'Year 1' survival rate reported by ORNL for a sedan is 99.7% but by year 15 that rate drops to 51%, suggesting that 49% of vehicles purchased 15 years ago have been retired.

These survival rates, though estimated for traditional ICE vehicles, represent our best guess for how long new vehicles remain in circulation year over year after being sold. However, it is likely that survival rates would be different for EVs. As compared to ICE vehicles, EVs do not have complex transmission, only have one moving part in the motor, and have regenerative braking that may improve brake life. A car battery may need to be replaced multiple times during the lifetime of a car, but this replacement does not mean

⁵⁷ This is a much more aggressive assumption than BNEF reportedly makes in its latest EV forecast, probably biasing our electric demand projections upwards.

⁵⁸ (Oak Ridge National Lab, 2016)

⁵⁹ (Ma, Nahal, Tran, & Hill, Thematic Investing: Overdrive - Global Future Mobility Primer, 2017)

⁶⁰ Conversely to our high proportion of electric SUVs, our assumption of continued PHEV sales is higher than BNEF's latest forecast.

⁶¹ (Oak Ridge National Lab, 2016)

the full retirement of the particular car. For these reasons, A&S, RMI, and other researchers believe that BEVs may have almost 2 to 2.5 times the useful life of an ICE when measured in miles, ultimately growing to 5x or 1 million miles.⁶² However, these estimates are for the lifetime mileage, whereas to calculate vehicle stocks we need calendar lives. While it would be convenient to assume that longer potential mileage lives yield equi-proportionate calendar lives, many cars are retired due to accidents, structural deterioration, or other factors unrelated to potential mileage. Morever, there is widespread agreement that the incorporation of autonomy and sharing, not yet factored in, will lead to more intensive vehicle use, offsetting a longer mileage life. As we will be dealing with autonomy and sharing in subsequent sections, we examine vehicle lifetimes in more detail below. In the meantime, in this conventional ownership scenario, we judgementally reduce the amount of vehicles that retire in a given year by 10% as a nod to the greater durability of conventionally-owned and driven BEVs but do not adjust vehicle lives for PHEVs, which continue to have ICE components. Of course, as more field data is made available this estimate can be refined.⁶³

Our stock turnover model thus captures the four types electric vehicles mentioned above to estimate the total electric vehicle stock. Figure III.3 below shows the stock of electric LDVs in our high and low cases.



Figure III-3: Total Stock of Electric Vehicles by Type, Conventional Ownership and No Autonomy

⁶² (Johnson & Walker, 2016) pg. 24; (Albright and Stonebridge Group, 2016) p. 58-59.

⁶³ If EVs lasted much longer in the fleet than we assume, our total EV stocks would not be much different through 2050 since much of the stock growth occurs past 2035 (so vehicles are not replaced even under our current assumptions). The largest effect would be a reduction in average EV fleet EI as less efficient vintages lingered longer in the stock. This could bias our 2050 power use estimate downward – though we doubt by much.

As we did for electric vehicle sales, we also compared our stock projections to other sources and present this comparison in Figure III.4. GTM estimates that there will be 11.4 million EVs on the road by 2025, in line with our low case total.⁶⁴ BAML forecasts that 60% of all vehicles on the road will be electric by 2050.⁶⁵ Furthermore, an RMI estimate from 2011 projected that 157 million EVs would be on the road by 2050, an estimate that is quite similar to our low case and below our high case. In addition, RMI believes 66% of the fleet will be electric cars while the remaining percentage will be trucks/SUVs.⁶⁶ While our modeling suggests the opposite breakdown, with trucks accounting for closer to 55% of the stock in 2040, the difference could easily be explained by the fact that RMI's scenarios incorporate extensive autonomy and sharing; we make these adjustments below. At least as long as conventional ownership continues, we see no reason why Americans will lose their love affair with SUVs when electric models with 300+ mile ranges become widely affordable.



Figure III-4: U.S. EV Stocks – All Types Comparison to other industry projections

⁶⁴ (Gavrilovic, The Impact of Electric Vehicles on the Grid: Customer Adoption, Grid Load, and Outlook, 2016)

⁶⁵ (Ma, Nahal, Tran, & Hill, Thematic Investing: Overdrive - Global Future Mobility Primer, 2017)

⁶⁶ (RMI)

To further support our projection of future EV stocks, we considered the regulatory environment around the U.S, as regulatory mandates alone will contribute significantly to near term EV growth. Overall, 8 states have announced an EV target, mandating a total of 3.3 million vehicles to be on the road by 2025.⁶⁷ California alone has established a target of 1.5 million by 2025.⁶⁸ The International Energy Agency (IEA) compiled a number of these mandates and used them to project that U.S. EV stocks will be 1.2 million by 2020, as compared to our projections of 1.6 million in our low case and 3.6 million in our high case.⁶⁹

While our numbers appear to be higher than these regulatory actions in the near term, the momentum for long term carbon reduction goals cuts the other way. E3's deep decarbonization report projects EV stocks out to 2050. In one scenario, they estimate the stock of EVs needed to decarbonize the LDV sector would be close to 320 million by 2050. In another scenario that uses a combination of EVs and fuel cell vehicles to decarbonize the LDV sector, E3 projects 200 million EVs. Both these scenarios require significantly larger stocks of EVs than presented in our low case. Our high case is slightly above E3's fuel cell / EV scenario but almost 75 million vehicles below their EV-only scenario 2050 stock estimate.

B. VMT ASSUMPTIONS

We next estimate how many miles each conventionally-owned electric vehicle in our stock will drive annually. In 2015, Idaho National Labs (INL) performed a survey that tracked the driving patterns of close to 15,000 PHEV and 7,000 BEV owners; we rely on the annual eVMT estimates that resulted from this survey to inform our initial-year eVMT assumptions. Overall, the three BEV vehicle models INL tracked (Nissan Leaf, Ford Focus electric, and Honda Fit EV) had very similar annual eVMTs averaging 9,640 miles. Conversely, the PHEV vehicle models INL surveyed had a wide range of annual eVMTs depending on the specific vehicle model analyzed. On the high end, the Chevy Volt had an estimated annual eVMT of 9,100 miles while the Toyota Prius PHEV had an estimated annual eVMT of 2,500 miles. Other PHEV models

⁶⁷ (IEA, 2016).

⁶⁸ Note the this represents a zero-emission vehicle mandate. We expect the majority of those vehicles to be EVs. (Trabish, 2017).

⁶⁹ (IEA, 2016).

tracked, including the Ford C-Max Energi and Ford Fusion Energi, had annual eVMTs closer to 4,000 miles.⁷⁰

The fact that these numbers are lower than the BEV estimates is not surprising. Ostensibly, one of the main advantages of PHEVs is their ability to travel longer distances by combining gasoline-powered engines with a battery pack. Due to the dual-drive trains, only a portion of these vehicles' annual miles traveled are driven using electric power, hence the need for an eVMT designation. While the Toyota Prius PHEVs surveyed averaged 2,500 eVMTs, they averaged 15,000 annual VMTs in total. On the other hand, BEVs only have electric drive trains and all of their VMTs are electric.⁷¹

The more surprising result was the large range in eVMTs between the different PHEV model types in the INL survey, though this outcome is most likely explained by the variance in battery size between the vehicle models. While the Chevy Volt has a 41 mile electric range, the Ford PHEV models have electric ranges closer to 21 miles and the Toyota has an electric range of only 11 miles. The U.S. Bureau of Transportation Statistics reports that Americans drive about 40 miles per person per day, an amount that would allow the Chevy volt user to drive on electric power throughout the day and then recharge overnight.⁷² The Ford and Toyota models could not operate in this way and thus require the use of gasoline more often to cover their mileage needs.

It is difficult to predict which PHEV type will be popular in the future and thus difficult to determine what the "correct" eVMT assumption is for our analysis. For simplification purposes, we choose a mid-point value of 5,000 eVMT to represent our annual eVMT value for PHEVs. We think this is a fair assumption as drivers of these vehicles will start to demand longer electric ranges. The Prius PHEV surveyed above has actually been discontinued by Toyota as of June 2015 and their latest model, named the Toyota Prius Prime, increased their electric range from 11 to 21 miles.

The eVMT values for both PHEVs and BEVs, though, are noticeably lower than the average VMTs of ICE LDVs today. For ICE cars in 2015, the average annual VMT was 11,327 miles and for SUVs it was 11,855 miles.⁷³ Current models of electric vehicles often do not have the same drive range as the ICE equivalent

Electric_Transport_Draft _10_5_17

⁷⁰ (Carlson, 2015)

⁷¹ (Carlson, 2015)

⁷² (U.S. Bureau of Transportation Statistics, 2001-2002)

⁷³ (U.S. Department of Transportation Federal Highway Administration, 2015) Table VM-1

vehicle due to the limitations of current battery technology. However, we expect the annual miles driven using electricity to increase as battery technology continues to improve and battery ranges increase. In order to capture the effect of battery improvement for the future years of our analysis, we fit a curve to projected battery energy density increases and use the percent increase over time to gross up the total electric vehicle miles for both PHEVs and BEVs. IEA expects almost a 68% increase in battery energy density by 2025, and we make the simplifying assumption that this density improvement will directly correlate with increased annual eVMTs for both BEVs and PHEVs.⁷⁴ Figure III-5 below shows the energy density improvement for batteries expected in the near term with our mathematical fit towards the long term. These assumptions are consistent with forecasts by BAML that project that average EV battery capacity will allow for a 296 mile range on all EVs by 2030 and well below A&S's prediction of 250 mile average range by 2020.^{75,76}





Electric_Transport_Draft _10_5_17

⁷⁴ (IEA, 2016)

⁷⁵ (Ma, Nahal, Tran, & Hill, Thematic Investing: Overdrive - Global Future Mobility Primer, 2017)

⁷⁶ (Albright and Stonebridge Group, 2016)

We then use the annual VMT for ICE vehicles as the baseline distance the average electric car owner would drive in a year under conventional ownership prior to autonomy. In other words, in this scenario we linearly trend annual eVMTs for PHEVs and BEVs from their current average levels to the average VMT of conventional vehicles in 2015 as reported by the FHWA. For BEVs, the large expected increase in battery energy density in the near terms leads EVs to achieve the same VMT as CVs before 2020. Therefore, in effect, we assume battery technology will not limit electric vehicle miles driven by BEVs from 2025 onwards and they will drive as many annual miles as a traditional ICE vehicle. However, though the large increase in battery density does significantly increase PHEV's annual eVMT, it does not reach the average VMT of an ICE vehicle as reported by FHWA within the time horizon we analyze. This result makes intuitive sense; if a car owner purchases a PHEV, we would not expect them to drive all their miles on electric power alone.

In addition to the baseline effect of relaxed range constraints on electric mileage, the operating costs of EVs is lower than CVs. Through common fuel price elasticity effects, we expect EVs to ultimately be driven slightly more than CVs, all other factors equal. As a result, we adopt most of Kim, el al's⁷⁷ estimate of 10% additional VMT from electrification's savings alone as a high case. Based largely on data on typical EV and CV costs in (Walker & Johnson, 2016) and (Binny, Kockelman, & Musti, 2011) our own simplified calculations of EV drivers' response to reduced fuel and operating costs is at this same approximate level even when slightly higher highway taxes are assumed.⁷⁸ This increase begins to take effect on all BEVs in 2025 and reaches 10% added VMT by 2040. In the alternative, we later assume that road pricing and other travel demand management policies erase the lower operating cost impact on VMT – clearly a lower bound.

C. ELECTRIC VEHICLE ENERGY INTENSITY PROJECTIONS

Even if we assume the ownership model will not change, as we assume in this chapter, EVs are likely to become steadily more energy-efficient over time. Present-day EVs have also been improving slowly but steadily over time and are already about three to four times as energy-efficient as their gasoline counterparts. In this section, without assuming any further changes in autonomy, ownership, or sharing,

⁷⁷ (Kim, Rousseau, Freedman, & Nicholson, 2015)

⁷⁸ See Workpaper D.

Electric_Transport_Draft _10_5_17

we consider trends in individual EV electric efficiency through 2050 as an input to our conventional ownership base case.

It is important to note that we are not yet including a number of long-term factors affecting EVs at this point. First, a large growth in ridesharing would reduce the number of total VMTs versus less sharing, but would also tilt use towards a vehicle stock that could have a higher fraction of larger vehicles. Second, many researchers believe that, once AV penetration removes most human-driven vehicles from the roads, safety will improve so much that cars can become much lighter, shedding protective materials. This would create a quantum increase in AEV efficiency. In short, we are computing likely evolutionary improvements in EI for EVs that will evolve organically from today's models.



Figure III-6: Historic EV Efficiency Data

Figure III.6 shows historic data on EV efficiency (kWh/mile) from two sources, Argonne National Laboratory's Autonomie data base (labeled DOE) and EPA's fueleconomy.gov. Fortunately, these data divide vehicles by size and type, allowing us to avoid confusing trends in fleet composition with trends in

⁴⁴ Electric_Transport_Draft _10_5_17

efficiency by vehicle type. There is also surprisingly good agreement between the DOE and EPA data, with EPA light trucks looking much like DOE SUV-300s and EPA cars looking like DOE midsize autos – likely LEAFs, Volts, and Teslas.

As the figures show, there is a relatively small historic sample of EV efficiency data and these data are somewhat noisy due to the fact that very few vehicles were manufactured in early years and the decision to offer even a single new EV for sale could greatly affect the average. Nevertheless, there has been a dramatic downward trend in EI in the past 20 years. We do not expect improvements to continue at this rate, but we do expect them to continue.

In Figure III.7, we show the ANL Autonomie forecast of EI through the year 2050. ANL creates low, medium, and high-efficiency predictions for each type of vehicle. While it is likely that many vehicles in the fleet will be PHEVs, we forecast efficiency for BEVs and assume that PHEVs show the same percentage efficiency improvements.⁷⁹ In effect, this forecast embeds an assumption that technology will continue to improve, but at a pace that declines slightly each year. This follows well-established theories of the returns to R&D and manufacturing learning curves, assuming there are no technology breakthroughs. While we agree that breakthroughs are certainly possible, we believe they are more likely to occur in connection with AVs, as explained in the nest chapter. We also later employ a high-efficiency case to reflect the very real chance of faster technical improvements.⁸⁰

⁷⁹ We also assume that all BEVs will have 300 mile ranges by the mid-2020s so we focus only on BEV-300s.

⁸⁰ An extensive non-technical discussion of lightweighting suggesting even higher efficiency potentials is in (Lovins, 2011) chapter 2.





(Source: Autonomie)⁸¹

Figure III.7 shows that most of the many vehicles types follow similar efficiency trends. According to the model, by the year 2050 electric cars will achieve an efficiency rate of 0.2 kWh/mile, SUVs will sit around 0.3 kWh/mile and pickup trucks will use about 0.4 kWh/mile, which is more or less equivalent to the efficiency of small SUV 100 (red circle) and midsize car 300 (blue diamond) right now.

To reduce complexity, we choose one representative auto sedan and one SUV types as the two composite archetypes in our model. ANL's medium and high-efficiency cases are plotted for both archetype vehicles in Figure III.8. In the figure we put unweighted average of Compact BEV-300 and Midsize BEV-300 into "Cars" and unweighted average of Small SUV BEV-300 and Midsize SUV BEV-300 into "SUVs". The bars on

⁸¹ (Autonomie, 2016)

the figure represent the range of different technology level, where the negative bar stands for high technology level and the positive bar stands for ORNL's low technology case.



Figure III-8: Forecasted Composite Models from Figure 7 Trends

The results in Figure III.8 track very closely with (EPRI & NRDC, 2015) results (see figure III-5); especially for passenger cars, where they estimate about 230 WH/mile in 2050. Their estimate for light trucks, 275 WH/mile, is well below our low end (just over 300 WH/mile) due to a jump in efficiency between 2017 and 2022 taken from AEO (U.S. Energy Information Agency, 2013) projections.

D. CONVENTIONAL OWNERSHIP PRE-AUTONOMY RESULTS

The combination of these assumptions represents the three main inputs to the kaya identity formulation presented in the above section of this report. Our EV projections, eVMT estimates, and expected vehicle energy intensities are multiplied by each other to calculate our conventional ownership base case (or

47 Electric_Transport_Draft _10_5_17 stage one) electricity consumption projections. Table III.9 presents five key metrics for the years analyzed: (1) the total stock of EVs; (2) the portion EVs makeup of the total stock of LDVs;⁸² (3) the average VMT / vehicle for the EV fleet; (4) the fleet's overall energy intensity; and (5) the total expected electricity demand.

Total Fleet Total Total Portion Number Average Fleet Number of Stock of AV in eVMT/ Average Total TWh EV Electric Case Year EV in Service Service Vehicle Efficiency TWh Bump (%) (peryr) (kWh/mile) (TWh) (TWh) 2015 406,076 0.2% 0 7,179 0.9 0.32 2025 17,086,996 6.6% 10,075 0.34 59.0 0 Base High 2030 52,378,548 19.7% 10,734 0.33 187.9 0 2040 166,919,164 59.6% 0 11,039 593.0 0.32 2050 251,742,035 85.4% 0 11,231 0.31 886.2 2015 406,076 0 0.32 0.9 0.2% 7,179 2025 7,063,273 10,061 2.7% 0.34 24.3 0 **Base Low** 2030 20,532,231 7.7% 10,729 0 0.33 73.6 2040 81,511,381 29.1% 0 11,049 0.32 289.2 2050 145,941,420 49.5% 0 11,236 0.31 511.7

0.9

59.0

194.0

651.9

973.8

0.9

24.3

76.0

317.9

562.3

Table III-9: Estimated Electricity Consumption

Overall, we project 2050 electricity demand of 890 TWh and 510 TWh in our high and low cases, respectively, without taking the 10% VMT increase into account. These figures represent roughly 23 and 13%, respectively, of the current electricity demand of 3900 TWh and 20 and 11%, respectively, of EIA's projected 2050 electricity consumption of 4,500 TWh.^{83,84} With the added effect of a 10% increase in VMT, the projected electricity demand is 970 and 560 TWh, comprising 22% and 12% of 2050 demand, respectively. One of our most surprising – and perhaps most incorrect – findings is that the interim results do not change very significantly when modified by the rest of our analysis.

⁸² Total stock of vehicles is taken from EIA's AEO 2017 projection.

⁸³ (EIA, 2016) Table 2.2

⁸⁴ (EIA, 2017)

On top of our interim electricity projections, it is important to highlight the other results from our conventional ownership analysis. In Table III.9, the VMT / vehicle changes asymmetrically year over year. The large jump from 2015 to 2025 is a result of the large increase in battery energy density that occurs between those two years. The relatively stable VMT / vehicle value from 2025 onwards shows the combined effect of the price elasticity effect result from cheaper EV operation as well as the assumption that PHEV models will likely never fully operate on electric fuel alone. While final eVMT number is higher than that of a conventionally owned ICE model, it is not as high as it could be if the fleet only operated with BEVs.

Furthermore, Table III.9 shows that the energy intensity of EVs does not decrease as dramatically as may be expected due to the projected improvement in battery technology. While it is true that our energy intensity improves year over year, the make-up of our electric vehicle stock also changes towards light trucks and SUVs which have considerably higher energy intensity than sedans. In effect, we find that the combination of these two trends basically cancel each other out, and the fleet's energy intensity over time remains relatively stable and even may increase in the short term – unless and until autonomy allows for radical change in vehicle design.

IV. The Impact of Autonomous Vehicles

A. INITIAL ASSUMPTIONS AND OVERVIEW

In this section we examine the power impacts of commercially available, fully-self-driving ("autonomous") light-duty vehicles. Of course, various levels of IT assistance to drivers is already sold in many LDVs, and it is universally agreed that successively more sophisticated systems will be sold each year until fully-autonomous, i.e. fully driverless vehicles are commercially available for use on designated roadways.⁸⁵ We oversimplify by treating the transition to AVs as a bright line before and after Level 4 or 5 AVs sold and allowed to be used with relatively few restrictions. This may well occur at different times in different cities and states across the U.S.; our projections are simply intended to show the national totals, increasing as the number of areas and vehicles sold both rise.

As part of this gross simplification we ignore changes in VMT or EI induced by autonomous features in LDVs that fall short of L4/L5 autonomy. Although it is possible that people will drive more in less-than-fully- driverless AVs, or that these vehicles may have higher or lower EI than comparable CVs, we do not invest in trying to quantify these effects in the years before fully autonomous AVs dominate. Also, partially and fully-autonomous commercial vehicles are already finding their way into many applications, and this trend is sure to continue, but we reserve this for later commercial and freight research. Finally, as noted in the introduction, we grossly assume that all AVs are electric, significantly biasing our electric power demand upward.⁸⁶

B. TIMING AND NARRATIVES

There is near-universal agreement that motor vehicles will ultimately be fully autonomous or self-driven. There is, however, a cacophony of opinions as to when and how the autonomy revolution will occur – not

⁸⁵ Although there is agreement that driver assistance IT features will increase, a minority of experts believe that fully-driverless vehicles will never reach unrestricted commercial operation. In this article we side with the majority on the question of whether driverless cars will ever be introduced but employ forecasts that show relatively slow growth.

⁸⁶ A few analysts predict that fully autonomous AVs may never be allowed to be sold to the general public. Should this occur, power demand will probably fall close to the range computed in the previous chapter.

to mention its implications for travel, the economy, and our built environment. As the most recent U.S. Department of Transportation long-range planning study concluded:

Continued introduction of automation features to vehicles will likely lead to improvements in safety and eventually could enhance the capacity of our roadways. While the technical feasibility of these features is becoming increasingly apparent, the timeline for the mainstream adoption of automated features and the impact of these features on safety, highway capacity and travel and settlement patterns remains unclear. The advance of these potentially transformative technologies makes it difficult for transportation planners to plan for long-term transportation system needs.⁸⁷

On one end stand highly optimistic writers such as Arbib and Seba (A&S, also known as "Rethink X") (Arbib & Seba, 2017) who predict that shared AVs will handle 95% of all passenger-miles by 2030, all but ending individual auto ownership. A&S are not alone; (Albright Stonebridge Group, 2016) predicts almost 100% VMT as "transport-as-a-service" (TAAS) by 2035, while Rocky Mountain Institute (Walker & Johnson, 2016) (Barclays, 2015) and (Bank of America Merrill Lynch, 2017) also predict relatively rapid, high-dislocation futures. At the other extreme, researchers such as (Litman, 2017) and (Niewenhuijsen, 2015) predict that 100% level 5 autonomy in the fleet will not occur until 2070 or later.⁸⁸ In between, analysts' estimates cover a very wide range of adoption trajectories between now and 2050, as illustrated in Table IV.1.

⁸⁷ P.207 (U.S. Department of Transportation) P.207

⁸⁸ Specifically, (Niewenhuijsen, 2015) convened a Delphi panel that predicts only 50% L5 penetration in the fleet by 2070, whereas (Litman, 2016) predicts 100% by this time. Niewenhuijsen's own econometric prediction is that 75% of sales are L4 or L5 by 2050.

Table IV-1: Forecasts of AV Penetration

Forecasts of AV Penetration								
	2020	2030	2040	2050	2060	2070		
	%AV	%AV	%AV	%AV	%AV	%AV		
Davis & Espinosa (2015)	25% (2012)	+75% (L3)						
IEEE (2012)				75%				
Kim et al (2015)				100% L4				
Bierstadt et al (2014)								
Greenblatt + <u>Saxena</u> (2015)				"Majority of LDVs could be ATs"				
Litman (2014, 2015, 2016, 2017)	<	Independent Mobiltiy Begins	50-75% of fleet, 90% of sales, 65% of travel	"Significant Mobility Increase due to Reduced Traffic" <	100% (2060)			
BAML (2017) ^f		30-40% (L3+)						
IHS (2016) ^c	0.1% (3700 vehicles)	5.4%, 1.6mm	4.5mm sales (2035)					
Milakiset al (2015) (Netherlands) ^d				61% of sales optimistic case				
Snelder, et al (2015) ^d					100% (2055)			
Nieuwenhuijsen (2015) ^d				75% of sales [simulation]		50% (2070) [Delphi]		
BCG (2015) ^e		10% of sales (2035)						
Bansal and Kokelman (2015)e				25%-87% of fleet (2045)				
Albright-Stonebridge		"Fifteen to twenty years" to commercial introduction						
Underwood (xxx) ^g	L4 introduced 2025		70% by 2045					
Johnson (2016)								
Elon Musk (2017)		100% of new cars "50/50 odds" L5 by 2025						

a p.25 b Fig 2 and 115.6mm US Households (HHs), p.11 c14/5 only. P5/7 and 3/7 d Nieuwenhuijsen (2015) p.43 and p.117 e Bansal and <u>Kokelman</u> (17) p.51, 49 f p.26 g Expert Panel Results, p.89 - level 4

The predictions in Table IV.1 are based on a wide variety of approaches, including consumer surveys, expert judgment and/or bass curve-fitting based on similar technologies and transport system changes, travel choice models, elasticity estimates driven by modal costs, and combinations of these and other approaches. As noted in chapter I, analysts stress that so little is known about cost trends for AV purchase and operation, the timing and degree of realization of AV benefits, and the pace at which our infrastructure can accommodate AVs, that penetration predictions are almost wild guesses. Changing

52 Electric_Transport_Draft _10_5_17 one or two key assumptions well within plausible ranges can change predictions dramatically, as when (Bansal & Kockelman, 2016) conclude that L5 vehicle penetration could be as low as 25% and as high at 87% of the 2045 fleet.⁸⁹

Beyond differences in numerical outcomes, however, some of these estimates come with somewhat concrete scenarios or narratives⁹⁰ as to how the AV market will unfold. In particular, A&S advance a robustly-argued view that the motor transport market, which now largely involves self-owned vehicles and fleets driven by owners or employees, will shift to a TAAS model at an astonishing speed. The A&S narrative is built around rapid reductions in the per-mile-of service costs of AVs, which will all be electric due to the large fuel and maintenance cost advantages and the ability to amortize ownership over a much longer mileage lifespan. They foresee full regulatory approval of self-driving cars by 2021, after which time the TAAS firms quickly convert essentially their entire fleets. By 2023, AVs are heading to what they call "mainstream adoption" and by 2030 shared AVs (i.e., TAAS) provide fully 95% of all passenger miles.

The scenarios at the other end of the prediction spectrum are much more conservative in their views of the speed of cost reductions, the timing of regulatory approvals, consumers' shift away from car ownership to TAAS, and the ability of urban infrastructure to accommodate AVs. In direct opposition to A&S, IHS principal analyst Jeremy Carlson predicts that "ownership [of vehicles by individuals and firms] in mature markets will remain strong."⁹¹ As an example of adoption paced by infrastructure, JN⁹² cites Shladover's (Shladover, 2015) specific prediction that L4 AVs will permitted only on some urban streets in the 2030s, while it will take until the 2040s until L4 and L5 AVs are permitted everywhere.⁹³

Between these two extremes there are several general narratives with many variations. Boston Consulting Group (Lang, et al., 2016) posits three futures. In the first, self-driving vehicles begin as self-owned luxury vehicles and gradually propagate into the LDV fleet as they become progressively cheaper. In this future, ride- and car-sharing does not take off substantially, current ownership models remain dominant, and the

⁸⁹ The variables Bansal and Kockelman changed were the rate of decline in AV costs and the willingness to pay for AV features. See their Table IV.2.

⁹⁰ We use these two terms interchangeably.

⁹¹ (IHS Automotive, 2016), p.3

⁹² (Niewenhuijsen, 2015)

⁹³ For additional studies discussing infrastructure pricing, see (Underwood, Automated, Connected, and Electric Vehicle Systems: Expert Forecast and Roadmap for Sustainable Transportation), (Litman, Evaluating Public Transit Benefits and Costs: Best Practices Guidebook, 2017) and (Kim, Rousseau, Freedman, & Nicholson, 2015)– as well as Chapter VI.

size of the LDV fleet grows or declines very little. Their second scenario, "Robo-Taxis Take Over," is essentially the A&S scenario above: extremely cheap TAAS using AVs and large ownership declines. Their third scenario, "Self-Driving Vehicles Rule the Streets," is essentially a hybrid in which cities and states accelerate self-owned AV uptake.

Importantly, the extent to which any of these scenarios (or, more likely, something in between) comes to pass is very much a function of socio-political factors that simply cannot be estimated from any sort of economic or deterministic model. If AVs capture the fancy of Americans and become the next "must have" technology, consumers will push policymakers to enable AV use and change the travel infrastructure, much as the "highway lobby" and car-loving Americans expanded roads and highways in the 1960s. Conversely, an effective political campaign by incumbents, a highly visible cyber- or physical disaster involving AVs, and/or fiscal gridlock over the funding of AV infrastructure could easily delay AV adoption.⁹⁴

Given all these considerations, the work we find most persuasive is Lavasani, Jin, and Du's (LJD)⁹⁵ estimates of Bass or "S-curves" using parameters selected by comparing AVs to other types of technologies, similar and dissimilar, for which there are full adoption histories. In brief, LJD fit a generalized Bass curve using parameters for the probability of adoption of AVs by initial users, an imitation factor that increases with penetration, an estimate of ultimate market size, the date of commercial introduction, the price difference between otherwise-similar CVs and AVs, and GDP growth. The equation employed by LJD, the parameters they selected, and a summary of their reasoning for each, are shown in Table IV.2 below.⁹⁶

 $N(t) = m \left(\frac{1 - e^{-(p+q)t}}{1 + \frac{q}{p} e^{-(p+q)t}} \right)^{96}$ The model equation is

. Source: (Lavasani, Jin, & Du, 2016) and (Jin, 2017)

⁹⁴ This point is also made by (Bansal & Kockelman, 2016) p.61

^{95 (}Lavasani, Jin, & Du, 2016)

Table IV-2: Parameters for LJD Bass Diffusion Model*

Parameter	Value	Summary Reasoning	
P – initial adoption probability	.001	Roughly midway between similar factor for adopti	
		of autos in 20 th century and adoption of HEVs	
Q - imitation factor	.34	Roughly the midrange of Q values from 8 studies of	
		alternative vehicle adoption rates	
M – market size (vehicles)	87 MM	75% of 2015 U.S. households	
Price difference between CV	31%	Assumed AV price premium	
and AV vehicles			
GDP per capita	8.913	U.S. Data	

Figure IV-3: Forecasted AV market penetration curve



Source: (Lavasani, Jin, & Du, 2016) Figure 2

The results of LJD's base estimate, shown in Figure IV.3, is that cumulative AV sales rise from 1.3 MM in 2030, five years after introduction, to 70 MM by 2045 and saturation by 2060. With the possible exeption

55 Electric_Transport_Draft _10_5_17 of the 2050 flattening out, this result looks reasonable from a variety of standpoints. The commercial introduction date is close to the prediction of many observers, including Tesla's founder, Elon Musk. LJD thoughtfully selected parameters for their model based on the actual sales ramp for the Toyota Prius, the largest-selling breakthrough in motor vehicles in a generation, and then amped up adoption estimates using parameters taken from the adoption history of cellphones and internet. Their estimates are consistent with IHS (2016), which projects 21 MM global AV sales (vs LJD's 8 MM in the U.S.) They are roughly between McKinsey high- and low – disruption forecast from 2016.⁹⁷ A

If there are items to question in the LJD forecast, it is the post-2045 flattening. This is of course tied to their estimated total assumed market size of 87mm homes, which we believe is not strongly justified. We therefore continue AV growth linearly at the 2040-45 growth rate through 2050, the end of our forecast horizon.





Source: (Davidson & Spinoulas, 2015) Figure 2.1

Ironically, perhaps the most appropriate revolutionary transport technology to compare AVs to is the introduction of cars themselves. The displacement of animal transportation by autos was as large a revolution in its day as autonomy will be in ours, and otherwise bears as much similarity to the introduction of autonomy. As shown in Figure IV.4,⁹⁸ autos took about 25 years to reach 60% saturation.

⁹⁷ (McKinsey&Company; Bloomberg New energy Finance, 2016) Exhibit 6

⁹⁸ Figure 2.1 of (Davidson & Spinoulas, 2015) originally from Felton (2008).

Electric_Transport_Draft _10_5_17

This is important because, unlike most of the technologies in Figure IV.4, autos required the construction of a huge new physical infrastructure -- paved roads, parking lots, traffic signals, and so on. Electric power was another technology requiring a new, capital-intensive physical network, and it, too, took about 25 years to reach 60% of homes. Cell phones, which took only 20 years to reach 90% saturation, needed another new infrastructure, but one that could lean heavily upon the existing power, telephone, and internet networks with relatively little physical disruption. LID's estimate for AVs shows it reaching 60% saturation about 18 years after commercial introduction. That's about one-third faster than autos and roughly as fast as the internet and probably about as fast as can realistically be expected.

LID do not take an explicit position as to whether AVs will supplant all CV sales by then, nor a position as to whether all AVs will be EVs. The EV question is not so controversial -- most observers think that almost all AVs will also be EVs by the 2040s if not sooner, and we agree. However, their market size is based on a count of 75% of current U.S. households. This implicitly rejects a scenario in which ownership plummets and robotaxis dominate all transport. It also implies that the remaining households either drive non-autonomous gasoline, hydrogen, or electric vehicles and/or use ridesharing. One reason we do not worry about the ownership model is that the modeling exercises in the literature seem to show that a switch from personal ownership to an autonomous taxi (AT) fleets greatly reduces the total number of vehicles in the fleet but does not reduce overall VMT; see chapter V for further discussion of dynamic ridesourcing, sharing, pooling, and seamless mobility.

C. VMT CHANGES FROM AUTONOMY

There is widespread agreement that vehicle autonomy will trigger significant changes in the travel patterns of many Americans (along with changes in EI, explored later). Some of these changes will reduce VMT, while others are expected to increase it significantly.⁹⁹ Tables IV.5 and IV.6 show two taxonomies of AV VMT effects from (Kockelman K. M., et al., 2017) and (Litman, 2017) respectively.

⁹⁹ From the energy standpoint, what counts most is the miles vehicles travel and the energy used per mile. The number of passengers in the car is not important from the EI standpoint, except insofar as adding passengers in one vehicle causes a second vehicle to travel less. If so, the effect is fully reflected in VMT, so for the moment we need not focus on passengers per vehicle or passenger-miles *per se*.

Table IV-5: Factors Influencing VMT

Factors Potentially Increasing VMT

Vehicle miles traveled are influenced by a variety of factors, and CAV technology is most likely to affect VMT through changes in these factors. Influences that could increase VMT include:

- Increased travel demand. Automated vehicles promise to make transportation more convenient and affordable, particularly within car sharing or self-driving taxi programs. Self-driving cars (and other vehicle types) will eliminate one of the biggest transportation costs, the value of time, by giving people the opportunity to engage in other activities while traveling – such as work, sleep, and play. People will have fewer incentives to minimize or optimize their travel, thus potentially increasing vehicle travel (Ecenbarger 2009, Ohnsman 2014).
- Zero-occupancy VMT. If automated vehicles perform many empty trucking backhauls return trips without cargo or passengers – VMT could increase due to empty vehicles traveling between a drop-off and the next pick-up.
- Reduced trip chaining. Automated vehicles could lower incentives for trip chaining (making stops on the way to another destination) by making zero-occupancy trips possible. For example, a selfdriving vehicle could take one family member to work, then return home empty to take another person to work or to school, etc. This effect would be smaller in a car sharing or self-driving taxi scheme than with private vehicle ownership, but it still could increase VMT.
- Shift away from public transportation and nonmotorized modes. Increased convenience and affordability could make self-driving cars more attractive transportation options than transit, biking, or walking. A shift away from public transportation and toward lower-occupancy automated vehicles will increase travel. Self-driving transportation also promises to provide a solution for firstand-last-mile travel (the challenges of getting a commuter to and from a transit hub). While this can be seen as a desirable outcome, it may also increase vehicle travel as more people choose self-driving cars even for short trips that could be completed by walking or biking.
- Urban form and development patterns. Because people would be able to engage in other activities while traveling in fully automated vehicles, they may be more willing to accept a longer wor commute in order to live in a more affordable home. This would give an incentive for urban sprawl, and in turn would generate more miles of travel. This is particularly likely for multiperson household for which the members of the household travel in different directions for work, school, etc.
- Location of parking facilities. Fully automated vehicles could make onsite parking obsolete because vehicles will be able to park themselves outside of downtown or other congested areas. If, however, these satellite parking facilities are located far from points of interest like office centers, residential, or commercial areas, VMT could increase due to empty backhauls.
- Private ownership of automated vehicles. Private ownership of automated vehicles would not
 raise VMT directly, but it may magnify the impact of other factors described in this section. For
 example, the private owner of a fully automated vehicle might choose to send the vehicle back home
 during the day to avoid expensive downtown parking.
- Increased mobility of nondrivers. Automated vehicles would offer underserved populations, such as those under age 16, senior citizens with difficulties driving, and persons with disabilities, greater opportunity to travel. While this has many benefits for society, it would also increase VMT.

Factors Potentially Decreasing VMT

While automated vehicles clearly have a significant potential to increase VMT, they also are likely to affect some factors in the opposite direction—reducing VMT.

- Pay-per-use self-driving vehicle programs. Provision of car sharing, taxis, and ride hailing services via automated vehicles are likely to discourage unnecessary travel, because people would have to evaluate the added value of each trip and pay for each one taken.
- Lower car ownership. If people own fewer vehicles due to a proliferation of car sharing options, unnecessary travel could be reduced.
- Increased vehicle occupancy. Connected and automated vehicles in car sharing or taxi fleets are likely to have technologies that make carpooling more convenient. They will have optimized route planning, making sharing part of a ride with another passenger more convenient and cheaper. Companies like Uber and Lyft that are developing self-driving taxis are already proposing services for shared rides, such as UberPOOL and Lyft Line, that will become even more attractive with automated vehicles.
- CAVs used as first-and-last-mile solution in combination with public transportation. If CAVs are used as feeder services to transit routes and not to replace entire trips that could be completed with transit, travel may be reduced. Adding a ride in an automated vehicle at the first-andlast-mile to a transit ride could offer a transportation solution appealing enough for some people to forego travelling solely by car.
- Fewer vehicles. Assuming CAV car sharing or taxi fleets become prolific, there will be fewer total vehicles on the road, thus tending to reduce VMT.
- Less travel related to searching for parking. One of the features that CAVs are likely to offer is the ability to easily locate available parking and drive to it. That will eliminate miles spent looking for parking.

Table IV-6: Autonomous Vehicle Impacts on Total Vehicle Travel

Autonomous Vehicle Impacts on Total Vehicle Travel					
Increases Vehicle Travel	Reduces Vehicle Travel				
More convenient and productive travel (passengers can rest and work) will reduce travel time costs, stimulating more vehicle travel.					
Provides convenient vehicle travel to non-drivers (people too young, old, disabled, impaired, or otherwise lacking a drivers' license. Sivak and Schoettle (2015c) estimate that, accommodating non-drivers' latent travel demands could increase total vehicle by up to 11%.	More convenient shared vehicles allows households to reduce total vehicle ownership and use. Increases vehicle ownership and operating costs, further reducing private vehicle ownership.				
Self-driving taxis will travel more for empty backhauls.	Self-driving transit vehicles improve transit services.				
Can make sprawled, automobile-dependent locations more attractive.	Reduced pedestrian risks and parking demands makes urban living more attractive.				
Reduces traffic congestion and vehicle operating costs, which induces additional vehicle travel.	Reduce some vehicle travel, such as cruising for parking spaces.				

Self-driving vehicles can affect total vehicle travel (VTM) in various ways.

Source: (Litman, Evaluating Public Transit Benefits and Costs: Best Practices Guidebook, 2017). p 8.

Many researchers have estimated some or all of these travel impacts. As with forecasts of AV sales, they have employed every conceivable approach and arrived at an extraordinarily wide set of estimates. At the high end, both KPMG (KPMG, 2015) and A&S estimate that the net effect of all these factors will

Electric_Transport_Draft _10_5_17

¹⁰⁰ (Greater Ann Arbor Region Prosperity Initiative , 2017)

double VMT and passenger-miles (respectively) by 2050. Albright-Stonebridge (2015) summarized the phenomenon of VMT increases from AVs as follows:

Though this is the main view expressed by researchers, an increase in VMT should not be taken as the automatic result of AVs, since policymakers may be motivated to disincentive some or all of possible increase in VMT, using a range of policy tools enabled by 'smart' cars, such as taxation or fees on a per mile basis. How much of a social and environmental impact shifts in VMT ultimately have depends on the size of the VMT increase, the resulting increase in demand for new roads and far-flung development (i.e. sprawl), and the emissions profile of Level 4 AVs.¹⁰¹

Other researchers find much smaller effects, though most agree (or at least suspect) that the net effect is likely to be significant and positive. Contrarily, the most recent long-term plan from the U.S. Department of Transportation does not list autonomy as one of the most important drivers of increased VMT through 2045 – instead emphasizing population growth, aging Americans, and telecommuting.¹⁰²

With some license, it is possible to parse the mileage effects of autonomous vehicles into a relatively small number of rough categories. Appendix A shows each of these categories as a row, with estimates of VMT impacts from different researchers shown in each column. In order, the effects are:

Row A: Increased travel due to effective road capacity expansion due to automation;

Row B: Increased travel due to Lower costs of travel per mile, excluding the driver's time;

Row C: Urban Travel induced by Decreased cost of Driver's Time, incl. parking search;

Row D: Induced Intercity Mode Shifts Due to Decreased Drivers' Time Costs;

Row E: Induced Travel Due to Lower Costs of Serving "Underserved Populations";

Row F: Empty Travel by AVs; and

Row G: Reduced VMT Due to Automated Parking Searches;

Row H shows aggregate VMT effects, when authors provided them, combining the effects they studied.

There are at least two long-term effects of automation on VMT that are conspicuous in their absence from our table. The table does not contain a row showing the effects of long-term urban design changes nor

¹⁰¹ Arbib and Seba p.21. For a well-argued view that AV-induced VMT increases will be fully offset by other factors, see (Litman, 2016).

¹⁰² (U.S. Department of Transportation), p.133

Electric_Transport_Draft _10_5_17

one for shifts to mass transit enabled by integrated multimodel systems – that use AVs for the "last mile." For example, there is quite a lot of research suggesting that AVs will eventually enable narrower road lanes and greatly reduce total paved surfaces. This would allow for greater density and more greenspace in urban areas, promoting lifestyles that rely less on motorized transport. We defer further discussion of these topics to Chapter VII.

While all of the numbers in the table are expressed as percentage increases in VMT due to one isolated factor, the table in Appendix A does not pretend to be a complete meta-study, and the entries reflect vastly different techniques, assumptions, and annual values that serve as the basis for the percentage result shown. Interested readers will want to consult the notes to the table carefully, and often the full underlying source documents.

The first effect shown on Row A is the effect of increased road capacity. AVs will effectively increase the capacity of current roadways because AVs can travel smoothly at close intervals, navigate intersections automatically, and otherwise manage traffic more intelligently. AVs will also be able to automatically reroute themselves (if allowed) to even out traffic flow. In other words, roads will ultimately have greater throughput at faster overall speeds once autonomy is widespread.

Part of this effect does not require that roads be congested; uncongested roads may also allow for more rapid travel, inducing greater demand. Crossings, intersections, and merges may also flow more smoothly and quickly. Moreover, greater effective roadway capacity induces travel wherever roads are congested. Additional travel is induced until the roadways fill up to the same equilibrium level of congestion and travel times as was in place prior to the capacity expansion.¹⁰³

These effects are essentially impossible to quantify well, as to either magnitude or timing, because they are so dependent on the evolution of both the road system and AV penetration levels, area by area. (Kim, Yook, Ko, & Kim, 2016) performed a fascinating simulation of the effect of closer vehicle headways on traffic speeds in Korea on "national highways" (similar to noncongested interstate highways in the US) and "expressways" (similar to US congested urban freeways) as a function of the penetration of AVs.

¹⁰³ See (Litman, 2017) for a good recent survey of induced travel studies.

Road type	Target headway	Proportion of the autonomous vehicles						
		0%	20%	40%	60%	80%	100%	
National highways	0.5s	1.00	1.07	1.15	1.26	1.42	1.67	
Express ways	0.5s	1.00	1.04	1.10	1.18	1.25	1.39	

Table IV-7: Autonomous Vehicle Penetration and Vehicle Speed Increases¹⁰⁴

Table IV.7 shows the percentage increase in traffic speeds as the percentage of AVs in the traffic stream rises. For 0.5 second headways, the table shows that speeds increase more than linearly as AV penetration increases. Of equal interest, the simulated increase in speed (and therefore throughput) was quite large at 100% penetration – 67% and 39% for national highways and expressways, respectively. An increase in road capacity reduces congestion, inducing more people to drive and – at least in conventional vehicles – often equilibrates back at similar but enlarged congestion. Increased capacity due to AVs thus ought to increase VMT by allowing more vehicles to traverse the same route even if average speed does not increase.

As Row A in Appendix A shows, apart from (Kim, Yook, Ko, & Kim, 2016) the few researchers who have attempted to isolate the VMT increases from effective capacity expansion have not found very large effects. It is possible that these effects have been lumped into other categories, such as increased travel due to time savings or higher speeds, which in turn translate into time savings¹⁰⁵. Due to surprisingly few and small magnitude results in the literature and the possibility that capacity effects may be subsumed into the effects of other rows on the table, we do not adjust VMT separately for this autonomy effect. It does seem likely that the effects of increased capacity are likely to be felt mainly where AVs concentrate early, or when overall national concentrations begin to become significant. In our view, this is late in our forecast window, so in our view the downward bias from omitting this effect alone lies outside of our timeframe.

¹⁰⁴ (Kim, Yook, Ko, & Kim, 2016)

¹⁰⁵ This would make sense because increased roadway capacity induces travel because it enables more cars to travel within the same time period, i.e. the value of increased capacity is the time savings it creates.

Row B of the table, reduced AV per-mile costs, requires a parsing of EV and AV effects. Setting aside more rapid travel (row A) and the former-drivers' time savings (Rows C,D), the main two sources of lower costs for *passenger-owned* AEVs will be the fuel and maintenance savings provided by EVs (whether or not autonomous) and ultimately lower insurance costs for AEVs (only). The first of these savings was included in our conventional ownership base case above. Some of the fuel savings are gas tax savings, and these are very likely to be replaced by some sort of fee in order to fund deferred road system maintenance and the costs of AV-specific infrastructure. We examine the impacts of this possibility separately in Chapter VI.

The net effect of all this is that only lower AV insurance costs, which are highly likely to be assessed as a lump sum, are a savings attributable to AVs alone. For quite some time these are likely to figure more into purchase decisions (hence AV adoption rates) rather than incremental driving. As a result, we do not adjust VMT for this effect.

Most importantly, fully autonomous vehicles will induce greater travel by freeing up the time of the person who would otherwise drive the car (Row C). This effect has captured the imagination of travel forecasters, who forsee an era when commuters use their time in vehicles to sleep, watch TV, work, and so on. A&S (2017) talk about roving entertainment parlors and "Starbucks on wheels."¹⁰⁶ As travel planner Stelios Rodoulis puts it, "AVs will become a place of activity rather than just a means of transport."¹⁰⁷

As a result of these new uses of former drivers' time, automated vehicles may also change where people live and the distances they are willing to travel. This could lead to increased settlement of exurban areas and reductions in agricultural land and open space.¹⁰⁸ Many researchers have observed that the time commuters are willing to travel to and from work has remained relatively constant across many decades and countries. (Laberteaux, 2014) points out that workers have been willing to travel and average of 1.2 hours/day for about the last 200 years. Each time a new travel mode allowed for more rapid commuting, the average commuting distance has expanded until this average duration was reached. Litman calls this effect "Marchetti's constant."¹⁰⁹

¹⁰⁶ (Albright Stonebridge Group, 2016) p.21

¹⁰⁷ (Rodoulis, 2014) p. 12

¹⁰⁸ (U.S. Department of Transportation), p.83-4.

¹⁰⁹ (Litman, 2014)

Electric_Transport_Draft _10_5_17

Estimates of the travel induced by freeing up drivers' time vary mainly due to different estimates of the quality and value of the time in AVs relative, to time at home or the office, and to differences in elasticities of added travel due to reduced effective commute time. A survey-based study by Milakis, et al. suggests that commuters are quite varied in their tolerance of different commuting periods, though travelers with the longest commutes were least happy.¹¹⁰ Dissatisfaction with longer commutes will undoubtedly decline significantly for some commuters while many others will probably not change their travel habits.

Figure IV.8 shows one research team's estimated changes in VMT as a function of AV penetration (which enables greater traffic flow efficiency) and the "value of travel time reduction." This value is expressed as a fraction of the driver's wage rate, ie. a value of 0.5 on the horizontal axis means that an hour in the AV working or recreating is worth one-half the value of an unfiltered hour of work or recreation. At that value of time, the figure shows a predicted 2.5% increase in VMT with 20% AV penetration and about 12% increase at 75% penetration.

As shown in Appendix A, these differences yield a wide range of VMT increases, from 4% to 46%. Without pretending to have anything approaching the mean of a well-defined distribution of outcomes, we adopt three time-savings VMT cases: low (+15%), mid (+20%) and a high sensitivity (+40%) discussed later, all referring to the ultimate 2050 VMT effect. These estimates do not yet incorporate the effects of pooling, which could affect this quite significantly, as discussed further below.¹¹¹

Figure IV.8 suggests that we should implement VMT increases from time savings proportionately to AV fleet penetration, back-loading these increases into the out years. In the present version of the model we do not do this. Rather we implement the ultimate level of VMT increases for each AV as it joins the fleet.¹¹² This boosts average annual VMT for each AV from about 11,700 to about 14,000 miles per year in the

¹¹⁰ (Milakis, Cervero, van Wee, & Maat, 2015)

¹¹¹ This estimate seems plausible based on elementary elasticity calculations. (Litman, Evaluating Public Transit Benefits and Costs: Best Practices Guidebook, 2017) suggests that a shortcut for computing travel induced by time savings is to monetize the time savings and apply a long-run elasticity of -0.3. Suppose the average driver commutes for one hour, the average wage is \$20, all monetary vehicle costs equal \$0.85/mile (Walker & Johnson, 2016) Figure 8, and AVs effectively free up 66% of drivers' former time behind the wheel. Time savings are then 30% of the cost of the trip and induced travel is + 9%. Recognizing that these may be underestimates, the figure we employ is double this. It is difficult to see this particular effect getting much larger than this.

¹¹² As an example, (Kockelman K. M., et al., 2017) p. 128 cost-benefit analysis of AVs assumes that VMT increases occur on a per-vehicle basis, changing relatively little between 10% AV penetration levels (+20%/vehicle) and 90% penetration levels (+10%/vehicle).

+20% case.¹¹³ This has little effect on our 2050 estimates, but could bias our near-term power estimates upward.

Figure IV-8: (a) VMT change and (b) VHT change vs VOTT change by market penetration (no capacity change)¹¹⁴



The same driver time savings effect is predicted to cause some travelers to shift from current intercity modes (primarily airlines) to self-driving cars for some intercity trips (Row D). Stephens, et al¹¹⁵derive an *upper bound* estimate of 3% of current LDV VMT, but La Mondia, et al¹¹⁶ contains detailed Michigan state trip and survey data that allows for what we think is a more realistic calculation of about 0.6%.¹¹⁷ While

¹¹³ It is also interesting to consider how income inequality affects the value of time and thereby AV choice. Highlypaid, time-starved workers are much more likely to purchase full AVs and use the time productively while in them, but they also will be sensitive to the length of time in their vehicle even if they are working. As Laberteaux (2014) predicts, the commuting VMT effect will probably be largest for the same low- to middle-class commuters who now commute long distances so they can choose communities and schools where they want to raise their families. ¹¹⁴ (Auld, Karbowski, & Sokolov, 2016) p. 10.

¹¹⁵ (Stephens, Taylor, Moore, & Ward, 2016)

¹¹⁶ La Mondia, et al (2015)

¹¹⁷ See Workpaper B for calculations based on LaMondia.

this is a relatively small VMT effect, Perrine and Kockelman¹¹⁸ speculate that AVs could cause as much as a 30% drop in airline revenues from these short trips. Due to the modest projected size of this effect we do not add VMT increases beyond the three cases just discussed.

The next element increasing travel is AV's ability to provide travel to so-called underserved populations, namely the young, elderly, and disabled (Row E). According to the National Academy of Science¹¹⁹, about 3.6mm Americans use a wheelchair and 11.6mm more use a cane or walker.¹²⁰ One third of all current Americans have a mobility disability, and this group is expected to grow by 77% by 2045.¹²¹ It should be noted that many members of these groups today ride in conventional taxis, chauffeured cars, or shared-ride services. Accordingly, a more accurate way to describe this factor is that autonomy will lower the costs of travel for these underserved groups, and through a traditional price elasticity effect these groups will use autonomous shared-ride services more intensively.

Although autonomous taxis are expected to be cheaper and more ubiquitous (hence faster service) than human-driven taxis, it is worth noting that the absence of a driver will change the quality of service to these same underserved segments. Some passengers benefit from the ability of a driver to help them into and out of cars, and parents may feel safer having someone else in the car with their dispatched child. These considerations temper our willingness to endorse the high end of VMT gains for underserved populations.

As shown along Row E, a number of researchers have estimated the percentage effect of this factor. KPMG and BGR use survey data and a literature review to estimate very large increases in travel by young non-drivers and the steadily increasing ranks of elderly Americans, yielding as much as 50% increases in VMT. Analyzing NHTSA survey data and other calculations, Sivak and Schoettle (Sivak & Schoettle, 2015) and Harper, et al. come up with estimates in the 10-15% range. Without pretending to have any claim on accuracy, we judgmentally select relatively conservatives value of 8% and 15%, respectively, for VMT increases in our low and mid scenarios. Because we think it will take a few years for these underserved

¹¹⁸ (Perrine & Kockelman, 2017)

¹¹⁹ (Alonso-Mora, Samaranayake, Wallar, Frazzoli, & Rus, 2017)

¹²⁰ The Academy also notes that autonomous and shared mobility services may not be a service improvement for riders who need a drivers' assistance to enter and leave the vehicle, and that other regulators considerations affect this balance. (p.86)

¹²¹ (U.S. Department of Transportation) p.14.
populations to become comfortable with intensive AV use, we phase in these per-vehicle increases linearly over the first ten years of commercial AV use.

Finally, Rows F and G show the final two isolated AV VMT effects reported in the literature, empty vehicle backhaul and reduced parking search. These estimates come from one literature review (Stephens, Taylor, Moore, & Ward, 2016). In view of the fact that these two effects are estimated to be very similar in size and of opposite sign, we treat them as net zero in our work and do not analyze them further.

Table IV-9 summarizes our treatment of VMT increase factors.

	Low			Mid
AV VMT Effect	impact	Timing	Impact	Timing
Road Capacity Effect	0		+5%	
Lower Time Cost for Driver		per		Linear Phase in 2040-
(Intra- and Intercity)	+ 15%	vehicle	+20%	2050
		per		
Increased Access	+ 8%	vehicle	+15%	per vehicle
Total	+23%		+40%	per vehicle

Table IV-9:Assumed VMT Effects of AVs

Before leaving the topic of VMT, we note that the VMT effects here do not factor in several important effects likely to offset some and perhaps most of these increases: ridesharing, urban redesign for lower travel; telecommuting, and infrastructure pricing. Each of these effects are explored in later sections.

D. THE EFFECT OF AVS ON ELECTRIC INTENSITY

Categorizing AV El Effects

Autonomy is predicted to affect greatly the amount of energy (most likely, electricity) used *per mile* of travel by any given vehicle type. To illustrate, the question here is how much kWh use will differ between a fully-autonomous four-passenger sedan and a conventionally-driven four passenger sedan, both of similar size and user attributes and both driven between the same two destinations. Once again, we note that sharing and new ownership models are not yet factored in; we are simply trying to get our arms around the impact of autonomy on per-mile vehicle kWh use.

There are a variety of reasons why electricity use per mile is predicted to differ. Although the effects are sometimes categorized and often named differently, five multi-faceted and somewhat overlapping categories stand out in the literature:

- Traffic Smoothing- reducing braking and acceleration in urban areas at low as well as high average speeds;
- Intersection Management reducing braking, acceleration, and stops due to better intersection management; can be considered a subelement of traffic smoothing;
- Higher Average Speeds faster travel on uncongested highways at speeds where aerodynamic drag takes a measurable energy toll;
- Platooning multiple cars or trucks driving close enough together at high speeds to reduce drag on the vehicles following the leader;
- Rightsizing/Performance designing and manufacturing AVs that have smaller powertrains and therefore smaller batteries than conventional counterparts; and
- Lightweighting designing and manufacturing AVs that have lower weights due to the absence of conventional vehicle safety equipment and therefore higher efficiencies.

These are far from distinct categories. There is a fine line between improving electric efficiency by avoiding braking and acceleration and reducing it by enabling traffic to go fast enough to increase drag. Similarly, it may be impossible, either in retrospect or prospect, to separate the EI effects of rightsizing vs lightweighting.

The results of literature reviews examining the size of these effects are summarized in Table IV-10. Note that all these effects do not assume or require any differences in vehicle form factors, occupancy per vehicle, or trip choices. This is purely the result of an AEV operating differently than a CV with an otherwise identical carrying capacity. One additional category, onboard electricity loads unique to AVs, is discussed briefly below.

As distinct from some of the AV effects on VMT, autonomy's EI effects appear to be sensitive to the fraction of AVs in the fleet in their locality. Kyung-Hwan Kim, et al's¹²² simulated effects of AV concentration on average travel time, shown in Table IV-7, demonstrate that urban travel time savings increases nonlinearly with AV concentration. This roughly corresponds to the traffic smoothing element of EI; the higher average speeds in Kim's simulations are the result of fewer slowdowns and stops. Intersection management will also improve as the fraction of AVs improves, and rightsizing and downweighting will occur more as CVs decline as a percentage of the fleet. More completely, AVEI

¹²² (Kim, Yook, Ko, & Kim, 2016)

benefits appear to vary with a combination of AV concentration and traffic conditions, as noted in this communication from Prof. Christos Cassandras:

Under heavy traffic conditions, the benefit of CAVsis minimal and may even hurt because of the conservative way that CAVs operate to ensure safety.

Under light traffic conditions, the benefits of CAVs manifest themselves with as low a penetration rate as 10%, which is really encouraging if we can confirm it. In terms of energy consumption, the improvements are of the order of 40%.

As traffic intensity increases, the critical penetration rate also goes up. There is a critical traffic level at which one needs 100% penetration to match conditions under non-CAV presence. It is still too early to tell whether this "critical level" is high enough to argue that most of the time such heavy traffic conditions do not occur. One argument to make is that if we can lower congestion while traffic is still relatively light, then the probability of reaching that "critical level" is reduced!¹²³

When examining AV EI effects, we must therefore be attentive to at least these three parameters: the point at which AVs are concentrated enough to begin to change EI; the terminal level of EI changes when AVs saturate; and the shape of the curve between them. We discuss each of these below, but our approach to these parameters is mainly to use the literature to give us a final level of EI effect at AV saturation and then use linear phase in effects from the inception of commercial AVs in 2025. We do not adjust for the average level or variability of traffic on any road segments.

¹²³ Email from C. Cassandras; posted online with workpapers.

Table IV-10: Estimates of Energy Intensity Impacts of AVs

	(Percentages as reported by autions, baselines vary)					
		Stephens ^b	MWL ^g	BGR ^k	Greenblatt and Saxena	A&S (2017)
A	Generalized Traffic Smoothing	-16% ^c	-10% ^h	-15% ^l		-20%*
в	Intersection Management	2%-6% ^m	NA	NA	NA	
С	Higher Average Speed ^a	+8% ^d	+4 to 25% ⁱ	+30% ^m		
D	Platooning	-2.5% ^e	-12%	-10% ^k		
E	"Rightsizing" and Performance	-50% ^f	-33% ⁱ	-50%	-45% ^l	
F	Weight Reduction of Vehicles	-50% ^r	-33% ⁱ	-50%	-45% ¹	

Estimates of Energy Intensity Impacts of Avs

*Citing Gonder, Earleywine, and Sparks (2012)

*Includes reduced sstop-starts, acceleration, and intersection V2I/V2V improvements, so combines two categories within Stephens (206) and other papers. Full automation. *Stephens, et al (2016) omits collision avoidance (upper bound 0-2%)

Midpoint of full automation estimate. Figure 8

⁴Sum of intersection V2I/I2V and drive profile

*Midpoint of platooning full automation bar. Figure 8

'Midpoint of vehicle resizing bar. Figure 8

*Midpoint between strong response and dystopian nightmare scenarios Table 3 p. 14; ignoring crash avoidance and "congestion mitigation" (0 to '-4% across their four scenarios) *Eco-driving

Highway speeds. Note there is zero effect in other scenarios

Product of performance improvements (.885) and rightsizing (.775)

*Brown, Gonder, and Repac (2014). Platooning is 10% average overall saving potential (Table 1, row (a))

'Efficient routing plus efficient driving (Table 1, row (b) + ©))

"Faster travel (Table 1)

Greenbalt and Saxena p.860

"pp.20-21, upperbound at full

Traffic Smoothing

The first category is traffic smoothing, also various called – or combined with – "Eco-Driving," increased capacity, or increased traffic throughput. AVs are expected to move more efficiently than human-driver cars, collectively as well as individually. Due to their ability to see and respond to traffic conditions immediately and smoothly break to stop, turn, and avoid collisions, AVs are expected to be able to accelerate less often, and perhaps less quickly, and brake less often and less severely than otherwise-identical CVs. They should thereby require less juice than a CV to traverse an otherwise-identical route with otherwise-identical traffic – although, once AVs get to an as-yet unknown tipping point, traffic will not be otherwise identical.

To make matters more complex, there appears to be evidence of an opposing effect of AVs on EI during the period before AVs are plentiful enough to significantly improve throughput, namely AVs leading to greater initial congestion. This effect would occur in the early stages of AV introduction, when commuters immediately realize that they have more productive time while commuting and therefore are more willing

> 70 Electric_Transport_Draft _10_5_17

to travel further and a little longer, hence less concerned with traversing congested routes. The effect would presumably be erased as the number of AVs and the amount of AV-dedicated infrastructure increases to the point where the added initial congestion is erased by added throughput capacity.

In a fascinating exercise, (Auld, Karbowski, & Sokolov, 2016) (AKS)¹²⁴ document this phenomenon using an activity-based transportation model of the Ann Arbor, Michigan urban area. The model simulates 1.2 million trips with on an average day for the 290,000 travelers in Ann Arbor's county. The model also allows travelers to choose more or longer trips in AVs in response to them reclaiming the value of the time they would have spent driving. Former drivers can alter their routes and/or trips in response to their newfound time, with their cost of time during travel reduced by assumed levels of 25% to 75%.

This trip choice model produces an extremely detailed profile of each trip, namely the speed profile of each trip on a minute-by-minute basis as that trip proceeds through congested and uncongested roads and intersections. AKS then link these time-and-speed trip profiles to Argonne National Lab's Autonomie vehicle energy use simulation software, which translates each trip for each vehicle into an extremely detailed accounting of kWh use during that trip. AKS model a number of scenarios with different penetrations of AEVs and different time values, comparing the simulated kWh used per mile (factoring in speeds, stops, etc on the trip profile) for otherwise identical vehicles.

Remarkably, the AKS simulations showed that AVs induced so much more travel on Ann Arbor's roads that congestion increased markedly – and the increase went up, not down, as the penetration of AVs rose. For the highest levels of induced travel, caused by drivers valuing their in-vehicle time at 75% of their wages, total travel increased about 5% but time in vehicles increased 7.5%, meaning that the average speed of travel declined (i.e., congestion increased). Even more remarkably, AKS tried simulations in which they assumed that high penetrations of AVs allowed the effective capacity of Ann Arbor's main roads to increase as much as 77%. Even then, they found that induced travel caused so much congestion on secondary and feeder roads that average kWh per mile increased slightly.

These results are obviously for only a single study with tremendously complex and sophisticated models. However, the literature on this topic shows surprising agreement with the proposition that's AVs will initially make congestion worse, or as Davis and Spinoulas¹²⁵ put it, "things will get much worse before

¹²⁴ (Auld, Karbowski, & Sokolov, 2016)

¹²⁵ (Davidson & Spinoulas, 2015)

they get better." These authors divide the future into three stages: minority AVs in the fleet – majority but not universal AVs, and a fully-AV fleet. Congestion increased in phase 1, begins to get lower in phase 2 as infrastructure also changes, and is much better by phase III. As noted earlier, Underwood¹²⁶ also discusses stages like this quite extensively. Accordingly, it is difficult to apply their numerical results with great confidence. However, it is not difficult to accept the premise that AVs will initially increase congestion, lower average speeds, and modestly increase kWh until AVs increase *and* we build and manage an infrastructure that enables the efficiency benefits of traffic smoothing to be realized.

Perhaps a better way to say it is this: On all congested roads there is now an equilibrium amount of congestion, balancing drivers' time value and other operating cost penalties against alternative routes and the value of travel. With AVs, the initial effect will be to unbalance that equilibrium between CV drivers, who "pay" all the value of their driving time, and AV drivers who do not. Given the significant driver time savings full AVs will enable, it may take decades before anything approaching a new equilibrium is established while the AV/CV composition of the fleet, traffic management techniques, passenger demographics, and consumer tastes all rapidly evolve.

As shown on row A of Table IV.10, the three researchers who have studied the early literature on traffic smoothing estimate ultimate savings of ten to fifteen percent off a (usually implicit and/or vague) no-autonomy base case. Understandably, these studies don't appear to reflect the AKS effect of initial congestion increases. For our purposes, however, we cannot ignore this effect, as (assuming it is widespread) it could initially increase realized EI even as AEVs get progressively more efficient.

We choose to reflect all of this in our estimates in the following way. For the first ten years of AV introduction, to account for added congestion we *reduce the otherwise-projected technology-based improvements in all EVs' El by 50%*. We do this for all EVs, whether autonomous or not, as they'll all be stuck in the same AV-induced traffic. Starting in tenth year, we linearly restore the lost technical efficiency improvements in the EV fleet over the next ten years.

With respect to longer-term improvements in EI due to traffic-smoothing, we adopt Stephens, et al's estimate of 15% reduced EI once AVs reach saturation, which we assume occurs around 2055. This estimate is most recent, and it also attempts to reduce savings during periods that are already

¹²⁶ (Underwood)

uncongested. Beginning in 2035, we linearly phase-in El improvements for traffic-smoothing over a period of 20 years, ending with a total effect of 15%. Obviously, these are all barely-educated guesses, but we believe they adjust power use estimates in a directionally-appropriate manner.

Better Intersection Management

When intersections become properly outfitted, AVs will also able to navigate crossings, turns, and merges with fewer stops, starts, and slowdowns, further reducing energy use.¹²⁷ Among the authors in Table IV-10, only Stephens, et al.¹²⁸ examined this category distinctly (see Row B). From their review, they concluded that EI should decline by a midpoint estimate of 4% for all "city driving." Estimates in this research these are highly uncertain, as we are only now at the earliest stages of developing strategies for managing intersections and traffic with connected vehicles. As noted above, professor Cassandras sometimes finds intersection-based savings of 40%

We adopt the Stephens midpoint estimate as the ultimate value of EI savings in our study. We apply this by weighting each year's linearly phased-in value by the 72% of driving estimated to be urban in that year.¹²⁹ Recognizing that it will take time to retrofit intersections and that savings estimates will increase as AVs become more commonplace, we implement this improvement in EI, on a per-AV basis, starting in 2035 and ramping up linearly to the full effect in 2055.

Faster Travel

There is also a second countervailing effect of AV intelligence, or more precisely a combination of an EI and travel-induced offset. Drivers who use navigation software today know that they often recommend longer routes that are less congested and therefore have lower travel times. AVs will be able to continuously analyze traffic route alternatives and similarly divert to alternate longer but quicker paths, implying higher average speeds (though presumably fewer stops and starts). Both the longer distance

¹²⁷ Although a case can be made for separating the effects of better intersection management from other aspects of traffic smoothing, we combine the two effects together in one category.

¹²⁸ (Stephens, Taylor, Moore, & Ward, 2016)

¹²⁹ See this website for specific cite of table IV-10: <u>https://www.fhwa.dot.gov/policyinformation/statistics/2015/</u>

and the higher speed imply higher electricity use for the same origin-destination pair, perhaps offset by a smoother trip.

We treat the VMT portion of this combined effect as part of AV-induced travel, discussed in the section above. However, higher average speeds can significantly affect realized EI. Results of the AKS simulation aside, most researchers think that AVs will enable cars to travel faster with equal or greater safety, especially during periods when congestion does not limit traffic speeds. Since AVs should ultimately reduce congestion once they dominate the roads, the ability to travel more quickly should gradually become more common as the AV fleet grows. Again separating out higher travel distances (a VMT effect) due to rerouting, this effect will also increase electricity use. Of course, the degree of the increase depends on both the magnitude of the average speed increase and the aerodynamic properties of future AVs. While there is no doubt that manufacturers will continuously improve aerodynamic performance, most researchers agree that such improvements are unlikely to offset speed-induced EI increases during periods where these increases occur.

As shown on Row C of Table IV-10, there is quite a range of estimated effects from average speed increases, with (Stephens, Taylor, Moore, & Ward, 2016) estimating an upper bound of 8% EI increase (after weighting across different types of driving) and the other two literature reviews finding effects of 20 to 30%. However, as with eco-driving, only Stephens, et al. apply the increases to non-peak hours. In effect, these authors recognize that congestion is likely to be the limiting factor for speed during peak hours for some time to come, negating AVs' ability to travel more quickly with better safety when roads are congested. We agree with this view and adopt Stephens et al's estimates, phased in linearly for AVs only over the years 2030-2035.

<u>Platooning</u>

The fourth major category of AV EI impacts is reduced aerodynamic resistance via platooning. This is projected to be a large source of energy savings for large trucks, but the effect extends to passenger vehicles traveling at high speeds on limited access highways. This effect has been studied extensively and documented in practice; the main uncertainties around this effect is when passenger AVs will be technologically ready to platoon, the extent to which the practice will prove practical on a large scale, and the speeds at which the platoon will operate.

As shown in Table IV-10 Row D, energy savings estimate again show a large difference between MWL and BGR's earlier upper-bound estimates and Stephens, et al's estimates weighted by driving type. We again adopt Stephens' estimates and phase them in linearly between 2030 and 2035. Note that the El increases and reductions from faster travel and platooning are assumed to occur over the same time period and partially cancel each other out.

Rightsizing, Performance Reductions, and Weight Reduction

The fourth major type of AV EI impact is a composite effect that will occur only as soon as manufacturers and consumers begin manufacturing AVs that carry an amount of passengers and freight equivalent to a CV in vehicles that are smaller and/or lighter. This is expected to occur from reduced size and weight of AVs when crash survival is no longer a major design imperative and downsizing of the engine and powertrain become feasible, enhanced by possible reductions in acceleration capabilities since AVs should have less need for rapid acceleration. Stephens, et al summarize these effects nicely:

Current vehicle designs typically use engines with power capabilities far in excess of the power needed to meet average driving demands (because sizing is instead driven by customers' desire for fast acceleration performance). CAVs; powertrain sizing could therefore not only be reduced in response to smaller vehicle sizes, but also in response to relaxed demands for fast vehicle acceleration capabilities. An engine sized closer to a vehicle's average power requirements would spend more time operating in its region of highest fuel efficiency, thus improving the overall vehicle fuel economy.¹³⁰

These effects are sometimes vaguely referred to as "rightsizing," but one should be careful to separate out the phenomenon of matching the passenger and cargo size of a vehicle to each trip, which is enabled by various types of sharing and not a change in vehicle EI. While attempting to include only vehicle EI changes, we follow the literature reviews shown in Table IV-10 and lump these categories together on Rows E and F.

As these rows show, researchers believe that there is enormous potential for weight reduction and powertrain resizing in "crash-free" personal transport. These improvements are by definition over and above the EI improvements to all vehicles, which are expected to come partly from increased use of lighter materials. Unlike the prior rows, the authors largely agree, based on a wide variety of evidence that the

¹³⁰ (Stephens, Taylor, Moore, & Ward, 2016) p.8

upper-bound potential for weight- and power-related improvements is in the vicinity of 50%. Also unlike many of the other effects, these improvements apply to the average vehicle regardless of when, how, or where it is driven.

The difficulty in applying this factor to electricity use lies in the timing of these improvements. The technology to reduce weight in vehicles is widely known, but current consumers mainly seem to want heavier cars loaded with safety features, many of which themselves add further weight. We do not expect that consumers' desire for safety shifts over the coming decades. Accordingly, AVs will have to be prevalent enough in the overall fleet to change consumers' perceptions of the safety value of weight relative to the cost of that weight in higher vehicle purchase and operating costs. Segregated infrastructure may eventually help here, too, as a lighter vehicle that encounters only other AVs on the high-speed portion of its trips may be more acceptable.

The exception to this overall picture is that the onset of AVs may lead manufacturers to make specialized lower-speed, lower-weight cars especially aimed at urban-core autonomous taxi fleets. Because these vehicles would be used overwhelmingly within cities for low and medium-speed travel, consumers may prefer a lower price point to greater weight and size. Although some future owners will undoubtedly buy these for their own use, we explore this shift in fleet EI the following chapter.

With respect to self-owned vehicles, we note that the long-term response of U.S. drivers to lower CV capital or operating costs has consistently included the purchase of larger, heavier, less-fuel-efficient vehicles. Stephens, et al¹³¹ also observe that autonomy could also reverse some of these EI benefits by allowing vehicle owners to afford larger AEVs than they would otherwise buy – a topic they note has not yet been studied. However, at some point AVs will become prevalent enough that manufacturers will be comfortable marketing lighter but equally safe vehicles to individual owners. At this point, the entire fleet can begin to realize very substantial efficiency gains.

It is sheer speculation to assume the period in which this might occur, but (Underwood, Automated, Connected, and Electric Vehicle Systems: Expert Forecast and Roadmap for Sustainable Transportation)'s thoughtful discussion of the staging of AV fleet changes supports a start date of the year 2040.¹³²

¹³¹ (Stephens, Taylor, Moore, & Ward, 2016) p. 24

¹³² Underwood's ((Underwood, Automated, Connected, and Electric Vehicle Systems: Expert Forecast and Roadmap for Sustainable Transportation), p. 48) discussion of the stages of AV introduction supports this view. (Rodoulis, 2014) puts the start of lightweighing at 2040. (Kockelman K. M., et al., 2017), p. 123 shows assumptions

According to our penetration estimates, by 2040 about 23% of all vehicles will be autonomous in our base case (2025 introduction) and 6% if AVs do not enter until 2030. At this point we assume that some consumers will start to recognize the value of downsizing and policymakers will start rewarding manufacturers with future equivalents of CAFÉ credits. The phenomenon will undoubtedly begin in urban areas, where lighter conventional cars are most often seen today, and spread gradually to all vehicle types. We employ two cases, one in which the initial one-fifth of the savings (i.e. 10%) occurs linearly over the decade 2040-2050 (i.e., 1% a year) and a second in which the savings grow more quickly, i.e. 1.5% per year.

Onboard Electronics and Appliances

Autonomous vehicles will need to carry onboard control and communications electronics, a power use that does not appear to be reflected in the El's forecasted by Oak Ridge above. In additional, passengers who do not need to drive will undoubtedly use more electronic devices more intensively during travel time, perhaps including appliances such as coffeemakers and microwave ovens. One writer envisions a traveling Starbucks Coffee Café on wheels, which sounds quite attractive provided one can power machinery decent portable expresso machine.

As to additional appliance plug loads, the effect does not look to add substantially to vehicle power use, at least until weight downsizing has taken effect well into the future. A 300-watt plug load operating continuously over a one-hour commute would use less than the power required to move a current Nissan Leaf one mile. Over an hour commute a car goes perhaps 30 miles, so this would be a 4% increase in El for heavily-loaded EVs.

As of result of these figures, we do not adjust our El estimates for onboard electronics. These electronics will certainly increase energy use, but these increases are likely to be overshadowed by other larger effects in both the positive and negative direction. We acknowledge that this slightly biases our power demand figures downward.

that AVs will reduce overall crashes by 50-90% with only 10% AV penetration, but by about 87.5% with 50 % penetration.

The Net Future Energy Intensity of AEVs

Table IV-11: Summary of Treatment of El effects of Els.

Effect	Impact	Timing	
Traffic Smoothing	-15%	50% reduction in technology	
		improvements in EI for the first	
		10 years, then linear phase- in	
		from 2035	
Intersection Management	-4%	Linear phase-in for urban EVs	
		starting in 2035 and fully	
		implemented by 2055	
Higher Average Speed	+8%	Linear phase-in from 2030-2035	
Platooning	-2.5%	Linear phase-in from 2030-2035	
Rightsizing/Weight Reduction	-50%	Phased in linearly at 1% per year	
		or 1.5% per year starting in 2040	

Table IV-11 shows the assumptions we make regarding AV EI changes in table form. In Figure IV.11, we superimpose each of these effects on our conventional ownership base case EIs for EVs. Recognizing that both the magnitude and timing of these effects are simply directional guesses, the results in figure IV. 12 look plausible to us. After initially making fleet energy efficiency slightly worse, AV-enabled EI savings reduce autonomous electric SUV EI to 0.3 kWh/mile by 2050; sedans reach about 0.18 kWh/mile. These are not bold, revolutionary increases, but they are large enough to offset a good portion of autonomy-induced VMT growth. With stronger policies or market trends that made AVs more common sooner than 2050, accelerated AV infrastructure, and policies that encourage rightsizing and lightweighting, the literature clearly indicates greater technical potential than we employ. Therefore, AV EI could be significantly lower in 2050 or the years following.





V. Pooling, Sharing and Seamless Mobility Networks

A. INTRODUCTION

In this section we consider a third layer to our electric power forecasts, the impacts of the many emerging shared and pooled modes and businesses, including various forms of what are being called mobility networks. It is important to bear in mind that sharing the use of a vehicle by dividing its exclusive use between two families in succession is very different than two riders who are strangers "sharing" a single ride between two points. Casually, we refer to the latter as pooling rather than sharing. The impacts of sharing and pooling on VMT and EI are different. As showing in Table V-1 the terminology in this area is diverse and overlapping.

Table V-1:Shared Versus Pooled Modes

	Other Terms	Simple Definition	Examples
Shared Modes	Ridesourcing, Ridehailing, TAAS, MAAS, Dynamic Ridesourcing	The same vehicle is used for successive trips that are independent of each other	Car-sharing services such as zipcar, ridesharing or ridesourcing companies such as taxis, Lyft
Pooled Modes	Ridespitting, TAAS, MAAS	Combining independent passengers going between two similar origins and destinations into the same vehicle	Traditional Carpools, Uberpool, Lyft Line, shared taxis ("Ridesplitting")

133

Although ridesharing in various forms has long been a small part of U.S. transport, and larger in some other parts of the world, the topic is gaining enormous attention now for two primary reasons. First, in many realms outside of transportation there is a shift from the one-time sale of a hardware products hardware to the sale of products from that hardware commonly called an "as a service" (AAS) model.

¹³³ As Susan Shaheen noted in an email correspondence dated 7/21/2017-8/2/2017, "To call a paid/commerical trip ridesharing is incorrect. Ridesharing has long been defined in policy/regulation as an incidental trip (it would have happened by the driver anyway). There is no commercial transaction (i.e., not a paid driver) involved in ridesharing (maybe a few bucks for gas, tolls, wear and tear). Ridesharing does not require commercial insurance."

This model has spread progressively into many industries and is especially popular among millennial consumers, some of whom embrace values in which ownership of things is less preferred than buying service from shared or third-party-owned assets.¹³⁴ Already, average U.S. household vehicle ownership went flat around 2000 and declined 5-6% from 2006-12.¹³⁵ This has led some observers to declare that auto ownership will give way to a shared, AAS model, ¹³⁶ and that the U.S. will reach "peak car ownership" as early as 2020.¹³⁷

In addition, a new-generation-of-transportation-network-companies (TNCs), also referred to as Mobilityor Transportation-as-a-Service (MAAS or TAAS), have rapidly grown to become some of the largest transportation firms in the world. The firms, currently led by Didi and Uber, were *not* initially pooled modes, and the energy impacts of their non-pooled business should reflected in the VMT and EI forecasts in the EV and AV layers in Chapters III and IV. However, these firms now also offer a ridesplitting or pooled service. Thus, well-established and well-funded players appear poised to pursue pooled TAAS and disrupt the ownership model.

The onset of shared/pooled modes is made more complex by their interaction with autonomy. Today, carsharing and ridesharing occur in conventional vehicles (albeit with ever-increasing levels of driver-assist technologies). Once commercial autonomy arrives, most analysts predict that conventional carsharing will decline as customers shift to on-demand autonomous taxis (ATs); those who continue to share cars will share mutually- or fleet-owned AVs. Carpooling, which is already a pre-AV mode with modest and declining U.S. use, will lose its drivers and thereby ostensibly become cheaper and more heavily used, including as part of multi-modal mobility networks.

Some experts also predict that the onset of autonomy will itself cause a downsizing of the average size of vehicles in use. In Chapter IV we noted that we did not expect this to become widespread among selfowned AVs until the concentration of AVs was high enough to reduce the chance of a CV-AV collision at

¹³⁴ See (Bank of America Merrill Lynch, 2017) p.172-174.

¹³⁵ Per-capita figures from (Litman, 2016) Figure 7; per-household (Bank of America Merrill Lynch, 2017) p. 153, citing "McKinsey and Sivak et al").

¹³⁶ "Cars are going to undergo a lot of changes in the coming years. One of the biggest: you probably won't own one." (Higgins, 2017). (Bank of America Merrill Lynch, 2017) p.153 quotes GM President Mary Barra as saying "We do believe the traditional ownership model is being disrupted."

¹³⁷ (Johnson & Walker, 2016) cited in (Bank of America Merrill Lynch, 2017) p. 161.

high speeds, perhaps sometime in the 2040s. However, we expect that autonomous vehicles specifically designed for intracity use, aka autonomous taxis, could immediately enter the fleet with a lower EI than conventional vehicles. In other words, by shifting the average composition of the entire vehicle fleet with unusual rapidity, the onset of ATs could shift the average EI of the total fleet as the number of ATs grows. We acknowledge this possibility, but we do not adjust for it.

Finally, many experts foresee a future network of "seamless mobility," where rail transit modes feed public and private buses, mini-buses, vans, and purpose-built city cars with varying sizes and on-demand routes that intersect frequently with transit stations. Shaheen, et al (Shaheen, Chan, Bansal, & Cohen, 2015) and Ciari and Becker (Ciari & Becker, 2017) among others call this "shared mobility," an "innovative transportation strategy that enables users to gain short-term access to transportation modes on an as-needed basis". In this vision, only the final part of the system consists of light-duty vehicles, and then only when demand levels do not allow larger microtransit HDVs.

In these "seamless" mobility systems (SMSs), the goal is to shift the same overall passenger-miles into vehicles "sized for purpose" and therefore much more efficient per PM. Operated efficiently, the overall total EI per passenger-mile for such a seamless mobility system is a blend of future fixed-route mass transit EI, bus and mini-bus EI, and LDV EI, all operating at high load factors. Overall energy savings in the shift to seamless mobility can therefore be viewed as either VMT reductions in LDV modes offset by much smaller VMT increases by higher-capacity, higher-load factor modes, or by a weighted average shift in overall EI per passenger-mile. We examine guesstimates of these overall effects in section F below.

		Definition	Model	Example Firms	Imact of Autonomy	Assumed Impact of VMT
_	Ridesourcing-TNCs-TAAS taxi- with driver	Pre-arranged per on-demand non-pooled individual vehicle ride-specific transport, pair per-trip or "as-a- service"	P2P	Uber, Lyft, Didi	Eliminates driver- centric modes, shifing the vehicles that become autonomous to type VII	
=	Ridesharing, including vanpooling, carpooling, and slugging	Driver-controlled routing and passenger selection that is acquaintance-baed organization based, or ad-hoc	B2P	No firms	Eliminates driver- centric modes, shifing the vehicles that become autonomous to type VII	
≡	Ridesplitting - pooled TNCs/TAAS	Same as row I, but riders of similar routes share vehicle	B2P	Uberpool, Lyftline	Widely seen and becoming autonomous pooled taxis/TAAS	Reduce VMT
2	Casharing fleet firms 1-way, 2 way	User share access to 3rd party fleet on as-needed basis, paying annual fee plus time-based usage charge	Zipcar Car2Go	B2P	Could increase this form of carsharing due to lower cots of high- use Avs and ability to summon vehicles	Neutral
>	Fractional carsharing via ownership, Hypbrid P2P, P2P, and P2P marketplace	Individually or jointly-owned vehicles are shared via non-commercial, peer-to-peer arrangements	P2P	Turu Getaround Flightshare	All versions may continue to exist but cheaper Ats may reduce market size	Neutral
N	Autonomous taxis, robotaxis, autonomous TAAS	Same as I	B2P	Same as l	Enables this mode	
IIV	Shared or pooled autonomous TAAS	Same as Row III but driverless, same as Row VI but pooled rides	B2P	Same as II	Enables this mode	Reduce VMT
	Source: Based primarily on Stc	ocker and Shaheen (2016). Danits Courier Network Servic.	es and oth	er minor modes.		

Table V-2: Forms of LDV and Shared and Selected Non-Shared Mobility

83 Electric_Transport_Draft _10_5_17

Table V-2 shows a taxonomy of the prominent shared and pooled modes. The upper block of rows are current modes that use conventionally-driven vehicles. These modes will continue to exist until such vehicles are completely eliminated, assumedly beyond our forecast horizon, but many are projected to decline as travelers shift to similar modes that use AVs. The most widely-predicted qualitative effect of autonomy on each of the top-block modes is summarized in the sixth column of the table and discussed below.

As in previous chapters, the ultimate objective of this section is to attempt to bound the impact of pre- and post-autonomy shared and pooled modes on VMT and EI by mode and time frame. Consistent with our layered methodology, the impacts we seek are changes to eVMTs and EIs by mode from the estimates already adopted in Layers 1 and 2.

B. NON-POOLED DYNAMIC RIDESOURCING

The first row of the table is the well-known mode technically known as dynamic ridesourcing (DRS) or ridehailing, more commonly known as "taxis and ubers" or as transportation network companies TNCs.¹³⁸ These B2P platform firms use firm-owned, driver-owned, or driver-leased fleets to sell on-demand rides on a per-ride basis. In their original form they are shared but not pooled vehicles.

Non-pooled ridesourcing (confusingly, a "shared" mode) has been around since the birth of the taxi industry in the 1920s. However, during only in the last few years, smartphone-enabled TNCs (real-time or dynamic ridesourcing, or DRS) such as Lyft have emerged and grown extremely quickly. Since our VMT and EI predictions are based first on traditional annual vehicle VMT, then on the boost due to electrification, and then on the boost from autonomy, it is possible that they do not capture the impacts of this new pre-autonomy mode.

The data on these modes is, so far, largely private, and there is some disagreement over the effects of the non-pooled version of DRS on VMT. There is general agreements that DRS acts to both increase and decrease VMT in a large number of ways, before and after autonomy. Rodier, Alemi, and Smith (RMS)

¹³⁸ Traditional ridesharing has been around for decades, using mechanisms such as bulletin boards. Dynamic ridesourcing is the formal name for rides in "shared" vehicles that can be arranged on-demand using smartphones. See (Agatz, Erera, Savelsbergh, & Wang, 2009) for a formal description of dynamic ridesharing.

(Rodier, Alemi, & Smith, 2016) whose Table 1 is reproduced as Table V-3 below, divide the VMT impacts of DRS into six categories: auto ownership, trip generation, mode choice, destination choice, route choice, and urban form. Within each category, most of these impacts have several subcategories. As shown in Table V-3, even within one category the subcategories often have opposing impacts on VMT. For example, under route choice, the table notes that LDV VMT may either increase or decrease congestion and prompt longer routes, as well as increase VMT through diversions to pick up passengers.

Many analysts argue that the short-term *net* effect of these influences is to divert some trips that would otherwise have occurred via transit, bikes, or walking, thus increasing VMT. An unpublished doctoral dissertation by Alejandro Henao found that 34% of DRS passengers would have walked or biked, had the TNC option been unavailable.¹³⁹ When including the VMT the driver incurred cruising without a passenger, Heneo computed an 85% increase in VMT in Denver for TNC vehicles. In other words, vehicles driven by TNC drivers add 85% more miles in a day than would be driven by the driver of that vehicle using it only for non-TNC use, plus the travel by each of that driver's passengers in whatever mode they would otherwise have chosen. This is obviously a very large effect per TNC vehicle, but it is based on a very limited sample.

Other studies also show a sudden but substantial diversion from transit into TNC vehicles. Former N.Y. Transport Commissioner Bruce Schaller estimated recently that 43,000 TNC vehicles provided as many trips in 2016 as the City's 13,437 taxicabs.¹⁴⁰ Although data are apparently not public on the percentage of these rides that were shared, Schaller estimates that the TNCs induces 600mm miles of *additional* LDV VMT, after deducing for pooling and the diversions from taxis. Schaller writes that, "Results in this report thus show that current volumes of pooled rides combined with exclusive ride trips are producing large overall increases in mileage – not reducing congestion of carbon emissions." ¹⁴¹ Indeed, Schaller believes that TNCs are largely responsible for ending a twenty-year trend towards increased transit ridership in New York. A similar trend towards lower transit ridership has been seen in California mass transit, consistent with the growth of non-pooled TNCs, but Taylor (2017) suggests that immigrant car ownership rather than TNCs are the primary cause.

¹³⁹ (Henao, 2016)

¹⁴⁰ (Schaller Consulting, 2017) p. 1

¹⁴¹ (Schaller Consulting, 2017) p.11

There is also significant belief in the fact that the long-run effect of non-pooled TNCs may be to lead to lower car ownership and long-term reduced VMTs by those who would have otherwise purchased a car and then experienced lower out-of-pocket costs per mile driven. One oft-cited study by (Fagnant & Kockelman, 2015) modeled a scenario in which all riders in the central portion of Austin, Texas used SAVs for transport – not rideshared, but available on demand for all trips in the urban core. The authors found that one SAV could replace 11 conventional vehicles – a remarkable reduction that many other studies confirm. However, and more importantly from our standpoint, total VMT was increased versus the non-shared scenario. (Zhao & Kockelman, 2017) repeat this finding and cite more examples of VMT increase in their literature review.¹⁴²

However, there is not yet complete agreement that non-pooled TNCs increase short-term VMT relative to the status quo. "Depending on the specific circumstances and characteristics of the local context," Circella, et al¹⁴³ write, "on-demand ride services may act as a VMT-additive or VMT-subtractive force." Many researchers also remind us that these non-pooled modes can become pooled modes on a moment's notice – or more systematically, if policies encourage or mandate pooling – offsetting these VMT increases (although not always entirely, as we will see in the next section).

A very distinguished Committee for Review of Innovative Urban Mobility Services was recently convened by the National Academy of Science. After examining the available evidence on the effect of ridesharing on VMT, the Committee agreed that there are the multiple opposing effects shown in Table V-3. "It is too early to determine which of these competing forces will predominate, and effects are likely to play out in different ways depending on local circumstances." ¹⁴⁴ This statement alone would warrant an assumption of zero VMT impact from ridesharing as a rough middle course.¹⁴⁵

¹⁴² (Fagnant & Kockelman, 2014) note that the net total energy impacts of SAVs may still be lower than CVs due to the large reduction in energy required to create a car fleet only 1/11th the size of a CV fleet. As our focus is electricity for transport itself, we neither examine nor dispute this. We also note that studies that assume mandated or otherwise high levels of ridesharing within AT fleets clearly find reduced levels of VMT (see, for example, (Rodier, Alemi, & Smith, 2016) and the references cited therein).

¹⁴³ (Circella, Tiedeman, Handy, Alemi, & Mokhtarian, 2016), p. 39

¹⁴⁴ (Transportation Research Board, 2015) p.101

¹⁴⁵ Further anecdotal support comes from the U.S. Department of Transportation's recent major long-term travel forecast and policy study, which did not cite ridesharing as an important trend affecting future travel. (Circella, Tiedeman, Handy, Alemi, & Mokhtarian, 2016)

Finally, after full autonomy enters we have already accepted the view that non-pooled AV fleets will prompt a significant increase in VMT through price reductions, reclaimed time, and other factors. In a way, what we are exploring here is the precursor effects occurring now in vehicles that are almost entirely non-EV and human-driven, but nonetheless are inducing more travel in somewhat similar ways.

Even accepting the proposition that non-pooled, pre-autonomy TNC vehicles are triggering greater VMT prior to autonomy, we cannot determine the size of the effect on power use without determining (1) the number of TNC vehicles that will be non-AV EVs in every year prior to universal full autonomy; and (2) the net added VMT per such vehicles induced by non-pooled TNC service. Clearly, this product is effectively zero today because so few TNC vehicles are EVs today. Until EV ranges and charging procedures get much better, we do not see EVs as good candidate vehicles for TNCs. In addition, the per-vehicle incremental VMT will be much less than the induced travel by AV TNC fleets, as time savings from not driving are already a part of current TNC modes.

Given the current disagreements over both the sign and magnitude of the effects of non-pooled, preautonomy DRS on VMTs we omit any added effect from our VMT calculations. Certainly we do not expect significant power use increases for TNC fleets until EVs get larger ranges. At that point, we are prepared to believe that there will be a pre-autonomy boost for power use from non-pooled, TNC-induced travel, and that our transport power use predictions starting in the mid- 2020s (when long-range EVs that are not AVs may start to become common) are biased downward.

We can use Schaller's results to get an idea of whether this "EV VMT bump" will have a significant impact on power demand. If we assume all 600mm incremental VMT are supplied by Nissan LEAFs at 0.33 kWh/mi, the incremental demand is 198 GWh. This is an insignificant fraction of total U.S. power use, but that is really not the point. This demand is in fact concentrated entirely in the service area of Consolidated Edison, whose 2016 sales were about 20,000 GWh. If we were to convert all TNC vehicles in the New York to EVs, Con Ed sales would increase by about 1% - a noticeable, if not large, amount in an era where electricity sales are largely flat. Of course, the entire TNC fleet could take longer to electrify because these vehicles are driven more intensively than private cars and therefore need much more frequent charging.¹⁴⁶ Nonetheless, more of these vehicles will gradually become EVs, and may be used for ridesourcing or ridesplitting before driverless AVs are widespread. We think it is likely that electric utilities in large urban areas will get a slight bump in electric sales from DRS-induced VMT (above current trend) as EV DRS expands in dense urban and suburban centers. This is likely to occur prior to the much larger multifaceted increase in VMT from widespread AVs that we think will start ramping up in the 2030. However, this bump should work itself down to zero as the entire TNC fleet converts to electric AVs, as our modeling predicts will occur in the 2030s onward.

¹⁴⁶ NYC Tax and Limousine Commission (New York City Taxi and Limousine Commission, 2013) provides a detailed analysis of the difficulties converting the NYC taxi fleet to electric drive; similar considerations apply to TNC fleets. However, new and faster charging are in the works, and we fully expect many TNC EVs by the mid-2020s.

Category	Possible Outcomes	Effects on VMT/GHG
Auto Ownership	If DRSs replace private auto for all travel needs at a lower cost, then auto ownership declines and use of non-SOV modes increases.	- VMT/GHG*
Trip Generation	If access to a car and transit is limited and DRS is affordable, then new trips may be induced.	+ VMT/GHG*
	If travel time and costs are lower by DRS than SOVs, then DRS increases and SOVs decrease.	- VMT/GHG*
Mode Choice	If time and cost are lower by DRS than transit, then DRS increases and transit decreases.	+ VMT/GHG*
	If overall travel time and cost for DRS (first/last mile) and transit are lower than SOVs, then DRSs and transit increase and SOV decreases.	- VMT/GHG*
Destination	If overall travel time and cost for all modes are reduced to central areas relative to outlying, then travel to central areas is more likely.	- VMT/GHG
Choice	If overall travel time and cost for all modes are reduced to outlying areas relative to central, then travel to outlying areas is more likely.	+ VMT/GHG
Danta	DRS travel to pick-up and drop-off passengers and/or relocation miles.	+ VMT/GHG
Choice	If congestion worsens, then longer routes are possible to avoid congestion and minimize travel time.	+ VMT/GHG
	Stop and start travel.	+ GHG
Urban	If overall travel time and cost for all modes is reduced to central areas relative to outlying, then demand for residential and employment space may be greater in central areas.	- VMT/GHG
Form	If overall travel time and cost for all modes is reduced to outlying areas relative to central, then demand for residential and employment space may be greater in outlying areas.	+ VMT/GHG

Table V-3 – Dynamic Ridesharing	Services: Potential Outcomes	and Effects on VMT/GHGs
---------------------------------	------------------------------	-------------------------

* mediated by induced travel; single occupant vehicle (SOV); - = reduce; + = increase

Source: (Rodier, Alemi, & Smith, 2016) Table 1

Effects of DRS on EI

While the VMT kaya term is clearly very sensitive to pooling, its implications for EI are not so clear. A high proportion of pooling might cause vehicle owners to upsize their vehicles, shifting the fleet to somewhat larger but fewer vehicles. Greenblatt and Saxena¹⁴⁷ estimate that adding a second person to a single-occupant average vehicle increases the vehicles energy consumption by 0.6%, without assuming any vehicle size changes. Additionally, LDVs dedicated to pooling might be designed differently – e.g., contain separated passenger compartments or be simply larger – which could affect vehicle EI. In this limited context, consistent with Greenblatt and Saxena, we believe that the EI impact of sharing and

Electric_Transport_Draft _10_5_17

¹⁴⁷ (Greenblatt & Saxena, 2015), Supp Paper, p.5

pooling alone is unlikely to be large (nor easily predicted). Accordingly, we leave LDV EI as we have computed it so far for each vehicle type over time, including the multiple effects of autonomy.

C. TRADITIONAL CARPOOLING

The first pooled form of transport (row II) is an aggregation of the most traditional forms of carpooling and vanpooling, including the type of ad-hoc ridesharing known as casual carpooling or slugging.¹⁴⁸

These forms of pooling have been occurring for many years, though they have declined substantially in the past few decades. A recent workshop at the UC Institute for Transportation Studies reached the rather stark conclusion that "carpooling is a failure for commute trips," dropping from 36% of commute trips in 1980 to 9% today.¹⁴⁹ These declining impacts on VMT are presumably already embedded in VMT forecasting models. Although travel-to-work patterns may change through better telework options and urban design, both explored in Chapter VI below, there is no particular reason why electrification alone would change travelers' willingness to carpool.¹⁵⁰ As a result, we see no reason to modify our VMT or El figures to account for this small, and declining pooled mode.

¹⁴⁸ Slugging occurs when travelers who want transport across a specific route stand in a designated location and drivers who wish to pick up such passengers voluntarily do. It typically occurs in commuting corridors where (1) many sluggers are likely to be workers with similar backgrounds going to similar locations, giving a modicum of assurance of mutual safety, and (2) adding a second occupant to a vehicle allows the driver to use HOV lanes. Of course, slugging now uses apps, see http://wtop.com/dc/2016/05/looking-carpooling-slugging-theres-app/ accessed 6/21/17.

¹⁴⁹ (University of California Davis Institute, 2017)

 ¹⁵⁰ If anything, the significantly lower per-mile operating costs of EVs would discourage these modes. In fact, the
10% eventual increase in VMT from electrification implemented in Chapter III stems partly from formerly
carpooled traffic.

D. CAR-SHARING AND VMTs

Two pre-autonomy modes involve car-sharing. In these modes, travelers do not solicit a ride, they rent a vehicle from a dispersed fleet under more flexible terms than traditional car rentals. The key distinction between Rows IV and V is that travelers reserve vehicles from a business-owned fleet in Row IV, making the mode B2P, whereas the car-sharing arrangements in Row V involved individually owned vehicles that owners are willing to let others share for a rental fee – a model similar to AirBnB. Once autonomy hits, we assume that both forms of car-sharing decline as autonomous DRS grows, as explained further below.

Much has been written about car-sharing disrupting the traditional ownership model. For example, the Rocky Mountain Institute¹⁵¹ predicts that by 2035 U.S. auto sales will decline by about 33%, from about 18 to 12 million vehicles per year. Bank of America/Merrill Lynch cites a Boston Consulting Group prediction of an even larger possible sales decline, 59%, and cites other estimates that vehicle demand will peak in the 2020s.¹⁵² Barclay's automotive group predicts that the total U.S. LDV fleet will decline to 103mm (mainly shared) vehicles from 246mm today.¹⁵³

Several market research firms and consultants argue that the U.S. market will not embrace car-sharing at the higher levels seen in Europe and emerging in Asia. As an example, over a year after BAML's citing their work, the Boston Consulting Group wrote:

The US is different. Because residents of the country's sprawling and sparsely populated interior regularly drive long distances, the potential for car sharing is almost nil across most regions. Car sharing stands a much better chance of catching on in densely populated urban centers such as Boston, New York, and San Francisco. But the comparatively low total cost of vehicle ownership and the convenience of driving one's own car will encourage many people in the US to purchase a new car rather than forgo ownership.¹⁵⁴

¹⁵¹ (Walker & Johnson, 2016) p.20

¹⁵² (Bank of America Merrill Lynch, 2017), p.23

¹⁵³ (Barclays, 2015)

¹⁵⁴ (Lang, et al., 2016) p.9

Similarly, market researchers at the Kelley Blue Book find that only 15% of car-sharing users report that sharing is an alternative to ownership.¹⁵⁵ The converse view is expressed by (Bank of America Merrill Lynch, 2017), who writes:

"Peak Stuff": it's all about experience and sharing

We are seeking a dramatic shift in consumer preferences towards prioritizing experiences and the purpose of goods and services over materialism – as well as new ownership preferences as "access" and "rental". Over the past 50 years, the US economy has shifted focus from manufacturing goods to providing services – from 62% services in 1970 to more than 90% by 2012. This is reflected in General Motors employing c.600,000 workers in 1960 vs. Facebook's c.13,000 and .57,000 today.¹⁵⁶

However, BAML also agrees that car-sharing will decline with the onset of autonomous taxis, and emphasizes growth in Europe and Asia over the Americas in the meantime.¹⁵⁷ Car-sharing has been growing much more rapidly outside the U.S., although even here Ciari and Becker (Ciari & Becker, 2017) note that the only country with seamless nationwide car sharing (Switzerland) has only achieved a 2.5% market share.¹⁵⁸

The focus of our work is the impact of carsharing, whatever its level, on total VMT. If drivers travel as much in cashared vehicles as in self-owned cars these high levels of fleet declines have zero effect on transport power use – the same number of miles are driven in fewer shared cars.¹⁵⁹

There is a wide spectrum of opinion concerning the VMT impacts of car-sharing. It is generally agreed that there are two general effects: (1) VMT are increased by drivers who otherwise could not afford access to cars; and (2) VMT are decreased by drivers who forgo purchase of a car (perhaps a second car) and therefore drive less, and also drive less because the costs of ownership are no longer sunk (i.e. per mile out-of-pocket costs are higher). However, the magnitude of these two effects are disputed (see (Martin

¹⁵⁵ Kelley Blue Book, 2016, p.14

¹⁵⁶ (Bank of America Merrill Lynch, 2017) p.172

¹⁵⁷ (Bank of America Merrill Lynch, 2017) p. 167-170

¹⁵⁸ (Ciari & Becker, 2017) section 4.1.1 p.57. While it is well beyond our scope to resolve this debate fully, our estimates of the potential size of the market for carsharing do not jibe with very high levels of fleet decline. Threeand-a-half million carsharing drivers might take as many as 28MM vehicles off the road, but this is about 10% of the U.S. fleet.

¹⁵⁹ Interestingly, in this simple example (to a first approximation) long-term electricity for manufacturing is also unchanged; half as many cars are made twice as frequently. More generally, however, all of the modes in this chapter have the directional effect of lowering the size of the LDV fleet and therefore lowering manufacturing power use.

& Shaheen, 2011); (Lovejoy, Handy, & Boarnet, 2013)) cite literature showing 27 to 68% declines in VMT by car-sharers. A more recent survey by Stocker and Shaheen¹⁶⁰ reports reductions of 27% to 43% (as does Martin and Shaheen,¹⁶¹ also widely cited); Chen and Kockelman¹⁶² also endorse this view. In contrast, Tal and Cohen-Blankshtain and Sperling¹⁶³ express doubts that car-sharing VMT savings are large. Tal and Cohen-Blankshtain note that most VMT impact predictions are based on user surveys that over-predict the true effects of sharing, especially in the long run.¹⁶⁴ These effects put a lower bound of net zero VMT savings from car-sharing, approximately balancing the increase (1) and decline (2) above.

We can use a back-of-the-envelope calculation to show that carsharing's impact on power use will almost surely be small. At present, U.S. car-sharing services are enjoying something of a boom, gaining about 100,000 new customers a year. If we assume this growth continues unchanged for the next 20 years carsharing membership will total about 3.4mm drivers.¹⁶⁵ If we further assume that these ~3.5MM drivers reduce their VMT by 80% - an extreme upper bound from Martin and Shaheen – 31 billion vehicle-miles will be avoided. While this is certainly a positive outcome from every standpoint, this represents less than 1% of what is likely to be more than 3 trillion-miles of total LDV travel by 2040. Assuming further that the EI of shared EVs is 20% lower than non-shared EVs,¹⁶⁶ the saved electricity is about 11,2000 GWh, probably less than 0.21% of electricity use in the 2040s.¹⁶⁷ This result is consistent with a more sophisticated calculation by Chen and Kockelman.¹⁶⁸ Thus, car-sharing will not alter transport electric

¹⁶⁷ The details of this calculation are: 80% reduction in 11,400 miles/yr for 3.4mm drivers is:

Electric_Transport_Draft _10_5_17

¹⁶⁰ (Stocker & Shaheen, 2016), p.11

¹⁶¹ (Martin & Shaheen, 2011)

¹⁶² (Chen & Kockelman, 2016)

¹⁶³ (Tal & Cohen Blankshtain, 2011) and (Stevens M. R., 2017).

¹⁶⁴ (Tal & Cohen Blankshtain, 2011)

¹⁶⁵ Susan Shaheen *Carsharing Trends and Research Highlights* (Feb., 2017) powerpoint for the EPA, accessed August 28, 2017. Current car-sharing membership in North America, including Canada, is short 1.5mm drivers. Shaheen and Cohen report car-sharing statistics regularly in the *Innovative Mobility Carsharing Outlook* available at ttsrc.bnerkeley.edu

¹⁶⁶ As shown in Figure EI-1, there is a maximum of about a factor of Z in EV EIs, converging gradually over time. (Lovejoy, Handy, & Boarnet, 2013) p.3 note that shared vehicle fleets tend to have newer (hence more efficient) cars that average self-owned vehicles. The same point is made by Chen and Kockelman (2016)

³¹ bN VMT avoided @ .33 kWh/mile – 10.230 BN kw

The remaining 20% of car-shared driving is 7.75 bN VMT driven at EI 20% below an average .33 kWh/mile = 511mm kWh

¹⁶⁸ In brief, these authors use estimates of the ultimate market penetration of car-sharing among all U.S. households (10% in their medium scenarios), reduced VMT for each sharing driver (31%), a 24% increase in fuel efficiency for shared vehicles, and allocation of reduced rides to other modes of travel. Fuel energy reduced (by gasoline vehicles, presumably) in the middle scenario was about 5% of all "local household transport-related

demand by much unless membership growth well exceeds current rates and its drivers drive significantly less than they otherwise would, and/or car-sharing drivers share EVs substantially smaller than they'd otherwise own.¹⁶⁹

E. PRE-AUTONOMY POOLED DYNAMIC RIDESHARING OR RIDESPLITTING

The next mode to examine from Table V-2 is the growth of pre-autonomy *pooled* dynamic ridesplitting (Row III) and its consequent effect on VMT and EI. With respect to VMT, there are two conflicting effects. If two taxi riders going between exactly the same two points rideshare the entire trip, there is roughly half the VMT of the two alternative taxi rides. The larger the number of riders sharing their route, or equivalently, the more that ridesplitting increases average vehicle occupancy, the greater the VMT savings. This effect is the core environmental and congestion benefit of pooled DRS.

There is, however, an offsetting effect of unknown size. In Section B above we explored the proposition that non-pooled DRS is already induce greater passenger-miles of LDV travel than would occur without it. Here we must add to the uncertainties regarding non-pooled DRS VMT uncertainties the additional, quite significant factor that pooled DRS rides are substantially cheaper than non-pooled rides. Through the price elasticity of demand we can expect positive added travel, tipping the scales further in the direction of added VMT. Nonetheless, as shown below, the net overall effect of pooled DRS (as distinct from the uncertain non-pooled version) is generally regarded to be lower VMT.

There is little disagreement that shared rideservices are substantially cheaper than individual non-pooled service. BAML¹⁷⁰ estimates the cost difference as over 50%, from \$2.75/mile to \$1.32/mile, while others say that TNC pooling discounts are closer to 25% on average. (They will become cheaper still when driverless, but we discuss these effects in the following section.) Thus, the net additional effect of ridesplitting on VMT depends on the VMT reductions when drivers combine otherwise overlapping trips less the new shared VMT coming from passengers diverted from transit or who would not have traveled at all.

energy use." Translating the latter to a percent of total U.S. power demand would reduce this percentage by about three quarters, into the range of 1-2%. Chen and Kockelman (2016).

¹⁷⁰ (Bank of America Merrill Lynch, 2017), p.13

To our knowledge, no one has publicly forecasted the long-term penetration of pooled DRS in a manner resembling the EV and AV sales forecasts discussed above. Many analysts postulate a level of ridesplitting to see what the effects might be, but these are not forecasts or even market potentials.¹⁷¹ BAML reports broad survey-based global data from the Boston Consulting Group (BCG) claiming that 45% of passengers under 30 are "willing" to share a ride in a self-driving car, and that Uberpool has reduced VMT by 100 MM VMT over two years in 36 global cities.¹⁷² Yet, the UC Davis Pooling and Pricing Workshop concluded that "Americans still dislike riding with strangers." The Albright-Stonebridge Group (2016) concludes that:

Until autonomy is safely available, very small increases in overall utilization will come from incremental improvements by mobility services to attract customers: more convenience from TNCs such as better ETAs, corporate payment integration, carpooling options, or additional features such as car-seat availability; or convenient point-to-point car sharing with multimodal integration or valet services; or transformational change in utilization will only be possible once autonomous technology and related enabling policies are in place.¹⁷³

Without recognizing the distinction we make here between pooled TNC and SMS-based ridesplitting, a few researchers have made very rough upper-bound estimates of the impact of pooling. Interestingly, almost all of these apply after the onset of full autonomy. Some of these estimates provide little detail, which others are based on hypothesized levels of pooling. BGR (2014) place an upper bound (i.e. ultimate level) of -12% of VMT from all forms of pooling and Stephens, et al (2016) find a lower bound of zero and an upper bound in the same range, 300 to 400 MM VMT saved from an average of 5.6 Trillion VMT.¹⁷⁴ Greenblatt and Saxena (Greenblatt & Saxena, 2015) hypothesize a 10% shift from single- to double-occupancy in autonomous vehicles and find a 3% decrease in total energy use, corresponding largely to a 3% decline in VMT.

¹⁷¹ For example, in Paul Hawken's recent compilation of climate mitigation measures, both ridesharing and carsharing are *assumed* to increase pooling among U.S. commuters from 10% to 15% and increase average carpool size from 2.3 to 2.5 persons by 2050. (Hawken, 2017) p. 145.

¹⁷² (Bank of America Merrill Lynch, 2017) p. 167. BCG itself declined to forecast ridesharing, while going on to forecast modest amounts of carsharing, but noted that ridesharing would divert customers away from carsharing. Similar survey data for universities is in (Rodier, Alemi, & Smith, 2016) p. 122.

¹⁷³ (Albright and Stonebridge Group, 2016)

¹⁷⁴ (Brown, Gonder, & Repac, 2014) Table 1 (j); (Stephens, Taylor, Moore, & Ward, 2016) Table 2; (Greenblatt & Saxena, 2015) p.860. From Stephens Table 2, we subtract the upper and lower limit estimates of Total VMT in the Full – With Rideshare from the the Full – No Rideshare and compare them to the average of the VMT range of 2.7 to 8.5 TN miles total in the With Rideshare scenario.

Most of these forecasts appear to suffer from an omission of the additional VMT induced by the fact that pooled rides are 25% or more less expensive, and from the fact that congestion may be reduced, thereby encouraging more and longer trips (see Table V-3). "Although no direct empirical evidence of the effect of pooling on induced travel is available to date," RAS (2016) note, "solid empirical evidence shows that reduced congestion lowers the cost of driving and increases the quantity of vehicle travel."¹⁷⁵

The proposition that ridesplitting has modest and somewhat small net impacts on VMT comes from RAS' own comprehensive simulations of urban travel in San Francisco. They simulated travel in San Francisco using the activity-based travel model of the Metropolitan Transportation Commission of the SF Bay area under three sets of assumptions concerning pooling. In the minimum scenario, riders coming and going over points separated by not more than one mile not more than 15 minutes apart were assumed to be entirely pooled up to a maximum of 20% of all trips. Under the moderate case, the max wait time was 30 minutes and the maximum origin/destination proximity was five miles. RAS included greater travel induced by lower congestion, though apparently not greater travel induced by lower pooled ride prices.

In the moderate ridesplitting case – 30 minute and 5 mile buffers, respectively – pooling reduced total VMT by 8.9%, even when accounting for induced travel from lower congestion. However, in the minimum case, with 15 minute waits and a one-mile buffer, total VMT savings was insignificant. RAS also found that pooling was greatly increased by VMT fees of 10c a mile, equivalent to a "gas tax" on EVs of almost 100% at 30 cents/kWh power.

In the end, we are not convinced that pooling by itself will make large inroads into VMT in the absence of strong promotional policies. If we simply use a published Uber statistic of 21 MM VMT avoided in the first three months of 2016,¹⁷⁶ assume that it correctly adjusts for all the net induced and reduced driving effects in Table V-2, and add 20% for non-Uber pooling, the annualized effect at .33 kWh/mile (i.e., 100% electric miles) is only 33 GWh less power use. Even if this were to grow at a rate of 10% per year through 2050, a factor of 28 growth, power savings would be 927 GWh, less than 0.3% of current

¹⁷⁵ (Rodier, Alemi, & Smith, 2016) p. 123.

¹⁷⁶ <u>https://www.nytimes.com/2016/03/31/technology/car-pooling-helps-uber-go-the-extra-mile.html</u> accessed 7-19-17

U.S. power use. However, combining pooling with transit and other policies to encourage seamless mobility systems may yield a different result; we examine this possibility next.

F. SEAMLESS MOBILITY SYSTEMS

A variety of terms are used to refer to transportation information and payment platforms that enable travelers to find and use trip-specific combinations of traditional transit and new pooled and non-pooled TNC modes to provide rapid, easy travel. The typical vision for these systems is that a traveler uses their smartphone to book a trip "on demand;" a special-purpose, highly efficient taxi picks up the traveler(quite possibly pooled with another traveler) and takes them to a bus and/or rail mass transit system; they travel on this as far as they can towards their destination; and then another urban taxi is waiting for them at the transit stop they exit to bring them "the last mile." We refer to these systems as Seamless Mobility Systems (SMSs), but they are also often referred to as integrated multimodal systems, shared mobility, and more broadly as transport-as-a-service or mobility-as-a-service, though the latter terms include companies that provide only LDV transport. The goal of SMS systems is to make urban travel between most points nearly as fast and convenient as, and cheaper than, driving or taking a TNC car.

Researchers differ on the essential features of an SMS, but four main elements are quite prominent ((Kamargianni, Li, Matyas, & Schafer, 2016); Mani (2014)):

- Information integration. A single smartphone app or website has all the information necessary to plan and schedule any trip and guide the traveler during the trip;
- Payment integration. The same (or another seamless connected) application allows the traveler to pay for the entire trip with a single payment;
- Operational integration; schedules and operating processes are coordinated to make transfers between modes quick and easy; and
- Physical or infrastructure integration. Transfer hubs such as rapid transit stops are also built to facilitate quick and easy mode transfers.

As of this writing there are no cities that often complete SMSs, but the leaders of many non-U.S. cities, including Paris, Athens, Mexico City, and Helsinki have reportedly made vows that translate as strong support for shifting in-city auto travel to SMSs.¹⁷⁷ Kamargianni, et al (2016) examines ten emerging

¹⁷⁷ Gordon Sander, Christian Science Monitor, 6/23/17 <u>https://www.csmonitor.com/World/Europe/2017/0623/An-offer-Finns-can-t-refuse-Helsinki-woos-car-owners-to-give-up-their-autos</u>. Accessed 7/29/17.

efforts to adopt elements of SMSs, one of which, the SHIFT program, is operating already in Las Vegas.¹⁷⁸ Many more U.S. cities are making progress implementing one or more of these elements. In Chicago, a single transport smart card pays for both transit and some carsharing companies, and in San Francisco one payment card applies to over 20 transit systems and some parking.¹⁷⁹

The Effects of Seamless Mobility Systems

SMSs take passenger- and vehicle-miles away from trips in LDVs and shift them to a combination of modes that are naturally pooled and far more energy-efficient, especially traditional mass transit. The first- and last-mile portion of the SMS trip, expected to occur in LDVs or mini-buses integral to the SMS, is also likely to be more efficient than ordinary LDV travel because many of the vehicles used by the SMS would be optimized to operate on low-speed urban roads and would pool passengers. In our Kaya identity framework, SMSs do not change *passenger*-miles travelled much up or down; instead, they shift travel to modes with much lower EI per passenger. They can be seen as a strategy for substituting a flexible but overall more efficient mix of modes/technologies for the current less integrated and efficient mix dominated by single-occupant LDVs.

There is no requirement that SMSs use EVs or EAVs, but the general view is that such systems naturally lend themselves to these vehicle types. As emphasized by Johnson and Walker (2016) and A&S (2017), EAVs are ideally suited to intensive fleet use because (a) they will initially have higher fixed costs but much lower operating costs per mile than CVs; and (b) they are likely to be much more reliable than CVs in intensive use, with lower maintenance costs, higher availability, and much longer lifetimes. Moreover, most first- and last-mile travel will go back and forth to transit hubs where electric charging will probably be available, so range and charger locations should not be an issue. The Albright-Stonebridge group puts it even more strongly, arguing that SMSs simply won't grow quickly until full driverless technology is available:

Until autonomy is safely available, very small increases in overall utilization will come from incremental improvements by mobility services to attract customers: more convenience from TNCs such as better ETAs, corporate payment integration, carpooling options, or additional

¹⁷⁸ Mani (2014) examines multimodal integration as of that date in London, Paris, Singapore, Hong Kong and New York City. He notes that two cities, London and Singapore, have authority over all modes of travel in their cities and therefore do not need a new mandate to plan and implement SMSs.

¹⁷⁹ For example, (Dinning & Weisenberger) p. 124 review current examples of payment integration in U.S. transit systems.

features such as car-seat availability; or convenient point-to-point car sharing with multimodal integration or valet services; or transformational change in utilization will only be possible once autonomous technology and related enabling policies are in place.¹⁸⁰

Nonetheless, there are already several encouraging trends with today's technologies. We have already noted the progress many U.S. and foreign cities have made creating parts of SMSs with current technologies. In addition, after a long period in which auto use went up much faster than transit ridership, traditional U.S. transit PMs increased about 1.66% per year over the decade 2005-15, twice as fast as population and three times faster than automobile miles.¹⁸¹ Many cities have responded by adding to their transit systems, including some 41,000 miles of new track between 2000 and 2010.¹⁸² Still, it should be noted that many transit systems in the U.S. are in dire financial shape and have large deferred maintenance problems.

If we were able to predict the degree to which SMSs will penetrate American cities between now and 2050 it would not be too difficult to quantify their effect on electric power use. If we know the rough number and average length of trips that an SMS will cause to be diverted away from autos and the approximate mix of alternative trip modes we can calculate the approximate impact on transport power. For example, if an average 10-mile auto trip in a single-occupancy electric SUV (.5 kWh/mi) can be diverted to one pickup mile in an efficient electric sedan (.3 kWh/mi), 8 miles on an electric urban subway (.06kWh/mi¹⁸³), and a final mile in another efficient EV, the total electricity demand for this trip would decline from 5kWh to 1.08 kWh, a reduction of 78%.

However, unlike innovations such as driverless cars, SMSs are almost entirely a policy-driven phenomenon that need not await either electrification or autonomy. The barriers to implementing SMSs today in major cities are not technological, they are institutional, commercial, and economic. To implement an SMS a city needs to raise the investment necessary to create a full-scale seamless system and find ways to integrate operation and payments between multiple public agencies and private TNC firms – a very large institutional challenge.

Electric_Transport_Draft _10_5_17

¹⁸⁰ (Albright and Stonebridge Group, 2016) p. 47.

¹⁸¹ American Public Transit Association, 2016 Factbook, Figure 2.

¹⁸² American Public Transit Association, 2016 Factbook, Appendix A.

¹⁸³ Andrade et al. 2014 http://seekdl.org/upload/files/20141111_053056.pdf

Predicting the growth potential for SMSs is therefore an exercise that is proportionately more weighted towards predicting municipal transport policy leadership and less a function of technology and cost shifts, recognizing nonetheless that SMSs and autonomous taxis have very strong synergies. While we have no formula for making such predictions, it seems possible to bound the potential for SMS transformation simply by looking at current U.S. public transit systems and examining some possible growth rates. Because bus and rail transit systems are, by definition, the backbone of SMSs, one city's SMS cannot grow much faster than transit ridership.

According to the American Public Transit Association, U.S. transit ridership increased 18% in the decade following 2005 to 59.6 billion passenger-miles. If this trend were to continue to 2050, ridership would increase 73% (population would increase greatly during this period as well). Suppose that a strong push for SMSs across the U.S. doubled or quadrupled this growth, to about 150% or 300% ridership increases. Obviously this would mean that many urban transit systems would expand dramatically during the next 30 years, doubling or tripling their capacity and reach, requiring many billions of dollars of public or private investment. However, APTA statistics show that in the 10 largest US SMSAs about 13% of commuters use transit, more than double the U.S. average, and that in some areas almost one third of all commuters use transit. If these numbers can be achieved in some cities without SMSs, it seems possible that well-run SMSs could push U.S. transit use quite a bit higher.¹⁸⁴

The approximate transport power implications of this concerted policy push can be easily bounded. To get an upper bound on the reductions in power demand that this SMS growth would enable we first assume that, in the absence of strong SMS policies transit ridership remains flat at 60 billion PMT. We also simplify the calculation by assuming that SMS systems shift average LDV auto miles to transit miles, ignoring the first and last mile LDV use (or, equivalently, assuming its EI equals transit EI per PM). Finally, we assume that the power used for transit is zero, so that a shift of one passenger from an electric LDV to an SMS saves 100% of the electricity used by the LDV but does not increase power use

¹⁸⁴ A simulation of alternative transport scenarios for Lisbon, Portugal conducted by the OCED's International Transit Forum (2015, p.21) modeled city travel on a typical weekday with and without a "high capacity" transit system that was part of a seamless mobility system. The high-capacity transit scenario was able to reduce total VMT by 30 to 45%. This suggests that urban travel could be diverted significantly to a much larger transit system, at least in one European city.

for transit. Obviously, all of these assumptions are made to simplify the calculation, not because they are realistic.

The result of this simple calculation shows that a doubling of transit ridership growth rates, which would yield 150 billion transit PMT (triple 2015 levels) would save less than 30 billion kWh (TWh) at 0.33 kWh/mile, a little under 1% of current U.S. power. Quadrupling the growth rate to yield a 300% increase by 2050 would save 60 TWh, about 2%. The calculations of these results are shown in workpaper C. So, while SMSs seem to be an excellent idea that could significantly affect commuting in large urban areas, they will affect power use significantly only in American cities that make a concerted effort to greatly reduce or even eliminate intracity car-only trips.

VI."Wild Card" Factors

In this chapter we consider a handful of factors that will influence future LDV travel in especially unpredictable ways: (1) Road Infrastructure Costs, including AV-specific infrastructure, and the manner in which LDV travelers will or will not pay for it; (2) telecommuting, e-commerce, and other electronic substitutes for personal or business travel; and (3) redesign of urban areas to reduce the need to travel. While each of these factors may be reflected to a degree in our baseline view of flat per-capita VMT growth, and are also clearly related to changes in our three Revolution layers, they share the attributes of being especially uncertain as to their impacts. Accordingly, before finalizing our projections we consider whether we can learn enough to modify our power demand estimates, or at least determine the likelihood of significant upside or downside potential.

A. INFRASTRUCTURE AND ROAD PRICING

The system by which vehicle users pay for building and maintaining roads is another major facet of transportation that will be disrupted by the Three Revolutions. As it stands, the U.S. road system is underfunded, deteriorating, and getting progressively lower proportions of its funding from "user fees" of any kind. The growth of EV mileage, currently miniscule, will greatly exacerbate this situation and
likely force a reset of the US approach to collecting revenues from vehicles to pay for roads, which we generally refer to as road user charges (RUCs).¹⁸⁵

U.S. roads, which currently cost about \$103 billion a year, now get less than 50% of their funding revenues from user fees; the remainder comes from other revenue sources that are far more politically contentious and less predictable.¹⁸⁶ Meanwhile, the federal Highway Trust Fund is projected to have a deficit rising to over \$80 BN by 2025, while the 2017 Infrastructure Report Card estimates that the backlog of road and bridge "capital needs" is \$836 billion; other sources call for spending of up to \$177 billion/year.¹⁸⁷ Meanwhile, about 10% of the 607,000 bridges in the U.S. are classified as structurally deficient and the overall U.S. road infrastructure is ranked 18th in the world.¹⁸⁸ The situation in the states is sadly similar; a 2009 report for the State of Texas found a gap of more than \$150 billion between estimated road infrastructure needs through 2030 and all federal and state tax revenues for transport.¹⁸⁹

It is important to understand that most of these funding and shortfall estimates do not appear to incorporate two important developments. First, the advent of AVs will create pressure to better maintain existing roads. At least with current technologies, AVs rely on well-marked and well-maintained roads for safe, reliable operation. A recent report for the U.K.'s Royal Automotive Club (Johnson, 2017) provides a fascinating window into how maintenance needs will change as progressive levels of autonomy migrate into the fleet:

There are a myriad of other implications for road infrastructure, some requiring detailed highways engineering expertise to articulate. For example:

• A fully automated transport system can be expected to reduce the need for sharp braking and could be operated on a surface with only a modest level of friction. Potentially this could allow current Polished Stone Values and texture depth requirements to be relaxed (Dunford et al., 2014).

¹⁸⁵ We assume that the infrastructure required to charge EVs is installed by a combination of utilities and third party providers, but that the cost of this infrastructure is paid for through inclusion in the costs of electric power and/or dedicated costs to EV users. Accordingly, this section is about changes to physical and IT systems triggered by AVs. For more on EV infrastructure and its funding, see, e.g. (Melaina & Helwig, May 2014) (Fitzgerald, Nelder, & Newcomb, 2016)

¹⁸⁶ U.S. National Economic Council (hereinafter USNEC) (2014) p. 103; U.S.DOT 2016A p. 203

¹⁸⁷ (American Society of Civil Engineers, 2017) pp. 19,20; (Mendez, Monje, & White, 2017). For a good discussion, also see (Kahn & Levinson, 2011). For current press coverage, see (Appelbaum, 2017).

¹⁸⁸ (U.S. Department of Transportation)

¹⁸⁹ (Texas Department of Transportation, 2009)Figure 2 p. 9.

- Lamb (2015) notes that because CAVs will run consistently in the same lane positions there will be greater wear and tear in the wheel tracks, and that either the road area beneath the tracks will need to be strengthened, or maintenance repairs will need to be more frequent.
- The lane-keeping assist systems which are now a feature of certain cars are reliant on road markings to accurately determine the boundaries of lanes, implying that these markings therefore need to be maintained in good condition for the system to work.

With regard to the latter, as levels of automation increase, the need for the maintenance of these kinds of markings may become less important, as communication networks start to provide all the information required for the CAV to know where it is. However, contrary arguments have been put forward by a number of commentators. For example, Weeratunga and Somers (2015) argue that static communications will need to be maintained to a much higher standard than currently. In any case, until level 5 CAVs are commonplace, maintenance standards will need to be updated and aligned as systems evolve.

Experience in other transport sectors, such as aviation, suggests that the approach to maintenance has to change as automation increases, and maintenance costs typically increase – partly because the infrastructure has to be better maintained for safety reasons, and partly because it becomes more sophisticated, meaning that the maintenance workforce has to be more skilled and, therefore, charges more for its services (Bernhardt & Erbe, 2002).

Beyond increased maintenance, all levels of government will soon begin to face demands to redesign

and remodel parts of the road system and related parts of cities to accommodate AVs. As the Eno

Center on Transportation recently wrote ((Lewis, Turner, & Rogers, 2017) p.17),

For example, a predictable driving environment, such as well-marked traffic lanes, is necessary for current AV technology, so cities and states need to improve lane striping and signage. Construction workers and emergency vehicles could communicate with AVs via a smartphone app or some type of wireless signal, rather than using hand gestures or sirens and flashing lights. Traffic signals may need to be reconfigured to either communicate wirelessly to approaching vehicles or to ensure that, no matter the position of the sun, AVs can view and register the traffic light.

Improving roadways to better accommodate AV technologies poses significant costs, which is challenging especially for cities and states already struggling to upkeep infrastructure. Whether it is better roadway conditions or advanced sensors and transmitters, the upgrades could cost states and localities millions or billions of dollars in repairs and upgrades. At the same time, full AV deployment may reduce revenue streams such as parking fees and traffic fines that help pay for such upgrades or fund other public expenses.

Remarkably, there are virtually no published estimates of the cost of roadway revisions needed to accommodate AVs; the experts we spoke with on this topic uniformly agreed that the numbers were likely quite large but simply impossible to estimate at this early stage. However, we can gain a glimpse from some of the pilot programs underway. In England, Johnson (Johnson, 2017) noted:

It is difficult to judge the costs of adapting existing infrastructure for CAV use because so little information on costs is available, but, for reference, Highways England spent £3.0bn in 2015/16, including £1.9bn on its capital programme (ORR, 2016). As an indication of the potential scale of costs, it cost Highways England £90 million to adapt a 7-mile stretch of motorway for hard shoulder running at the M4/M5 interchange, and the 27 miles of the M6 toll road cost £900 million to construct.

Korea, which spent 10 BN Euro on annual transport investment and maintenance total in 2013, has recently announced its intention to retrofit its entire highway system at an estimated cost of about US\$62 billion.¹⁹⁰ In the U.S., the state of Ohio will reportedly spend about \$2BN to retrofit "smart mobility corridors", including 35 miles of four-lane highway between Dublin and East Liberty, Ohio. Although the outlays apply to more than this corridor, if we use only this mileage this amounts to \$57 MM/mile of highway. If this were to apply to the entire U.S. highway system (164,000 miles) the cost would be more than \$9 trillion.

These estimates appear to apply almost entirely to highways. In urban areas off the highways, infrastructure changes are also certain to be initially expensive, though perhaps later offset by savings. Apart from increased maintenance of local roads to allow AVs to operate, local transport officials will have to accommodate both AVs and CVs on the same roadways for several decades. This will call for retrofitting traffic signs and signals for AVs while maintaining the current ones. Similarly, many routes may initially work better if AVs and CVs are given separate lanes, entrances or exits, and dropoff and parking areas. For the decades during which both types of cars are on the road but shifting steadily in their proportions, road transport planners, builders, and operators will be under constant pressure to create two parallel, linked, and steadily shifting urban road infrastructures – a costly proposition.¹⁹¹

This does not refute the fact that complete AV fleets could eventually enable lower overall roadway capital and operating costs. Many observers note that all-AV fleets will make much more efficient use of the road system and thereby reduce the need for total roadway surfaces. In addition, AVs can be much lighter, reducing roadway wear and tear. Many other features of the roadway system might

¹⁹⁰ See <u>https://stats.oecd.org/index.aspx?datasetcode=itf_inv-mtn_data</u> acc. 8/17/17 for total Korean outlays; see South Korea to Build Smart Highways for Driverless Cars, GovInsider, https://govinsider.asia/smart-gov/south-korea-to-build-smart-highways-for-driverless-cars/ acc. 8/7/17

¹⁹¹ See, among others, Alessandrini, et al (2014) and (Litman, Smart Growth Reforms: Changing Planning, Regulatory, and Fiscal Pracices to Support More Efficient Land Use, 2016) for discussions of the the likely evolution of urban roadway infrastructure as AVs increase in the fleet.

ultimately become cheaper or more efficient.¹⁹² In the interim, however, the costs of transitioning the highway and local roadways to accommodate AVs are clearly many billions of dollars. These added costs make it that much more likely that the U.S. and other countries will transition away from their current reliance on petroleum fuel taxes to some other approach to RUCs.

B. POSSIBLE RUC DESIGNS AND LEVELS

The cost of new and maintained roadway and related infrastructure, and the means of paying for it, are gigantic questions overhanging the future of U.S. transportation. These questions have been among the most durably controversial domestic policy topics since the end of World War II, perennially debated by transportation economists, policymakers, and road stakeholders (one representative of the American Trucking Association recently noted that he has testified in Congress in favor of RUC changes 31 times).¹⁹³ Now, as EVs (and subsequently AVs) destabilize the U.S.'s longstanding political solution to road funding, forecasting the eventual outcome is little more than a guessing game.

However, there is no shortage of studies, proposals and pilots from which a solution can be drawn.¹⁹⁴ With respect to form, most of the proposals that would be perceived as a road use charge (i.e., potentially affect auto use on the margin) fall into one of these categories:

- a) Tolls and Congestion pricing, meaning fees that are assessed by time period and road section when and where congestion occurs, or for a pre-designated area such as central London; if the fees apply only to specific roads, and are not time-dependent, they are usually called tolls, but tolls are now often computed dynamically to mimic congestion pricing;
- b) Pure VMT charges, i.e. charges based only on total miles traveled on roads;
- c) Hybrid systems that include both congestion and distance pricing;

¹⁹² See (Rodoulis, 2014) for a good qualitative discussion.

¹⁹³ The seminal economic works date back to Pigou and Knight in the 1920s; more modern contributions include (Small, Winston, & Evans, 1989) (Langer & Winston, 2008); the literature is nicely surveyed by R (Rouwendal & Verhoef, 2006). See (Viegas, 2001) for a good articulation of why road pricing alone is usually too narrow a concept upon which to base urban transport policy decisions.

¹⁹⁴ In addition to the following, see Appendix A of Sorenson (2010).

d) Fixed fees, such as higher annual registration fees or special charges;

Some taxonomies call the use of public-private partnerships a different alternative to funding roads, but from the standpoint of drivers paying the costs of driving, these are simply financing mechanisms; they must recoup their investments from road users or non-users somehow.

The use of tolls is widespread and growing throughout the world, including semi-private tollroads. Meanwhile, tolls are increasingly becoming time-varying. Congestion pricing has been used in Central London since 2003, raising GBP 1.2 billion of revenue, reducing traffic accidents 40% and increasing average speed from 8.6 to 20 mph.¹⁹⁵ Singapore and Stockholm have also adopted center-city congestion fees, and as of this writing, New York Governor Andrew Cuomo is considering introducing congestion pricing in Manhattan.¹⁹⁶

Pure VMT charges have been proposed frequently, including by then-U.S-Secretary of Transportation Mary Peters in 2008, who described them as inevitable, and by the U.S. National Surface Transportation Infrastructure Financing Commission.¹⁹⁷ In 2009 a broad coalition of government and NGO agencies known as Moving Cooler engaged Cambridge Systematics to examine, among other policies, a nationwide VMT fee starting at the equivalent of a \$.60/gallon fuel tax and rising to \$1.25 by 2050. In that same year the Netherlands proposed such a fee, but later rejected it in favor of a gateway toll system. A federally-sanctioned study of a national VMT fee was prepared by (Hanley & Kuhl, 2011); the U.S. Government Accountability Office (GAO) studied VMT fees in 2012; Oregon implemented a voluntary VMT fee to replace gas taxes in 2015; and California completed a road charge pilot in March 2017 and is now compiling the results.¹⁹⁸ Lawmakers in Massachusetts introduced a legislative proposal for a VMT fee of no less than 2.5 cents/mile in January, 2017.¹⁹⁹

The fourth approach, annual registration fees, is becoming fairly widespread in U.S. states; whether it is a stopgap measure or long-term approach remains to be seen. According to the New York Times, ten

¹⁹⁵ (Thorpe, 2017)

¹⁹⁶ (Russell-Carroll, 2014) re: Singapore and London. (Langer & Winston, 2008) propose a nationwide system of congestion fees that raises \$120 billion a year, more than current total roadway spending in the U.S.

¹⁹⁷ National Surface Transportation Infrastructure Financing Commission (2009); (Grush, Hassan, & Khalsa, 2009) p.1.

¹⁹⁸ U.S. Government Accountability Office (2012); (Oregon Department of Transportation, 2017); (U.S. Library of Congress, 2014); <u>https://www.californiaroadchargepilot.com/about/pilot-status/</u> acc 8/17/17 ¹⁹⁹ Senate Bill 1945, filed 1/19/17, Section 63E.

states have adopted lump-sum fees of up to \$200/year to replace lost gas tax revenues, and four more are considering it.²⁰⁰ As this approach is neither mileage- nor efficiency- specific, it would not (at least in theory) alter either VMT or EI among EV owners. Other approaches such as feebates have more complicated effects, and approaches such as development impact fees are not properly considered RUCs.²⁰¹

Back-of-the-Envelope Impact Calculation

We do think that added roadway user fees (much less their specific level and form) are an assumption consciously considered in either the EV forecasts we use, our baseline assumption regarding VMT, or the three layers of adjustment we have made for EVs, autonomy, and shared/pooled modes. It is therefore incumbent on us to try to determine the extent to which an increase in RUCs for EVs and AVs, which we agree is inevitable, would affect our estimates.

From the standpoint of EV electricity use, the salient questions involve the extent to which added RUCs of whatever kind affect VMT and EI, including price-induced reductions in travel, shifts between modes and long-term design changes that reduce EI. There are hundreds, if not thousands, of permutations as to how a revised system of road charges could affect each of these dimensions of travel, especially when federal approaches layer on separate state and city charging schemes. For example, a schedule of VMT fees fixed for all LDVs and charged by the mile would reduce driving but incent no improvements in EI; tolls that single out SOVs would encourage pooling; feebates would induce faster improvements in EI; congestion pricing would lower VMT at certain times and places; and so on.

Creating a sensitivity calculation for this factor is particularly difficult because we know almost nothing about either the magnitude of the outlays needed nor their design and incidence. More completely, we do not know:

- (a) The rate at which spending will increase or decline for maintenance of the current roads;
- (b) The cost of local or intercity infrastructure specifically added to accommodate and realize the benefits of AVs, alongside added infrastructure to relieve congestion;

²⁰⁰ (Tabuchi, 2017)

²⁰¹ (Forkenbrock & Hanley, 2006)

- (c) The level of spending on mass transit and seamless mobility systems and the portion of this that will be collected from some form of road user charges;
- (d) The portion of the charges in (a)-(c) that will be paid for via collection approaches directly tied to vehicles or travel, versus paid for from private funds, general tax revenues, and other mechanisms not perceived as a cost of travel.
- (e) Of the portion collected directly from travellers in one form or another, the time-shifting and shaping of collections by the use of financing mechanisms;
- (f) How all the time series of charges in (e) will be apportioned between LDVs and freight vehicles;
- (g) How the charges in (e) will be apportioned between different types of LDV vehicles; and
- (h) The degree to which the charges will be perceived, and paid for, per mile of operation versus paid for in ways not perceived as short- or long-term prices for the use of roads, such as registration fees.

Recognizing this massive uncertainty, do not think it is practical to attempt a detailed analysis of the wide range of possible RUC outcomes and the range of their impacts on VMT and EI. However, we believe we can get a rough, order-of-magnitude range by examining two simple pricing scenarios: a flat 2.2 2017 cents per mile charge and a larger 2.4 cents per mile (\$.60/gal @ 25 mpg) escalating to double its level in real terms by 2050. The first level of charges is similar to the GAO's estimate of the level needed to maintain current roads, indexed for inflation. It also happens to equal Jenn, Azevedo, and Fischbeck's (Jenn, Lima Azevedo, & Fischbeck, 2015) sophisticated calculated lifetime-equivalent payment for a current EV and is below the recent Massachusetts proposal. The second level is similar to the 2009 Moving Cooler proposal, translated to a pure VMT fee.

Based on a review of the literature, we employ a long-run RUC elasticity of -0.2 as our base case and later explore sensitivities with a level of -0.35. Using current average electricity rates (which we assume are constant in real terms through 2050) and 2050 estimated Els, the 2050 reductions in VMT are about 24% and 42% for elasticities of -0.2 and -0.35, respectively, for the \$0.048/mile RUC. Obviously those are extremely crude order-of-magnitude estimates for a single terminal year, but we believe that they are an improvement over an assumption of few user changes occurring by 2050.

In both cases, this simple VMT fee is intended to serve as a proxy for an inevitable mix of RUC fees, including urban area-specific congestion pricing, the extensive use of time-varying toll segments, VMT fees, pay-as-you-drive insurance, and fees indexed to vehicle efficiency or occupancy, such as feebates. The general effect of all these measures will be to reduce VMT and increase EI, at least in the long run, as would occur with our simple VMT fee. We find a total cost of \$0.052 per mile in 2017, and costs of \$0.045 and \$0.040 in the high and low cases, depending on assumed EI improvements out to 2050.²⁰²

VMT fee elasticities are slightly less straightforward, but still relatively easy to implement. Several researchers have calculated both short- and long-run elasticities for various aspects of travel cost. When instituting a VMT fee, fuel elasticities and toll elasticities could be comparably relevant, as both are related to distance traveled. VMT elasticity to fuel price is, however, more directly related to total miles traveled over a period of time as a VMT tax is less spatially restricted than a toll system. A toll is necessarily tied to a specific piece of infrastructure and incents users to either choose a different form of transportation (public transport or pooling) or use an alternate route. Fuel prices or VMT fees, on the other hand, are independent of the path taken and their effect can therefore be directly tied to total VMT.

According to Deakin et al. (Deakin, Harvey, Pozdena, & Yarema, 1996) short-run travel is relatively inelastic to price, with elasticities in the -.1 to -.3 range for driving costs. Deakin notes that long-run elasticities have a wider range of outcomes, with anywhere from -.05 to -.8 depending on the specific circumstance. In our (admittedly limited) review of elasticity studies, results seem to converge around the .2-.3 range. In a 39-year cross-sectional times series of US states, Small and Van Dender (Small & Van Dender, 2007) find that the long-run VMT elasticity to fuel price is -.21. In a review of long run time series for fuel price elasticities, Lee (Lee, 2000) finds long-run travel elasticities are around -.33. In their study using a sample from the National Highway Travel Survey, (Binny, Kockelman, & Musti, 2011) find a mean elasticity of -.25 for fuel costs. Consistent with this range, in conducting a sensitivity analysis of costs and benefits to road pricing, Langer and Winston (Langer & Winston, 2008) use VMT elasticities of -.1, -.3, and -.5 in their analysis.

²⁰² The details of this calculation can be found in Workpaper E.

We agree that a sensitivity approach to potential VMT effects of a VMT fee is in order. Based on the literature, we therefore use a high case and a low case for elasticity; the low case being -.2 and the high case being -.35.

Snapshot results of the effect on VMT in the year 2050 can be expressed in a 4x4 matrix, below:

Table VI-1: VMT reductions in 2050 based on Electric Intensity, Road Price, and Elasticity

	35 Elasticity	2 Elasticity
High Base El		
.048\$ RP	-42%	-24%
Policy Case El		
.022\$ RP	-17%	-10%

The result is a 10% to 42% reduction in VMT in the year 2050 when the full effects of our four VMT fee scenarios are applied. However, we use only the -.2 elasticity for our two base scenarios.

Impacts on El

Any form of road pricing that affected LDVs in proportion to their efficiency would induce greater EI in the long run. As we have already created an accelerated-EI scenario, we believe we have already illustrated one possible level of the effect of RUCs on EI. The effect of an RUC scheme that provided an EI incentive would, in our view, accelerate the likelihood, and perhaps the timing, of our high-EI scenario.

C. ELECTRONIC SUBSTITUTES FOR TRAVEL

As electronic communication becomes better and cheaper, perhaps soon incorporating virtual reality (VR), it is possible that travel to physical workplaces will diminish in favor of tele-work or telecommuting. Similarly, the continuing rapid expansion of e-commerce, now reaching into groceries and other goods not thought to be suitable for e-commerce, raises the possibility that people will make fewer physical shopping trips, lowering total LDV travel while concurrently increasing freight deliveries.

Telecommuting using past and current communication technologies, some of which are far inferior to methods available today, has been studied extensively, with mixed results. In its last national long-term study, the U.S. Department of Transportation concluded that:

Looking ahead to the next 30 years, the most influential factors affecting commuter travel are likely to be two trends highlighted earlier: the size of the workforce and the growth in flexible schedules and teleworking. The portion of Americans in the workforce is expected to decline as the population ages, moderating growth in the number of commuters. The continued growth in teleworking and the use of flexible schedules will also serve to moderate demand for commuting, particularly at peak travel times. These changes may combine to slow growth in congestion in metropolitan areas.²⁰³

Three of the study's authors, Vendez, Monje and White²⁰⁴ further note that telecommuting is growing faster than any other actual method of physical travel to work.

With the ongoing explosion in mobile connectivity, this trend seems to be evolving. The latest Gallup Survey of the American Workplace has replaced the term telecommuter with "remote worker," reminding us that workers may be working from anywhere, not just home. Gallup's numbers bear this out: the number of companies offering "flexibility" as to work location has tripled since 1996, and the number of workers who take advantage of this is now an astonishing 43%, up from 39% in 2012. The number of workers working entirely remotely increased 5% since 2012 to 20%.²⁰⁵ Circella, et al²⁰⁶ also reports robust growth in telecommuting, especially among millennials, although the percentage of families who report that they telecommute regularly is only about 4%.

This observed increase in remote work is among the factors baked-in to the very low growth in FHWA forecasts of VMT growth and the even lower (i.e., flat to declining) forecasts of VMT growth by forecasters like (Litman, 2016). However, and despite the ongoing improvements in connectivity and communications quality, we find it difficult to add an additional decrement to VMT from telecommuting.

This is because there is surprisingly strong agreement in the literature we can find that telecommuting has a complex of effects that, in the aggregate, do not seem to change long-term total travel very much.

²⁰³ (U.S. Department of Transportation)

²⁰⁴ (Vendez, Monje and White, 2017) p.6

²⁰⁵ (Gallup Organization, 2016) p. 149ff

²⁰⁶ (Circella, Tiedeman, Handy, Alemi, & Mokhtarian, 2016) p.31

In some studies of telecommuting, the total annual VMT of telecommuters declined, but in others the VMT saved from a daily commute were replaced by shopping, errands, and family-oriented trips. For example, Lyons (2002) reports on findings by Hjornthol (2002) that "the net effect [of telecommuting] gives no reduction in travel activity. Stationary communication seems to be a supplement to activities based on mobile technology, but it gives people more spatial and temporal options."

Circella, et al's (2016) very recent summary of the topic provides a thoughtful summary:

For many years, information communication technology (ICT) has been seen as a trip replacement strategy and thus a solution for many societal problems, including urban congestion, dependence on non-renewable energy sources, air pollution, and greenhouse gas emissions, as well as rural underdevelopment, reduced economic opportunity for the mobility-limited, and the struggle to balance job and family responsibilities. Certainly, technological solutions such as telecommuting can function as a substitute for commute trips (Zhu 2012) and can replace *some* [sic] travel, but at the same time they can generate additional travel as well. Mokhtarian (2009) discusses a number of reasons for which ICTs can respectively have no relevant effect on travel (*neutrality*), generate new travel (*complementarity*), alter travel that would have occurred anyway (*modification*), or reduce travel (*substitution*), (Salomon and Mokhtarian 2008).

Perhaps the best encapsulation of the topic comes from a 1997 quote by Mokhtarian, who says:

"...the idea that telecommunications technology could substitute for travel dawned on people soon after the invention of the telephone...Historically, transportation and communications have been complements to each other, both increasing concurrently, rather than substitutes for each other. And we have no reason to expect that relationship to change."²⁰⁷

We reach a similar conclusion regarding electronic retailing or e-commerce (we blend the two concepts here, focusing on their collective impact on LDV travel). Intuitively, one would think that increased online commerce would reduce the 20% of all trips reportedly devoted to retailing, with a corresponding increase in the volume of retail delivery freight. While the latter does appear to be occurring, the Department of Transportation²⁰⁸ reports that it has not yet detected any reduction in shopping trips. A host of studies by travel researchers conclude that electronic shopping complements rather than

²⁰⁷ (Mokhtarian, 1997) as quoted in (Lyons, 2002) p. 342.

²⁰⁸ (U.S. Department of Transportation Federal Highway Administration, 2015), p.19

replaces physical shopping, with offsetting effects that include the fact that e-commerce enourages large, distant distribution and retail centers and thus longer shopping trips when they occur.²⁰⁹

D. THE BUILT ENVIRONMENT AND VMT

Here we explore the extent to which additional alterations in the built environment could affect trends of vehicle miles traveled, beyond the assumptions and calculations that have been made so far in this paper. The built environment can affect people's mode choice for daily transportation needs, as well as housing choice and preference and travel distance to work, school, and basic amenities. Strategic choices regarding the built environment, therefore, could impact the number of vehicles, as well as distance traveled per vehicle.

There are two bodies of literature relevant to potential VMT impacts of the built environment. The first is literature surrounding the effects of built environment on congestion; the second pertains to literature examining the effects of urban characteristics. These two complimentary but distinct sets of work highlight a broader divergence in long-term land-use opinions/trends.

Highway Expansion

Broadly, congestion management for roadways has most frequently taken the form of roadway expansion to ease traffic flows. Unfortunately, according to Outwater et al. (2014) "experience shows that supply-side solutions to traffic congestion provide mobility benefits that are mostly short-lived". As congestion eases, reduced congestion lowers the cost of driving and increases the quantity of vehicle travel (CARB 2014a). This effect results in an initial mean short-term elasticity of road investments of between .3 and .6. ²¹⁰

Further, with later "induced growth" – structural shifts in land use development – vehicle travel has been shown to increase or even return to previous levels of congestion, locking in low-density development for decades to come. To that effect, the Victoria Policy Institute found that even in

²⁰⁹ See, for example, (Visser & Lanzendorf, 2004)), (Weltevreden J. , 2006), (Fichter, 2003), (Mokhtarian P. L.,

^{2004), (}Anderson, Chatterjee, & Lakshmanan, 2003)), and (Rotem-Mindali & Salomon, 2007).

²¹⁰ (Handy & Boarnet, 2014); Cervero 2002b in (Outwater, et al., 2014) 114

relatively slow-growth regions with modest congestion problems, highway capacity expansion increases suburban development by 15-25% (Litman, 2017). Other researchers have found long-run elasticities of .6-1 for highway expansion and VMT, indicating that highway expansion could have no discernable impact on long-term congestion.

A marked increase in roadway expansion could therefore increase total vehicle miles traveled. However, the baseline assumptions of our model are built from FHWA assumptions for traffic growth over the next 35 years, and these assumptions are derived from a baseline that includes increased highway growth. We therefore find no need to further modify our model to account for highway expansion.

Urban Design

Urban design has for years been proposed as a solution to urban sprawl (Kenworthy & Laube, 1996) a phenomenon that many in the field of urban planning, as well as in nonprofit and government circles, view as negative.²¹¹ Documented negative effects of sprawl (or "costs") include traffic congestion, increased infrastructure expense, inconvenient and uncomfortable travel conditions, pollution emissions, excessive energy consumption, inadequate mobility for non-drivers, and reduce physical fitness and health outcomes.²¹² The policy objective of land-use-based mobility has been to reduce these additional costs, many of which arise directly from traffic congestion or vehicle miles traveled in traditional ICE vehicles. As a result, the potential to moderate travel demand by changing the built environment is one of the most heavily-researched subject in urban planning²¹³, often motivated by the desire to reduce the environmental and health impacts of travel.²¹⁴

The wide range of potential impacts on VMT is further complicated by the many variables that constitute the built environment. Cervero and Kockelman (1997) initially identified '3 Ds' -

²¹¹ (Bolick, 2000); (Cervero & Murakami, 2010)

²¹² (Litman, 2014); (Salon, Boarnet, Handy, Spears, & Tal, 2012)

²¹³ (Ewing, et al., 2015)

²¹⁴ (Boarnet & Crane, 2001)

density, diversity, and design – that influence travel behavior, in an attempt to categorize explanations as to why the built environment should affect travel demand. At its base, the "density" theory of why built environment should affect travel demand is an intuitive one; a given trip becomes shorter as a destination becomes nearer.²¹⁵ More compact development also has a number of related attributes, such as less parking, better transit, more diverse land uses, and bicycle- and pedestrian-friendly urban design, many of which could discourage vehicle use, and which are treated separately as "diversity" and "design".

Cervero and Kockelman later expanded their variables to include destination accessibility and distance to transit, which are two diaggregated components of the initial "density" variable.²¹⁶ These variables remain the cornerstone of research into the effect of built environment on travel demand and vehicle miles traveled, and a subset of the variables (or some variation on them) has been used to quantify the relationships between the build environment and travel behavior, with researchers often converting statistical models based on these variables into elasticities (Stevens 2017).

1. Urban VMT Effects in Academic Literature

While causal explanations for why the built environment should affect travel demand are logically sound, what has been less clear in the literature is the *extent* to which a difference in built environment affects overall vehicle miles traveled.

According to Ewing et al., "the vast majority" of [disaggregated travel studies] show significant relationships between development patterns and travel behavior (Ewing, Bartholomew, Winkelman, Walters, & Anderson, 2008). Cervero and Murakami (2009) find moderately strong negative elasticity between population density and VMT per capita in an analysis of 370 urban areas in the US, with the elasticity of population density and VMT/Cap of -0.381 (Cervero & Murakami, 2010). They note that the largest VMT reductions would come from creating compact

²¹⁵ (Boarnet & Crane, 2001)

²¹⁶ (Ewing, Bartholomew, Winkelman, Walters, & Anderson, 2008)

communities which have below-average roadway provisions, more pedestrian/cycling infrastructure, and in-neighborhood retail activities which invite non-motorized travel.

In a meta-analysis of the build environment travel literature conducted by Ewing and Cevero (Ewing & Cervero, 2010), the paper found weighted average elasticities of between -0.00 and -0.22, with destination accessibility most strongly related to VMT, concluding that "almost any development in a central location is likely to generate less automobile travel than the best designed, compact, mixed-use development in a remote location". A second meta-analysis of compact development studies was conducted by (Stevens M. R., 2017). While Stevens finds elasticities of up to -0.63 (between distance to downtown and VMT, controlling for self-selection bias), the conclusion he makes is the opposite of that of Ewing & Cervero, concluding that "if anything, planners should probably assume for now that compact development will have a small influence on driving, until and unless they are given a compelling reason to believe otherwise." Stevens argues that while "it is possible that the benefits of building compact communities do exceed costs when all benefits and costs are accounted for ... the burden of proof is arguably upon planning researchers ... to demonstrate that the benefit of planning interventions outweigh the costs." Regardless of the interpretation and cost/benefit ratios of compact design, in general the academic literature does suggest a potentially significant reduction in VMT related to various changes in built environment. Ewing notes that "based on the planning literature...compact development has the potential to reduce VMT per capita by anywhere from 20 to 40% relative to sprawl", which is consistent with our review.

The correlation between urban form and reduced VMT may be confounded by self-selection bias as well, with people who are more willing to use public transportation more likely to live in urban environments.²¹⁷ If true, this phenomenon would result in an overstatement of the impact of built environment on personal vehicle use. This appears not to be the case, however, as the Ewing & Cervero (2010) meta-analysis found that controlling for self-selection bias appears to increase the absolute magnitude of elasticities, indicating that any effect from TOD on VMT could be

²¹⁷ (Circella, Tiedeman, Handy, Alemi, & Mokhtarian, 2016)

greater than indicated. Even so, considerations must be made for the existing conditions of land use and transportation infrastructure in accounting for compact development in transportation modeling. Ewing et al. (2008) notes that "the cumulative effect of compact development also depends on how much new development or redevelopment occurs relative to a region's redevelopment pattern." Taking into account predictions of regional growth rates and housing stock replacements, Ewing et al. predict that compact development has the potential to reduce total US VMT by 10-14%.

2. Land Use VMT Effects in Policy Literature

We are not ready to accept this conclusion as a final estimate of the potential influence of urban design. The reasons for this are several-fold -- not least of which being that planning agencies and departments across the US are vastly heterogeneous. While some cities and government agencies have actively fought against urban sprawl, implementing policies that include road and parking pricing, mixed use zoning, investments in alternative planning modes, household travel planning programs, and overall aggressively seeking to increase urban density, a majority of other urban areas are becoming less dense (Kolko, 2017).

In addition to this heterogeneity, so-called "Smart Growth Principles" (many of which correlate to the 5Ds described earlier) present several barriers that make them challenging to implement, and "trying to implement those policies requires adopting a whole set of additional policies that are much less appealing to most Americans" (Downs, 2007). In light of these barriers, we do not think it is most likely to assume that the entire U.S. achieves the full potential of 10-14% reduction in VMT possible through aggressive planning policies.

Our review of policy-oriented literature reflects this. According to a 2012 report by Cambridge Systematics, "an integrated set of land use strategies achieves cumulative GHG reductions from .3 to 2.1 percent improvement over the baseline" (Cambridge Systematics, 2009) implying only slightly higher baseline VMT improvements.²¹⁸ In a model simulation of eight pilot test

²¹⁸ As noted in Ewing et al. 2008, a 30% reduction in VMT would be expected to produce a 28% reduction in CO2, factoring in penalties from cold starts and lower vehicle operating speeds.

scenarios, (Outwater, et al., 2014) found that in the application of eight different scenarios (the most dramatic of which include a 30% shift in growth from suburban areas to denser, urban core areas and adding integrated transportation services), the maximum reduction in VMT was -9% amongst the five locations simulated, with most effects being much lower (in the 1-2% range).

In sum, our review of the literature indicates that the upper bound of VMT effects from strict urban planning mandates across the US would be 9%, with a more likely scenario in the 0.3-2.1% range. Accounting for ride sharing and seamless mobility (as is done in Chapter V above) incorporates some, but not all, of the potential VMT impact of land-use based mobility initiatives (Zhang, 2004). That being said, we recognize that transit oriented development and Smart Growth policies are, for the most part, less dramatic scenarios than that forced in the "ride sharing/seamless mobility". We therefore assume that the VMT result of a concerted nationwide effort towards compact urban design policies would save an additional 2% of VMT by 2050 in addition to our seamless mobility scenario. We add these savings in our "policy case" scenario presented in the following chapter.

E. CONCLUSION

The three "wild cards" we have surveyed have generally done a poor job of living up to their label. Of the three, we have concluded that electronic travel substitutes are unlikely to result in significant VMT differences not already captured in the range of outcomes in the three layers of modeling above. As this factor is more likely to reduce travel than increase it relative to our forecasts, our decision to ignore it presents an unknown upward bias in our power demand numbers. Our review also indicates that urban design will, at most, add 2% on top of our existing scenarios. As urban redesign is largely policy-driven, not an exogenous factor, our non-policy scenarios amount to a prediction that the most likely outcomes exclude a significant policy shift that could, if adopted, reduce travel.

Charges for the use of infrastructure in a manner that affects driving is also a true wild card. It is far beyond our ability to predict how the U.S. federal government and the states will cope with the deterioration of existing roads and the need for infrastructure to service AVs. Even today, well before the advent of AV-specific infrastructure, these questions push the U.S. Congress and many states to the

political breaking point. About all that can be said of this wild card is that it, too, presents almost entirely downside risk to transport power demand. Today, no LDV pays anywhere near its full share of the cost of roadway infrastructure; total infrastructure funding is far short of funding needs; and as yet electric vehicles pay even less than gasoline cars. Regardless of whether infrastructure becomes increasingly privatized or built and maintained via public-private partnerships, it is hard to see anything but an increase in the marginal price signal experienced by EVs and later EAVs. We thus construct two very simple scenarios in which U.S. policy shifts to implement some form of price signal above experienced by all LDVs and calculate that these would have the effect of reducing VMT by 8.5% to 32.3%

VII. Results and Observations

A. Exploring the Range of Outcomes Via Scenarios

The authors of the hundreds of pieces of research we have relied upon have each made dozens of assumptions underlying their work.²¹⁹ As we have compiled this research we have made dozens more. Were we to catalog these comprehensively, we would end up with a huge list and an infeasibly large number of possible scenarios and sensitivity runs that could be examined.

However, over the course of our research a handful of assumptions stand out as particularly important, either because they describe an important fork in the development path for U.S. passenger transport or because they have relatively strong and direct effects of LDV power use. Remembering that we have excluded the possibility of hydrogen fuel,²²⁰ Table VI-1 shows the remaining variables we place in this category.

Even the greatly foreshortened list in Table VII-1 contains a large set of variables. Based solely on our judgement, we create two "bookend" scenarios that we think are near the edges of the probability space in which the true future outcome resides. We perform a number of sensitivity studies around the two main scenarios, described in more detail later in this chapter. Table VII-2 shows these scenarios

²¹⁹ As noted in Section I, we have made no attempt to ensure that underlying assumptions in these diverse works are consistent with each other or with our own parallel assumptions.

²²⁰ More accurately, assumed that either hydrogen fuel does not affect EV sales as we have projected them, and/or that the production of hydrogen is done with on-grid electricity in the U.S. and used by FCVs with approximately the same total power requirements per mile as electricity is delivered to and used by EVs.

in abbreviated form; Appendix B contains a detailed description of all scenarios and sensitivity calculations.

Table VII-1: Variable Summary

Variable Name	Description	High	Low	Notes
EV Sales	The rate of EV sales, or more completely,	High	Low	*See Ch. III for a
	the growth of LDV EVs in the fleet;			description of our EV
				sales methodology
Cheap EV	The extent of the mileage effect from	0	-10%	
	lower EV operating costs;			
AV Entry Year	The year in which commercial fully-	2025	2030	
	autonomous AV sales begin;			
AV VMT Effects	The overall (net) long-term effect of AVs	-23%	-40%	
	on VMT (due to a number of effects, each			
	with their own ranges and uncertainties),			
	and how in the aggregate this phases;			
	this is aggregated with "Cheap EV" for a			
	total high factor of -50%			
AV Sales	The rate of AV sales, or more completely,	Base		*See Ch. IV
	the growth of LDV AVs in the fleet;		-	
AV EI	The overall (net) long-term effect of AVs	-21.5%	-13.5%	* Sum of effects of
	on realized kWh used per mile from			traffic smoothing,
	various effects, and how this phases in;			intersection
				management, faster
				travel, and platooning
Energy Intensity	The level at which EVs (whether	High	Low	
	autonomous or not) increase their energy			
	efficiency;			
Rightsizing/weight	Whether and when AVs allow a further	-1%	-1.5%	
reduction	substantial gain in EI due to			
	lightweighting and/or rightsizing,			
	implemented as a per-year increase			
	starting in 2040;			
Pooling/Shared	Whether Pooling, Sharing, or Seamless	0	-2%	
VMT Reduction	Mobility Systems will reduce future VMT			
	as well as shift it to higher-density			
	modes;			
Urban Design	Whether redesign of our urban areas	0	-2%	
	reduces VMT;			
Road Pricing	The form in which road pricing is adopted	\$.022	\$.024	
	over the next decade or two;			
Road Pricing	The increase in real road pricing cost by	\$0	\$.024	
Addition Through	the year 2050			
2050				
Elasticity	The sensitivity of driving in EVs and	2	35	
	electric AVs to road prices.			

	at ing	X0 X0
El Effects	Rightsiz /weigł reducti	-1.0%
	Platooning	-2.5% -2.5%
	Faster Travel	8.0%
	Intersection Management	-4.0% -4.0%
	Traffic smoothing 1	-15.0% -15.0%
	Energy Intensity	High Low
	Urban Design	0% 2%
	Pooling / shared VMT reduction	0%
Vehicles VMT Effects	Elasticity	-0.20 -0.20
	Road Pricing Addition through 2050	\$0.000 \$0.024
	Road Pricing Start	\$0.022 \$0.024
	VMT Effects (AV + cheap EV)	High Low
	AV entry year	2025 2030
	EV Sales	High High
	Scenario Name	High Base Policy Case

Table VII-2: Scenario Descriptions

123 Electric_Transport_Draft _10_5_17

We label the first scenario our High Base Case because it contains what we subjectively see as an overall combination of future events that represent the highest electricity use scenario we think could realistically occur: high EV sales; early AV entry; high ultimate increases in VMT from EV price reductions and AV time reductions; no reduction in VMT from pooling; base case improvements in energy intensity for EIs generally and small (1%/year) *additional* lightweighting efficiencies for AVs; road charges equal to current average total levels, escalating with inflation (applying uniformly to all EVs and AVs); and relatively low travel sensitivity to road pricing.

From the standpoint of environmental policies and technical efficiency improvements, it is fair to regard this as a pessimistic – and, in total, not entirely likely -- case. Americans react to cheaper operating costs for EVs by driving them 10% more, and then drive another 40% more when full AVs become available – a combination of time savings for commuters, increased recreational travel, and increased access to travel by underserved populations. For increases anything like this huge increase in driving to occur over the next 32 years, urban sprawl must continue unabated, immigration must remain strong, millennials must go back to the suburbs as their families grow, and AVs must demonstrate that they can deliver much more throughput on congested roadways without forcing higher road user costs on AV passengers. At the same time, lightweighting of AVs occurs at a slower rate and we do not boost the efficiency advantages of AVs even though they are driven much more.

We do not think it likely that all of these factors will occur together, making this something of an upper bound. With the possible exception of extreme VMT increases from autonomy, we would be surprised if any of these factors had larger positive effects on power use, while we have made consistently conservative assumptions regarding the factors that reduce power demand. In addition, we assume all AVs are electric, an assumption biasing our results upwards.

At the other end of the spectrum we design a strong environmental policy scenario, or Policy Case for brevity. This case assume that federal, state, and/or local policies cause nearly every variable that leads to lower travel and/or higher efficiency to change to what we believe is possible.²²¹ This includes

²²¹ Arguably, the one environmental policy lever we do not employ is mandatory pooling, ridesplitting, or carsharing. While we do assume a huge increase in seamless mobility systems, which pool passengers in LDVs for the "last mile," we do not include policies that force higher average occupancy per se or higher carsharing. Both of these may come about from higher road prices, but not (in our scenario) from policies directed specifically at these variables.

unspecified travel demand management policies that reduce the increase in VMT from lower EV costs to zero and the increased VMT from AVs to 23%, after which we further reduce driving from the response to road pricing for all vehicles that begins at 2.4c/mile in 2025 and increases to double that level in real terms by 2050.²²² In addition, we increase mass transit by a factor of four, assume high efficiency gains for EVs, assume AV lightweighting begins in 2040 at 1.5%/year, and assume urban redesign further reduces travel 2% by 2050. Under current political conditions it is quite unlikely that all of this will occur, but technology breakthroughs or a stronger public support for climate policies as climate change worsens in the coming decades makes this a worthwhile bookend to our forecasts.

B. Main Scenario Results

Table VII-3 summarizes LDV transport power demand from our calculations for the milestone years between now and 2050. As the table shows, 2050 LDV power use is approximately 1140 TWh and 570 TWh, in the High Base and Policy Cases, respectively. As these cases are intended to approximate upper and lower likely boundaries, the results are surprisingly close together. Whereas the earlier literature surveys described in Section II found upper and lower bounds differing by as much as a factor of ten, our calculations suggest that the difference between our likely boundary cases is only about 600 TWh, 15 percent of today's power use.

²²² As noted earlier, this is approximately the policy scenario from *Moving Cooler*.

Policy Case	/	Total		Total	Fleet Averag	Fleet Averag	
Case	Year	Number of EV in Service	Portion Stock Electric	Number of AV in Service	e eVMT / Vehicle	e Efficien cy (kWh/	Total TWh (TWh)
			(%)		(per yr)	mile)	
	2015	406,076	0.2%	0	7,179	0.32	Base
	Base	16,890,7					High
	High	19	6.5%	0	9,087	0.34	ingn
		52,379,5		3,182,83			
	2030	66	19.7%	3	10,290	0.35	187
		166,979,		65,615,6			
	2040	970	59.6%	83	13,420	0.33	742
		252,371,		180,263,			
	2050	537	85.6%	265	16,927	0.27	1140
	,						
	2015	406,076	0.2%	0	7,179	0.32	1
	ł	17,086,9			,		
Policy	2025	96	6.6%	0	8,508	0.31	45
Case		52,378,5			,		
	2030	48	19.7%	196,278	8,826	0.30	140
		166,928,		17,786,5			
	2040	240	59.6%	50	8,865	0.29	435
		251,932,		128,559,			
	2050	162	85.5%	496	10,038	0.23	570

Electricity Consumption Summary

To put this range of power demand in perspective, the U.S. generated 4,085 TWh of electrical energy in 2016.²²³ Absent increases from electric transport and the conversion of other end uses such as heat from carbon fuels to electricity, the approximate level of growth in power sales in the U.S. is roughly zero (0.8%/year in ElA's latest forecast, including EVs). Even in our high use case, adding 1000 TWh to U.S. supplies in the next 32 years would add about 0.6% to annual electricity sales growth. Since we

²²³ U.S. DOE (2017) p.131.

have not yet examined the electrification of freight transport or other sectors, forecasted power sales for a widely electrified 2050 economy will boost annual growth above this figure. However, carbon pricing and other climate and energy efficiency policies could easily reduce the baseline growth of electric power.

All in all, electric and autonomous passenger vehicles will represent a large and very important new demand for power, but not one that will be difficult to supply from carbon-free sources. In 2015 the U.S. electric power industry added 18,754 MW of all types of generation, a level quite representative of the last 20 years. At a 50% average load factor, this generation would supply 82 TWh, about of tenth of what LDVs will need by 2050, but added in just one year. ²²⁴ Wind and solar 2015 additions alone will supply about 36 TWh of power; if this level remained unchanged for the next 32 years these sources would provide 1150 TWh of additional power in 2050, coincidentally roughly equal to our High Base case.²²⁵

Put in another perspective, the U.S. DOE reports that it expects wind and solar ("variable renewable electricity") will double their total current output of about 300 TWh between now and 2030 under a "no clean power plan" scenario, and with no other changes in federal or state carbon or renewables policy. Most of this doubling will occur by 2024, when current tax credits expire, and under traditionally conservative EIA cost estimates for wind and solar.²²⁶ One additional doubling in the 20 years between 2030 and 2050 would equal nearly all LDV power use, and it is highly likely that the rate of wind and solar growth will far exceed one doubling in 20 years.

We do not mean to imply that the growth of electric transport poses no issues whatsoever for the U.S. power sector. As noted in Chapter I, the size of EV loads poses enormously important challenges for the redesign and management of a larger, two-way distribution system with intelligent charging, reformed rate structures, and new distribution regulation and business models. As new supplies are created, the overall power grid must make a transition to carbon-free operation in what Smil (2016) and others note is shorter period than all other similar energy transitions have occurred. And all this must occur in the

²²⁴ https://www.eia.gov/electricity/annual/html/epa 04 06.html acc. 8/30/17

 ²²⁵ <u>https://www.eia.gov/electricity/annual/html/epa_04_06.html</u> acc 8/30/17. In this calculation wind capacity additions of 8,214 MW are assumed to operate at 40% capacity factors and all solar power (3320 MW) has an assumed CF of 25%.
 ²²⁶ U.S. DOE (2017) p. 57

context of higher demands for power grid resilience against ever-strengthening climate extremes, cybersecurity threats, and changes to the industry structure and business models. By any measure, this is a turbulent landscape. Our only point is that, as the industry copes with its many challenges, supplying LDVs in the aggregate with carbon-free power looks manageable, and indeed provides the industry with significant added revenues that will undoubtedly prove useful.

Although all our calculations treat the U.S. as a single aggregate, our calculations and the literature both support the view that there will be a very high potential for variation in transport power demand growth by region and urban vs. rural areas. Rural areas that electrify more slowly due to the longer average distances driven and less density in charging infrastructure may see gradual, small EV demand growth, while urban areas that make a concerted effort to shift all transit and autos to electric rapidly will exceed national average demand growth significantly. Urban areas that make a concerted effort to reduce all non-pooled auto travel through redesign and seamless multimodal systems, but meanwhile electrify as rapidly as possible, will be somewhere in the middle.

C. Factor Analysis and Sensitivity Calculations

In Figures VII-4 and VII-5 we deconstruct 2050 LDV electricity use in our High Base and Policy Cases, respectively. Starting from the left, the first bar in Figure VII-4 is a contrived starting point that shows the energy that would be used by our projected 2050 EV fleet if those vehicles were unchanged in their annual average travel from today and they used today's average electricity per mile. For reference, these figures are 252 MM EVs (85% of the total LDV fleet) and 180 MM AVs (61% of fleet); 11,400 miles driven per year; and a weighted average of efficiency of .41kWh/mile. The second bar on the chart, EV VMT, shows the added power from the presumed increase in travel induced by lower EV operating costs. Of course, this increased travel applies only to each EV as it enters the fleet. Similarly, the third bar shows the increased energy from the substantial added AV travel in this scenario, applied to each AV as it enters the fleet.

Figure VII-4: High Base Case Waterfall



Figure VII-5: Policy Scenario Waterfall



These are the main factors driving electricity use up; the remaining factors have the opposing effect. The fourth bar, EV EI, shows the reduction in power use attributable to the low case improvements in EI efficiency through 2050 forecasted by the National Academy of Engineering. The fifth bar, AV EI, shows our highly conservative estimates of efficiency improvements specifically enabled by AVs, such as platooning. The final bar shows the very modest effects of charging all vehicles a current 2.2 cents per mile for road use, indexed to inflation at an assumed long-run VMT price elasticity of -0.2. The chart shows that even the modest low-end efficiency gains projected for EVs and AVs wipe out the rather significant increases in per-vehicle VMT by 2050, whereas road pricing has a relatively small effect at this case's assumed level and elasticity.

The decomposition of the Policy Scenario in Figure VII-5 suggests an even greater importance for potential efficiency improvements. The leftmost base bar on this figure is conceptually the same as the base bar in Figure VII-4, that is, the projected 2050 EV and AV fleet in 2050 operating at today's mileage and efficiency levels (the size of the two base bars differ by a few TWh due to some small technical features of the scenarios).²²⁷ In this scenario there is no increase in VMT due to EVs per se, so only one factor, increased VMT from AV entry (second bar on the chart), increases power use above the base bar level. Having started commercial sales five years later, the 2050 AV fleet is only 128 MM vehicles (50%

²²⁷ The difference is that in the High Base case L5 AVs enter commercial sales in 2025, versus 2030 in the Policy case.

below the High Case AV level), and these vehicles are driven only 23% more (rather than 40%), so it is no surprise that the incremental power demand from this factor is 164 TWh, versus over 400 TWh in the High Base Case.

Conversely, the factors that reduce power use are larger in this scenario. Higher EV EI reduces demand by 370 TWh, enough to offset not only this scenario's increases from AV travel, but almost enough to offset the much higher AV VMT increases in the High case. Paradoxically, AV EI savings are lower in this case than in the High Case, partly because we change the per-vehicle AV EI very little between these two scenarios and partly because the lower penetration of AVs in this scenarios allows for lower AV-induced efficiencies. Road pricing that increases slowly in real terms has a larger effect than in the High Case; at the same assumed elasticity of -0.2 the effect is just over 20% of ultimate total demand.

Table VII-6 shows 2050 total LDV power use in a series of sensitivity calculations. In order of appearance, the sensitivity scenarios examine the start date for AV sales, high vs. low EV sales, road pricing elasticities and a revised scenario ("EV mandate") in which all new internal combustion (ICE) auto sales are halted after 2040. As expected, the table shows that EV sales are a very important driver of power demand, swinging 2050 demand by about 200 TWh in the policy scenario and 300 TWh in the High Base scenario. While this is a very significant difference, it again highlights the fact that the ballpark in which 2050 LDV power demand will play is somewhere in the vicinity of 600 to 1200 TWh. The remaining sensitivities do not change the character of the main scenarios, including the case in which ICE sales stop in 2040; this scenario adds only about 50 TWh (5%) to 2050 power use.

Table VII-6: Sensitivity Calculations

Sensitivity Cases				
AV Start Date	2025	2030		
High Base	1140	1032		
Policy Case	583	570		
EV sales	high	low		
High Base	1140	741		
Policy Case	570	380		
Road Pricing Elasticities	0.35	0.2		
High Base				
\$0.022	1083	1140		
\$0.024	924	1050		
Policy Case				
\$0.022	600	653		
\$0.024	454	570		
EV Mandate	On	Off		
High Base	1188	1140		
Policy Case	604	570		

D. Concluding Observations

It is beyond both our means and expertise to provide anything approaching a complete discussion of the implications of our findings for energy, transport, and climate policy. Instead, we provide a small set of policy observations that speak mainly to the primary focus of our analysis, the intersection of transport changes and the power industry.

With respect to our electric power demand results, many of our observations echo the words of far more seasoned transport researchers, whether in the relatively recent Three Revolutions literature or transport policy discussions going back decades. In spite of the massive uncertainties surrounding the future of transport, only a few dimensions of the coming disruptions seem amenable to policy measures large enough to influence power demand by large amounts. First among these is obviously any policies that shift LDV transport away from ICEs in any mode, but especially in LDVs. On this point there is a

somewhat unusual confluence of support from clean energy and climate policy advocates and the great majority of the electric power industry.

Beyond electrification of LDVs per se, the policy approaches to reducing carbon seem to divide into these categories:

- (A) shift drivers and later, single occupants of AVs -- out of SOVs and into either pooled rides or, much better, integrated multimodal on-demand mobility systems, via any number of policy tools;
- (B) encourage or require electric LDVs to become more efficient more quickly than otherwise, much as CAFE and ZEV standards have forced ICE fleet efficiency gains; or
- (C) Harvest the vehicle and system efficiency improvements theoretically offered by AVs as soon as possible after they are introduced.

Obviously, in our framework, category A shifts travel to more efficient modes, and reduces VMT generally, while categories B and C reduce EI.

In the realm of Category A, there are only a handful of well-known policies, albeit each with thousands of variations, that could make a big difference. Widespread (probably federal) road pricing changes could significant affect LDV travel through own-price effects and also shift travel to more efficient modes. The fact that half of federal roadway spending is now made from general revenues amounts to an astonishingly large, under-recognized, and regressive subsidy to auto travel and its carbon emissions today, and to EV and AV use tomorrow. It is encouraging to see New York considering congestion pricing anew.

The other policy levers that show useful potential are the creation of seamless mobility systems, harnessing the incredible power of IT, connectivity, and analytics to provide urban travel that is nearly as fast and convenient as autos, along with new urban designs that reduce travel. Although it is difficult to see these ideas scaling to the point where they could change power use or carbon by very large amounts, they remain important because they have an unmatched portfolio of co-benefits: better health, improved land use, improved affordable housing and job access, and an overall improved urban social fabric.

The second category of policies, efficiency improvements, are a familiar refrain in U.S. transport policy. CAFÉ standards have demonstrated that the technical efficiency of autos can improve dramatically when stimulated by policies, albeit not without a hiccup now and then. Replicating this trajectory for EVs and AVs has the potential to save trillions of dollars of power system costs as well as significant carbon in the years before full grid decarbonization.

From the policy standpoint, the autonomous vehicle revolution is exceedingly complex. In their early years, we agree that it is likely that AVs will cause more driving, sprawl, and congestion, supporting the somewhat widespread view that "things will get worse before they get better." In the longer run, wisely deployed autonomous vehicles could enable vast energy efficiency improvements through both better system management and lightweighting of an accident-free fleet. It may also free up large amounts of urban pavement, improve mobility for some underserved populations, and significantly lessen unproductive time behind the wheel.

This is an area where much more work is needed. We need much better data on the realistic changes we will need to make to our road and communications infrastructure to accommodate AVs at each penetration level, and how these changes can be staged so they need not be completely redone as the AV fleet grows. We also need better data on how these vehicles will co-exist with conventionally-driven cars and trucks and how efficiency and safety improvements can be accelerated in the presence of mixed fleets. Finally, there is almost no data on how much the infrastructure changes for AVs will cost, much less on how we will finance them. The interrelation between these little-explored but critically important variables is illustrated in figure VII-7.

With the possible exception of the latter, enormous amounts of research are now underway. In the meanwhile, rapid and complete electrification and a carbon-free grid remain the cornerstones of transport decarbonization – a task that looks, *in the aggregate*, entirely manageable for the U.S. electric supply industry.

Figure VII-7: Key AV Relationships from the Standpoint of Power Demand



Bibliography

77th Oregon Legislative Assembly. (2013). Enrolled Senate Bill 810.

- Adam, C., & Schefter, K. (2017). *Plug-in Electric Vehicle Sales Forecast Through 2025 and the Charging Infrastructure Required.* Institute for Electric Innovation; Edison Electric Institute.
- Agatz, N., Erera, A., Savelsbergh, M., & Wang, X. (2009). Sustainable Passenger Transportation: Dynamic Ride-Sharing.
- Albright and Stonebridge Group. (2016). *Autonomous Vehicles and Policy: Shaping the Future of Mobility*. Albright and Stonebridge Group.
- Alessandrini, A., Cattivera, A., Holguin, C., & Stam, D. (2014). CityMobil2: Challenges and Opportunities of Fully Automated Mobility. In G. Meyer, & S. Beiker, *Road Vehicle Automation* (pp. 169-184). Springer. doi:10.1007/978-3-319-05990-7_15
- Alexander, M. (2015). Environmental Assessment of a Full Electric Transportation Portfolio, Volume 2: Greenhouse Gas Emissions. NRDC/EPRI.
- Alonso-Mora, J., Samaranayake, S., Wallar, A., Frazzoli, E., & Rus, D. (2016, January 17). On-demand high-capacity ride-sharing via dynamic trip-vehicle assignment. (M. F. Goodchild, Ed.)
 Proceedings of the National Academy of Sciences (PNAS), 114(3), 462-467. doi:10.1073/pnas.1611675114

American Society of Civil Engineers. (2017). America's Infrastructure Report Card.

- Anderson, W. P., Chatterjee, L., & Lakshmanan, T. (2003). E-Commerce, Transportation, and Economic Geography. *Growth and Change, 34*(4), 415-432.
- Appelbaum, B. (2017, August 8). Public Works Funding Falls as Infrastructure Deteriorates. *The New York Times*. Retrieved from https://www.nytimes.com/2017/08/08/us/politics/infrastructure-trump.html
- Arbib, J., & Seba, T. (2017). *Rethinking Transportation 2020-2030*. RethinkX.
- Auld, J., Karbowski, D., & Sokolov, V. (2016). Assessing the Regional Energy Impact of Connected Vehicle Deployment. World Conference on Transportation Research. Shanghai: Transportation Research Procedia.
- Autonomie. (2016). Retrieved from www.autonomie.net: http://www.autonomie.net/docs/ANL%20-%20BaSceFY15%20-%20Autonomie%20-%20Merge_ Results%20-%20160122.xlsx

Bank of America Merrill Lynch. (2017). Thematic Investing: Overdrive - Global Future Mobility Primer.

Bansal, P., & Kockelman, K. M. (2016). Are Americans Ready to Embrace Connected and Self-Driving Vehicles? A Case Study of Texans.

Barclays. (2015). Disruptive Mobility: AV Deployment Risks and Possibilities. Barclays Capital Inc.

- Barth, M., Boriboonsomsin, K., & Wu, G. (2014). Vehicle Automation and Its Potential Impacts on Energy and Emissions. In G. Meyer, & S. Beiker (Eds.), *Road Vehicle Automation*. Springer International Publishing Switzerland.
- Bartholomew, K. (2008). Cities and Accessibility: The Potential for Carbon Reductions and the Need for National Leadership. *Fordham Urban Law Journal, 36*(2).
- Bert, J., Collie, B., Gerrits, M., & Xu, G. (2016). *What's Ahead for Car Sharing?* The Boston Consulting Group.
- Bhuiyan, J. (2016, May 16). The complete timeline to self-driving cars. *Recode*. Retrieved from https://www.recode.net/2016/5/16/11635628/self-driving-autonomous-cars-timeline
- Binny, M. P., Kockelman, K. M., & Musti, S. (2011). The Light-Duty-Vehicle Fleet's Evolution: Anticipating PHEV Adoption and Greenhouse Gas Emissions Across the U.S. Fleet. *Transportation Research Record*(2252), 107-117.
- BNEF. (2017). Electric Vehicle Outlook 2017.
- Boarnet, M. G., & Crane, R. (2001). *Travel by Design: The Influence of Urban Form on Travel.* Oxford University Press.
- Bolick, C. (2000). Subverting the American Dream: Government Dictated "Smart Growth" is Unwise and Unconsitutional. *University of Pennsylvania Law Review, 148*(859).
- Boske, L. B., & Harrison, R. (2013-2014). *Oregon's Voluntary Road User Charge Program*. University of Texas at Austin, Center for Transportation Research; Lyndon B. Johnson School of Public Affairs.
- Brown, A., Gonder, J., & Repac, B. (2014). An Analysis of Possible Energy Impacts of Automated Vehicle. In G. Meyer, & S. Beiker (Eds.), *Road Vehicle Automation* (pp. 137-153). Springer.
- Buczek, K., DeNoia, M., Johnstnoe, E., & Wiesner, H. (2016). Duke University. Duke University Energy Initiative.
- Cahill, E., Taylor, B., & Sperling, D. (2013). Low-Mass Urban Microcars for Emerging Vehicle Markets of Megacities. *Transportation Research Record*, 30-37.
- Cambridge Systematics. (2009). *Moving Cooler: An Analysis of Transportation Strategies for Reducing Greenhouse Gas Emissions.* Urban Land Institute.
- Carlson, B. (2015). Electric Vehicle Mile Traveled (eVMT): On-road Results and Analysis. IDL.
- Center for Automotive Research. (2016). *The Impact of New Mobility Services on the Automotive Industry*. Ann Arbor, MI: Center for Automotive Research.
- Cervero, R. (2001). Induced Demand: An Urban and Metropolitan Perspective.

- Cervero, R., & Murakami, J. (2010). Effects of built environments on vehicle miles traveled: evidence from 370 US urbanized areas. *Environment and Planning A*, *42*(2), 400-418.
- Chen, T. D., & Kockelman, K. M. (2016). Carsharing's life-cycle impacts on energy use and greenhouse gas emissions. *Transportation Research Part D: Transport and Environment*, *47*, 276-284.
- Childress, S., Nichols, B., Charlton, B., & Coe, S. (2015). Using an Activity-Based Model to Explore the Potential Impacts of Automated Vehicles. *Transportation Research Record*(2439), 99-106.
- Ciari, F., & Becker, H. (2017). How Disruptive can Shared Mobility Be? A Schenario-Based Evaluation of Shared Mobility Systems Implemented at Large Scale. In G. Meyer, & S. Shaheen (Eds.), *Lecture Notes in Mobility*. Springer International Publishing. doi:10.1007/978-3-319-51602-8_3
- Circella, G., Tiedeman, K., Handy, S., Alemi, F., & Mokhtarian, P. (2016). *What Affects U.S. Passenger Travel? Current Trends and Future Perspectives*. National Center for Sustainable Transportation.
- Clements, L. M., & Kockelman, K. M. (2017). Economic Effects of Automated Vehicles. *Transportation Research Record*.
- Cohan, D. (2017). Electric car sales predictions are all over the map. The Hill.
- Cooper, A., & Schefter, K. (2017). *Plug-in Electric Vehicle Sales Forecast Through 2025 and the Charging Infrastructure Required.* Institute for Electric Innovation; Edison Electric Institute.
- Davidson, P., & Spinoulas, A. (2015). AUTONOMOUS VEHICLES WHAT COULD THIS MEAN FOR THE FUTURE OF TRANSPORT? Davidson + Spinoulas.
- Davis, R. J., Murray, M. N., & Welch, J. G. (2017). *How Much Should Hybrids and Electric Vehicles Contribute to Roadway Funding?* The Howard H. Baker Jr. Center for Public Policy.
- Deakin, E., Harvey, G., Pozdena, R., & Yarema, G. (1996). *Transportation Pricing Strategies for California: An assessment of congestion, emissions, energy, and equity impacts.* The University of California.
- Deloitte. (2013). Plugged In: The Last Mile Who will build out and pay for electric vehicle public charging infrastructure?
- Dinning, M., & Weisenberger, T. (n.d.). Multimodal Transportation Payments Convergence-Key to Mobility. In G. Meyer, & S. Shaheen (Eds.), *Disrupting Mobility* (pp. 121-133).
- Dounis, S., & Langan, C. (2017). UBS Evience Lab: When Will Plugs Shadow Pumps? UBS Global Research February.
- Duranton, G., & Turner, M. A. (2011, October). The Fundamental Law of Road Congestion: Evidence from US Cities. *The American Economic Review*, *101*(6), 2616-2652.
- Eberts, R. W. (2017). Valuing a Mature highway System In Search of the Holy Grail. *Transportation and the Economy*.
- Edmunds. (2017). *Elimination of Federal Tax Credits Likely to Kill U.S. EV market*. Edmunds. Retrieved from https://static.ed.edmunds-media.com/unversioned/img/industry-center/analysis/EV_Report_April17.pdf
- EIA. (2016). Electric Power Annual 2015.
- EIA. (2017). Annual Energy Outlook 2017 (Reference Case).
- Energy Transitions Commision. (2017). A new elecricity era: How to decarbonize energy systems through electrification. Climate Policy Initiative; Copenhagen Economics.
- EPRI & NRDC. (2015). Environmental Assessment of a Full Electric Transportation Portfolio Volume 1: Background, Methodology, and Best Practices. EPRI & NRDC.
- EPRI & NRDC. (2015). Environmental Assessment of a Full Electric Transportation Portfolio Volume 3: Air Quality Impacts.
- Ewing, R., & Cervero, R. (2010). Travel and the Built Environment: A Meta-Analysis. *Journal of the American Planning Association*, *76*(3).
- Ewing, R., & Cervero, R. (2017). "Does Compact Development Make People Drive Less?" The Answer Is Yes. Journal of the American Planning Association, 83(1), 19-25. doi:10.1080/01944363.2016.1245112
- Ewing, R., Bartholomew, K., Winkelman, S., Walters, J., & Anderson, G. (2008). Urban Development and Climate Change. Journal of Urbanism: International Research on Placemaking and Urban Sustainability, 1(3), 201-216.
- Ewing, R., Tian, G., Goates, J., Zhang, M., Greenwald, M. J., Joyce, A., . . . Greene, W. (2015). Varying influences of the built environment on household travel in 15 diverse regions of the United States. Urban Studies, 52(13), 2330-2348.
- Fagan, A. (2017, May 11). Israel Tests Wireless Charging Roads for Electric Vehicles. *Scientific American*. Retrieved from https://www.scientificamerican.com/article/israel-tests-wireless-chargingroads-for-electric-vehicles/
- Fagnant, D., & Kockelman, K. (2015). Preparing a Nation for Autonomous Vehicles: Opportunities, Barriers, and Policy Recommendations. *Transportation Research Part A*, 77, 167-181.
- Fagnant, D., & Kockelman, K. M. (2014). The Travel and Environmental Implications of Shared Autonomous Vehicles, Using Agent-Based Model Scenarios. *Transportation Research Part C, 40*, 1-13.
- Federal Highway Association. (2017, May 4). *Forecasts of Vehicle Miles Traveled: Spring 2017.* Retrieved June 30, 2017, from Office of Highway Policy Information: https://www.fhwa.dot.gov/policyinformation/tables/vmt/vmt_forecast_sum.pdf
- Fichter, K. (2003). *E-Commerce: Sorting Out the Environmental Consequences*. Berlin, Germany: Massachusetts Institute of Technology and Yale University.

- Fitzgerald, G., Nelder, C., & Newcomb, J. (2016). *Electric Vehicles as Distributed Energy Resources*. Rocy Mountain Institute. Retrieved from http://www.rmi.org/pdf_evs_as_DERs
- Foley, A., Tythera, B., Calnan, P., & Gallachóirab, B. Ó. (2013, January). Impacts of Elctric Vehicle charging under electricity market operations. *Applied Energy*, *101*, 93-102.
- Forkenbrock, D. J., & Hanley, P. F. (2006, March). Mileage-Based Road User Charges. *Public Roads, 69*(5). Retrieved from https://www.fhwa.dot.gov/publications/publicroads/06mar/02.cfm
- Gallup Organization. (2016). State of the American Workpace. Gallup, Inc.
- Gavrilovic, T. (2016). *The Impact of Electric Vehicles on the Grid: Customer Adoption, Grid Load, and Outlook.* GTM Research.
- Gnau, T. (2017, February 15). Ohio DOT to Heavily Invest in Autonomous Vehicle Infrastructure. Retrieved from http://www.govtech.com: http://www.govtech.com/fs/Ohio-DOT-to-Heavily-Invest-in-Autonmous-Vehicle-Infrastructure.html
- Greater Ann Arbor Region Prosperity Initiative . (2017). Planning for Connected and Automated Vehicles.
- Green, D. L., Park, S., & Liu, C. (2014). Analysing the Transition to Electric Drive Vehicles in the U.S. *Futures, 58*, 34-52.
- Greenblatt, J. B., & Saxena, S. (2015, July 6). Autonomous taxis could greatly reduce greenhouse-gas emissions of US light-duty vehicles. *Nature Climate Change*, *5*, 860-863.
- Greene, D. L. (2011). What is greener than a VMT tax? The case for an indexed energy user fee to finance us surface transportation. *Transportation Research Part D, 16*, 451-458. doi:10.1016/j.trd.2011.05.003
- Grush, B., Hassan, K., & Khalsa, P. (2009). Four Steps to Nationwide VMT and TDP. ITS Asia 2009.
- Gucwa, M. (2014). Mobility and Energy Impacts of Automated Cars. Automated Vehicle Symposium.
- Handy, S., & Boarnet, M. G. (2014). *Impact of Highway Capacity and Induced Travel on Passenger Vehicle Use and Greenhouse Gas Emissions.* California Environmental Protection Agency: Air Resources Board.
- Handy, S., Tal, G., & Boarnet, M. G. (2010). DRAFT Policy Brief on the Impacts of Telecommuting Based on a Review of the Empirical Literature.
- Hanley, P. F., & Kuhl, J. G. (2011). National Evaluation of Mileage-Based Charges for Drivers: Initial Results. *Transportation Research Record: Journal of the Transportation Research Board*, 2221, 10-18. doi:10.3141/2221-02
- Harper, C. D., Hendrickson, C. T., Mangones, S., & Samaras, C. (2016). Estimating potential increases in travel with autonomous vehicles for the non-driving, elderly and people with travel-restrictive medical conditions. *Transportation Research Part C, 72*, 1-9. doi:dx.doi.org/10.1016/j.trc.2016.09.003

Hawken, P. (Ed.). (2017). Drawdown. New York: Penguin.

- Helveston, J. P. (2016). *Emerging Automotive Trends: Chinese, Electric, & Shared*. Institute for Sustainable Energy.
- Henao, A. (2016). Impacts of Ridesourcing Lyft and Uber as a ne Form of Urban Mobility: A Focus on VMT, Mode Replacement, Parking, and Travel Behavior.
- Higgins, T. (2017, June 20). The End of Car Ownership. The Wall Street Journal.
- http://insideevs.com. (n.d.). Retrieved May 2017
- IHS Automotive. (2016). Autonomous vehicle sales Forecast 21 mil. globally in 2035, according to IHS Automotive.
- International Energy Agency. (2016). *Global EV Outlook 2016: Beyond One Million Vehicles.* Paris, France: OECD/IEA.
- Jenn, A., Lima Azevedo, I., & Fischbeck, P. (2015). How will we fund our roads? A case of decreasing revenue from electric vehicles. *Transportation Research Part A, 74*, 136-147.
- Jin, X. (2017). Email correspondence.
- Johnson, C. (2017). *Readiness of the road network for connected and automous vehicles.* London, UK: Royal Automobile Club Foundation.
- Johnson, C., & Walker, J. (2016). *Peak Car Ownership: The Market Opportunity of Electric Automated Mobility Services*. RMI.
- Kahn, M. E., & Levinson, D. M. (2011). *Fix It First, Expand It Second, Reward I tThird: A New Strategy for America's Highways.* The Brookings Institution.
- Kamargianni, M., Li, W., Matyas, M., & Schafer, A. (2016). A critical review of new mobility services for urban transport. *Transportation Research Procedia*, *14*, 3294-3303.
- Karim, D. M. (2017). Creating an Innovative Mobility Ecosystem for Urban Planning Areas. In G. Meyer, S. Shaheen, G. Meyer, & S. Beiker (Eds.), *Disrupting Mobility*. Springer International Publishing. doi:10.1007/978-3-319-51602-8_2
- Kaya, Y. (1990). *Impact of carbon dioxide emission control on GNP growth: Interpretation of proposed scenarios.* Paris: , Response Strategies Working Group.
- Kenworthy, J. R., & Laube, F. B. (1996). Automobile Dependence in Cities: An International Comparison of Urban Transport and Land Use Patterns With Implications for Sustainability. *Environmental Impact Assessment Review*, *16*, 279-308.
- Kessler, J., & Schroeer, W. (1995). Meeting mobility and air quality goals: Strategies that work. *Transportation*, 22, 241-272.

- Kim, K., Rousseau, G., Freedman, J., & Nicholson, J. (2015). The Travel Impact of Autonomous Vehicles in Metro Atlanta through Activity-Based Modeling. *The 15th TRB National Transportation Planning Applications Conference.*
- Kim, K.-H., Yook, D.-H., Ko, S.-Y., & Kim, D.-H. (2016). An Analysis of Expected Effects of the Autonomous Vehicles on Transport and Land Use in Korea. New York, NY: Marrion Institute, New York University.
- Kockelman, K., Boyles, S., Stone, P., Fagnant, D., Patel, R., Levin, M. W., . . . Li, J. (2017). An Assessment of Autonomous Vehicles: Traffic Impacts and Infrastructure Needs-Final Report. The University of Texas at Austin, Center for Transportation Research. Retrieved from https://library.ctr.utexas.edu/ctr-publications/0-6847-1.pdf
- Kolko, J. (2017, May 24). Return to cities an Urban Legend, Mostly. The New York Times, p. A18.
- Kooroshy, J., Ibbotson, A., Lee, B., Bingham, D., & Simons, W. (2015). *The Low Carbon Economy*. Goldman Sachs.
- Kooroshy, J., Lee, B., Chow, F., Burger, S., Schirmacher, J., Costa, D., . . . Gandolfi, A. (2016). *The Low Carbon Economy: Technology in the Driver's Seat*. Goldman Sachs.
- KPMG. (2015). Connected and Autonomous Vehicles The UK Economic Opportunity. Retrieved from https://www.kpmg.com/BR/en/Estudos_Analises/artigosepublicacoes/Docum ents/Industrias/Connected-Autonomous-Vehicles-Study.pdf
- Laberteaux, K. (2014). *How Might Automated Driving Impact US Land Use?* Toyota Research Institute-North America; Toyota Motor Engineering & Manufacturing North America.
- Lang, N., Rusmann, M., Mei-Pochtler, A., Dauner, T., Komiya, S., Mosquet, X., & Doubara, X. (2016). *Self-Driving Vehicles, Robo-Taxis, and the Urban Mobility Revolution.* The Boston Consulting Group.
- Langer, A., & Winston, C. (2008). *Toward a Comprehensive Assessment of Road Pricing Accounting for Land Use.* Brookings Institution Press. Retrieved August 7, 2017
- Lavasani, M., Jin, X., & Du, Y. (2016). Market Penetration Model for Autonomous Vehicles Based on Previous Technology Adoption Experiences. *Transportation Research Record Journal*.
- Lee, D. B. (2000). *Highway Economic Requirements System State Version: Technical Report Appendix C: Demand Elasticities for Highway Travel.* U.S. Department of Transportation Federal Highway Administration.
- Leinberger, C. B. (2009). The Option of Urbanism. Washington, D.C.: Island Press.
- Lewis, J. M. (2017, September 1). Senate No. 1945.
- Lewis, P., Turner, S., & Rogers, G. (2017). *Beyond Speculation: Automated Vehicles and Public Policy*. Eno Center for Transportation.

- Liebreich, M. (2016, December 14). A year of hectic change and off-taret predictions. Retrieved from https://about.bnef.com/blog/off-target-renewable-energy-predictions/
- Litman, T. (2014). *Win-Win Transportation Solutions: Mobility Management Strategies That Provide Economic, Social and Environmental Benefits.* Victoria Transport Policy Institute.
- Litman, T. (2016). Smart Growth Reforms: Changing Planning, Regulatory, and Fiscal Pracices to Support More Efficient Land Use. Victoria Transport Policy Institute.
- Litman, T. (2016). *The Future Isn't What It Used to Be: Changing Trends and Their Implications for Transport Planning.* Victoria Transport Policy Institute.
- Litman, T. (2017). *Evaluating Public Transit Benefits and Costs: Best Practices Guidebook.* Victoria Transport Policy Institute.
- Lovejoy, K., Handy, S., & Boarnet, M. G. (2013). *Impacts of Carsharing on Passenger Vehicle Use and Greenhouse Gas Emissions*. California Environmental Protection Agency Air Resources Board.
- Lovins, A. (2011). *Reinventing Fire: Bold Business Solutions for the New Energy Era.* Rocky Mountain Institute.
- Lyons, G. (2002). Internet: investigating new technology's evolving role, nature, and effects on transport. *Transport Policy*, *9*, 335-349.
- Ma, B., Nahal, S., Tran, F., & Hill, F. (2017). *Thematic Investing: Overdrive Global Future Mobility Primer*. Bank of America Merrill Lynch.
- Ma, B., Nahal, S., Tran, F., & Hill, F. (2017). *Thematic Investing: Overdrive Global Future Mobility Primer.* Bank of America Merrill Lynch.
- MacKenzie, D., Wadud, Z., & Leiby, P. (2014). A First Order Estimate of Energy Impacts of Automated Vehicles in the United States. *Transportation Research Board*, *14*(2193).
- Martin, E., & Shaheen, S. (2011). The Impact of Carsharing on Public Transit and Non-Motorized Travel: An Exploration of North American Carsharing Survey Data. *Energies, 4*, 2094-2114.
- Martin, E., Shaheen, A. S., & Lidicker, J. (2010). Impact of Carsharing on Household Vehicle Holdings. *Transportation Research Record*, 150-158.
- May, J. W., & Mattila, M. (2009). *Plugging In: A Stakeholder Investment Guide for Public Electric-Vehicle Charging Infrastructure.* Rocky Mountain Institute.
- McKinsey&Company; Bloomberg New energy Finance. (2016). *An Integrated Perspective on the Future* of Mobility.
- Melaina, M., & Helwig, M. (May 2014). *California Statewide Plug-In Electric Vehicle Infrastructure Assessment*. National Renewable Energy Laboratory.
- Mendez, V. M., Monje, C. A., & White, V. (2017). Beyond Traffic: Trends and Choices 2045 A National Dialogue About Future Transportation Opportunities and Challenges. In G. Meyer, & S. Shaheen,

Disrupting Mobility: Impacts of Sharing Economy and Innovative Transportation on Cities (pp. 3-20). Springer. doi:10.1007/978-3-319-51602-8_1

- Meyer, G., & Deix, S. (2014). Research and Innovation for Automated Driving in Germany and Europe. In G. Meyer, & S. Beiker (Eds.), *Road Vehicle Automation* (pp. 71-81). Springer International Publishing Switzerland.
- Milakis, D., Cervero, R., van Wee, B., & Maat, K. (2015). *Do people consider an acceptable travel time? Evidence from Berkeley, CA.* Elsevier.
- Mokhtarian, P. (1997). Now that travel can be virtual, will congestion virtually disappear? . *Scientific American*.
- Mokhtarian, P. L. (2004). A conceptual analysis of the transportation impacts of B2C e-commerce. *Transportation*, *31*(3), 257-284.
- Morrow III, W., Greenblatt, J., Sturges, A., Saxena, S., Gopal, A., Millstein, D., & Shah, N. (2014). Key Factors Influencing Autonomous Vehicles' Energy and Environmental Outcome. In G. Meyer, & S. Beiker (Eds.), *Road Vehicle Automation.* Springer International Publishing Switzerland. doi:10.1007/978-3-319-05990-7_12
- New York City Taxi and Limousine Commission. (2013). New York City Taxi and Limousine Commission 2013 Annual Report.
- Nichols, B., & Kockleman, K. (2014). Life-Cycle Energy Implications of Different Residential Settings: Recognizing Buildings, Travel, and Public Infrastructure. *Energy Policy, 68*, 232-242.
- Niewenhuijsen, J. (2015). Diffusion of Automated Vehicles. A Quantitative Method to Model the Diffusion of Automated Vehicles with System Dynamics. Delft University of Technology.
- NITI Aayog and Rocky Mountain Institute. (2017). *India Leaps Ahead: Transformative mobility solutions for all.* Retrieved from https://www.rmi.org/insights/reports/transformative_mobility_solutions_india
- Oak Ridge National Lab. (2016). Transportation Energy Data Book. Oak Ridge National Lab.
- Ohio Department of Transportation. (2016, December 1). Smart Mobility Corridor to Become Ohio's First "Smart Road". Retrieved from https://www.dot.state.oh.us/news/Pages/SmartMobilityCorridor.aspx
- Oregon Department of Transportation. (2017). Oregon's Road Usage Charge The OReGO Program Final Report.
- Outwater, M., Smith, C., Walters, J., Welch, B., Cervero, R., Kockelman, K., & Kuzmyaki, J. R. (2014). *Effect of Smart Growth Policies on Travel Demand.* Washington, D.C.: Transportation Research Board.
- Perrine, K. A., & Kockelman, K. M. (2017). Anticipating Long-Distance Travel Shifts Due To Self-Driving Vehicles. *Journal of Transportation and Land Use*.

144

- Polzin, S. E. (2006). *The Case for Moderate Growth in Vehicle Miles of Travel: A Critical Juncture in U.S. Travel Behavior Trends.* University of SOuth Florida, Center for Urban Transportation Research.
- RMI. (n.d.). Retrieved from new.rmi.org: http://new.rmi.org/RFGraph-US_projected_electric_vehicle_stocks
- Rodier, C., Alemi, F., & Smith, D. (2016). Dynamic Ridesharing: An Exploration of the Potential for Reduction in Vehicle Miles Traveled. *TRB 95th Annual Meeting*.
- Rodoulis, S. (2014). The Impact of autonomous Vehicles on Cities.
- Rogers, E. (2003). Diffusion of Innovations (5th ed.). New York, NY: Simon & Schuster.
- Rotem-Mindali, O., & Salomon, I. (2007). The impacts of E-retail on the choice of shopping trips and delivery: some preliminary findings. *Transportation Research Part A: Policy and Practice, 41*(2), 176-189.
- Rouwendal, J., & Verhoef, R. T. (2006). Basic economic principles of road pricing: From theory to applications. *Transport Policy*, *13*, 106-114.
- Russell-Carroll, J. (2014). A Glimpse into the Future: Road Pricing & Driverless Cars. *The Student Economic Review*, 28.
- Salon, D., Boarnet, M. G., Handy, S., Spears, S., & Tal, G. (2012). How do local actions affect VMT? A critical review of the empirical evidence. *Transportation Research Part D*, *17*, 495-508.
- Schaller Consulting. (2017). Unsustainable? The Growth of App-Based Ride Services and Traffic, Travel, and the Future of New York City. Brooklyn, NY: Schaller Consulting.
- Shaheen, A. S., Mallery, A. M., & Kingsley, J. K. (2012). Personal vehicle sharing services in North America. *Research in Transportation Business and Management, 3*, 71-81.
- Shaheen, S. A., Cohen, A. P., & Chung, M. S. (2009). North American Carsharing 10 Year Retrospective. *Transportation Research Record*, 35-44.
- Shaheen, S., Chan, N., Bansal, A., & Cohen, A. (2015). Shared Mobility: A Sustainability and Technologies Workshop. Definitions, Industry Developments, and Early Understanding. University of California Berkeley Transportation Sustainability Research Center and the California Department of Transportation.
- Shladover, S. (2015). Automation Deployment Paths. Limiting Automation Functionality or Geographic Scope. *TRB Annual Meeting 2015 Session 564*. Washington.
- Sivak, M., & Schoettle, B. (2015). *Influence of Current Nondrivers on the Amount of Travel and Trip Patterns with Self-Driving Vehicles.* Ann Arbor, MI: University of Michigan Transportation Research Institute.

- Small, K. A., & Van Dender, K. (2007). Long Run Trends in Transport Demand, Fuel Price Elasticities and Implications of the Oil Outlook for Transport Policy. International Transport Forum. OECD/ITF Joint Transport Research Centre. doi:10.1787/234582117245
- Small, K., & Van Dender, K. (2007). *Fuel Efficiency and Motor Vehicle Travel: The declining rebound effect*. Working Paper, University of California Irvine , Economics.
- Small, K., Winston, C., & Evans, C. (1989). Road Work. Washington, DC: Brookings.
- Sorensen, P. (2010). *System Trials to Demonstrate Mileage-Based Road Use Charges.* National Cooperative Highway Research Program; Transportation Research Board.
- Sperling, D. (2017, April 25). The Three Revolutions in Transportation. *Presentation*. Berkeley, CA.
- Stephens, T., Taylor, C., Moore, J., & Ward, J. (2016). *Vehicle Technologies and Fuel Cell Technologies Program: Prospective Benefits Assessment Report for Fiscal Year 2016.* Argonne, IL: Argonne National Laboratory.
- Stevens, M. R. (2017). Does Compact Development Make People Drive Less? *Journal of the American Planning Association, 83*(1), 7-18. doi:10.1080/01944363.2016.1240044
- Stevens, T. S., Gonder, J., Chen, Y., Lin, Z., Liu, C., & Gohlke, D. (2016). *Estimated Bounds and Important Factors for Fuel Use and Consumer Costs of Connected and Automated Vehicles*. National Renewable Energy Laboratory.
- Stocker, A., & Shaheen, S. (2016). Shared Automated Vehicles: Review of Business Models. OECD.
- Tabuchi, H. (2017, March 11). Behind the Quiet State-by-State Fight Over Electric Vehicles. *The New York Times*. Retrieved from https://www.nytimes.com/2017/03/11/business/energyenvironment/electric-cars-hybrid-tax-credits.html?mcubz=3
- Tal, G., & Cohen Blankshtain, G. (2011, June 30). Understanding the role of the forecast-maker in overestimation forecasts of policy impacts: The case of Travel Demand Management policies. *Transportation Research Part A: Policy and Practice, 45*(5), 389-400. doi:10.1016/j.tra.2011.01.012
- Texas Department of Transportation. (2009). VMT Vehicle Mileage Fee Primer.
- The Congress of the United States Congressional Budget Office. (2011). *Alternative Approaches to Funding Highways.*
- Thorpe, D. (2017). Will Autonomous Vehicles and Intelligent Transport Systems Cost or Benefit Cities? Retrieved from www.smartcitiesdive.com: http://www.smartcitiesdive.com/ex/sustainablecitiescollective/will-autonomous-vehicles-andintegrated-transport-planning-bring-extra-costs-or/1088414/
- Trabish, H. (2017). Can California hit 1.5M zero-emission vehicles by 2025? Utility Dive.

- Transportation Research Board, C. f. (2015). *Between Public and Private Mobility: Examining the Rise of Technology-Enabled Transportation Services TRB Special Report 319.* THE NATIONAL ACADEMIES OF SCIENCES, ENGINEERING, AND MEDICINE .
- Turnbull, K. F. (2015). *Towards Road Transport Automation: Opportunities in Public-Private Collaboration.* The National Academy Press.
- U.S. Bureau of Transportation Statistics. (2001-2002). Retrieved from U.S. Bureau of Transportation Statistics: https://www.rita.dot.gov/bts/sites/rita.dot.gov.bts/files/subject_areas/national_household_tra vel_survey/daily_travel.html
- U.S. Department of Transportation. (n.d.). *Beyond Traffic 2045: Trends and Choices.* Retrieved August 15, 2017, from htpps://cms.dot.gov/files/docs/Draft_Beyond_traffic_Framework.pdf
- U.S. Department of Transportation Federal Highway Administration. (2015). Retrieved from Highway Statistics 2015: https://www.fhwa.dot.gov/policyinformation/statistics/2015/
- U.S. Energy Information Administration. (2017, July). Monthly Energy Review.
- U.S. Energy Information Agency. (2013). Annual Energy Outlook 2013: With Projections to 2040.
- U.S. Energy Information Agency. (2014, July). Transportation Demand Module of the National Energy Modeling System: Model Documentation. Washington, D.C.
- U.S. Energy Information Agency. (2017). Annual Energy Outlook 2017. Washington, D.C.
- U.S. Library of Congress. (2014). National Funding of Road Infrastructure: Comparative Summary. Retrieved from https://www.loc.gov/law/help/infrastructure-funding/comparative.php
- U.S. National Economic Council. (2014). *An Economic Analysis of Transportation Infrastructure Investment*. Washington: The White House.
- Underwood, S. (n.d.). Automated, Connected, and Electric Vehicle Systems: Expert Forecast and Roadmap for Sustainable Transportation. Institute for Advanced Vehicle Systems, Connected Vehicle Proving Center. University of Michigan – Dearborn.
- United States Government Accountability Office. (2012). *Highway Trust Fund: Pilot Program Could Help* Determine the Viability of Mileage Fees fro Certain Vehicles.
- University of California Davis Institute. (2017, June 30). Pooling and Pricing, Workshop Overview.
- Viegas, J. M. (2001). Making urban road pricing acceptable and effective: searching for quality and equity in urban mobility. *Transport Policy*, *8*, 289-294.
- Visser, E.-J., & Lanzendorf, M. (2004). *Mobility and Accessibility Effects of B2C E-Commerce: A Literature Review.* Royal Dutch Geographical Society KNAG.
- Wadud, MacKenzie, & Lieby. (2016). Help or Hindrance? The Travel, Energy and Carbon Impacts of Highly Automated Vehicles. *Transportation Research Part A, 86*, 1-18.

Walker, J., & Johnson, C. (2016). *Peak Car Ownership: The Market Opportunity of Electric Automated Mobility Services*. Rocky Mountain Institute.

Weeratunga, K., & Somers, A. (2015). Connected Vehicles: Are we ready? Main Roads Western Australia.

- Weiss, J., Hledik, R., Hagerty, M., & Gorman, W. (2016). *Electrification: Emerging Opportunities for Utility Growth.* The Brattle Group.
- Weltevreden, J. (2006). *City centres in the internet age: Exploring the implications of b2c e-commerce for retailing at city centres in the Netherlands.* Utrecht University Repository.
- Weltevreden, J. W. (2007). Substitution or complementarity? How the Internet changes city center shopping. *Journal of Retail and Consumer Services,* 14, 192-207.
- World Energy Council. (2011). Global Transport Scenarios 2050. London: World Energy Council.
- Zhang, Y. J., Malikopoulos, A. A., & Cassandras, C. G. (2016). Optimal Control and Coordination of Connected and Automated Vehicles at Urban Traffic Intersections. *American Control Conference* (ACC), 2016. Boston: IEEE. doi:10.1109/ACC.2016.7526648
- Zhao, Y., & Kockelman, K. M. (2017). Anticipating the regional impacts of connected and automated vehicle travel in Austin, Texas. *International Journal of Sustainable Transportation*, 1-13.