# Heaven or Hell: What are the GHG emission implications for light-duty vehicles of autonomy and ride-hailing?

## PRELIMINARY RESEARCH AND RESULTS

Jennifer Hatch[1]
Will Gorman[2]

**ABSTRACT**. As has been well documented, the transportation sector is currently undergoing a profound transformation in the way that vehicles are powered, owned, and operated (Center for Automotive Research, 2016; Fagnant and Kockelman 2015; Sperling, 2017; Lovejoy, Handy, and Boarnet, 2013; Arbib and Seba, 2017). The complex interdependence of these transformations, as well as the fact that we are studying them concomitantly with their development, makes them particularly difficult to predict. Recent studies have shown preliminary evidence that ride-hailing has shifted travel miles dramatically away from traditional forms of transport such as public bus and rail service, biking, and walking, and towards ride hailing services, resulting in a significant increase in VMT (Clewlow and Mishra, 2017). At the same time, fleet ownership business models may have a significant impact on manufacturing emissions and vehicle efficiency. Building upon the model framework developed by Fox-Penner, Gorman, and Hatch, this paper considers the greenhouse gas implications of various light-duty transportation business model adoption scenarios, including the effects on manufacturing inputs, technology improvements, and total vehicle miles traveled. The goal of the paper is to build a more realistic and research based estimate of future transportation scenarios and their impact on personal vehicle emissions.

**KEYWORDS**. Autonomous vehicles, greenhouse gases, ride-hailing, business models

## 1. Introduction

As has been well documented, the transportation sector is currently undergoing a profound transformation in the way that vehicles are powered, owned, and operated. Electrification, ride-hailing services, and autonomy, the "three revolutions" underway in the transportation sector, will have significant impacts on everything from infrastructure to electricity systems, public health, and greenhouse gas emissions. (Sperling, Pike, & Chase, 2018) (Fagnant & Kockelman, 2015) (Arbib & Seba, 2017)

The complex interdependence of these transformations, as well as the fact that we are studying them concomitantly with their development, makes them particularly difficult to predict. In less than a decade, ride-hailing companies such as Uber, Lyft, and Ola have gone from rarified taxi replacements to companies that have not only upended the cab service but have also caused a significant transportation mode shift. Recent studies have shown preliminary evidence that ride-hailing has swung travel miles dramatically away from traditional forms of transport such as public bus and rail service,

[1] Research Fellow, Boston University Institute for Sustainable Energy, hatchj@bu.edu - Corresponding Author
[2] Ph.D. Program, Energy and Resources Group, University of California, Berkeley, Ca., gorman_will@berkeley.edu

biking, and walking, and towards ride hailing services, resulting in a significant increase in VMT (Clewlow & Mishra, 2017).

These services threaten to become even more dominant as autonomous vehicle technology becomes market-ready. In just a few years, autonomous vehicles have gone from closely monitored test-drives to driving the streets of Arizona. In 2017, the dominant players in ride-hailing in the United States, Uber and Lyft, both partnered with automakers to test autonomous vehicle technology in their ride-hailing model. Having fleets of autonomous vehicles could lower transportation costs causing an even greater mode shift away from public transportation as public transportation infrastructure costs increase due to necessary upgrades and declining ridership, and autonomous technologies mature (Bauer, Greenblatt, & Gerke, 2018).

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 and its implications for travel, the economy, and our built environment. Fleets of autonomous vehicles will behave differently than the personally owned vehicle model and have different implications for travel behavior, transportation emissions, refueling infrastructure, and more. Making planning and prediction even more complicated is the question of whether or not these new autonomous vehicles will be electric. Many scholars have attempted to quantify aspects of this transformation, including estimating increased vehicle miles travelled (VMT), energy (electric) demand, and city infrastructure needs (Fox-Penner, Gorman and Hatch, 2019) (Arbib & Seba, 2017), (Bansal & Kockelman, 2016), (Underwood).

Yet perhaps one of the most significant implications of the coming transformations has yet to be sufficiently bounded: the effect on GHG emissions as a result of the transformation. The base technology of autonomous vehicles will have a dramatic impact on society's ability to curb greenhouse gas emissions. The future of autonomous vehicles is often assumed to be electric; however, current autonomous vehicle development has often relied on internal combustion engine (ICE) technology.[3] [4]Business models for which autonomous vehicles will be used will also affect the total emissions attributable to light duty vehicles, as lifetime use of these vehicles extends or contracts.

Building upon the model framework developed by Fox-Penner, Gorman, and Hatch, this paper examines the greenhouse gas implications of several potential scenarios for the future of transportation, considering varying degrees of adoption of autonomy, ride hailing, and electrification, with hopes of building a more realistic and research based estimate of the future for personal vehicle emissions.

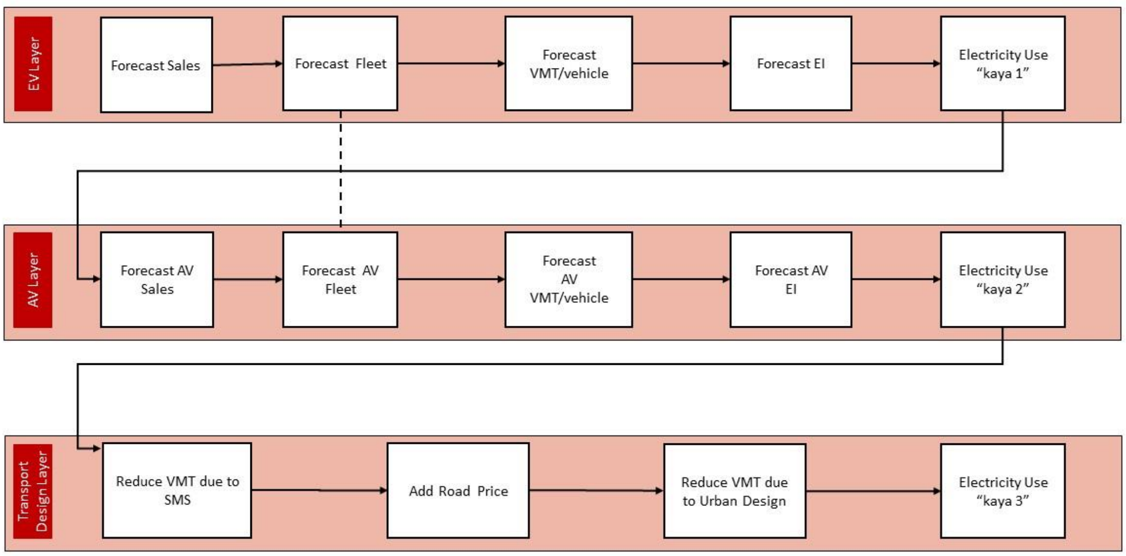
To provide these estimates, we first conduct an extensive literature review of parameters affecting the GHG emissions from the light duty vehicle (LDV) sector, including impacts from autonomous vehicles. This review includes an assessment of the LCA literature to incorporate upstream emissions, as well as a discussion of potential autonomous vehicle business models. Then, we develop a modelling framework that incorporates LCA parameters, vehicle adoption projections, stock modeling, efficiency improvements, and vehicle mile demand projections. From this modelling framework, we design the key scenarios that can be used to predict a range of outcomes for greenhouse gas emissions from autonomous vehicles.

[3] https://www.washingtonpost.com/technology/2019/03/20/ford-will-build-its-first-driverless-cars-new-plant-michigan/?utm_term=.c40ccb797d56
[4] http://fortune.com/2017/11/20/uber-volvo-self-driving-cars/

## 2. Foundational Work

In the model elaborated by Fox-Penner, Gorman and Hatch, the authors took a modeling approach based on the kaya identity framework (Fox-Penner, Gorman and Hatch, 2018). The original paper starts with a baseline in which none of the aforementioned transportation disruptions occur, and then factor in additional disruptions in a series of layers of calculations, as illustrated in figure 1.

*Figure 1: Original Model Concept*




*Source: Fox-Penner, Gorman, and Hatch 2018*

While we use this original framework to structure our analysis, our new analysis has two significant methodological improvements: first, we incorporate manufacturing and disposal emissions, in order to account for the higher initial emissions of electric vehicles; and second, we incorporate the effect of different business models on lifetime vehicle emissions. We also incorporate some updates to impacts that have been recorded in the literature since publication.

## 3. Model Improvements

### 3.1. Improvements to baseline GHG estimations

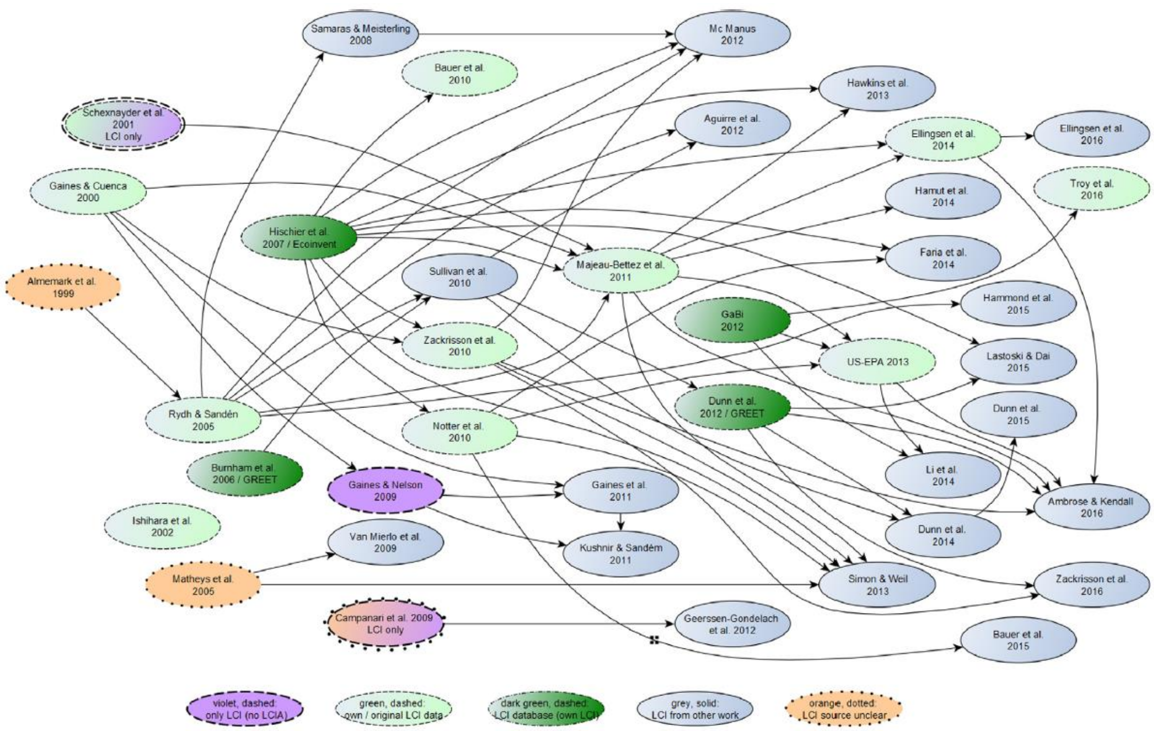
#### *3.1.1 LCA/Manufacturing Emissions*

Numerous papers have been written on the lifetime emissions of electric versus internal combustion engine vehicles. The increased attention to life cycle analyses of hybrid and battery-electric vehicles is well summarized by Ellingsen, who writes, "in order to avoid problem shifting, a life cycle perspective should be applied in the environmental assessment of traction batteries." (Ellingsen, et al., 2013)

Samaras and Meisterling assessed the lifetime vehicle emissions of plug-in hybrid electric vehicles, and found that the models available at the time provided insignificant benefit over traditional hybrids, but did pose a significant benefit over internal combustion engine vehicles (Samaras & Meisterling, 2008). Writing for the California Air Resources Board in 2012, Aguirre et al. use the GREET model developed by Argonne National Laboratory to determine that battery electric vehicles have the smallest environmental impact of models of light-duty vehicles (Aguirre, et al., 2012).

Peters, et al. produce an extraordinarily comprehensive mapping of the data sources for electric vehicle LCAs conducted over the past two decades, as seen in figure 2. The map demonstrates that although the literature is quite robust on this subject, there are only a handful of studies from which the data arises.

*Figure 2: LCA Data Sources*




*Source: Peters, et al. 2017*

For our analysis, we rely on the work of Ellingsen, Singh, and Stromman to incorporate manufacturing and disposal emissions. Given the available studies, we chose this paper for its analysis of both electric and ICE vehicles in order to maintain internal consistency, and for its attention to electric grid efficiency improvements (Ellingsen, Singh, & Stromman, The Size and Range Effect: lifecycle greenhouse gas emissions of electric vehicles, 2016).

## 3.2. Transportation Demand

### *3.2.1 Pooling, Sharing and Seamless Mobility Networks*

The impact of ride-hailing companies on vehicle miles traveled has, until recently, been difficult to quantify. The hypothetical forces from demand ride sharing (DRS) were thought to have both VMT-increasing and VMT-decreasing effects. (Rodier, Alemi, and Smith, 2016). The national academy of sciences similarly concluded as late as 2015 that it is "too early to determine which of these competing forces will dominate" (TRB, 2015).

Since that time, several researchers have managed to demonstrate that as of now, the impact of ride-hailing on vehicle miles traveled is almost certainly VMT increasing. Clewlow and Mishra find that 62% of ride-hailing rides would have been taken via walking, biking, or public transit, or would not have been taken at all (Clewlow and Mishra, 2017). Henao and Marshall find an increase in VMT of 83.5% when accounting for “deadheading”, induced travel, and ride substitution (Henao and Marshall, 2018). These increases are significantly greater than originally assumed, leading to an increase in our estimation of the VMT increases of ride hailing and autonomy. These ride-hailing studies can generally be thought to portend behavior of autonomous vehicle fleets. Caroline Rodier of UC Davis conducted an extraordinarily comprehensive analysis of the impacts of ride hailing services and includes the two papers mentioned above as well as many of the papers reviewed previously in Fox-Penner, Gorman, and Hatch (2018). After reviewing these studies she concludes that induced VMT from ride-hailing services is in the range of 8%-22%. In addition, new studies indicate that network vehicle travel without passengers can increase VMT anywhere from 10% to 60%.

We therefore revise our total estimate of VMT due to lower time cost for drivers, increased access, mode shift, and travel without passengers to 35% in a low-range estimate and 60% in a mid-range estimate, assuming that transportation policymakers will `address some of the most egregious impacts of ride-hailing by midcentury and aiming for a target estimate somewhere in the middle of the current literature on the subject.

#### *3.2.2 Business Model Impacts*

Many automotive, TNC, and software development companies have either explicitly or implicitly pointed to a variety of business models that are arising from the convergence of ride hailing and autonomy. A 2016 report from the Boston Consulting Group taxonomizes these business models by elaborating four “potential future scenarios” for the city of the future. These scenarios include fast and slow adoption of self-driving vehicles, a scenario of “robo-taxis”, and a new ride-sharing and public transit model incorporating autonomous technology (Boston Consulting Group, 2016). Similarly, in their discussion of AV transportation access, Dutta-Koehler and Hatch elaborate three models of potential autonomous vehicle penetration, including individually owned, taxi fleet, and ride-sharing (Dutta-Koehler and Hatch, in press). Because the energy use implications for individual vehicles are so different than in a ride-sharing/public transportation model, we limit our analysis to examining the taxi/fleet model and the individual ownership model.

For the individual ownership model, we maintain all the assumptions of previous layers of analysis, assuming that the VMT and energy intensity effects will remain consistent in both frameworks. We further break this model into two distinct scenarios: first, a scenario in which vehicles maintain similar useful lifespans in terms of years and vehicle miles to current vehicles in use today; and second, a scenario in which, much like the adoption of other technologies such as computers and cellphones, planned technological obsolescence reduces vehicle life spans by half.

In the fleet model simulation we replace 6.7 individually owned vehicles with 1 fleet vehicle. Many researchers have found that an autonomous taxi fleet would significantly reduce the number of vehicles in a subject area. For example, Fournier et al. found that a taxi fleet in Berlin that would serve passengers with a <1 minute wait time could decrease the vehicle population of Berlin by 89% (Fournier et al., 2017). While these studies shine light on the potential operation of AV fleets, for the purposes of this analysis we find a calculation of VMT replacement by existing taxi fleets most compelling. In order to do this calculation, we take the existing estimated lifetime VMT of a NYC cab (500,000 miles) and the estimated lifespan (6.6 years) in order to replace 6.7 individual vehicles during that time period, who each individually would have driven roughly 74,000 miles in that time (NYC Taxi Commission 2017).

### 3.3 Bounding the Study Area

The effects of ride hailing, ride sharing, and autonomy will almost certainly play out differently in different land use development scenarios. We are certain, however, that due to connectivity, distance, and other constraints, our particular modeling approach for autonomous taxi fleets does not apply to the proportion of VMT driven in rural areas in the United States – about 30% of VMT annually (NHWTA 2017). In modeling an autonomous taxi fleet, we therefore only apply the vehicle reduction from fleets to 70% of the total U.S. vehicle population.

It is open for debate whether the model will truly apply to sub- or peri- urban areas included in the NHWTA survey of urban VMT, but parsing these specifics is beyond the scope of this study. While there are significant limitations to such a broad approach to modeling vehicle adoption environments throughout the United States, we feel confident that our results are accurate enough to guide policy efforts going forward.

## 4. Scenarios

We use the two vehicle adoption cases elaborated in Fox-Penner et al., comprising an energy intense case and a policy case as elaborated in figure 3. As noted above, some of the numbers in these scenarios were updated based on the most recent literature. We also examine two electric grid emissions scenarios as the basis for our modeling efforts – one in which we use the EIA estimate of emissions intensity for the grid out to 2050, and another in which we apply a 95% linear decarbonization of the grid by 2050.

We then employ three different scenarios of autonomous vehicle adoption as discussed above – moderating the number of vehicles manufactures to supply total VMT for the fleet. Our three model scenarios are: a taxi or "sharing" model, where 6.7 vehicles are replaced by one taxi vehicle; traditional individual ownership, where the standard total fleet volume applies; and accelerated fleet turnover or "lease" model, where vehicles are retired at twice the current rate of traditional vehicles.

*Figure 3: Vehicle Adoption Cases modified from Fox-Penner et al.*

| *Variable Name* | *Description* | *Stress Case* | *Policy Case* |
|---|---|---|---|
| EV Sales | The rate of EV sales, or more completely, the growth of LDV EVs in the fleet; | High EV (90% by 2050) | |
| Energy Intensity | The level at which EVs increase their energy efficiency; | 0-20% | 15-40% |
| Cheap EV | The extent of the mileage effect from lower EV operating costs; | 10% | 0% |
| CAV Entry Year | The year in which commercial fully-autonomous CAV sales begin; | 2025 | 2030 |
| CAV VMT Effects | The overall (net) long-term effect of CAVs 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% | 60% | 35% |
| CAV Sales | The rate of CAV sales, or more completely, the growth of LDV CAVs in the fleet; | 75% by 2050 | |
| CAV EI | The overall (net) long-term effect of CAVs on realized kWh used per mile from various effects, and how this phases in (Sum of effects of traffic smoothing, intersection management, faster travel, and platooning) | -13.5% | -21.5% |
| Rightsizing/weight reduction | Whether and when CAVs allow a further substantial gain in EI due to lightweighting and/or rightsizing, implemented as a per-year increase starting in 2040; | -1% | -1.5% |
| Pooling/Shared VMT Reduction | Whether Pooling, Sharing, or Seamless Mobility Systems will reduce future VMT as well as shift it to higher-density modes; | 0 | -2% |
| Urban Design | Whether redesign of our urban areas reduces VMT; | 0 | -2% |
| Road Pricing | The form in which road pricing is adopted over the next decade or two; | \$.022 | \$.024 |
| Road Pricing Addition Through 2050 | The increase in real road pricing cost by the year 2050 | \$0 | \$.024 |
| Elasticity | The sensitivity of driving in EVs and electric CAVs to road prices. | -.2 | -.2 |

## 5. Preliminary Results

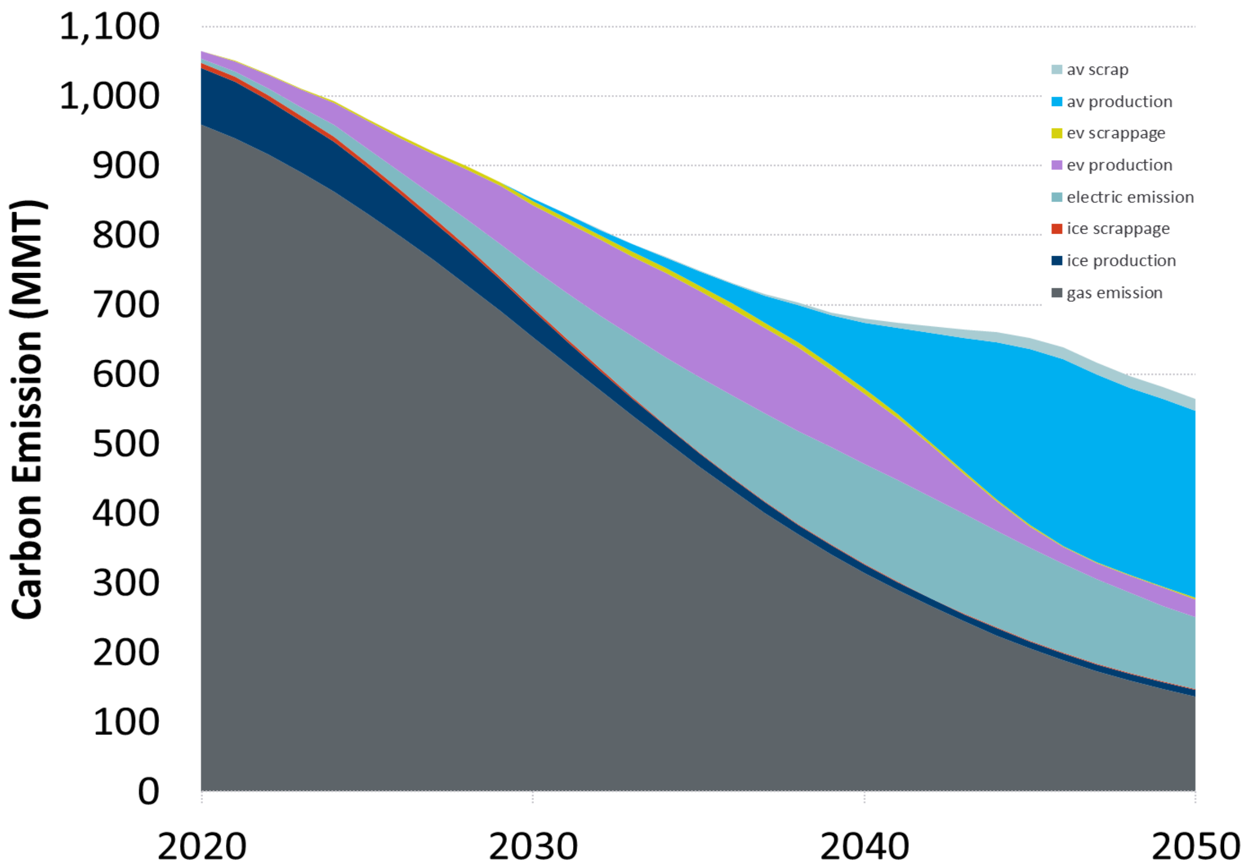
The preliminary results of our modeling efforts can be seen in figure 4. As in previous efforts to predict the GHG impacts of autonomous vehicles, there is a fairly large range of outcomes, ranging from a 20% reduction in GHG emissions by 2050 to an 80% reduction by 2050.

*Figure 4: Preliminary modeling results*

| | | Policy Case | | | Stress Case | | |
|---|---|---|---|---|---|---|---|
| | | | EIA Emissions | Decarb Electric Sector | | EIA Emissions | Decarb Electric Sector |
| | Year | TWh | MMT | MMT | TWh | MMT | MMT |
| **Sharing** | **2020** | | 1064 | 1057 | | 1065 | 1057 |
| | **2030** | | 850 | 808 | | 858 | 814 |
| | **2040** | | 607 | 472 | | 641 | 474 |
| | **2050** | | 401 | 183 | | 589 | 197 |
| **Conventional** | **2020** | | 1064 | 1057 | | 1065 | 1057 |
| | **2030** | | 851 | 809 | | 868 | 822 |
| | **2040** | | 650 | 500 | | 756 | 548 |
| | **2050** | | 523 | 245 | | 711 | 259 |
| **Lease** | **2020** | | 1064 | 1057 | | 1065 | 1057 |
| | **2030** | | 853 | 811 | | 878 | 830 |
| | **2040** | | 701 | 533 | | 891 | 636 |
| | **2050** | | 666 | 318 | | 854 | 332 |

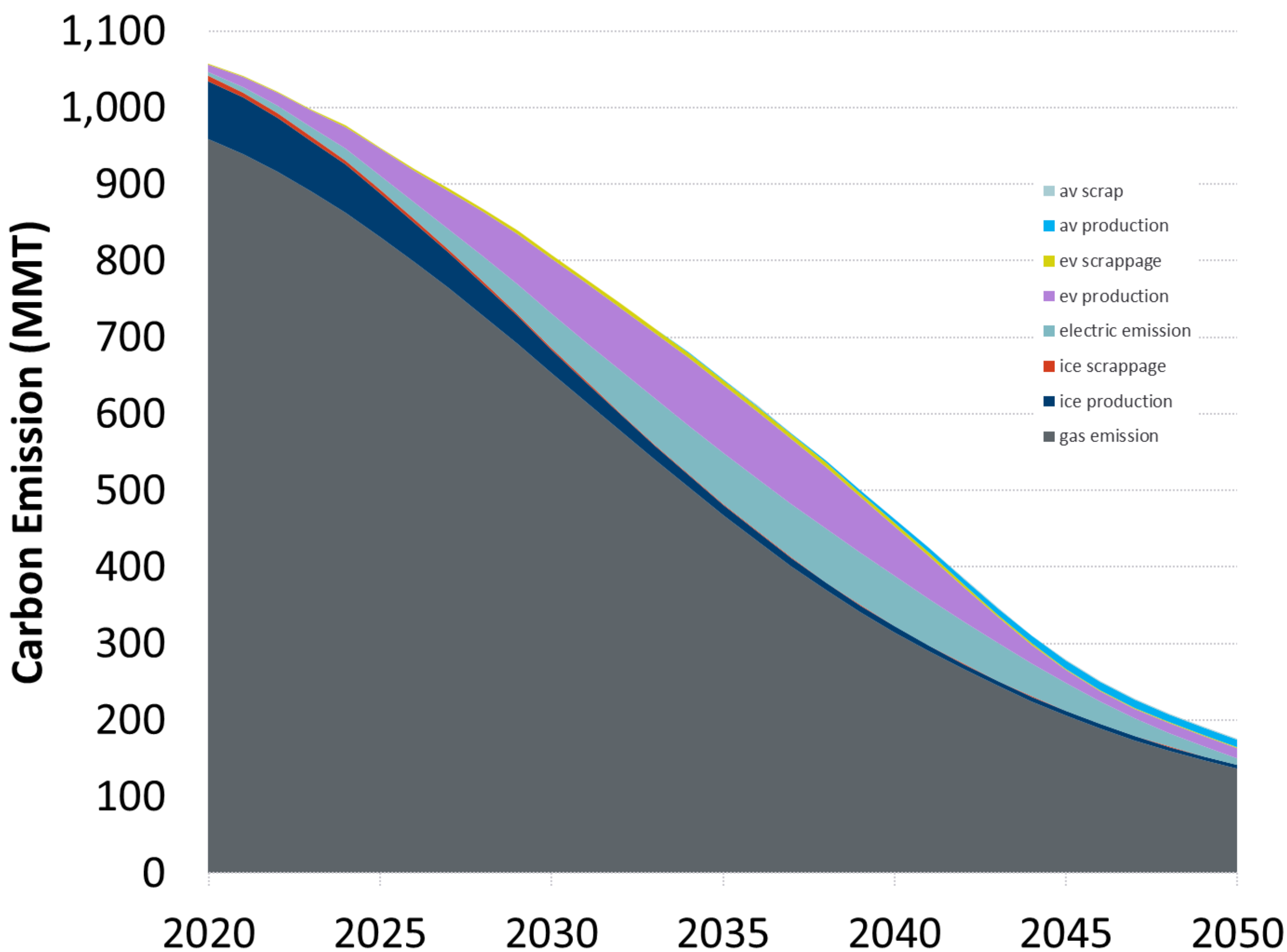
In a worst case scenario, even if we convert to all electric vehicles, the result is only a 20% reduction in GHG by 2050, spurred by an appetite for ever-newer technology, a desire for individually owned passenger vehicles, and a lack of policies to curb VMT growth. The outsized impact of a desire for new vehicle models is illustrated in figure 5, where, even under a policy scenario in which driving impacts are curbed, the emissions from AV production are significant enough to nearly double total vehicle emissions.

*Figure 5: Emissions under a policy case with EIA projections and an accelerated vehicle leasing model*



On the other hand, in a best case scenario, we see an 80% reduction in vehicle emissions by 2050. The remaining emissions in this scenario are almost entirely from the remaining ICE vehicles in the total vehicle fleet, indicating that a policy to require electric vehicles sooner than 2050 could make a significant impact in achieving any remaining emissions reductions.

*Figure 6: Emissions under a policy case with decarbonization of the electric grid and a vehicle sharing model*




Note that current preliminary results do not include consideration of urban vs rural VMT, indicating that our "best case" preliminary results may be slightly more optimistic than final results.

## 6. Bibliography


Aguirre, K., Eisenhardt, L., Lim, C., Nelson, B., Norring, A., Slowrig[i], P., & Tu, N. (2012, June). Lifecycle Analysis Comparison of a Battery Electric Vehicle and a Conventional Gasoline Vehicle. *Client: California Air Resources Board*.

Albright Stonebridge Group. (2016). *Autonomous Vehicles and Policy: Shaping the Future of Mobility.* Albright Stonebridge Group.

Alexander-Kearns, M., Peterson, M., & Cassady, A. (2016). *The Impact of Vehicle Automation on Carbon Emissions.* Center for American Progress.

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.

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.

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

Davidson, P., & Spinoulas, A. (2015). *AUTONOMOUS VEHICLES - WHAT COULD THIS MEAN FOR THE FUTURE OF TRANSPORT?* Davidson + Spinoulas.

Ellingsen, L. A.-W., Majeau-Bettez, G., Singh, B., Srivastava, A. K., Valoen, L. O., & Stromman, A. H. (2013). Life Cycle Assessment of a Lithium-Ion Battery Pack. *Journal of Industrial Ecology*.

Ellingsen, L. A.-W., Singh, B., & Stromman, A. H. (2016). The Size and Range Effect: lifecycle greenhouse gas emissions of electric vehicles. *Environmental Research Letters*.

Fagnant, D., & Kockelman, K. (2015). Preparing a Nation for Autonomous Vehicles: Opportunities, Barriers, and Policy Recommendations. *Transportation Research Part A, 77*, 167-181.

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.

Hawkins, T. R., Singh, B., Guillaume, M.-B., & Hammer Stromman, A. (2012). Comparative Environmental Life Cycle Assessment of Conventional and Electric Vehicles. *Journal of Industrial Ecology, 17*(1).

Kim, H., & Wallington, T. (2016). Life Cycle Assessment of Vehicle Lightweighting: A Physics-Based Model to Estimate Use-Phase Fuel Consumption of Electrified Vehicles. *Environmental Science and Technology*, 11226-11233.

Kim, H., De Kleine, R., Wallington, T. J., McLean, H. L., & Luk, J. M. (2017). Review of the Fuel Saving, Life Cycle Emission, and Ownership Cost Impacts of Lightweighting Vehicles with Different Powertrains. *Environmental Science and Technology*, 8215-8228.

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. M., 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.

KPMG. (2015). Connected and Autonomous Vehicles - The UK Economic Opportunity. Retrieved from https://www.kpmg.com/BR/en/Estudos_Analises/artigosepublicacoes/Documents/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.

Lavasani, M., Jin, X., & Du, Y. (2016). Market Penetration Model for Autonomous Vehicles Based on Previous Technology Adoption Experiences. *Transportation Research Record Journal*.

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.

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.

Niewenhuijsen, J. (2015). Diffusion of Automated Vehicles. *A Quantitative Method to Model the Diffusion of Automated Vehicles with System Dynamics*. Delft University of Technology.

Norderlof, A., Messagie, M., Tillman, A.-M., Ljunggren Soderman, M., & Van Mierlo, J. (2014). Environmental Impacts of hybrid, plug-in hybrid, and battery electric vehicles -- what can we learn from life cycle assessment? *International Journal of Lifecycle Assessment*, 1866-1890.

Rodier, C., Alemi, F., & Smith, D. (2016). Dynamic Ridesharing: An Exploration of the Potential for Reduction in Vehicle Miles Traveled. *TRB 95th Annual Meeting.*

Samaras, C., & Meisterling, K. (2008). Life Cycle Assessment of Greenhouse Gas Emissions from Plug-In Hybrid Vehicles: Implications for Policy. *Environmental Science and Technology*.

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.

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.

Underwood, S. (n.d.). *Automated, Connected, and Electric Vehicle Systems: Expert Forecast and Roadmap for Sustainable Transportation.* Dearborn, MI: Connected Vehicle Proving Center Institute for Advanced Vehicle Systems.

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

Weis, A., Jaramillo, P., & Michalek, J. (2016). Consequential life cycle air emissions externalities for plug-in electric vehicles in the PJM interconnection. *Environmental Research Letters*. doi:10.1088/1748-9326/11/2/024009

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

---

i