Essays on Automated Vehicles and the Future of Mobility

By

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S.M. Engineering and Management, Massachusetts Institute of Technology (2013)
S.M. Management Research, Massachusetts Institute of Technology (2017)

SUBMITTED TO THE SLOAN SCHOOL OF MANAGEMENT IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF

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Abstract

Automated vehicle (AV) and electric vehicle (EV) technologies are expected to substantially reduce the negative externalities of driving. Combined with ubiquitous ride-hailing platforms that facilitate ride-sharing (pooling), AVs promise to make automobile transportation faster, safer, cheaper, more convenient, and environmentally friendly. Yet the endogenous impacts of AVs on demand for driving are not well understood. My first paper explores the effect of AVs and pooling on the performance of both roads and public transit in a bimodal transportation system. I develop a dynamic model that describes how commuters choose between driving a car or riding public transit in response to the changing attractiveness of these modes in the presence of AVs and pooling. I show that the well-intentioned move to promote pooling may have the unintended consequences of leading to both worse public transit quality and more rather than less traffic congestion if the public transit downward spiral is triggered. In my second paper, I use conjoint analysis to estimate consumer preferences for the attributes of ride-hailing services. I show that because consumers have an inherent aversion to pooling, and prefer cheaper trips, consumer choice of pooling is likely to drop in the future if the cost of driving falls with the introduction of AVs as some predict. In my third paper, I study the role of the accelerated vehicle retirement programs ('cash-for-clunkers') in reducing transportation fleet emissions. I use a model of vehicle fleet turnover in the United States to show that achieving climate goals will likely require 'cash-for-clunkers' policies that incentivize the accelerated retirement of older, less-efficient vehicles to be replaced by electric vehicles, combined with a rapid transition to renewable electricity. I demonstrate that such policies can be an effective way to make the vehicle fleet less emission-intensive, but that the costs could be high. I show that combining 'cash-for-clunkers' with a gas tax or carbon price would help offset the costs incurred while also reducing driving demand, helping to achieve a low-emissions transition in time.

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Table of Contents

List of Figures

List of Tables

Unintended Consequences of Automated Vehicles and Pooling for Urban Transportation Systems

Abstract

Automated vehicles (AVs) have emerged rapidly in recent years, becoming a focus of high expectations and heated debates. Advocates argue that the arrival of AVs will make driving safer, greener, cheaper, and faster, bringing ubiquitous access to transportation while significantly reducing traffic congestion and environmental impacts. Skeptics, in contrast, suggest that the appeal of AVs will induce additional driving, offsetting or even overwhelming the positive effects of increased automation. Many analysts now believe that the solution lies in ensuring that most vehicle trips are shared to serve the same number of passenger miles with fewer vehicle miles, reducing traffic congestion. Yet these analyses fail to recognize that reducing congestion will induce yet more demand for driving, and attract riders from other transportation modes including public transit, which is already experiencing falling ridership in many cities. In this paper, we explore the impact of AVs and pooling on consumer mode choice and the effect on the performance of both road and public transit systems. We show that the well-intentioned move to promote pooling may have the unintended consequence of triggering a public transit death spiral, leading to both worse public transit quality and more rather than less traffic congestion. We argue that the deployment of AVs and pooling can be effective at improving the sustainability of urban transportation systems, but only when accompanied by policies that manage induced demand for driving and sustain public transit service quality.

1 Introduction

Automated vehicle (AV) technologies have improved rapidly in recent years with advances in artificial intelligence and sensor hardware. AVs hold the potential to ameliorate many of the negative externalities of automotive transportation, reducing vehicle accidents and lessening fuel consumption and traffic congestion through better traffic coordination. Various automakers and analysts have stated that fully automated vehicles capable of driving without the input of a human driver will be commercially available as early as 2025 (Mosquet et al., 2015; McKerracher et al., 2016). Although others are more skeptical about such early deployment, there is near-universal agreement that AVs will fundamentally change how we own and operate automobiles in the coming decades.

While the potential benefits of AVs for drivers are well understood, conflicting perspectives exist about the aggregate impact AVs will have on travel demand, traffic volumes, energy consumption, and the environment. Advocates argue that AVs will make driving safer, greener, cheaper, faster, and more convenient, promoting a vision where the ability to summon a vehicle on demand will lead to decreased vehicle ownership, hence reduced traffic, parking needs and environmental impacts. AVs will eliminate road congestion by utilizing advanced sensors and enabling vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication to minimize the distance between vehicles and increase travel speeds (Aria, Olstam, & Schwietering, 2016; Wadud, MacKenzie, & Leiby, 2016). At the highest level of automation, Level 5[1], AVs will be capable of navigating roads without any human intervention, allowing passengers to use their travel time more productively, whether working, entertaining, or sleeping.

Many researchers also recognize the potential for negative consequences from AVs. For example, AV fleets might induce additional travel demand (Harb, Xiao, Circella, Mokhtarian, 2017) including low- and zero-occupancy driving, and add overhead due to the repositioning of vehicles between rides (Fagnant & Kockelman, 2014; Wadud et al., 2016), partially or fully

[1] Level 3 enables some autonomy, but still requires the driver to be able to take control of the vehicles in emergency or difficult conditions. Level 4 enables full automation, but still might need the driver's intervention under some conditions, and Level 5 is full automation on any road under any conditions at any time (SAE On-Road Automated Vehicle Standards Committee, 2014).

offsetting the benefits of automated driving. Level 5 AVs would provide transportation to underserved populations who cannot drive conventional vehicles currently (Harper, Hendrickson, Mangones, & Samaras, 2016). New business opportunities may flourish in the field of goods delivery, retail, and services, adding to driving demand. People who 'park and ride' today, parking their cars at the suburban transit stops before taking a bus or a train, may instead choose to drive all the way into the city, as people generally prefer private vehicles to public transportation (Cox & Utt, 2002; Scheiner, 2010). In addition, since AVs do not need a human driver, the phenomenon of idle driving may emerge, with owners sending their vehicles to circle the block repeatedly rather than searching for a parking space, increasing congestion and wasting energy. An increase in energy consumption may also result from higher travel speeds and the addition of new features in AVs (Wadud et al., 2016). With the increasing dependence on automobile transportation, urban areas might experience even more congestion and pollution than today.

While the potential benefits and costs of AVs are relatively clear, our understanding of how these pieces fit together is less well developed. Some researchers have engaged in system-level discussions, such as the need to design for flexibility in urban mobility systems (Burns, 2013; Fagnant & Kockelman, 2013, 2015; Mervis, 2017; Milakis, van Arem, & van Wee, 2017), and the need to gain the buy-in of regulators, businesses, and entrepreneurs (Sumantran, Fine, & Gonzalvez, 2017). However, existing analyses largely fail to recognize the endogeneity that exists in AV impacts: if AVs make driving more attractive, demand for driving will increase, with consequences for both demand for road space and ridership of competing transportation modes.

Many are convinced that the solution to the problem of AV-induced demand for driving lies in requiring that most AV trips are shared, with multiple passengers sharing a single car to the same destination to reduce congestion, and demanding that AVs are electric-drive to reduce GHG emissions (Fulton, Mason, & Meroux, 2017; Sprei, 2017). Ride-sharing, also known as *pooling*, would reduce the number of vehicles on roads by serving the same demand for passenger miles with fewer vehicles, relieving congestion and reducing travel times *all else being equal*. However, these proposals mostly ignore the potential impact that reducing congestion will have on the demand for driving subsequently. If pooling is successful at reducing congestion and travel times, yet more driving will be induced, attracting passengers from other transportation modes (e.g., public transit, biking, walking). Public transit systems are already experiencing falling ridership in many cities with low gas prices and the introduction of ride-hailing services in recent years (NYCEDC, 2017; APTA, 2018; Fitzsimmons, 2018; Mallett, 2018; MTA, 2018; Schaller, 2018). The well-intentioned move to introduce AVs and pooling may, therefore, have the unintended consequence of triggering the public transit downward spiral, leading to both worse public transit quality and more rather than less traffic congestion.

In this paper, we analyze the impact of AVs and pooling on consumer choice between driving and using public transit, and the resulting impact that this demand has on the performance of both road and public transit systems. We develop a dynamic model of demand for urban transportation that highlights the underlying tension between automobile travel and public transit – with fewer cars on roads, driving becomes *more* attractive, while with fewer riders on public transit, riding becomes *less* attractive. Our model demonstrates that in the absence of other interventions, the promotion of pooling can have the unintended consequence of making traffic congestion worse, not better, if pooling triggers a downward spiral in public transit by reducing ridership and revenues, eroding public transit service quality. As transit riders switch to driving, traffic congestion on roads increases at the margin, and public transit revenues and service quality fall, leading yet more transit riders to switch to driving, likely to result in even higher congestion than before pooling was introduced. We show that AVs and pooling can be effective at improving the sustainability of urban transportation systems, but only when deployed in concert with policies that limit induced demand for driving and sustain public transit quality. Ultimately, effective policies to address the negative externalities of driving must decrease, not increase, the attractiveness of driving. We demonstrate, for example, that a vehicle miles traveled (VMT) tax (e.g. Parry & Small, 2005) coupled with partial reinvestment of the tax revenue in public transit creates a transportation system that moves more people, including by road, maintaining high quality and affordable public transit, and low traffic congestion.

Our research contributes to understanding the societal impacts that AVs could have, providing guidance on the design of policies and strategies intended to address the negative externalities of automotive transportation. In the face of bold, sometimes naïve claims that automated vehicles and pooling will solve transportation problems, we believe that models such as ours that make explicit assumptions about rider and driver behavior – and the interplay amongst transportation modes – will be critical to making informed policy decisions in this arena.

2 The Dynamics of Urban Transportation Demand

Automobiles have played a critical role in the development of modern society since the start of the 20th century, allowing flexible movement of people and goods, and stimulating economic growth. Post-World War II, personal cars helped people escape cities polluted by factories for the increasingly attractive and prosperous suburbs (Squires, 2002; Mikelbank, 2004). As cars became more comfortable and more roads were built, people settled in the suburbs farther away from city centers, making for ever-longer commutes.

The negative consequences of such car dependence have become increasingly apparent, including deaths from traffic accidents, air pollution in the form of both greenhouse gas emissions and ground-level pollution including particulates, VOCs, NOx, SOx, and ozone, and time and energy wasted in traffic jams. Today, the automotive fleet is one of the largest sources of greenhouse gases (GHGs) in the United States, with light-duty vehicles emitting 83% of GHGs from the US transportation sector in 2015, and accounting for more than 22% of total U.S. CO_2 emissions (EPA, 2017). Increasing travel demand has led not only to growth in emissions but also more congestion on roads, with American drivers spending an average of a full work week per year in congestion while commuting, costing an estimated $1,400 per driver in 2016 (Cookson & Pishue, 2017). These problems are global, and absent effective countermeasures, are likely to worsen, with the world population expected to grow to 9.7 billion people by 2050, of which 70% will be living in cities, resulting in a doubling of travel demand (Cookson & Pishue, 2017).

The main alternative to driving in most cities is riding public transit, such as commuter rail, subway trains, and buses. Public transit ridership is relatively low in the United States, accounting for less than 20% of trips outside of a handful of major cities such as New York City, Washington DC, Boston, and San Francisco (U.S. Census Bureau, 2017). After two decades of steadily increasing ridership, most transit systems have been experiencing falling ridership since 2015. The decline has been attributed to factors including low gasoline prices, and the increasing availability of ride-hailing services (e.g., Uber and Lyft) and bike-sharing (NYCEDC, 2017; APTA, 2018; Fitzsimmons, 2018; Mallett, 2018; MTA, 2018; Schaller, 2018). Many transit observers fear that this downturn and other technological change such as online shopping and telecommuting will trigger a 'death spiral' that sees this problem get successively worse, as a lack of ridership forces transit agencies to cut services and increase fares (Harrison, 2018). Sterman (2000) articulates the causal structure that explains these dynamics, showing how new automotive technologies could worsen the problem.

Here we develop a dynamic model that describes how commuters choose between driving a car or riding public transit, in response to the changing attractiveness of these modes in the presence of AVs and pooling. We introduce the key mechanisms in the model below, with full documentation of the model provided in the online supplement.

2.1 Congestion Regulates Demand for Driving

Demand for driving in cities is regulated by traffic congestion and travel times, equilibrating demand for road space relative to the available road supply. When drivers perceive an increase in travel time, the utility of driving goes down, and fewer people decide to drive until the marginal driver is indifferent about driving or taking public transit. Similarly, when travel times fall, for example, because of the expansion of the road network, the attractiveness of driving increases, leading to an increase in driving and traffic density until congestion returns once more. This dynamic has been frequently observed following road-building efforts intended to ease traffic congestion, with congestion returning and often worsening in as little as three years (Duranton & Turner, 2011). We represent this demand response of drivers over time (e.g., varying their discretionary trips, or moving house to change the distance of their commute) with a single feedback *B1* (Figure 1). While the various ways that consumer can adjust their demand for driving operate with different time delays, some short-run and some long-run, it is possible to represent them with a single feedback loop without losing the fundamental properties of the system.

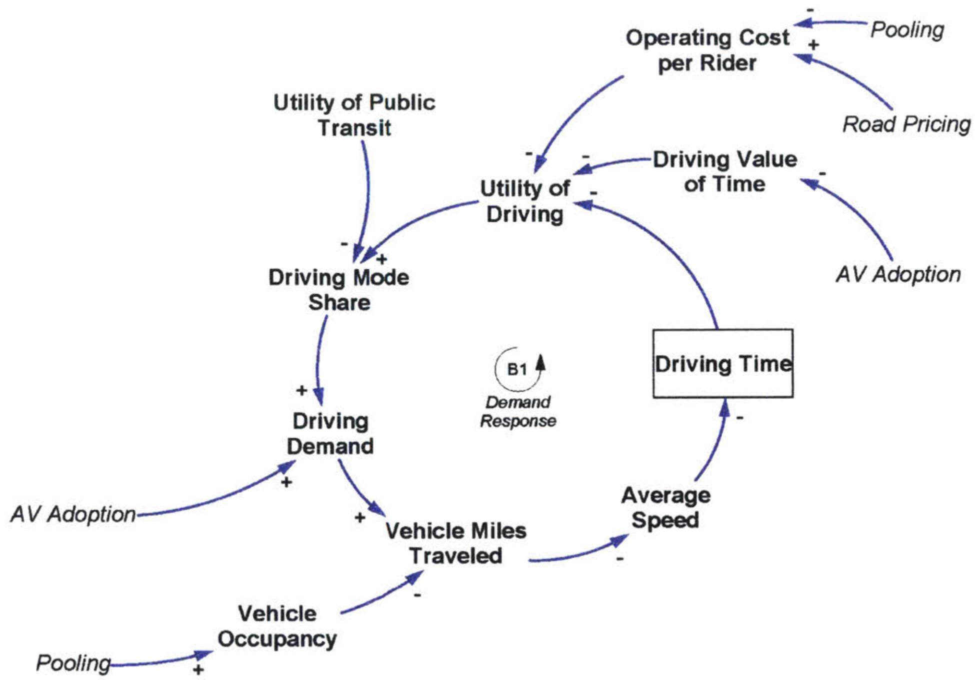


Figure 1. Driving Demand Response

We model commuters' choice between the two transportation modes that exist in major cities around the world today: driving a car (subscript d) or riding public transit (subscript p). In this bimodal transportation system, we estimate the fraction of people choosing driving, σ_d, using a binomial logit model (Train, 2009):

$$\sigma_d = \frac{e^{u_d}}{e^{u_d} + e^{u_p}} \tag{1}$$

where the utility of driving, u_d, is estimated as the sum of the operating cost, c_d, and the time cost of driving, c_T:

$$u_d = c_d \beta_d + c_T \beta_T \tag{2}$$

where β_d and β_T are the relative weights that commuters place on operating costs and time respectively. The operating cost reflects costs including fuel, registration, tolls, depreciation, and insurance, jointly represented as c_d^0, and road taxes c_{tax} , adjusted by the effect of average occupancy per vehicle in the fleet δ_c:

$$c_d = (c_d^0 + c_{tax})\, \delta_c \tag{3}$$

The time cost c_T is calculated as the product of commuter's perceived driving time T and their value of driving time p_T:

$$c_T = T\, p_T \tag{4}$$

Higher market shares of driving result in more miles of daily driving demand. Assuming the commuting population in the catchment area, n, and the average daily driving demand per person, d_n, the total daily driving demand of the city, in units of passenger-miles traveled, is given by:

$$d_{PMT} = n\, d_n\, \sigma_d \tag{5}$$

The effect of average occupancy per vehicle in the fleet δ_{VMT} determines the number of vehicle-miles traveled required to serve the daily driving demand:

$$d_{VMT} = d_{PMT}\, \delta_{VMT} \tag{6}$$

The number of miles driven, d_{VMT}, determines the average speed of the traffic flow, v, assuming constant road capacity. With more driving, road congestion increases, and the traffic speed is reduced relative to the free flow speed of traffic v_f (the maximum average speed determined by physical features of roads and vehicles):

$$v = v_f\, \delta_d \tag{7}$$

The effect of increased driving on speed δ_d is bounded by a maximum value of one and is computed assuming the elasticity of speed with respect to traffic ε_d,; even if there are only a few vehicles on the road the average traffic speed cannot exceed the free flow speed:

$$\delta_d = \min\left(1, \left(\frac{d_{VMT}}{d_{VMT}^0}\right)^{\varepsilon_d}\right) \tag{8}$$

where d_{VMT}^0 is the reference number of vehicle-miles traveled.

Given the speed of traffic and the average daily driving demand per person, the average travel time per person is:

$$\bar{t} = \frac{d_n}{v} \tag{9}$$

Finally, it takes time for commuters to perceive changes in travel time, which we assume is given by first-order exponential smoothing from the initial perceived driving time T_0 with perception time τ_T:

$$T = \int \frac{\bar{t} - T}{\tau_T} dt, T(0) = T_0 \quad (10)$$

2.2 Automated Vehicles Make Driving More Efficient and More Attractive

AVs have the potential to improve driving efficiency, mitigate congestion, strengthen crash-avoidance, and limit energy consumptions and pollution (Wadud et al., 2016). However, many of the benefits of AVs will only be realized when full automation (Level 5) becomes available, removing the need for a human driver and enabling new business models for vehicle ownership and use. Assuming full autonomy, many researchers have focused their attention on the optimal design of AV fleets and car relocation strategies (Fagnant & Kockelman, 2014; Chen, Kockelman, & Hanna, 2016). In the most optimistic analysis we have seen, the combined benefits of AV technologies could allow ride-sharing fleets of fully automated vehicles to reduce emissions per mile by about 90% relative to the conventional vehicles in use today (Greenblatt & Saxena, 2015).

When the level of automation increases, cars require less human intervention, allowing passengers to use their travel time more productively. Therefore, the reference value of driving time, p_T^0, is reduced by the effect of automation on the value of time, δ_{AV}:

$$p_T = p_T^0 \, \delta_{AV} \quad (11)$$

Automated vehicles are also expected to induce additional travel demand from existing drivers (Harb, Xiao, Circella, Mokhtarian, 2017), from underserved populations who cannot drive conventional vehicles currently (Harper et al., 2016), and as a result of new business opportunities. We calculate the average daily driving demand per person, d_n, as:

$$d_n = d_n^0 \, (\delta_{AV})^{\varepsilon_{AV}}$$

where d_n^0 is the reference level driving demand per person, and ε_{AV} is the elasticity of driving demand with respect to the level of vehicle automation.

The effect of vehicle automation on the value of time, δ_{AV}, depends on factors including the speed of technological progress, the rate of consumer adoption, and the stringency of the AV regulatory environment. The rate at which these developments occur is quite uncertain. For simplicity, we assume a linear change in the effect of the level of automation on travel time in the on-road vehicle fleet over time to the maximum effect δ_{AV}^{max}, calculated using a piecewise linear function, with parameters controlling the start time and duration of the technical change that can be varied in sensitivity analysis:

$$\delta_{AV}(t) = \begin{cases} 1, & t < \tau_0 \\ 1 - (1 - \delta_{AV}^{max})\dfrac{t - \tau_0}{\tau_f - \tau_0}, & \tau_0 \leq t \leq \tau_f \\ \delta_{AV}^{max}, & t > \tau_f \end{cases} \tag{12}$$

2.3 Pooling Further Increases Road Throughput

The concept of carpooling has been around for decades. Use of carpooling and ride sharing to commute to work in the US stood at about 20% of trips in 1980, but has since fallen to just 9% in 2016 (AASHTO, 2013; U.S. Census Bureau, 2016). However, pooling has enjoyed a renewed interest in recent years with the emergence of ride-hailing services such as Uber and Lyft, who offer pooling services (UberPOOL and Lyft Line) that match up riders taking similar trips. The major benefit of pooling for the consumer is that sharing a ride substantially reduces the cost of the trip.

While financially advantageous, many people find pooling inherently less attractive than a private ride, because of inconveniences including having to share the vehicle cabin with unknown passengers, and potentially having to take a circuitous route to one's destination to accommodate the needs of the multiple passengers (Krueger, Rashidi, & Rose, 2016). However, the effect of pooling can be substantial if consumers are willing to pool.

When only one person drives a car, the vehicle miles traveled is exactly equal to the number of passenger miles demanded. When multiple people share a vehicle, the driving demand of vehicles d_{VMT} is less than the sum of the passenger demands, reduced by the average occupancy ω. The effect of average occupancy is not linear in the average number of passengers per vehicle ω, as there is a need for additional miles to complete pick-ups and drop-offs, and is calculated using the elasticity of vehicle miles traveled with respect to ridership ε_{VMT}:

$$\delta_{VMT} = \omega^{\varepsilon_{VMT}} \tag{13}$$

As well as reducing the number of vehicle miles needed to deliver the same number of passenger-miles, pooling makes traveling by car cheaper, reducing cost by the effect of average occupancy δ_c, because the cost of vehicle operation can be shared amongst the passengers. Because not all cost can be shared (e.g., costs associated with placing an order, pick-ups, and drop-offs), the effect δ_c is nonlinear in the average number of passengers per vehicle ω, and is calculated using the elasticity of cost with respect to ridership ε_c:

$$\delta_c = \omega^{\varepsilon_c} \tag{14}$$

Pooling, therefore, activates the demand response feedback *B1* (Figure 1) in two ways. First, with fewer vehicles on the road, traffic density is reduced, lowering travel times and inducing yet more driving. Second, with lower driving costs, vehicle users take more and longer trips, increasing traffic density and average travel times, in turn decreasing the utility of driving. So, while AVs and pooling increase the throughput of people on roadways, the effect that these technologies will have on traffic congestion and pollution is less clear, dependent on the extent to which these technologies induce additional demand for driving.

2.4 Sustaining Public Transit Quality Depends on Ridership

The utility of public transit for riders is determined by attributes including the number and frequency of services, the reliability, comfort, and quality of those services, the convenience of routes, and the fare. We represent these attributes collectively as a stock of capabilities called PT Quality (Figure 2). The higher the quality of public transit, the higher the utility of transit relative to the utility of driving for commuters, leading to higher transit mode share and ridership. Higher ridership generates higher revenues, allowing for more reinvestment in maintenance and expansion, increasing PT Quality and leading to yet more transit ridership, a reinforcing feedback (*R1*). When PT Quality is sufficiently high, the mode share of public transit is high enough to generate a stream of revenues from ridership that allows for sustainable reinvestment in maintenance and service, keeping PT Quality high.

However, PT Quality also erodes over time, for example, due to aging and wear of equipment, a balancing feedback *B2*. The relative magnitude of the inflow of investments relative to the outflow of erosion is therefore critical in determining the state of the system. If the inflow falls below the outflow, the reinforcing feedback *R1* will become vicious rather than virtuous, where lower public transit quality will lead to lower utility and lower ridership, reducing investments in maintenance and expansion, and leading to even lower transit quality. In the absence of sufficient ridership revenues, government subsidization can contribute to the inflow of maintenance and expansion (feedback *B2*). However, the contribution of this feedback is likely to be much lower than revenue from ridership, because of the limited willingness of many governments to subsidize financially unsustainable public transit infrastructure. In addition, once public transit is locked in this downward spiral, the behavior of the system follows the capability trap dynamics described by Repenning & Sterman (2002). Building up the stock of PT Quality again from a low level will require sustained public sector investment, which will take time to deliver results, and is likely to even exhibit a 'worse-before-better' dynamic, with interruption of existing transit services required to perform required fixes (Lyneis & Sterman, 2016).

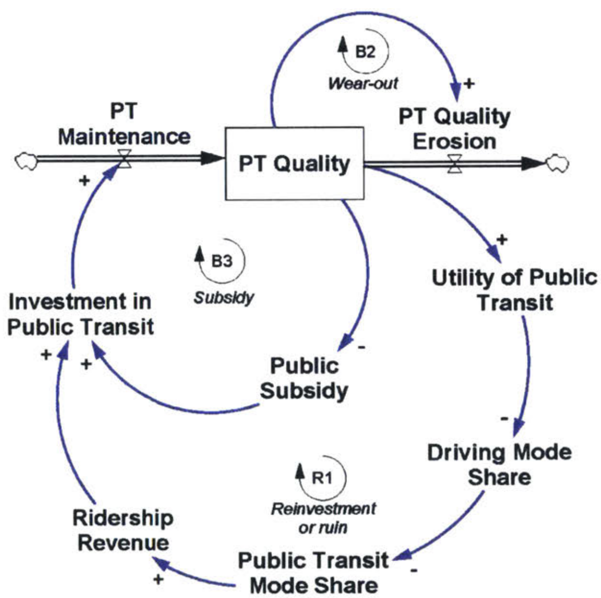


Figure 2. Public Transit Ridership Response

We model public transit quality Q as a stock with initial value Q_0, increasing with investments in maintenance and service (routes and frequency, comfort, reliability, safety, etc.), q_i, and decreasing over time through erosion of quality, q_o:

$$Q = \int_0^t (q_i - q_o)dt + Q_0 \tag{15}$$

We calculate the erosion of quality q_o as:

$$q_o = \frac{Q}{\tau_q} \tag{16}$$

where τ_q is the average lifetime of the assets, equipment, and other determinants of public transit quality.

The utility of public transit is a function of quality:

$$u_p = \beta_p \, Q^{\varepsilon_Q} \tag{17}$$

Where ε_Q is the elasticity of utility with respect to quality, and β_p is the relative weight that commuters place on transit quality (relative to the attributes of other transportation modes). The mode share of public transit is then a function of the utility of transit relative to the utility of driving:

$$\sigma_p = \frac{e^{u_p}}{e^{u_d} + e^{u_p}} \tag{18}$$

The ridership revenue that public transit generates is the product of the commuting population in city n, the public transit mode share σ_p, and the public transit fare f:

$$r = n \, \sigma_p \, f \tag{19}$$

The maximum revenue reinvestment authorized for maintenance and investment in public transit capabilities r_{max} is calculated as the product of revenue from ridership r and the maximum reinvestment fraction η_{max}:

$$r_{max} = r \, \eta_{max} \tag{20}$$

However, the whole authorized amount might not be needed to maintain PT Quality at the desired level. In that unlikely event, the actual amount of ridership revenue reinvested is, therefore, bounded by the maximum required investment r^*:

$$r_p = \min(r_{max}, r^*) \tag{21}$$

where r^* is the investment required to close the gap between the desired and actual quality, r_g, given the investment efficiency α_s, and the erosion rate q_o, to avoid the steady-state error (Sterman, 2000). We optimistically assume that transit systems monitor and budget for timely replacement of obsolete equipment and carry out maintenance sufficient to repair breakdowns and deterioration as they occur:

$$r^* = \frac{r_g + q_o}{\alpha_s} \tag{22}$$

The investment needed to close the gap is calculated as the difference between the desired and actual quality given the minimum time needed to allocate the investment τ_i:

$$r_g = \frac{Q^* - Q}{\tau_i} \tag{23}$$

When the actual quality is equal to the desired quality, additional investment is not needed, and the only reinvestment made is to compensate for the loss of quality due to erosion. Similarly, public transit quality determines the amount of government subsidy contributed for maintenance and expansion, such that as quality increases relative to the desired quality, the subsidy reduces:

$$s = s_{max}\left(1 - \frac{Q}{Q^*}\right) \tag{24}$$

The total investment made is, therefore, the sum of reinvestment of ridership revenue r_p and the government subsidy s:

$$q_i = r_p + s \tag{25}$$

2.5 The Potentially Unintended Consequences of AVs and Pooling

Considered in isolation, the dynamics of driving and public transit are easily understood. Yet the potential for significant unintended consequences emerges when we expand the boundary of the model to capture the endogenous interactions between driving and public transit (Figure 3). In particular, the promotion of pooling as a countermeasure for the potentially negative impacts of AVs may have the unintended consequence of increasing rather than decreasing traffic congestion and air pollution, by triggering a downward spiral in public transit quality. The key insight is that while roads become *more* attractive with fewer vehicles because there is less traffic congestion, public transit becomes *less* attractive with fewer riders because ridership revenues and service quality drop. By increasing the throughput of the road system, AVs and pooling have the potential to attract commuters away from public transit. If this effect is sufficiently large it can trigger a downward spiral in public transit quality, leaving commuters with no choice but to drive even as traffic congestion increases, resulting in more vehicle miles traveled (even with higher vehicle occupancy), longer travel times, and more air pollution.

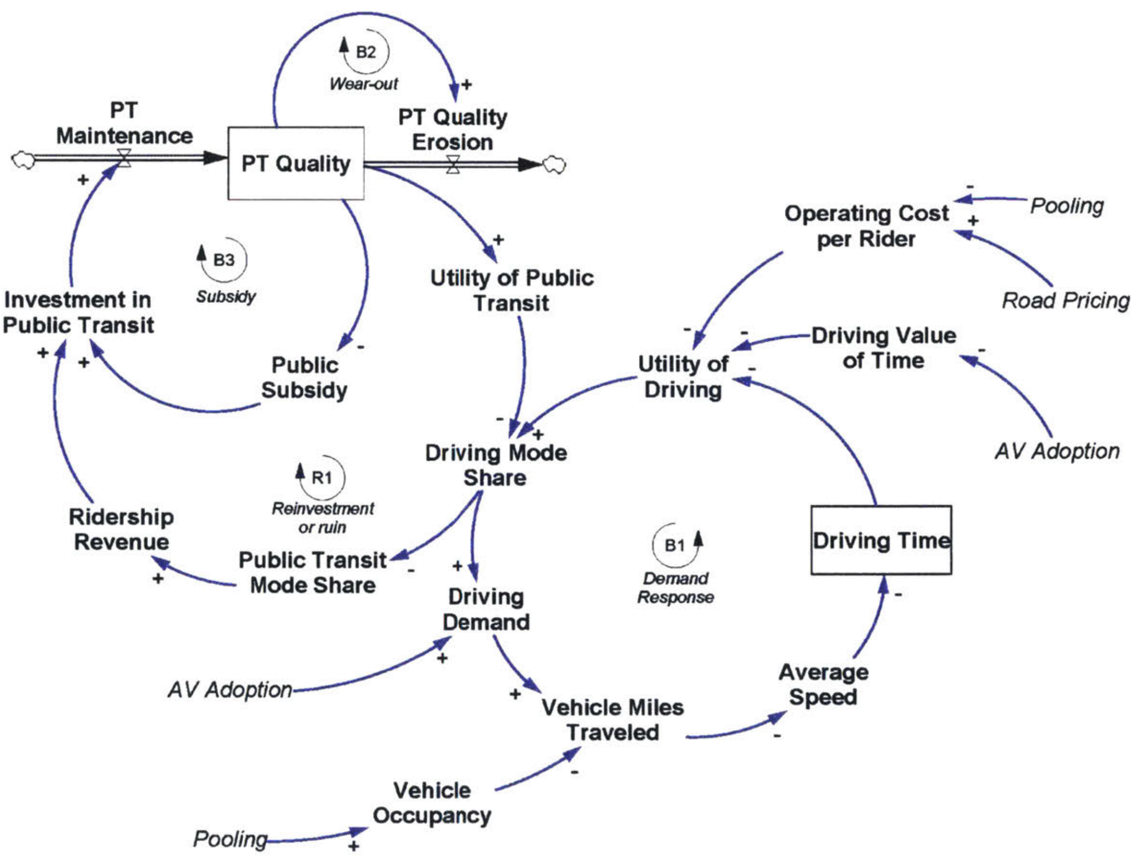


Figure 3. The Bimodal Urban Transportation System

3 Analysis

Next, we simulate the model to highlight the impact of AVs and pooling on the behavior of this bimodal transportation system further. We initialize the model in equilibrium (see Appendix A: Parameterization and Initialization of the Model). The model is deliberately stylized to highlight the dynamic impacts of AV deployment and is not calibrated to any particular city, with parameter values chosen to represent plausible scenarios. We have performed extensive sensitivity analysis (available upon request), finding the results in the paper to be robust across a wide range of plausible parameter assumptions.

We first describe the behavior of the transportation system as it operates today. We then analyze the effect of AVs and pooling on travel demand and mode choice, capturing the endogenous interactions that occur between modes. We conclude by testing the effect of policy levers intended to limit the extent to which AVs induce additional demand for driving, making driving less rather than more attractive.

3.1 Tipping Points in Commuter Mode Choice

We first describe the dynamics of this system as it operates today in the absence of AVs and pooling, using a vector plot (Figure 4) to show how the system behaves in response to the state of the system and the feedback structure described above. The horizontal axis shows a range of plausible values for the stock of perceived driving time, while the vertical axis shows the full possible range of the stock of public transit quality. Because the model has only two state variables (Perceived Driving Time and PT Quality), the two-dimensional vector plot fully describes all possible states of the system and is, therefore, an exhaustive representation of the system behavior. The arrows indicate the direction of change in the system's state variables.

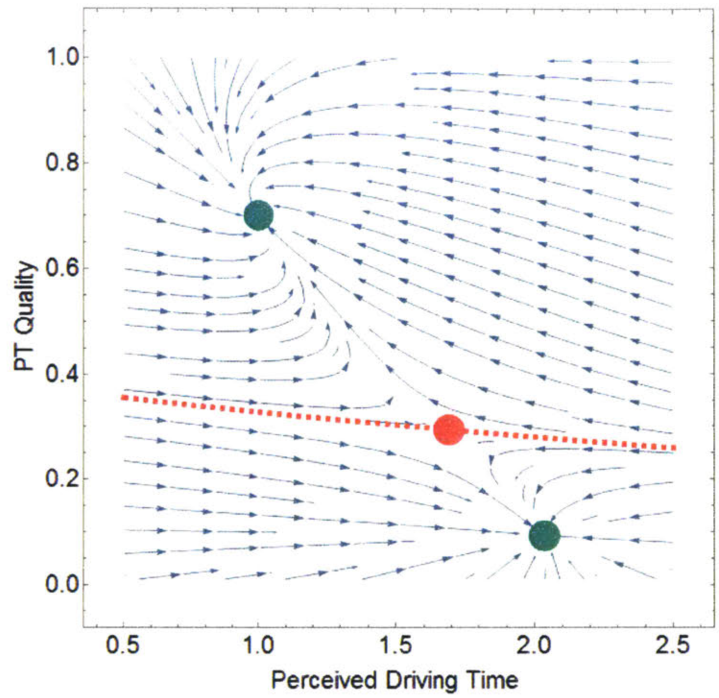


Figure 4. Phase Plot of the Existing Bimodal Transportation System

The state space is characterized by two stable equilibria (green dots) and one unstable equilibrium (red dot). Stable equilibria are points where the system will converge back to, given a small disturbance from that point as a result of the feedback structure of the system. Unstable equilibrium means that any small disturbance at that point would drive the system farther away, until it settles at one of the two stable equilibria, depending on the direction of the initial disturbance.

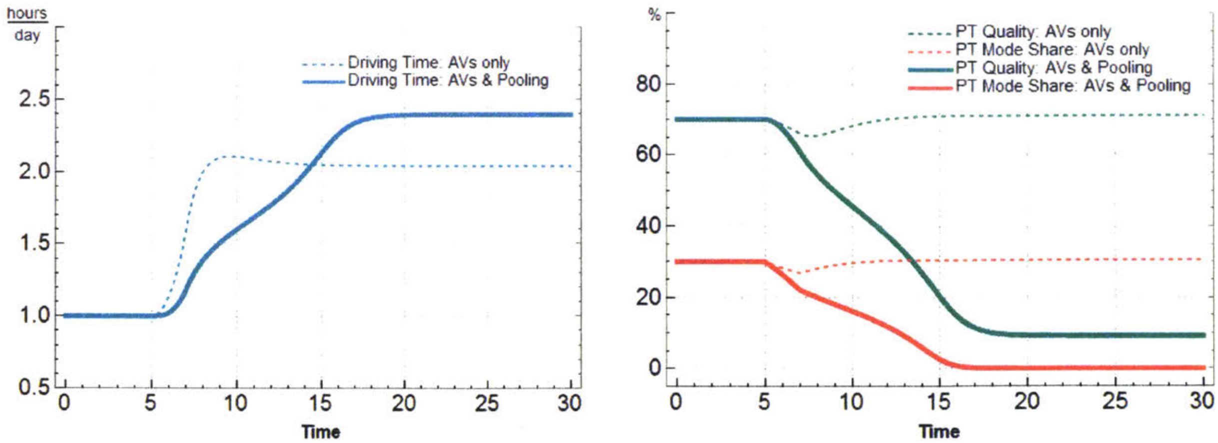
The model is initialized at the upper equilibrium, reflecting the current balance that exists in many cities today, with less than optimal quality of public transit and moderately congested roads. For small perturbations from this point, such as a temporary disruption to the quality of public transit as a result of track works, the system finds its way back to equilibrium, because transit riders switching to driving contribute to an increase in traffic congestion, having the effect of making driving less attractive. However, if the perturbation is sufficiently large that PT Quality falls significantly, a tipping point is crossed (indicated by the red dashed line) and the system settles at the other stable equilibrium, characterized by poor quality public transit that is heavily reliant on government subsidies, and highly congested roads. Even though the shift of transit riders to driving increases traffic congestion, reducing the attractiveness of driving, the loss of transit revenue combined with the erosion of public transit quality makes transit even less attractive, further decreasing transit ridership, revenue, and quality.

3.2 The Effect of AVs and Pooling

We next examine the consequences of increasing adoption of AV and pooling, conditional on AVs being safe, effective, and available at affordable prices. We acknowledge that a stream of literature exists examining barriers to consumer adoption of AVs (Fagnant & Kockelman, 2013; Kyriakidis, Happee, & De Winter, 2015; Haboucha, Ishaq, & Shiftan, 2017; König & Neumayr, 2017). However, we assume that these issues are transitory here, focusing on the consequences of AV adoption, assuming it is to occur.

We compare two competing scenarios: in the first, AVs are introduced, but used in the single-occupant manner consistent with the way private automobiles are used today. In the second, AVs are deployed with pooling in ride-sharing fleets. We recognize that pooling is likely to be inherently less attractive than a private ride for many people, due to the waiting time and additional travel time associated with ride-sharing (Krueger, Rashidi, & Rose, 2016). However, new technologies such as better route planning and the design of vehicles optimized for ride-sharing applications have the potential to change public perceptions. Our assumptions are deliberately favorable towards pooling, allowing for the maximum benefits of pooling to be realized (i.e. a substantial increase in the throughput of the road system), thus establishing an upper bound on the impacts that widespread adoption of pooled AVs may have. Simulation of these two markets over time are shown in Figure 5.

In the case where AVs are used as private vehicles (dotted lines), we see a significant increase in driving times in Figure 5(a) when AVs are introduced, because the increased attractiveness of driving leads to more and longer trips, increasing traffic congestion. Here the effect on public transit quality and ridership is small, dropping temporarily as AVs attract transit riders over to driving, but recovering as increasing traffic congestion makes driving less attractive. The specific magnitude of this effect is contingent on the assumption about commuters' elasticity of demand for driving with respect to the level of automation, a parameter that is highly uncertain. Nevertheless, comparing simulations with and without pooling allows the impact of further increasing road throughput with pooling to be understood.



(a) Effect on Driving Time

(b) Effect on PT Quality and Mode Share

Figure 5. Simulation of AVs-only vs AVs and Pooling

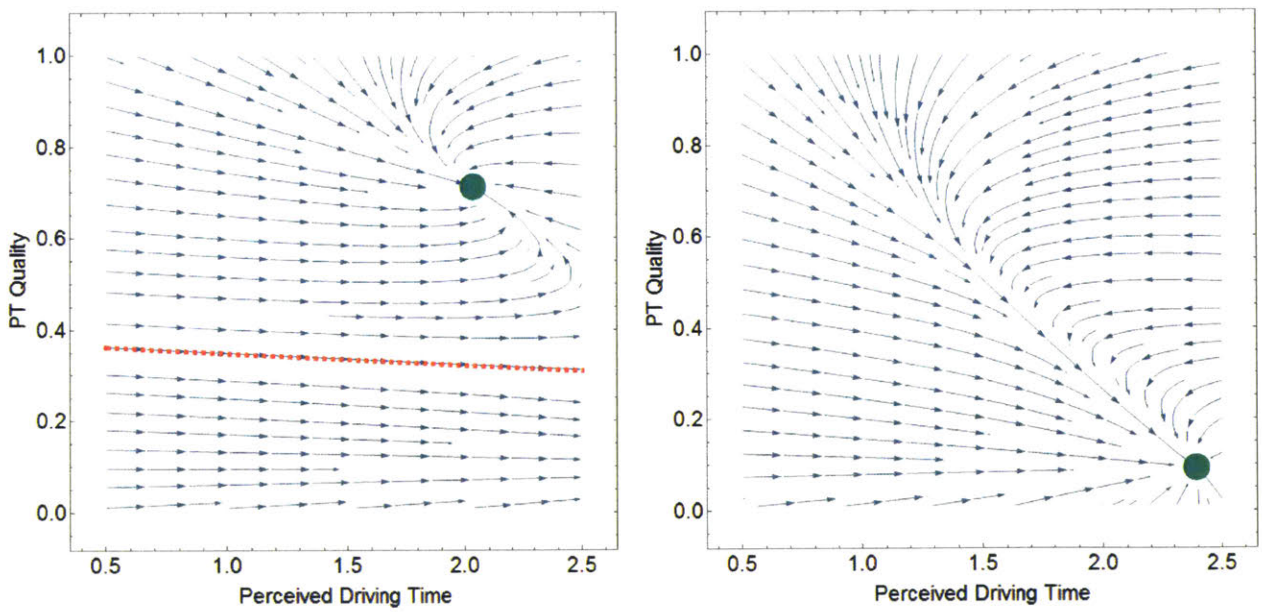
Next, we consider how the system responds if AVs are deployed as pooled vehicles in ride-sharing fleets, assuming a very moderate average occupancy of 1.5 persons per vehicle (solid lines in Figure 5). Initially, the addition of pooling appears to be working as intended, requiring fewer vehicles and moderating the increase in traffic congestion induced by the introduction of AVs compared with AVs without pooling (Figure 5(a)). However, success is short-lived. Less additional congestion means that more transit riders switch to driving compared to AVs without pooling, reducing transit ridership and revenues to the point where public transit quality begins to decline, triggering the death spiral (Figure 5(b)). In equilibrium, poor quality public transit forces most commuters to drive, even with high levels of traffic congestion and long drive times, an outcome worse than the AV-only case.

Thus, paradoxically, we observe that the well-intended effort to make driving efficient and affordable by pooling may have the unintended consequence of causing *more* rather than *less* driving, traffic congestion, and air pollution if pooling triggers the downward spiral in public transit quality.

Visualizing the dynamics of these AV-only and 'AVs and pooling' cases as vector plots, we see that the introduction of pooling changes the transportation system such that the decline of PT is much more likely. In the AVs-only case (Figure 6(a)), we see only one stable equilibrium in the parameter space, where the high equilibrium from Figure 4 has shifted to a point with longer travel times because AVs make driving more attractive leading to more traffic congestion.

A tipping point is still observed at PT Quality ≈ 0.35. If PT Quality falls below this level, the system can be seen to be moving towards another stable equilibrium (not shown), with low public transit quality (~0.2) and a Perceived Driving Time of more than 2.5 hours. The collapse of public transit, in this case, leads to very high levels of traffic congestion because most commuters drive and do so with low vehicle occupancy.

In the 'AVs and pooling' case (Figure 6(b)), we now see only a single stable equilibrium in the parameter space shown, representing a system with low-quality public transit and long driving times. No tipping point is observed, meaning that the dynamics of the system will see the system resolve to this equilibrium from any point in the parameter space shown. That is, the downward spiral in public transit quality is inevitable because pooling increases the throughput of roads while inducing comparably fewer vehicle trips and traffic congestion.



(a) AVs only (b) AVs and Pooling

Figure 6. Phase Plots with the Introduction of AVs and Pooling

3.3 The Effect of Average Vehicle Occupancy

How does average vehicle occupancy influence driving times? Thus far, we have only considered two cases: AVs only with average vehicle occupancy = 1, and AVs and pooling with average vehicle occupancy = 1.5. Here we simulate the model for all average vehicle occupancies between 1 and 3, plotting the effect on driving times (Figure 7). Beginning at average occupancy = 1 (the AVs only case), we see that marginal increases in average occupancy reduce driving times. However, the public transit tipping point is reached at approximately 1.25, at which point driving times increase dramatically, because the quality of public transit collapses, leading many transit riders to switch to driving, but average vehicle occupancy remains low. Further increases in average occupancy above 1.25 then lead to reductions in driving time again, because almost all commuters are already traveling by car, and increasing vehicle occupancy allows these passenger miles to be served with successively fewer vehicle miles. At very high levels of vehicle occupancy (~2.8 people per vehicle), the benefits of pooling bring the system back to the same level of driving time observed in the base case.

The implication of this is that while pooling may trigger the collapse of public transit quality, conditional on this outcome happening, the best option (in the absence of the sustained investment required to rebuilt public transit) is to increase the intensity of pooling as much as possible to maximize the efficiency of the road transportation system. Effectively, this result is replacing the existing public transit system with an automobile-based transit system, where automobiles start to act like buses. Whether this outcome is desirable from a societal perspective is a much broader conversation, requiring consideration of factors not considered here including access, equity, and resilience.

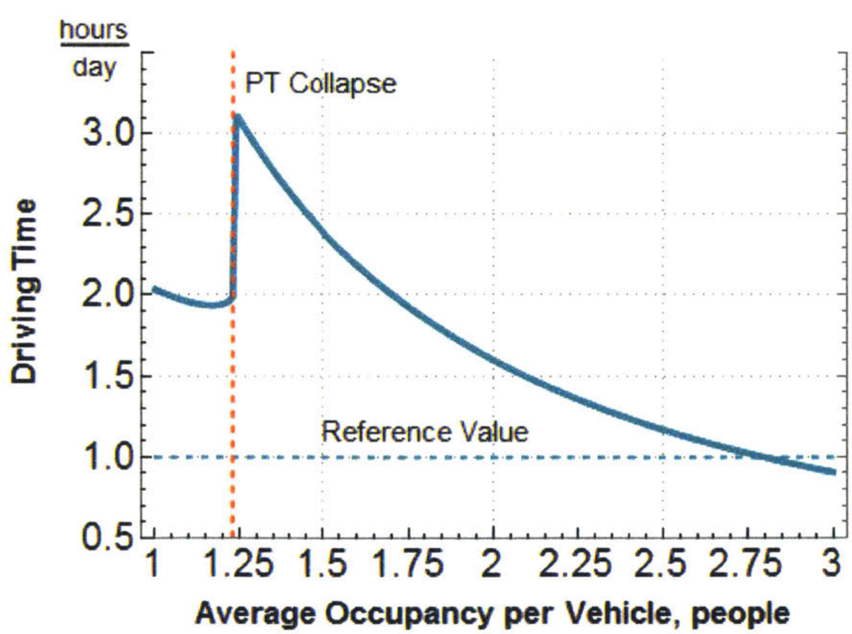
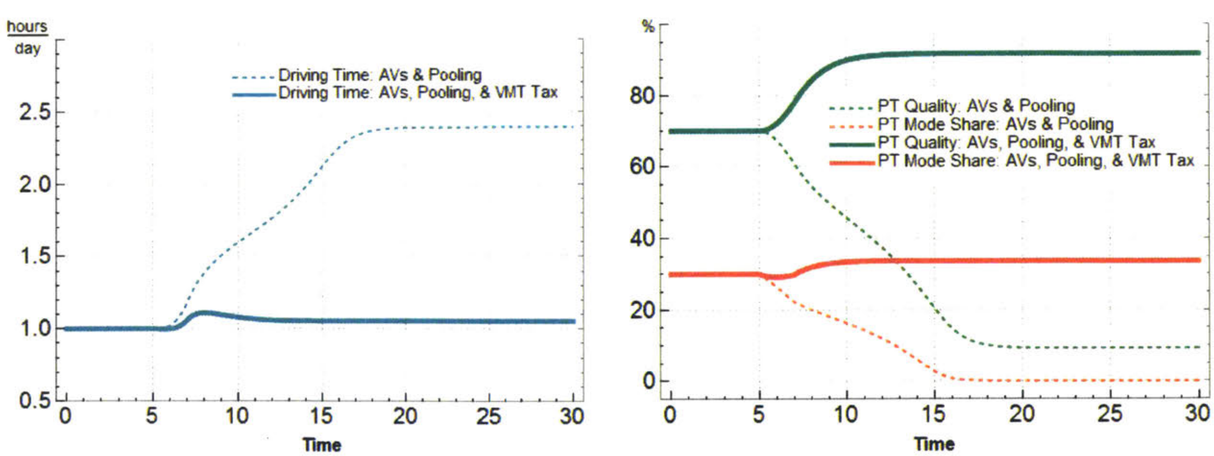


Figure 7. The Effect of Pooling Rate (Fleet Average Occupancy per Car) on Travel Time

3.4 Policies Regulating Travel Demand

The scenarios above demonstrate that the unregulated deployment of AVs and pooling has the potential to generate significant unintended consequences, leading to both the decline of public transit and worse traffic congestion. Such a result arises when the benefits of AVs, and pooled AVs in particular, cause driving to become substantially cheaper and easier, inducing yet more driving. It should therefore not be surprising that commuters shift to driving from other less-attractive transportation modes, an example of Forrester's 'Attractiveness Principle' (Forrester, 1974). In response, we now consider a policy aimed at addressing the negative externalities of driving that explicitly seeks to make driving *less* rather than more attractive. In this case, we implement a vehicle-miles traveled (VMT) tax of 35 cents/mile, imposed on all automobiles to internalize some of the impacts that driving has on traffic congestion and air pollution, and we reinvest 1% of these tax revenues in public transit maintenance and service.

With this policy, we observe that driving times remain close to the reference level of 1 hour (Figure 8(a)), and public transit quality and ridership increase rather than decrease (Figure 8(b)), an outcome that is substantially more appealing from a societal perspective. The VMT tax makes driving less attractive, and the reinvestment of tax revenues ensures that public transit sustains and indeed improves over time, providing commuters a compelling alternative to driving such that demand for driving remains modest, and driving times low.



(a) Effect on Driving Time

(b) Effect on PT Quality and Mode Share

Figure 8. The Implementation of a VMT Tax with Reinvestment in Public Transit

Examining the vector plot for this case, we see that the dynamics now pull the system to a single stable equilibrium with high PT Quality and low driving times. The system is unable to remain in a state with poor transit quality, or high driving times, because the more people drive, the more VMT tax revenue is generated, and the more PT Quality improves, making public transit ridership more attractive and generating more ridership revenues to sustain high quality. While the financial cost of driving increases, in this case, this outcome is ultimately advantageous for drivers and transit riders alike, because those who continue to drive, enjoy short driving times, and those who catch public transit enjoy a high quality of service, i.e., frequent and reliable services on convenient routes.

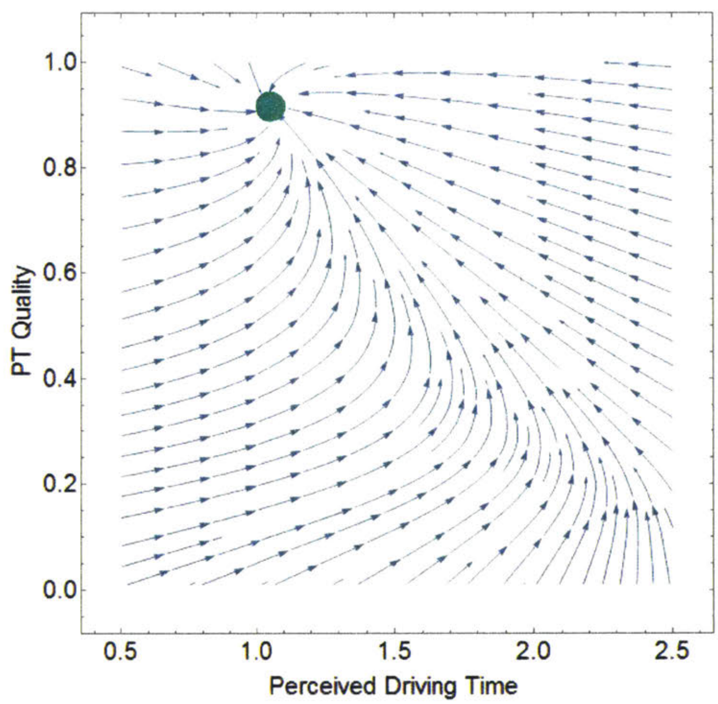


Figure 9. Phase Plot of VMT Tax with Public Transit Reinvestment

Directionally, this case demonstrates that the benefits of AVs and pooling including reduced traffic congestion and air pollution can be realized as intended, provided that they are deployed in concert with policies that manage induced demand for driving so as to sustain public transit ridership and service quality.

4 Discussion

At a time when urban travel demand is growing globally, and the negative consequences of automotive transportation are increasingly clear, it is not surprising that AVs have attracted enormous attention from automakers, technology companies, policymakers, consumers, and the media. AVs have the potential to make mobility more affordable, sustainable, and accessible. However, if these benefits are realized and driving becomes more attractive, demand for driving is likely to increase, inducing more and longer trips from the existing driving population, adding new travel demand from previously underserved population groups, and creating opportunities for new mobility-based businesses. Researchers are increasingly interested in pooling as a response to the potential for increased demand for driving, with more passengers per vehicle meaning the same amount of mobility can be provided with fewer vehicles. In this paper, we find that this conversation is considerably more complex, identifying the potential for significant unintended consequences once the effect of AVs and pooling on commuter mode choice and the viability of public transit are taken into account.

Our analysis shows that if demand for driving is un-capacitated, the rollout of AVs and pooling is unlikely to remediate traffic congestion in cities due to the effect of induced demand for driving and the adverse effect this has on public transit ridership. The increase in driving occurs specifically because AVs make driving substantially more attractive than it is today, assuming that the promised benefits of AVs such as safe and smooth driving without human input are realized. We demonstrate that if the AVs and pooling attract too many people away from riding public transit, a threshold is crossed beyond public transit collapses, resulting in high levels of driving and traffic congestion. These dynamics arise because lower road utilization makes driving more attractive, while lower transit utilization makes public transit less attractive (as a result of the effect on ridership revenues and service quality). While both the road and transit infrastructures are subject to these capability dynamics in the long-run, the critical distinction is that the level of service provided by the transit system (e.g., the frequency of buses and trains) can vary more quickly in response to changes in ridership revenues than the quality of road infrastructure in response to changes in road utilization.

To be clear, we are not suggesting that either AVs or pooling are inherently bad – quite the opposite. It is specifically because these innovations have the potential to make driving safer, cheaper, and easier, and therefore become highly attractive to many commuters, that the effect of these innovations on the entire urban transportation landscape must be thought through carefully. We find that the implementation of policies to manage AV-induced demand for driving can avoid the worst potential consequences of AVs such as increased traffic congestion, and build an urban transportation system that provides both high-quality public transit and roadways that keep moving.

While we do not highlight the environmental impacts of the various cases we consider in this paper, we do not see a reduction in vehicle fleet GHG emissions in any of our simulations even with plausible assumptions about improving vehicle fuel economy, because these benefits are overwhelmed by the increase in fleet VMT. These results highlight the need for continued efforts to introduce zero-tailpipe, low-carbon vehicles into the vehicle fleet, using fuel (electricity, hydrogen) from low-carbon sources, if the environmental impacts of driving are to be reduced.

For policymakers, our analysis provides guidance to address congestion and air quality concerns in urban areas. Effective policies will address the root causes of these externalities, causing vehicle users to internalize the externalities to a greater extent. Opportunities include road pricing (as we demonstrate in our analysis), and the expanded use of pooled / high-occupancy vehicle lanes. For future providers of AV mobility services, including automakers, transportation network companies, and technology companies, our analysis points to the business opportunities associated with pooling. It is in our VMT tax case that high levels of person-miles travelled are served with the lowest number of vehicle-miles travelled, suggesting that private value creation opportunities are also best served by ensuring that public transit quality is sustained, so that road-based transportation remains attractive.

Necessarily, our analysis has limitations. The model is deliberately stylized to highlight the dynamic impacts of AV deployment and is not calibrated to any particular city. The specific outcomes realized in each city will be influenced by the extent to which additional demand is induced, conditioned by factors such as geography, urban design, alternatives to vehicle use, and market structure. The process of AV adoption may also play an important role in how AVs impact travel. Factors such as risk aversion and heterogeneous consumer preferences may slow the speed and extent to which AVs are adopted. Given the long lags and irreversibility of investments in public transit vs. AVs, pooling, and mobility as a service, communities will have to choose the path to go down before enough data to resolve parameter uncertainty is available. Our analysis provides clarity about how the benefits of AVs and the amount of additional demand they induce are intrinsically linked.

Automated vehicles are likely to play a critical role in the future of urban mobility systems, and our analysis points to several important opportunities for future work. First, our model assumes that all consumers will be willing to share a vehicle with other passengers, when carpooling accounts for only a small fraction of vehicle trips today. Understanding consumer preferences for pooling is critical if pooling is to play a significant role in the future of mobility, particularly in the presence of falling vehicle costs. Second, it is likely to be decades before AVs reach Level 5 functionality, in which AVs are capable of driving without human intervention for any trip in any weather conditions. Understanding how AVs with lower operating capabilities affect our existing urban transportation systems will be critical if AVs are to gain societal and regulatory acceptance. Third, while we focus this analysis on competition between public transit and AVs, the potential also exists for these technologies to be complements, with AVs providing a solution to the 'last mile' problem for public transit. Exploring the potential for effective multi-modal trips involving AVs is an important opportunity in the conversation about what role public transit plays in an AV-enabled world.

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Appendix A: Parameterization and Initialization of the Model

Model Parameters

Table 1: Model Parameters

Parameter	*Value*
Relative weight of operating cost, $\beta_d, 1/(cents/mile)$	-0.005
Relative weight of driving time, $\beta_T, 1/(\$/(person \times day))$	-0.02
Reference operating cost, $c_d^0, cents/mile$	100
Commuting population in the catchment area, $n, people$	100,000
Average free flow speed v_f, mph	30
Elasticity of speed with respect to traffic ε_d	-2
Time to adjust the perceived driving time $\tau_{T,}, year$	1
Reference perceived driving time, $T_0, hours/(person \times day)$	1
Reference value of driving time, $p_T^0, \$/hour$	25
Reference level driving demand per person, $d_n^0, miles/(person \times day)$	20
Elasticity of driving demand to the automation effect on the value of time, ε_{AV}	-0.35
Maximum effect of automation on the value of time, δ_{AV}^{max}	0.5
Reference occupancy of vehicles, $\omega, people/vehicle$	1
Elasticity of vehicle miles traveled with respect to ridership, ε_{VMT}	-0.7
Elasticity of vehicle operating cost with respect to ridership, ε_c	-0.5
Reference public transit quality, Q_0	0.7
Average public transit quality relevance time, $\tau_q, year$	1
Desired public transit quality, Q^*	1
Elasticity of public transit cost with respect to quality, ε_Q	-0.8
Maximum reinvestment fraction η_{max}	0.25
Investment efficiency, $\alpha_s, 1/\$$	1×10^{-7}
Minimum time needed to allocate the investment, $\tau_i, year$	1
Maximum government subsidy, $s_{max}, \$/year$	1×10^6
Equilibrium mode share of public transit, σ_p^0	0.3

Model Initialization in Dynamic Equilibrium

To initialize the model in the dynamic equilibrium we use the fact that in equilibrium (constant PT Quality equal to Q_0), the inflow of investments in maintenance and expansion, q_i, should be equal to the outflow of erosion of quality, q_o. Thus, we calculate the equilibrium cost of travel by public transit

$$\widehat{c_p} = \left(\frac{Q_0}{Q^*}\right)^{\varepsilon_Q}$$

and the equilibrium value of the utility of driving

$$\widehat{u_d} = T_0\, p_T^0\, \beta_T \;+\; c_d^0\, \beta_d$$

to find the equilibrium weight of travel cost in the utility of public transit:

$$\widehat{\beta_p} = \left(\frac{\widehat{u_d}\, \mu \;-\log\left(\dfrac{1-\sigma_p^0}{\sigma_p^0}\right)}{\mu\, \widehat{c_p}} \right)$$

Next, we calculate the erosion rate in equilibrium

$$\widehat{q_o} = \frac{Q_0}{\tau_q}$$

and the equilibrium public subsidy

$$\hat{s} = s_{max}\left(1 - \frac{Q_0}{Q^*}\right)$$

to find the equilibrium public transit fare:

$$\hat{f} = \frac{\dfrac{\widehat{q_o}}{\alpha_s} - \hat{s}}{\eta_{max}\, n\, \sigma_p^0}$$

Finally, we calculate the equilibrium total daily driving demand of the city, in units of passenger-miles traveled

$$\widehat{d_{PMT}} = n\, d_n\, \left(1 - \sigma_p^0\right)$$

and the equilibrium number of vehicle-miles traveled required to serve the equilibrium daily driving demand

$$\widehat{d_{VMT}} = \frac{\widehat{d_{PMT}}}{\omega}$$

to find the equilibrium daily driving in vehicle-miles:

$$\widehat{d_{VMT}^0} = \frac{\widehat{d_{VMT}}}{\left(\dfrac{d_n}{T_0\, v_f}\right)^{\frac{1}{\varepsilon_d}}}$$

Model Documentation

```
Authorized Public Subsidy=
              Max Public Subsidy * (1-Relative PT Quality)
Units: $/year
Authorized public subsidy to invest in PT and bring the PT
                    quality to the desired level

AV Effect=
       IF THEN ELSE
         (SW AVs = 1,
          1 + RAMP( -(1-"Full Effect of AVs (value of time)") /
           (Full Effects Year - Effects Start Year),
            Effects Start Year, Full Effects Year),
          1
         )
Units: dmnl
Piecewise linear function representing actual level of the
              effect of vehicle automation

Average Driving Demand per person=
       Equilibrium Average Driving Demand per person*
         (AV Effect^Elasticity of Travel Demand to AVs)
Units: miles/person/day
Average driving demand in the area, as measured per person

Average Free Flow Speed=
       30
Units: miles/hour
Average speed of the traffic flow in the area if the roads are
              not congested

Average Speed=
       Average Free Flow Speed*Effect of VMT on Average Speed
Units: mile/hour
Average speed of the traffic flow in the area

Average Travel Time=
       Average Driving Demand per person/Average Speed
Units: hour/(day*people)
Actual duration of the average commute

Cents in $=
       100
Units: cents/$
Amount of cents in a dollar

Change in Perceived Travel Time=
       (Average Travel Time-Perceived Travel Time) / Time to Perceive Travel Time
Units: hour/(year*day*people)
Adjustment in the perceived duration of the commute in the area

Days in Year=
       350
Units: days/year
Number of days in a year

Desired Investment in PT=
       MAX(0,(Desired Quality-PT Quality) / Investment Horizon +
         PT Quality Erosion Rate) / Investment Efficiency
Units: $/year
```

The desired investment in capabilities to compensate for the erosion and bring the PT quality to the desired level

Desired Quality=
1
Units: dmnl
Desired quality of PT, reflects full level of service in the area

Driving Cost=
(Equilibrium Driving Cost+VMT Tax) *
(People per Car^Elasticity of Operating Cost to Occupancy)
Units: cents/mile
Operating cost of a vehicle per rider

Driving Cost Coefficient=
-0.005
Units: dmnl/(cents/mile)
Weight of the operating cost in the utility of driving

Driving Demand=
Population in the Area * Average Driving Demand per person *
(1-PT Ridership Share)
Units: mile/day
Total driving demand in the area per day

Driving Value of Time=
Equilibrium Value Of Time * AV Effect
Units: $/hour
A value of one hour of drivers' time

Driving Value of Time Coefficient=
-0.02
Units: dmnl/($/(day*person))
Weight of the value of time in the utility of driving

Driving VMT=
Driving Demand*Effect of Occupancy on VMT
Units: mile/day
Total number of miles traveled by all vehicles in the area per day

Effect of Occupancy on VMT=
People per Car^Elasticity of VMT to Occupancy
Units: dmnl
Effect of the average occupancy of vehicles on the number of miles driven

Effect of VMT on Average Speed=
MIN(1,Relative VMT^Elasticity of Average Speed to VMT)
Units: dmnl
Effect of the number of miles driven by vehicles in the area on the average traffic flow speed

Effects Start Year=
5
Units: year
The start year of the effects of ride-sharing, vehicle automation, and road pricing

Elasticity of Average Speed to VMT=
-2
Units: dmnl [-2,-0.1]
Elasticity of the traffic flow speed to the number of miles

```
              driven by cars, the effect of congestion on speed

Elasticity of Operating Cost to Occupancy=
       -0.5
Units: dmnl [-2,-0.1]
Elasticity of the operating cost of driving per rider to the
              average occupancy of a vehicle in the fleet

Elasticity of PT Travel Expenses=
       -0.8
Units: dmnl
Elasticity of costs incurred by PT passengers to the level of PT
              quality in the area

Elasticity of Travel Demand to AVs=
       -0.35
Units: dmnl [-2,-0.1]
Elasticity of the driving demand to the average level of
              automation offered by the fleet of vehicles in the area

Elasticity of VMT to Occupancy=
       -0.7
Units: dmnl
Elasticity of the number of miles driven by a vehicle to the
              average occupancy of the vehicle, reflects the overhead
              associated with picking up and dropping off of all passengers

Equilibrium PT Utility Coefficient= INITIAL(
       ((Equilibrium Utility of Driving * Ride Choice Logit Scaling -
        LN((1-Equilibrium PT Ridership Share) / Equilibrium PT Ridership Share)) /
        Ride Choice Logit Scaling) / Equilibrium PT Travel Expenses
)
Units: dmnl
Weight of the travel costs of PT for commuters to maintain
              dynamic equilibrium in the beginning of the simulation

Equilibrium Authorized Public Subsidy= INITIAL(
       Max Public Subsidy * (1-Equilibrium Relative PT Quality))
Units: $/year
Authorized level of public subsidy to maintain dynamic
              equilibrium in the beginning of the simulation

Equilibrium Average Driving Demand per person=
       20
Units: miles/person/day
Average driving demand in the area calculated per person in the
              beginning of the simulation

Equilibrium Driving Cost=
       100
Units: cents/mile
Operating cost of a vehicle per rider in the beginning of the
              simulation

Equilibrium Driving VMT= INITIAL(
       Equilibrium Driving Demand / Equilibrium People per Car)
Units: mile/day
Total number of miles driven by all vehicles in the area to
              maintain dynamic equilibrium in the beginning of the simulation

Equilibrium Perceived Travel Time=
       1
Units: hours/day/person
```

```
Average driving time of commuters in the area in the beginning
              of the simulation

Equilibrium Reference VMT= INITIAL(
       Equilibrium Driving VMT / (((Equilibrium Average Driving Demand per person /
        Equilibrium Perceived Travel Time) / Average Free Flow Speed)^
        (1/Elasticity of Average Speed to VMT)))
Units: miles/day
Total reference number of miles driven by all vehicles in the
              area to maintain dynamic equilibrium in the beginning of the
              simulation

FINAL TIME  = 30
Units: year
The final time for the simulation.

"Full Effect of AVs (value of time)"=
       0.5
Units: dmnl [0.1,2,0.025]
Maximum effect of automated vehicles on the value of driving
              time, reflects the average level of automation achieved by the
              fleet of vehicles in the area

Equilibrium Driving Demand= INITIAL(
       Population in the Area * Equilibrium Average Driving Demand per person *
       (1-Equilibrium PT Ridership Share))
Units: mile/day
Total driving demand in the area to maintain dynamic equilibrium
              in the beginning of the simulation

Equilibrium People per Car=
       1
Units: dmnl
Average occupancy of a vehicle in the beginning of the simulation

Equilibrium PT Fare= INITIAL(
       (Equilibrium PT Quality Erosion Rate/Investment Efficiency -
        Equilibrium Authorized Public Subsidy) / Max Reinvestment Fraction /
        Days in Year / Population in the Area / Equilibrium PT Ridership Share)
Units: $/(day*person)
PT fare to maintain dynamic equilibrium in the beginning of the
              simulation

Equilibrium PT Quality=
       0.7
Units: dmnl
Average PT quality in the area in the beginning of the simulation

Equilibrium PT Quality Erosion Rate= INITIAL(
       Equilibrium PT Quality / PT Quality Relevance Time)
Units: dmnl/year
PT Quality erosion to maintain dynamic equilibrium in the
              beginning of the simulation

Equilibrium PT Ridership Share=
       0.3
Units: dmnl
Relative mode choice of PT in the beginning of the simulation

Equilibrium PT Travel Expenses= INITIAL(
       ((Equilibrium PT Quality/Desired Quality)^Elasticity of PT Travel Expenses) *
        Reference PT Travel Expenses)
Units: dmnl
```

Travel costs of PT for commuters to maintain dynamic equilibrium
in the beginning of the simulation

Equilibrium Relative PT Quality= INITIAL(
Equilibrium PT Quality / Desired Quality)
Units: dmnl
Relative PT quality to maintain dynamic equilibrium in the
beginning of the simulation

Full Effects Year=
7
Units: year
The year when the full effects of ride-sharing, vehicle
automation, and road pricing

"Full Pooling Effect (people per car)"=
1.5
Units: dmnl [1,2.5,0.05]
Maximum multiplier of the average occupancy of a vehicle in the
area

Full VMT Tax=
35
Units: cents/mile
Maximum level of the VMT tax (road pricing)

Initial PT Quality Level=
0.7
Units: dmnl [0.01,1,0.01]
Initial value of the quality of PT in the area

INITIAL TIME = 0
Units: year
The initial time for the simulation.

Investment Efficiency=
1e-07
Units: dmnl/$
Efficiency of $ investment in PT maintenance. Reflects how much
$ are spent to increase PT quality by 1 unit

Investment Horizon=
1
Units: year
Time required to allocate the money to the investment in PT
quality

Max Public Subsidy=
1e+06
Units: $/year
Maximum possible level of public subsidy to the improvement of
PT in the area

Max Reinvestment=
Yearly Revenue*Max Reinvestment Fraction
Units: $/year
Maximum possible reinvestment in capabilities as determined by
the ridership revenue

People per Car=
Equilibrium People per Car * Pooling Effect
Units: dmnl
Average occupancy of a vehicle in the area

```
Perceived Travel Time= INTEG (
       Change in Perceived Travel Time,
              Reference Driving Travel Time)
Units: hour/(day*person)
The average duration of commute in the area

"PT Maintenance & Expansion Rate"=
       Investment in PT * Investment Efficiency
Units: dmnl/year
The rate of improvement of PT quality. Reflects maintenance of
              equipment and expansion of routes.

Equilibrium Utility of Driving= INITIAL(
       Equilibrium Perceived Travel Time * Equilibrium Value Of Time *
        Driving Value of Time Coefficient +
        Equilibrium Driving Cost*Driving Cost Coefficient)
Units: dmnl
Utility of driving for commuters to maintain dynamic equilibrium
              in the beginning of the simulation

Equilibrium Value Of Time=
       25
Units: $/hour
Average value of driving time for a rider in the beginning of
              the simulation

Investment in PT=
       MIN(Max Reinvestment, Desired Investment in PT) + Public Subsidy + VMT Tax
Reinvestment
Units: $/year
Actual available and allocated investment in PT quality

Max Reinvestment Fraction=
       0.25
Units: dmnl
Maximum fraction of total revenue that can be allotted to the
              maintenance of capabilities

Pooling Effect=
       IF THEN ELSE
         (SW Pooling = 1,
          1 + RAMP( ("Full Pooling Effect (people per car)"-1) /
           (Full Effects Year - Effects Start Year),
            Effects Start Year, Full Effects Year),
          1
         )
Units: dmnl
Piecewise linear function representing actual level of the
              effect of ride-sharing

Population in the Area=
       100000
Units: people
Total population of commuters in the area

PT Fare= INITIAL(
       Equilibrium PT Fare)
Units: $/(day*person)
Average trip fare for commuters

PT Quality= INTEG (
       "PT Maintenance & Expansion Rate"-PT Quality Erosion Rate,
```

```
        Desired Quality*Initial PT Quality Level)
Units: dmnl
Total quality of PT for commuters, represents important
        attributes, such as network of routes, frequency and reliability
        of service, etc.

PT Quality Erosion Rate=
    PT Quality/PT Quality Relevance Time
Units: dmnl/year
Rate of erosion of PT quality, reflects reduction of service
        level due to the wearing out of equipment and obsolescence of
        capabilities

PT Quality Relevance Time=
    1
Units: years
Average service life of the equipment and relevance of routes
        and other attributes that determine quality of service for
        commuters

PT Reinvestment Fraction of VMT Tax=
    0.01
Units: dmnl
Fraction of the revenue collected from VMT tax for the
        reinvestment in PT quality

PT Ridership Share=
    EXP(Utility of PT*Ride Choice Logit Scaling) /
     (EXP(Utility of PT*Ride Choice Logit Scaling) +
      EXP(Utility of Driving*Ride Choice Logit Scaling))
Units: dmnl
Mode share of PT

PT Travel Expenses=
     (Relative PT Quality^Elasticity of PT Travel Expenses) *
      Reference PT Travel Expenses
Units: dmnl
Travel expenses of a commuter who chooses PT

PT Utility Coefficient= INITIAL(
    Equilibrium PT Utility Coefficient)
Units: dmnl
Weight of the PT expenses in the utility of PT

Public Subsidy=
    MAX(0,MIN(Authorized Public Subsidy,
     Desired Investment in PT-Max Reinvestment
))
Units: $/year
Actual public subsidy, compensating for the insufficient
        investment in PT quality from ridership revenue

Reference Driving Travel Time=
    1
Units: hours/day/person [0.1,2,0.1]
Reference duration of an average commute in the area

Reference PT Travel Expenses=
    1
Units: dmnl
Reference level of travel expenses for a commuter on PT

Reference VMT= INITIAL(
```

Equilibrium Reference VMT)
Units: miles/day
Reference number of miles driven by all vehicles in the area

Relative PT Quality=
PT Quality / Desired Quality
Units: dmnl
Current quality of PT relative to the desired quality

Relative VMT=
Driving VMT / Reference VMT
Units: dmnl
Total number of miles traveled by all vehicles in the area
relative to the equilibrium value

Ride Choice Logit Scaling=
0.75
Units: dmnl
Scaling parameter of the binomial logit choice model,
sensitivity to the difference in utility values

Ridership Revenue=
Population in the Area * PT Ridership Share*PT Fare
Units: $/day
Daily revenue of PT generated from ridership

SAVEPER =
TIME STEP
Units: year [0,?]
The frequency with which output is stored.

SW AVs=
0
Units: dmnl [0,1,1]
Switch to turn on the effect of automated vehicles

SW Pooling=
0
Units: dmnl [0,1,1]
Switch to turn on the effect of ride-sharing

SW VMT Tax=
0
Units: dmnl [0,1,1]
Switch to turn on the road pricing

TIME STEP = 0.1
Units: year [0,?]
The time step for the simulation.

Time to Perceive Travel Time=
1
Units: year
Time to adjust the average commuters' perception of the
congestion level and everyday driving habits in the area, as
reflected in the average duration of commute

Utility of Driving=
Perceived Travel Time * Driving Value of Time *
Driving Value of Time Coefficient + Driving Cost*Driving Cost Coefficient
Units: dmnl
Total utility of driving for commuters

```
Utility of PT=
       PT Travel Expenses * PT Utility Coefficient
Units: dmnl
Total utility of PT for commuters

VMT Tax=
       IF THEN ELSE
         (SW VMT Tax = 1,
          RAMP( Full VMT Tax / (Full Effects Year - Effects Start Year),
           Effects Start Year, Full Effects Year),
          0
         )
Units: cents/mile
Piecewise linear function representing actual level of VMT tax

VMT Tax Reinvestment=
       Driving VMT * VMT Tax * PT Reinvestment Fraction of VMT Tax *
        Days in Year / Cents in $
Units: $/year
Actual reinvestment in PT quality from VMT tax

Yearly Revenue=
       Ridership Revenue * Days in Year
Units: $/year
Yearly revenue of PT generated from ridership
```

Hailing Rides Using On-Demand Mobility Platforms: What Motivates Consumers to Choose Pooling?

Abstract

Carpooling, in which multiple passengers share a single vehicle, has long been seen as an effective societal response to the negative externalities of driving, with benefits including reduced traffic congestion and lower greenhouse gas emissions. However, pooling has been historically unpopular in the United States, accounting for less than 10% of commuter trips, in part because of the difficulty vehicle owners face in finding another commuter with whom it is convenient to share. Recently, pooling has been of renewed interest, because the emergence of on-demand ride-hailing platforms (such as Uber and Lyft) has dramatically reduced these transaction costs, automating the process of rider matching, and offering pooled rides at comparatively low prices. The cost of driving is expected to fall even further in the coming years with the introduction of automated vehicles (AVs). Will the convergence of mobility-as-a-service and AVs be the breakthrough needed to see widespread adoption of pooling in the US? In this paper we estimate consumer preferences for the attributes of ride-hailing services, using a stated preference survey in which respondents choose between a private ride (like UberX or Lyft) and a pooled ride (like UberPOOL or Lyft Line). We show that because consumers have an inherent aversion to pooling, and prefer cheaper trips, the incentive to pool will shrink with lower ride prices, rather than increase. However, a significant income effect exists, with lower-income riders significantly more likely to pool, suggesting that pooling could play an important role in specific market segments, and compete with public transit services.

1 Introduction

Carpooling, the act of sharing trips to increase the number of passengers per vehicle, has long been known to be an effective way of conserving resources and mitigating traffic congestion, allowing the same number of passenger-miles to be served with fewer vehicle-miles (Fulton, Mason, & Meroux, 2017). As far back as World War II, propaganda posters encouraged the efficient use of war-time resources in the United States, suggesting provocatively that "When you ride ALONE you ride with Hitler! Join a Car-Sharing Club TODAY!" (World War II Posters, 1943). Despite the social benefits of carpooling, consumer willingness to pool has been modest at best historically. The use of carpooling in the US peaked at about 20% of commuter trips in 1980, but has since fallen to just 8.9% in 2017 (AASHTO, 2013; U.S. Census Bureau, 2017). This is in part due to the inconvenience for drivers of finding another commuter with whom it is efficient to share trips (Hwang & Giuliano, 1990), moderated by the income effect.

In recent times, however, carpooling (referred to hereafter simply as 'pooling') has enjoyed renewed interest with the emergence of on-demand ride-hailing platforms such as Uber and Lyft, with more than 20% of all Uber rides globally being pooled in 2016 (Lunden, 2016). By providing Mobility-as-a-Service (MaaS), and automating the process of matching passengers with drivers, these platforms dramatically reduce these matching costs, making it no harder to book a pooled ride than a regular individual ride. While many people consider pooling to be less convenient than a private trip, requiring passengers to share the vehicle cabin, and to take a longer route to one's destination to accommodate the other passenger(s), pooling has the benefit of substantially reducing travel costs. The market potential of MaaS could be further substantially unlocked by the emergence of automated vehicles (AVs), which may obviate the need to pay a person to drive the vehicle (Fulton et al., 2017). It is anticipated that the cost of driving in ridesharing fleets may fall from about $1-2/mile today to $0.40/mile or less with AVs (Fulton et al., 2017). Will the convergence of mobility-as-a-service and AVs be the breakthrough needed to facilitate widespread adoption of pooling?

In this paper, we use a discrete choice experiment to estimate consumer preferences for the attributes of ride-hailing services. We asked a nationally representative sample of 1,000 respondents to choose between an individual ride in a private car (similar to UberX or Lyft) and a pooled ride in a shared car (similar to UberPOOL or Lyft Line). Respondents were randomly assigned to one of two experimental conditions, making this choice assuming they were travelling either to the airport, a nudge towards a time-constrained trip, or traveling to go shopping, a less time-constrained trip. We use the resulting data to estimate the coefficients of the attributes of consumer utility using a binomial logit model. Our results show that pooling has an inherent disutility for riders, all else being equal, but that riders like faster and cheaper rides, explaining why a significant number of users choose the cheaper pooled rides offered in the real world. However, counter-intuitively, this also means that if the cost of driving falls, then so will the incentive to pool, because the cost savings from choosing a pooled ride over a private ride will be diminished. Unpacking our results further, we find evidence of a significant income effect, with low-income riders more likely to bear the inconvenience of pooling to save money. We also find, as expected, that riders are less likely to pool when they are under time pressure, where uncertainty in travel time is potentially problematic.

This paper makes important contributions to our understanding of the potential for pooling to play a significant role in the future of mobility. For the literature on sustainable operations and transportation policy, our findings highlight the attributes of ride-hailing services that influence consumers' decision to choose pooled rides (or not). Importantly, the major incentive to pool, the lower cost of travel, could decline if the future introduction of AVs leads to reductions in the cost of driving. For practitioners, our analysis informs the development of on-demand mobility services, vehicle fleet capacity planning decisions, and the design of urban transportation policies that will encourage pooling, such as the construction of high-occupancy vehicle lanes that reduce travel times for pooled rides.

The rest of the paper is organized as follows. In Section 2, we explore the potential for ride-hailing and AVs to increase consumer use of pooling. In Section 3, we describe the attributes of ride-hailing services, and introduce our random utility model of ride-hailing choice. In Section 4, we introduce our experimental design. We present the results of our model estimation in Section 5, and in Section 6 show the implications of reduced trip price on consumer ride-hailing choice. We conclude in Section 7 with a discussion of the consequences of our findings for transportation policy.

2 The Effect of Ride-Hailing and Automated Vehicles on the Attractiveness of Pooling

2.1 The History of Pooling in the United States

Pooling, defined as the act of sharing a vehicle trip with other passengers, has been available to commuters as long as people have been travelling by vehicle. From a societal perspective, the appeal of pooling is the opportunity to increase vehicle utilization to use resources more efficiently, reducing negative externalities of driving such as air pollution and traffic congestion (Fulton et al., 2017). However, the main appeal of pooling for consumers has always been the lower cost of travel. While pooling necessarily entails some degree of inconvenience since passengers face the likelihood of multiple stops along the route and must share the vehicle cabin, it allows multiple passengers to share the cost of the vehicle trip, reducing the per-passenger cost significantly.

In the U.S., carpooling emerged as a transportation mode at the beginning of the 20th century (Novak, 2012), when unlicensed pooling services known as 'jitney cars' became popular after the recession of the 1910s. The ride cost was just a nickel ('jitney' in slang) – about $1.28 in 2018 money (BLS, 2019), hence the word 'jitney cars.' Jitneys were first available in San Francisco, but expanded rapidly as the cost of automobiles fell after the introduction of the Model T Ford, operating in 40 cities by 1915. Competing with streetcars, city officials attempted to regulate jitney services, citing the revenue loss of existing public transit. By first requiring jitneys to be licensed, and later imposing liability bonds, which drivers had to deposit as liability insurance (Eckert & Hilton, 1972), the government substantially increased the operating cost of jitneys, and by 1918, they were virtually extinct.

Carpooling increased during World War II, when the US government asked citizens to share rides to save resources such as gasoline and rubber, and again during the 1970s, when a range of factors including the depletion of the U.S. oil fields, the OPEC oil embargo of 1973-1974, and the Iranian revolution of 1978 led to gasoline shortages for consumers (Cowan, 1973; Hamilton, 2011). HOV lanes were introduced to encourage people share their rides. In 1979, the National Task Force on Ridesharing was established by President Carter, who also announced several steps to encourage pooling, including tax subsidies and priority access to gasoline for pooled services (Walsh, 1979), but with limited success.

Since then, however, the share of pooling steadily declined, explained in part by lower oil prices and in part by the increased average income that amplified the inconvenience of finding riders travelling in the same direction (Hwang & Giuliano, 1990). Use of carpooling in the US in 1980 was at about 20% of commuter trips, but has since fallen to just 8.9% in 2017, see Figure 1 (AASHTO, 2013; U.S. Census Bureau, 2017).

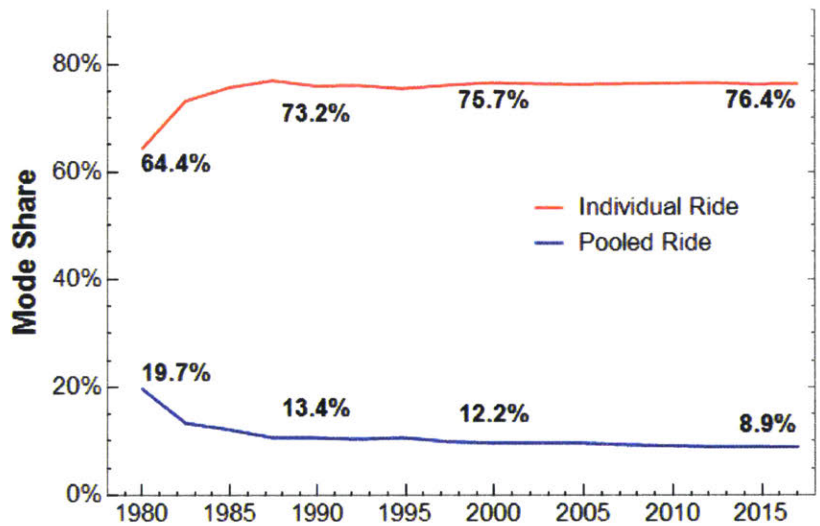

Figure 1. Mode Share of Commuters in the U.S.

2.2 Pooling in the Era of Ride-Hailing and Automated Vehicles

Pooling has enjoyed a renewed interest in recent years with the emergence of app-based ride-hailing platforms such as Uber and Lyft. These platforms create value by matching passengers wanting to take a trip with drivers willing to provide those trips, and in turn, have dramatically reduced the cost of matching multiple passengers taking similar trips. Pooled ride options now appear alongside individual rides in many ride-hailing apps, at prices often half to two-thirds of the price of an individual ride, making pooling much more attractive, especially for price sensitive individuals. The popularity of pooling has been steadily increasing in the ride-hailing context, with more than 20% of all Uber rides globally being pooled in 2016 (Lunden, 2016).

While ride-hailing accounts for only a small fraction of vehicle-miles travelled in the US today (BTS, 2018; FHWA, 2018), its popularity is expected to grow in the coming years as ride-hailing becomes an increasingly attractive alternative to vehicle ownership, particularly with the emergence of AVs. The development of AVs that use sensors and advanced algorithms to control the vehicle without the need for a human driver has progressed rapidly in recent years, and while AVs are not yet sufficiently mature for commercial use, some analysts have predicted that fully autonomous vehicles will be available commercially as soon as 2025 (ABI, 2018; Gustafson, 2018). Although AVs are likely to cost considerably more to build than conventional vehicles initially, owing to the cost of expensive sensor and computing hardware, many believe that the introduction of AVs will lead to a significant drop in the cost of ride-hailing, given that the human driver accounts for almost 50% of the vehicle operating cost today. (Chen, Kockelman, & Hanna, 2016; Cortright, 2017; Fulton et al., 2017). Without the cost of a human driver, and with additional cost savings that might be realized as a result of learning curves and scale economies for sensors and software, some analysts anticipate that the cost of driving in pooled vehicles may fall from about \$1-2 per person-mile today to less than \$0.40 per person-mile with AVs (Fulton et al., 2017).

Since ride-hailing has already made pooling easier, and the emergence of AVs is expected to make ride-hailing cheaper and more convenient, it seems plausible that pooling could play an increasingly prominent role in the future of urban transportation. At the same time, the falling cost of driving could have the adverse consequence of reducing the financial advantage of pooling, making pooling less rather than more attractive (e.g. Fulton et al., 2017; Litman, 2018). Quantifying what motivates consumers to pool, and how the incentive to pool is influenced by falling driving costs, is essential to understand the realistic potential for pooling to address the negative externalities of driving.

3 Estimating Consumer Preferences for Ride Attributes

The choice between individual and pooled rides is one that is frequently made by users of ride-hailing services. In this section, we formalize this choice in a discrete choice framework. Numerous prior studies have estimated the attributes of consumer mode choice, such as value of driving time, price, etc. (e.g. Kolarova, Steck, Cyganski, & Trommer, 2018; Steck, Kolarova, Bahamonde-Birke, Trommer, & Lenz, 2018; Correia, Looff, van Cranenburgh, Snelder, & van Arem, 2019; see also Gkartzonikas & Gkritza, 2019 for a review of existing choice studies). Frequently, however, these studies do not consider pooling as a mode choice, or consider pooling as part of a larger choice set, alongside walking, biking, public transit and driving (e.g. Yap, Correia, & Van Arem, 2015; Krueger, Rashidi, & Rose, 2016; Asgari, Jin, & Corkery, 2018), which doesn't allow to estimate the exact trade-off commuters face when choosing between pooled and individual rides. Here we concentrate on the choice between individual and pooled rides in the ride-hailing context, a choice that is frequently made by ride-hailing users in real life, contingent on choosing the ride-hailing services first. In doing so, we isolate the effects of pooling specifically from more complex patterns of mode substitution.

3.1 Attributes of Ride-Hailing Services

In transitioning from mobility-as-a-product (vehicle ownership) to mobility-as-a-service, a critical shift occurs in the attributes that influence consumer choice. Whereas car buyers have traditionally valued product attributes such as purchase price, operating cost, acceleration, and range, the attributes that users value in the ride-hailing context are primarily *service* attributes. Whereas few people remember the make and model of vehicle they travelled in the last time they used a ride-hailing service, they do remember whether they got from A to B safely, cost-efficiently, and on-time.

The attributes we include in this ride-hailing choice mimic the attributes that users actually consider when using prominent ride-hailing services such as Uber and Lyft. As we show in the app interfaces for these services (Figure 2), riders are commonly shown: a pickup time (in minutes), a price for each service (in dollars), and an estimated travel time to the destination (in minutes). Because of the dynamic nature of pooled rides, which can be matched even after a rider's trip has started, uncertainty exists in how long a pooled ride will take to get to the destination, over and above natural variation resulting from factors such as traffic. We, therefore, represent the travel time of the pooled ride as a time range as is observed in both the Uber and Lyft interfaces. For simplicity, we represent the travel time for the pooled ride as a deterministic estimate, acknowledging that Lyft provides a time range estimate for pickup time also.

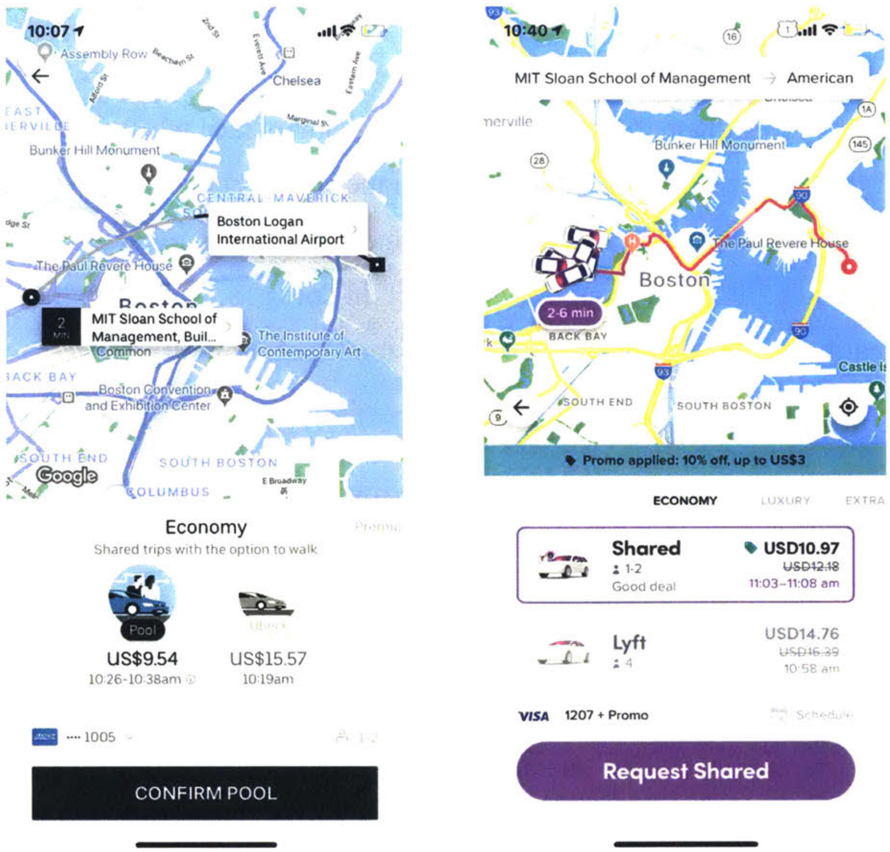

Figure 2: Interface of Uber and Lyft Ride-hailing Apps

3.2 Model

We model consumers' choice between an individual ride and a pooled ride using a random utility framework. We assume, as is common in discrete choice models, that consumer utility can be decomposed into an observable, linear-in-parameters part, and a stochastic and unobservable part that is i.i.d. over alternatives and respondents in our sample (Brownstone, Bunch, & Train, 2000).

In particular, the utility from alternative i for individual n is a function of alternative specific covariates x_{ni} with generic coefficients β for all alternatives (e.g. pickup time, travel time, ride price etc.), individual specific covariates z_n with coefficients γ_i for all alternatives except the reference one (e.g. age, gender, household income etc.), homoscedastic i.i.d. extreme value errors ϵ_{ni}, and an intercept α_i:

$$U_i = \alpha_i + \beta x_{ni} + \gamma_i z_n + \epsilon_{ni} \tag{1}$$

The probability of choosing alternative i is then given by:

$$P_i = \frac{e^{U_i}}{\sum_{j \in I} e^{U_j}} \tag{2}$$

where I is the set of alternatives, here the choice of individual or pooled rides.

4 Data Collection

The data we use for this study were collected using an online survey of a representative sample of the US population obtained from Qualtrics, a market research company. We purchased a sample of 1,014 respondents, representative with respect to gender, income, and political affiliation, which we included as a proxy for the respondent's inclination towards environmental sustainability. We further requested that 36% of these respondents have experienced using ride-hailing services such as Uber and Lyft, and 64% not, consistent with the most recent estimates of the current fraction of the US population that has experience using these ride-hailing platforms (Jiang, 2019).

4.1 Respondent Characteristics

Our sample is closely representative of the U.S. population with respect to age, gender, political affiliation, and prior experience with ride-hailing service (Table 1). The sample has slightly fewer 18-25-year-old people, more 65+ respondents, and relatively fewer people with $150K+ income, which is not uncommon in a sample from an online survey pool.

Table 1. Respondent's Demographic Information (N=1014)

Variable	Percentage	Count	Variable	Percentage	Count
Age			**Household income**		
18-25	7.50	76	Below $49,999	40.24	408
26-35	18.15	184	$50.000 - $99,999	32.84	333
36-45	15.09	153	$100.000 - $149,999	15.09	153
46-55	14.99	152	Above $150,000	9.07	92
56-65	19.82	201	Prefer not to answer	2.76	28
65+	24.45	248	**Adults per household**		
Gender			1	21.99	223
Female	49.01	497	2	59.27	601
Male	50.99	517	3	10.95	111
Political affiliation			4	5.52	56
Democrat	28.11	285	More than 4	2.27	23
Republican	28.60	290	**Children per household**		
Independent	41.12	417	0	65.09	660
Other	2.17	22	1	14.00	142
Education			2	14.40	146
Less than high school degree	2.96	30	3	3.94	40
High school graduate	20.81	211	4	1.48	15
Some college but no degree	23.27	236	More than 4	1.09	11
Associate degree (2-year)	12.62	128	**Cars per household**		
Bachelor's degree (4-year)	25.64	260	0	6.90	70
Master's degree	10.16	103	1	42.60	432
Doctoral degree	1.58	16	2	36.98	375
Professional degree	2.96	30	3	9.67	98
Occupation			4	2.47	25
Unemployed	18.74	190	More than 4	1.38	14
Student	3.25	33	**Used ride-hailing services before**		
Employed	48.03	487	Yes	31.56	320
Retired	29.98	304	No	68.44	694
Geography					
Urban	31.36	318			
Suburban	35.40	359			
Rural	24.56	249			
Unknown	8.68	88			

For those respondents who indicated that they had used ride-hailing services before, we asked about their frequency of use of ride-hailing services, individual and pooled, and their level of satisfaction with these services (Table 2). Consistent with the ride-hailing mode shares observed today, we see fewer people who request pooled rides on a regular basis. Respondents' satisfaction with pooled rides is observed to be lower than for individual rides (the share of respondents who were extremely satisfied was 8% lower, and the share of respondents who were neither satisfied nor dissatisfied was 10% higher for pooling), ($\chi^2 = 458.17, \mathrm{df} = 4$).

Table 2. Experience with Ride-hailing Services

Variable	Percentage	Count	Variable	Percentage	Count
Frequency of individual rides (N=320)			**Frequency of pooled rides (N=320)**		
Daily	18.44	59	Daily	18.44	59
Once a week	23.44	75	Once a week	15.31	49
Once a month	36.56	117	Once a month	14.06	45
Once a year	20.31	65	Once a year	17.19	55
Never	1.25	4	Never	35.0	112
Satisfaction with individual rides (N=316)			**Satisfaction with pooled rides (N=208)**		
Extremely satisfied	53.48	169	Extremely satisfied	45.67	95
Moderately satisfied	39.87	126	Moderately satisfied	37.02	77
Neither satisfied nor dissatisfied	5.38	17	Neither satisfied nor dissatisfied	15.87	33
Moderately dissatisfied	1.27	4	Moderately dissatisfied	0.96	2
Extremely dissatisfied	0.00	0	Extremely dissatisfied	0.48	1

4.2 Survey Structure

Each respondent was administered a survey comprising three parts, implemented using Qualtrics' survey software, and Conjoint.ly, an online conjoint analysis platform. In the first part of the survey, administered in Qualtrics, all respondents were asked basic questions about demographics and vehicle usage, including their age, gender, political affiliation, household composition, vehicle ownership, and previous experience with ride-hailing services.

The second part of the survey was a discrete choice experiment, administered in Conjoint.ly, in which they were asked in 8 scenarios to choose between an individual ride in a private car (similar to UberX or Lyft) and a pooled ride in a shared car (similar to UberPOOL or Lyft Line), where the choices varied with respect to trip price, pickup time, and travel time. Respondents were randomly assigned to one of two experimental conditions when completing this task. One group was choosing between private and pooled rides assuming they were traveling to the airport to catch a flight, a nudge towards a time-constrained trip. The other group was choosing assuming they were traveling to go shopping, a less time-constrained trip.

The levels used for each ride attribute in this experiment are shown in Table 3. As is standard when choosing between these services in real-world apps, the estimated travel time for an individual ride is shown as a discrete time (e.g. 12 minutes), while the estimated travel time for a pooled ride is shown as a time range (e.g. 12-18 minutes), reflecting uncertainty in how long the pooled ride will take for any individual, taking the need to also serve the trips of other passenger(s) in the vehicle into account. We systematically vary the amount of uncertainty in the time estimate so that the effect of time uncertainty can be identified separately from the main time effect. We selected levels for each attribute that were representative of the average characteristics of ride-hailing trips in the U.S. (SherpaShare, 2016; Iqbal, 2018; Vaccaro, 2018), and fare estimates from leading US ride-hailing companies (Lyft, 2018; Uber, 2018).

Table 3: Attributes and Levels in Discrete Choice Experiment

Attribute	Units	No. of Levels	Levels	
Pickup Time	minutes	3	2, 5, 8	
Travel Time	minutes	12	*MyRider*	*RiderPool*
			10	8-12, 6-14, 4-16
			15	12-18, 9-21, 6-24
			20	16-24, 12-28, 8-32
Ride Price	$/trip	6	*MyRider*	*RiderPool*
			-	$3.00
			$5.25	$5.25
			$7.50	$7.50
			$10.00	$10.00
			$15.00	$15.00
			$20.00	-

Conjoint.ly performed a quality assessment of the responses in an attempt to eliminate automatic clicking, using a proprietary algorithm to analyze time spent on each question, mouse movement, and other variables that measure the behavior of respondents. We also introduced a 5 sec threshold on each question, so that respondents could not answer too quickly.

Upon successful completion of the discrete choice block, respondents finished the third part of the survey in Qualtrics. Respondents disqualified by Conjoint.ly were thanked for their participation, and their responses were excluded from our analysis. Qualified respondents were asked to complete a post-survey questionnaire, including, for those who indicated in the first part of the survey that they had used ride-hailing services previously, questions about the frequency of their use of individual and pooled ride-hailing services, and their satisfaction each of these services. The three parts of the survey were then merged together and additional quality checks were performed, including ensuring that the respondent's country of residence was the United States, and that the overall sample was representative of the US population.

Before running the full survey, we performed a pilot test of the survey on Amazon MTurk, obtaining a convenience sample from 310 US respondents. We used the pilot to refine our questions and fine-tune the attribute levels, especially in relation to capturing the effect of uncertainty in travel time. The results we obtained in that pilot do not differ meaningfully from the results we present below.

5 Results

We estimate the utility coefficients in Eq. 1 from our stated preference data (Table 4) using the *mlogit* package in R (Croissant, 2018).

Table 4: Binomial Logit Results

	Utility coefficients				
	(1)	(2)	(3)	(4)	(5)
RiderPool:(intercept)	-0.607^{***} (0.060)	-0.676^{***} (0.118)	-0.600^{***} (0.120)	-0.487^{***} (0.132)	-0.262 (0.224)
Pickup Time (min)	-0.058^{***} (0.007)	-0.063^{***} (0.008)	-0.062^{***} (0.008)	-0.062^{***} (0.008)	-0.090^{***} (0.015)
Price ($)	-0.168^{***} (0.005)	-0.172^{***} (0.005)	-0.173^{***} (0.005)	-0.172^{***} (0.005)	-0.480^{***} (0.039)
Travel Time Mean (min)	-0.040^{***} (0.005)	-0.041^{***} (0.005)	-0.041^{***} (0.005)	-0.043^{***} (0.005)	-0.073^{***} (0.011)
RiderPool: Travel Time Uncertainty (min)	-0.015^{***} (0.004)	-0.017^{***} (0.005)	-0.016^{***} (0.005)	-0.015^{***} (0.005)	-0.027^{***} (0.008)
RiderPool: Age (yr.)		-0.002 (0.002)	-0.002 (0.002)	-0.002 (0.002)	-0.011^{***} (0.003)
RiderPool: Male		0.046 (0.060)	0.038 (0.060)	0.048 (0.061)	0.171 (0.106)
RiderPool: Republican		-0.078 (0.071)	-0.081 (0.071)	-0.090 (0.073)	-0.151 (0.125)
RiderPool: Independent		0.057 (0.068)	0.063 (0.068)	0.052 (0.069)	0.004 (0.118)
RiderPool: Low Income		0.310^{***} (0.057)	0.319^{***} (0.057)	0.306^{***} (0.060)	0.442^{***} (0.107)
RiderPool: Suburban		0.025 (0.064)	0.035 (0.064)	0.033 (0.066)	-0.046 (0.114)
RiderPool: Rural		0.022 (0.073)	0.032 (0.074)	0.019 (0.076)	0.031 (0.130)
RiderPool: Rushing			-0.178^{***} (0.054)	-0.169^{***} (0.055)	-0.290^{***} (0.096)
RiderPool: Cars per Person in Household				-0.163^{**} (0.067)	-0.294^{**} (0.119)
SD Pickup Time					0.107^{*} (0.060)
SD Price					0.527^{***} (0.057)
SD Travel Time Mean					0.104^{***} (0.037)
Observations	8,112	7,088	7,088	6,848	6,848
R^2	0.156	0.167	0.168	0.168	0.194
Log Likelihood	-4,742.000	-4,092.529	-4,087.090	-3,945.973	-3,823.193
LR Test	$1,757.262^{***}$ (df = 5)	$1,637.015^{***}$ (df = 12)	$1,647.891^{***}$ (df = 13)	$1,598.285^{***}$ (df = 14)	$1,843.846^{***}$ (df = 17)

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Beginning with our most aggregated model 1, we see first that pooling has a negative and statistically significant intercept, meaning that, all else being equal, pooling has an inherent disutility for consumers. This likely reflects that many people would prefer not to share the cabin of the vehicle with other passengers, and that the need to take a circuitous route to accommodate other passengers is a time-consuming inconvenience. The result is consistent with prior findings that freedom of driving alone, and unwillingness to carpool with people outside their own family, are the most important factors that influence commuters' choice not to carpool (Hwang & Giuliano, 1990). Based on the relative magnitude of our pooling intercept and price coefficients, we can value this pooling inconvenience at -0.607 / -0.168 = $3.61 per ride in our experiment. As expected, we see that the coefficients of the key ride-hailing service attributes are all negative and highly statistically significant, as expected. That is, consumers prefer rides that are cheaper, have faster pickup times, and shorter travel times. The negative price coefficient in particular explains why a significant number of ride-sharing users would be willing to choose cheaper pooled rides even though pooling has other inconveniences. The magnitude of the pickup time coefficient is greater (with an implied value of time of $20.71 per hour) than the magnitude of the travel time coefficient (what has an implied value of time of $14.29 per hour), suggesting that time spent waiting to be picked up is relatively more important than time spent in the vehicle, probably an example of hyperbolic discounting or inconvenience of waiting outside in possibly poor weather. We find that uncertainty in the travel time of pooled rides is also influential, with each minute of uncertainty in time estimate equivalent to -0.04 / -0.015 = 2.67 minutes of additional travel time.

In model 2, we include several pooling-demographics interaction variables to test how our sample's preference for pooling variables varies with respondent demographics. Most of these are not statistically significant, with the exception of the dummy variable we include for low-income respondents (below $50,000 per household per year). The coefficient of our dummy for low-income respondents is strongly positive, suggesting that people with low incomes are more likely to choose pooling, which is likely because they are more willing to tolerate the inconvenience of a pooled ride to save money. The offset for the inconvenience of pooling is 0.310/-0.172 = -$1.80, meaning that people with low incomes value the inconvenience of pooling to be much less than people with higher incomes.

In model 3, we add an interaction variable that captures the experimental condition in which we nudged half our sample into thinking they were taking a trip to the airport, a time-constrained trip. Here we see that, as expected, people who are in a rush are less likely to choose pooling, which we attribute to the stress involved in taking a trip that both takes longer and has more time uncertainty. In model 4, we include an interaction variable for pooling and car ownership, finding that respondents who own more cars in the household per person are less likely to choose pooling, conditional on having already chosen to use ride-hailing. We speculate that this finding may be explained by car owners being more socialized to having their own private space in their vehicle compared with public transit users, making them more likely to choose an individual rather than pooled ride.

We now use mixed logit, which assumes that alternative specific covariates x_{ni} (e.g. pickup time, travel time, ride price, etc.) have individual specific coefficients β_n with normal distribution for all alternatives, such that utility from alternative i for individual n becomes:

$$U_{ni} = \alpha_i + \beta_n x_{ni} + \gamma_i z_n + \epsilon_{ni} \tag{3}$$

In model 5, the significance of all coefficients from prior models is confirmed (with the exception of intercept), while we also see the negative and statistically significant coefficient for age, meaning that younger people are more likely to pool, possibly due to less tolerance among the older generation for sharing the ride with other passengers and the fact that younger generation has higher degree of tech-savvy required to access app-based ride-hailing services.

6 Policy Analysis

The implications of consumer ride-hailing preferences in the context of future mobility can be illustrated by considering a hypothetical scenario in which the cost of driving is assumed to fall significantly over time, which we base on the projected decrease due to the introduction of AVs described by Fulton & Bremson (2014). Here, we simulate how the market share of pooling changes over time for a specific ride-hailing choice for a standard 5-mile trip (an individual ride (*MyRider*) with pickup time of 3 minutes and travel time of 16 minutes, and costing \$11.25, versus a pooled ride (*RiderPool*) with pickup time of minutes and travel time of 16-24 minutes, and costing \$6.75), where the per-vehicle cost of driving falls from an assumed \$2.25/mile to \$0.60/mile after 10 years (Figure 3).

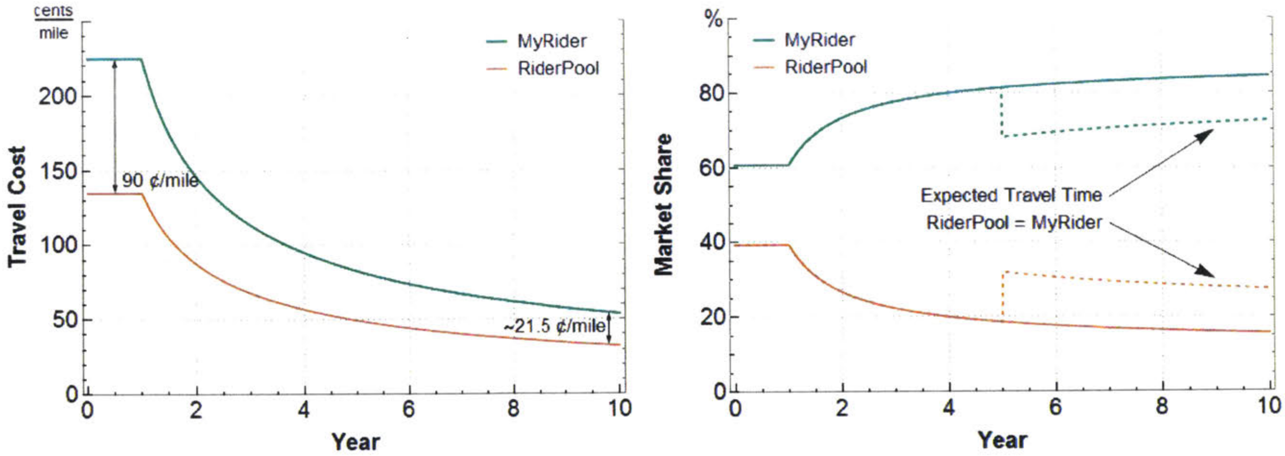

Figure 3: Simulation of Pooling Choice with Falling Driving Costs

We assume that a pooled trip is shared by two passengers with the cost per person of 60% of the individual ride, reflecting the overhead associated with pooled trip coordination, such as cost of matching riders and additional travel required to accommodate pick-up and drop-off of each passenger. Importantly, it can be seen in the left panel of Figure 3 that as the cost of driving falls, the incremental cost of taking a private ride over a pooled ride falls in absolute terms, even though it remains constant in percentage terms. It is for this reason that the market share of the private *MyRider* service increases over time as the cost of driving falls (the right panel of Figure 3), because the magnitude of the financial savings that come with pooling falls similarly.

Simulating scenarios in this way allows stakeholders considering how to promote pooling, such as cities, the opportunity to explore how they can design policies to their advantage. Policies that make pooled rides more attractive may include faster pickup times (e.g. pooled rides have priority picking up passengers at airports), faster travel times (e.g. dedicated lanes that allow pooled vehicles to move quickly), and cheaper pooled rides (e.g. per-vehicle road pricing). For example, in the right panel of Figure 3, we simulate the introduction of dedicated carpool lanes in year 5 that have the assumed impact of prioritizing the movement of pooled rides through the city such that the time penalty associated with pooling is eliminated (dashed lines). Here we see that the market share of the pooled ride service *RiderPool* increases nearly 10%, because the utility penalty associated with the time-uncertainty of pooling is removed.

7 Discussion

The rapid emergence of automated vehicle technologies offers potential benefits for commuters, such as lower cost, increase travel speed, higher safety, and opportunity to use travel time more productively. However, researchers increasingly believe that if many of these benefits are realized, then considerable additional demand for driving will be induced, with the potential to worsen traffic congestion and air pollution. It is for this reason that pooling is gaining attention (e.g., Fulton et al., 2017; Sprei, 2017) as a potential countermeasure by serving the same number of passenger miles with fewer vehicle miles. While consumer use of pooling is modest today, the growth of on-demand mobility platforms such as Uber and Lyft has renewed interest in pooling because these platforms effectively automate the task of rider-matching. Understanding what motivates consumers to choose pooling, and how those incentives change over time, is critical if pooling is to play a significant role in the transition to sustainable mobility.

Our analysis quantifies the factors that affect consumers' choice of pooled rides, and clarifies the opportunities and challenges that exist if consumers are to find pooling increasingly attractive. Pooled rides take at least as long as individual rides today, and are perceived to be inconvenient, but they are cheaper. These cost savings explain the increasing use of pooling today, including for low-income segments of the population for whom pooling is increasingly competitive with conventional public transit. It could, therefore, be problematic if the cost of driving fell in the future, as some people expect, because the financial incentive to pool will diminish – why would a rider choose pooling when it is inconvenient and when an individual ride is only marginally more expensive?

This realization provides guidance on the design of urban transportation policies that will encourage riders to choose pooling. Pooling becomes relatively more attractive if pickup times are faster (for example, because pooled rides have priority picking up passengers at airports); if travel times are faster (for example, because high-occupancy vehicle lanes allow pooled vehicles to travel more quickly); and if the cost of pooled rides is cheaper than private rides (for example, because of per-vehicle road pricing). For policymakers, the consumer preference coefficients we estimate can be used to simulate the increase in pooling that might be expected for a given policy intervention.

Our study inevitably has limitations, motivating opportunities for future research on this topic. While we deliberately consider consumer choice between individual and pooled rides, it is increasingly clear that pooling also interacts with public transit systems, with potentially wide-reaching implications. Understanding whether pooling helps public transit by covering the 'last-mile' trips or competes with it by drawing riders away, potentially leading to its decline, is of critical importance. While multiple related studies and reports exist (e.g. Yap, Correia, & van Arem, 2016; Clewlow & Mishra, 2017; Schaller, 2018; Graehler & Mucci, 2019; Hughes, 2019), opinions remain mixed on whether ride-hailing and pooling is a complement or substitute for the use of public transit. Further, pooling will only be effective at reducing traffic congestion and air pollution if policies are put in place such that result from the use of pooling do not simply induce yet more driving. Finally, several other sources of heterogeneity in pooling use exist that should be investigated, including spatial determinants such as trip length, and also whether the trip is being paid for by the individual rider or by their employer.

Pooling provides the opportunity to increase vehicle utilization and use resources more efficiently, reducing negative externalities of driving such as air pollution and traffic congestion, and offering lower travel cost for consumers. Ride-hailing and automated vehicles have reinvigorated the possibility that pooling can play a meaningful role in urban transportation management. However, if new technologies will make driving cheaper, the main attractiveness of pooling – relatively low price – becomes less effective. If we are to rely on pooling to address the negative externalities of driving, we need urban policies that make pooled rides more attractive.

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Model Documentation

```
Average Trip Length=
            5
Units: mile
Average length of a ride-hailing trip

Cents per Dollar=
      100
Units: cents/dollar
Conversion from cents to dollars

Cumulative Experience= INTEG (
      Experience Change,
            Initial Cumulative Experience)
Units: vehicles
Cumulative production experience

Effect of Sales on Ride Price=
      (Cumulative Experience/Initial Cumulative Experience)^
       LOG(1-Price Learning Curve Strength,2)
Units: dmnl
Effect of production experience on cost of travel

Effective Ride Price Individual=
      Price of Ride per mile Individual * Average Trip Length / Cents per Dollar
Units: dollar
Total price of individual trip

Effective Ride Price Pool=
      Price of Ride per mile Pool * Average Trip Length / Cents per Dollar
Units: dollar
Total price of pooled trip

Experience Change=
      Vehicle Sales
Units: vehicles/year
Change in production experience

FINAL TIME  = 10
Units: year
The final time for the simulation.

Individual PickUp Time=
      3
Units: min
Pick up time of individual trip

Individual Travel Time=
      16
Units: min
Travel time of individual trip

Initial Cumulative Experience=
      100000
Units: vehicles
Initial level of production experience

INITIAL TIME  = 0
Units: year
The initial time for the simulation.
```

```
Logit Choice Scaling Sales=
       2
Units: dmnl
Scaling factor of binomial logit

PickUp Time Weight=
       -0.05
Units: dmnl/min
Weight of pick up time in utility

Policy Effect=
       1 / Pool Travel Time Multiplier
Units: dmnl
Adjustment to make travel time in pooled and individual trips
              the same

Pool Intercept=
       -0.796
Units: dmnl
Inconvenience of pooling

Pool Market Share=
       EXP(Utility of Pool*Logit Choice Scaling Sales) /
        (EXP(Utility of Pool*Logit Choice Scaling Sales) +
         EXP(Utility of Individual*Logit Choice Scaling Sales))
Units: dmnl
Market share of pooled trips

Pool PickUp Time=
       7
Units: min
Pick up time of pooled trip

Pool Policy=
       0
Units: dmnl [0,1,1]
Switch that assumes HOV lane for pooled vehicles, making travel
              time of pooled trip similar to individual trip

Pool Price Fraction=
       0.6
Units: dmnl
Fraction of price of pooled ride from the full price of
              individual ride. Assuming 2 people per vehicle occupancy of
              pooled ride, the reduction is not directly proportional due to
              some overhead costs.

Pool Travel Time=
       Individual Travel Time * Pool Travel Time Multiplier *
       IF THEN ELSE
         (Time < 5 :OR: Pool Policy = 0,
          1,
          Policy Effect
         )
Units: min
Travel time of pooled trip

Pool Travel Time Multiplier=
       1.25
Units: dmnl
Multiplier of the pooled trip duration vs. individual trip
```

Price Learning Curve Strength=
    0.35
Units: dmnl [0,1,0.05]
Strength of the learning curve of travel cost

Price of Ride per mile Individual=
    Reference Price of Ride per mile * Effect of Sales on Ride Price
Units: cents/mile
Cost of individual ride per mile

Price of Ride per mile Pool=
    Price of Ride per mile Individual * Pool Price Fraction
Units: cents/mile
Cost of pooled ride per mile

Reference Price of Ride per mile=
    225
Units: cents/mile
Reference cost of travel per mile

Ride Price Weight=
    -0.24
Units: dmnl/dollar
Weight of price in utility

SAVEPER =
    TIME STEP
Units: year [0,?]
The frequency with which output is stored.

Technology:
    CV, "AV L3-L4", AV L5

TIME STEP = 0.0078125
Units: year [0,?]
The time step for the simulation.

Travel Time Weight=
    -0.071
Units: dmnl/min
Weight of travel time in utility

U1 Individual=
    Effective Ride Price Individual * Ride Price Weight
Units: dmnl
Price attribute of utility of individual trip

U1 Pool=
    Effective Ride Price Pool * Ride Price Weight
Units: dmnl
Price attribute of utility of pooled trip

U2 Individual=
    Individual PickUp Time * PickUp Time Weight
Units: dmnl
Pick up time attribute of utility of individual trip

U2 Pool=
    Pool PickUp Time * PickUp Time Weight
Units: dmnl
Pick up time attribute of utility of pooled trip

U3 Individual=

```
       Individual Travel Time * Travel Time Weight
Units: dmnl
Travel time attribute of utility of individual trip

U3 Pool=
       Pool Travel Time * Travel Time Weight
Units: dmnl
Travel time attribute of utility of pooled trip

Utility of Individual=
       U1 Individual + U2 Individual + U3 Individual
Units: dmnl
Total utility of individual trip

Utility of Pool=
       Pool Intercept + U1 Pool + U2 Pool + U3 Pool
Units: dmnl
Total utility of pooled trip

Vehicle Sales=
       IF THEN ELSE
         (Time < 1,
          0,
          100000
         )
Units: vehicles/year
New vehicle sales
```

Accelerating Vehicle Fleet Turnover to Achieve Climate Policy Goals

Abstract

Reducing carbon emissions from the U.S. transportation sector is crucial to achieving climate goals set by leading nations of the world and limiting global warming by 2°C by the year 2100. Recent efforts by policymakers and car manufacturers have focused on increasing the adoption of low- or zero- emission vehicles in new vehicle sales. However, despite persistent efforts, the sales of these vehicles remain very low, and the existing vehicle fleet would require decades to be fully replaced by zero-emission vehicles, during which time vehicle greenhouse gas (GHG) emissions would continue to accumulate in the atmosphere. Achieving climate goals will likely require policies that incentivize the accelerated retirement of older less-efficient vehicles to be replaced by new higher-efficiency vehicles. However, a tension exists between incentivizing the adoption of fuel-efficient gasoline vehicles that are more attractive to consumers in the short-run, but which have more limited long-run emission benefits, and incentivizing emerging zero-emissions vehicle technologies, which are less attractive to consumers currently, but which are necessary for deep GHG emissions reduction in the long-run. We use a model of vehicle fleet turnover in the U.S. to show that to reduce vehicle fleet emissions in time, effective 'cash-for-clunkers' policies should incentivize the purchase of electric vehicles only, alongside a rapid transition to renewable electricity. We demonstrate that such policies can substantially reduce vehicle fleet emissions, but that implementation costs remain relatively high. Combining 'cash-for-clunkers' with a gas tax or carbon price would help offset the costs incurred while also reducing driving demand, helping to facilitate a timely low-emissions transition.

1 Introduction

Reducing greenhouse gas (GHG) emissions to achieve climate goals and limit global warming to no more than 2°C requires effective policies aimed at improving the most polluting sectors of the world economy. However, global GHG emissions are not on track to achieve these goals. The United Nations Environmental Programme finds that the world is failing to meet the goal set by the Paris Agreement, and the drastic actions are necessary to bring the pollution reductions back on track (UNEP, 2018). To achieve the required emissions reductions, reliance on traditional policies is not sufficient and identifying and addressing sensitive intervention points is necessary (Farmer et al., 2019). Reducing carbon emissions from the transportation sector is crucial to achieving these goals. The transportation sector is responsible for 28% of all U.S. GHG emissions from the U.S. The majority of the U.S. transportation footprint, approximately 60% of transportation emissions, is due to the roughly 250 million light-duty vehicles (cars, SUVs, and pickup trucks) on the roads today (EPA, 2018).

Since 1970, GHG emissions from the global transportation sector more than doubled, increasing faster than any other energy-using sector and reaching 8.05 Gt CO_2/year in 2016, when allocating emissions from electricity (IEA, 2019). In order to limit the CO_2-equivalent concentration in the atmosphere at the level below 450 ppm by the year 2100 (required to maintain global warming below 2°C), the world needs about 40-70% reduction by 2050 relative to 2010, and almost zero emissions in 2100, according to the IPCC assessment AR5 (IPCC, 2014). The long-term strategy submitted after the Paris Climate Change Agreement by the U.S. pledged to reduce emissions by 80% below the 2005 level by 2050 (UNCC, 2016). In 2018, after a short term dip, transportation emissions in the U.S. almost returned to the peak level of 1.98 Gt CO_2/year observed in 2005, and since 1990, increased more than 20% (EPA, 2019b). This means a reduction of more than 80% from the 2018 level by 2050 is needed to meet the climate goals established by pledges of the Paris Agreement.

In the transportation sector, most efforts by policymakers and car manufacturers have focused on increasing the share of new vehicle sales going to low- or zero- tailpipe emissions vehicles, for example, mandating the minimum fuel economy of new vehicles through the Corporate Average Fuel Efficiency (CAFE) standards (NHTSA, 2018). CAFE, created in 1975, has reduced transportation emissions below what they would have been: the National Academy of Sciences found that gasoline consumption would have been about 14% higher if vehicle fuel economy had not improved over time as required by CAFE standards (National Research Council, 2002).

However, the impact of CAFE is constrained by the slow turnover of the vehicle fleet due to the durability of new vehicles. The average light-duty vehicle (LDV) in the United States has a useful life of 16.6 years (Keith, Houston, & Naumov, 2019), but many remain in use for 30 years or more (especially more polluting light trucks). Even if policies such as CAFE are effective at improving the fuel economy of gasoline vehicles, and sales of zero-tailpipe emission electric (EV) and hydrogen fuel cell (HFCV) vehicles grow, decades are required to replace the existing vehicle fleet, during which time GHG emissions will continue (Keith, Houston, et al., 2019). Given the rate at which low- and zero- emission vehicles technologies are being adopted currently, it is likely that accelerated turnover of the vehicle fleet will be required if 2050 climate goals are to be reached.

C4C policies have been used in the past to stimulate sales and increase the fuel economy of new vehicles introduced into the fleet. However, the effectiveness of C4C programs remains an open question given with the current landscape, with stringent fuel economy standards mandating that automakers steadily increase the average fuel economy of new vehicles sold, and with a wider range of technologies available that can lower automobile GHG emissions. In particular, a tension exists between incentivizing the adoption of fuel-efficient gasoline vehicles that are more attractive to consumers in the short-run, but have more limited long-run emission benefit, and incentivizing emerging zero-emissions vehicle technologies such as EVs and HFCVs which are less attractive to consumers currently, but which are necessary for deep GHG emissions reduction in the long-run.

In this paper, we extend a model of the vehicle fleet turnover calibrated for the United States to analyze the effect of policy incentives for accelerated vehicle retirement, also known as 'cash-for-clunkers' (C4C). We show that C4C policies aimed at incentivizing sales of new fuel-efficient vehicles provide additional reduction in greenhouse gas emissions by the year 2050, relative to the baseline that relies on natural fleet turnover and reasonable assumptions about future improvements in the fuel economy of new vehicles. We further show that modest improvements in emissions reduction can be achieved if C4C is used to incentivize the purchase of fuel-efficient gasoline vehicles, with greater emissions reduction possible if the C4C incentive is limited to the purchase of electric vehicles only. However, both policies remain relatively expensive, with greater and more cost-effective emissions reduction possible if C4C is combined with a gas tax that generates revenue and moderates driving demand, and if renewable electricity is used to recharge EVs. This research contributes to the literature on transportation and climate change, evaluating the practical steps needed to achieve meaningful emissions reduction from the on-road vehicle fleet.

2 The Road to a Low Emission Vehicle Fleet

Federal and several state governments in the United States employ a wide range of policies to promote a transition to alternative, low-, or zero- tailpipe emissions vehicles. Several tax credits exist for buyers of EVs that offer up to $7,500 tax credits from the federal government, and additional incentives of up to $2,500 in several state (U.S. DOE, 2019). In addition, California and nine other states follow the Zero-Emission Vehicle (ZEV) mandate, requiring that the market share of zero-emissions vehicles increases from 4.5% in 2018 to 22% in 2025 (CARB, 2018, 2019). Despite this substantial policy support over many years, alternative fuel vehicles have only achieved low single digit market shares in the United States to date (Figure 1).

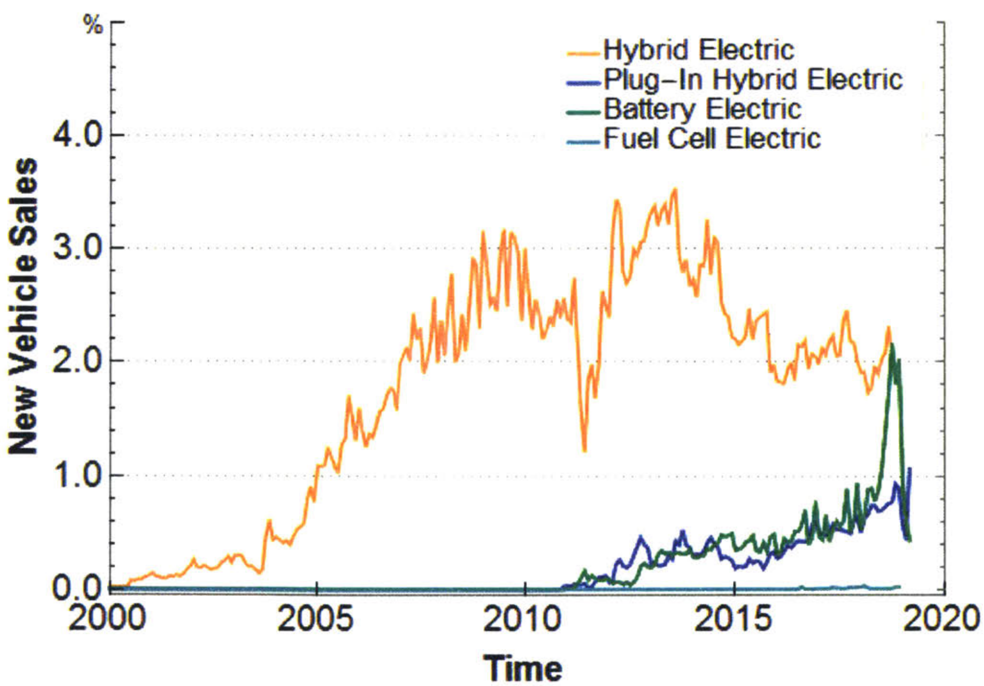

Figure 1. Sales of Low- and Zero-emission Vehicles in the U.S.
Data sources: (Auto Alliance, 2018; HybridCars.com, 2018; Automotive News, 2019)

In addition to technology-specific policies, the Corporate Average Fuel Economy (CAFE) standards aim at improving the average fuel economy of new LDVs (cars and light trucks). These standards use a harmonic mean average of the specific mix of vehicles produced by manufacturers and the system of governmental credits for the use of 'green' technologies to mandate the minimum average fuel economy of the fleet of new vehicles offered for sale. Adjusted for credits and accounting for the difference between test and real drive conditions, the CAFE standards currently require an average fuel economy of new cars to be 44.2 miles per gallon (MPG) and the fuel economy of new light trucks to be 31.4 MPG by 2025. The future trajectory of the standards beyond 2025 has not been defined yet. However, with the focus on new vehicle sales, even if these policy standards evolve to require new vehicles sold in 2050 be 75% more fuel efficient than today (which in itself is an extremely ambitious if not impossible goal in the absence of EVs dominating the market), the expected reduction in fleet emissions will not exceed 40% owing to the slow rate of fleet turnover (Keith, Houston, et al., 2019). These emissions reductions could be even harder to achieve given the plans of Trump administration to introduce the Safer Affordable Fuel-Efficient (SAFE) Vehicles rule, expected to freeze the CAFE standards between 2020 and 2025 at the level of 37 and 25 MPG for cars and light trucks respectively (NHTSA, 2018).

While these efforts to reduce the environmental impact of new vehicles entering the vehicle fleet are important, a more effective policy should consider the fleet of all vehicles on roads, which is the result of the accumulation from new vehicle sales and the depletion from vehicle retirements over time. People tend to have a poor intuitive understanding of processes that involve stocks, flows, and accumulation (Sterman, 1989, 1994, 2008), which leads to underestimating the impact of the less-efficient vehicles that stay in the fleet for many years on fleet fuel consumption and greenhouse gas emissions.

Our surveys show that people underestimate how long it takes for new vehicles to move through the fleet. We asked MIT graduate students and MTurk respondents the following question: *"Consider a hypothetical scenario where an all new vehicle technology is introduced in the United States that is superior to existing vehicle technologies in every way (including cost, performance, fuel availability, and environmental impact) such that it immediately achieves 100% of all new vehicle sales. Assume the rates of vehicle sales and retirements remain at* *today's levels. Please estimate how many years you think it would take for the new technology to make up 90% of the on-road vehicle fleet in the United States."* Replacing 90% of the existing U.S. fleet of vehicles requires almost 20 years, given current rates of vehicle retirements (Keith, Houston, et al., 2019). In our surveys, respondents underestimated this time by about 4 years.

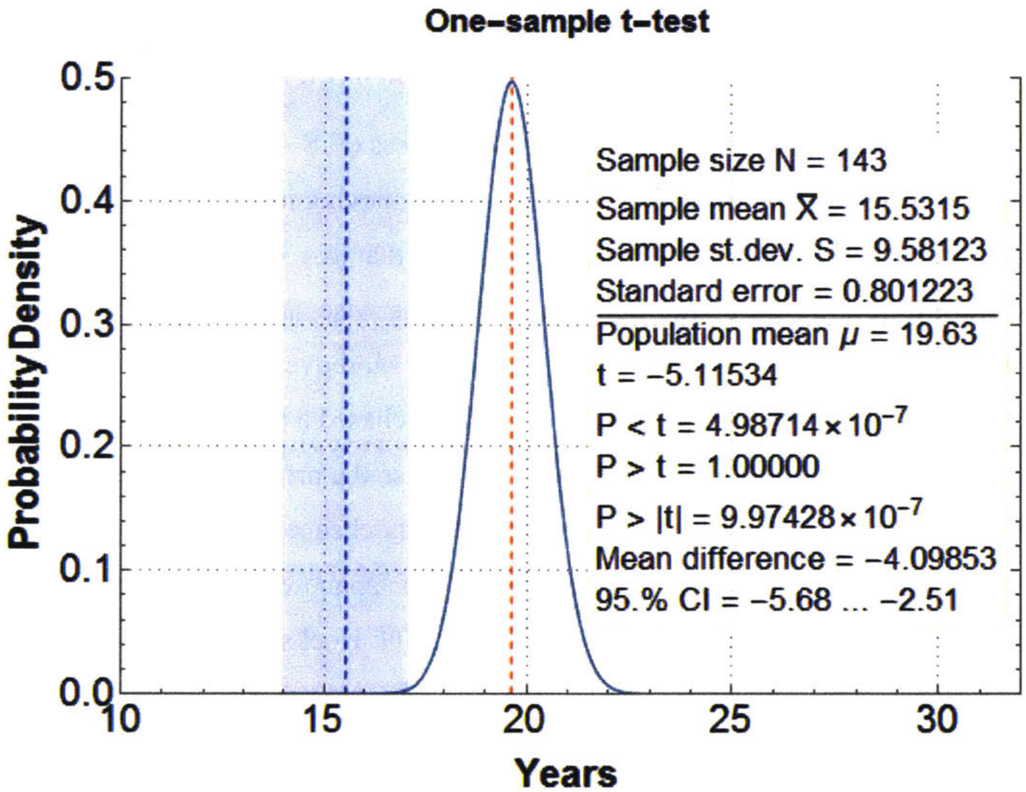

Figure 2. MTurk Survey, 90% Vehicle Turnover

Programs that accelerate the replacement of old and inefficient vehicles currently in the fleet provide an opportunity to move the vehicle fleet emissions to a new trajectory that achieves a meaningful reduction by 2050. Such programs are not new and have been attempted by many governments since the 1990s, but no program has focused explicitly on reducing greenhouse gas emissions, including the most recent example in the U.S. in 2009 (Morrison, Allan, & Carpenter, 2010).

3 Cash for Clunkers

In 2009, the US government introduced the Cars Allowance Rebate System (CARS), commonly known as Cash for Clunkers. This program was mainly aimed at boosting automotive sales, after the precipitous decline on the heels of the economic crisis of 2008. Auto sales fell 18%, plunging to the lowest number in a decade, with U.S. manufacturers hit hardest, with sales declining between 28% and 36% (Vlasic, 2008). The CARS program provided incentives between $3,500 and $4,500 per vehicle to consumers who traded in a low fuel-efficiency vehicle and purchased a new and higher fuel-efficiency vehicle. Traded-in vehicles were destroyed so that they did not re-enter the used vehicles market. The program lasted from July 1, 2009, to August 24, 2009, and generated about 680,000 transactions at the cost of $3 billion (Li, Linn, & Spiller, 2013).

While the government declared the program success (U.S. DOT, 2009), further research reported mixed results. The program was successful in achieving its main objective of inducing additional vehicle sales. However, researchers estimated that just 370,000 purchases of vehicles in July and August of 2009 would not have happened otherwise, and the sales of new vehicles dropped after the program expired (Mian & Sufi, 2012). Moreover, more than half of the incentives went to households that would likely have purchased a new vehicle in the next two months anyway (Hoekstra, Puller, & West, 2017). Because the program required the purchase of a new fuel-efficient vehicle, many consumers chose to buy cheaper and more fuel-efficient vehicles such as the Toyota Corolla, boosting the sales of Japanese cars more, and reducing the average selling price of new vehicles sold (B. Simon, 2009; Hoekstra et al., 2017).

The CARS program required the replacement purchase vehicles to be more fuel efficient than the average vehicle available on the market, increasing the average fuel economy of all new vehicles sold in July 2009 by 0.6 mpg, and in August 2009 by 0.7 mpg (Sivak & Schoettle, 2009). Despite reducing fleet emissions, researchers calculated that program costs exceeded the value of benefits (as calculated by the difference between the subsidy and environmental benefits) by about $2,000 per vehicle (Abrams & Parsons, 2009). The estimates of the cost of carbon reduction varied widely, ranging from $92 and $288 (Li et al., 2013) to between $200 and more than $500 per tonne CO_2 (Knittel, 2010). At the same time, the CARS program prevented emissions of 4.4 million tonnes CO_2, from the fuel savings resulted from the discarding of old 'clunkers', while some savings resulted from the fact that the program stimulated sales of more fuel-efficient vehicles than otherwise would have occurred (Lenski, Keoleian, & Bolon, 2010). Most of the benefits of the program went to just 2% of the U.S. counties (mostly urban centers) that received 50% of pollution reduction benefits (Lenski, Keoleian, & Moore, 2013).

While this and other examples of similar policies (see Morrison et al., 2010) provide important evidence of how an accelerated vehicle retirement program can be successful, the specific impacts do not generalize to the current U.S. market. Today, the higher average fuel economy of vehicles in the fleet, new mix of available makes and models of vehicle platforms with lower emissions (including more options of low-and zero- emission vehicles), evolved fuel economy standards, and most recent climate objectives, all creating a different playing field. The direct environmental benefits of accelerated vehicle retirements program accrue due to accelerated replacement of less fuel-efficient old vehicles in the fleet through incentivized sales of new and more fuel-efficient vehicles (Van Wee, Moll, & Dirks, 2000; Kim, Keoleian, Grande, & Bean, 2003; Spitzley, Grande, Keoleian, & Kim, 2005; Morrison et al., 2010). However, to the best of our knowledge, there is no study that considers the indirect benefits of an accelerated vehicle retirements program that incentivizes the replacement of less fuel-efficient cars with zero-emission vehicles (e.g. EVs) and provides opportunities for market formation, increasing EV sales further. Next, we consider a cash-for-clunkers (C4C) program designed to reduce vehicle fleet emissions by mandating minimum fuel economy standard for replacement vehicles, and compare the effectiveness and efficiency of traditional C4C policy with incentives to buy more fuel-efficient fossil-fuel vehicles with a more advanced policy that allows to buy EVs exclusively.

4 Modeling the Dynamics of Accelerated Fleet Turnover

To explore the dynamics of the U.S. vehicle fleet turnover in the presence of C4C policy, we extend a fully calibrated extant model of the U.S. LDV fleet (Keith, Houston, et al., 2019), modifying it to include the effect of C4C policy on the retirement of vehicles with low fuel efficiency and their replacement with new vehicles having higher fuel efficiency (Figure 3). The model tracks cars and light trucks in the U.S. fleet from the initial sale of new vehicles until vehicles are discarded from the fleet. The model is behaviorally robust and incorporates established formulations from fleet diffusion models (Struben & Sterman, 2008; Keith, Naumov, & Sterman, 2017a; Keith, Naumov, & Struben, 2019), discrete consumer choice (e.g. McFadden, 1981a; Ben-Akiva & Lerman, 1985; Brownstone, Bunch, & Train, 2000), and behavioral decision-making (H. A. Simon, 1959; Cyert & March, 1963; Morecroft, 1985; Sterman, 1989).

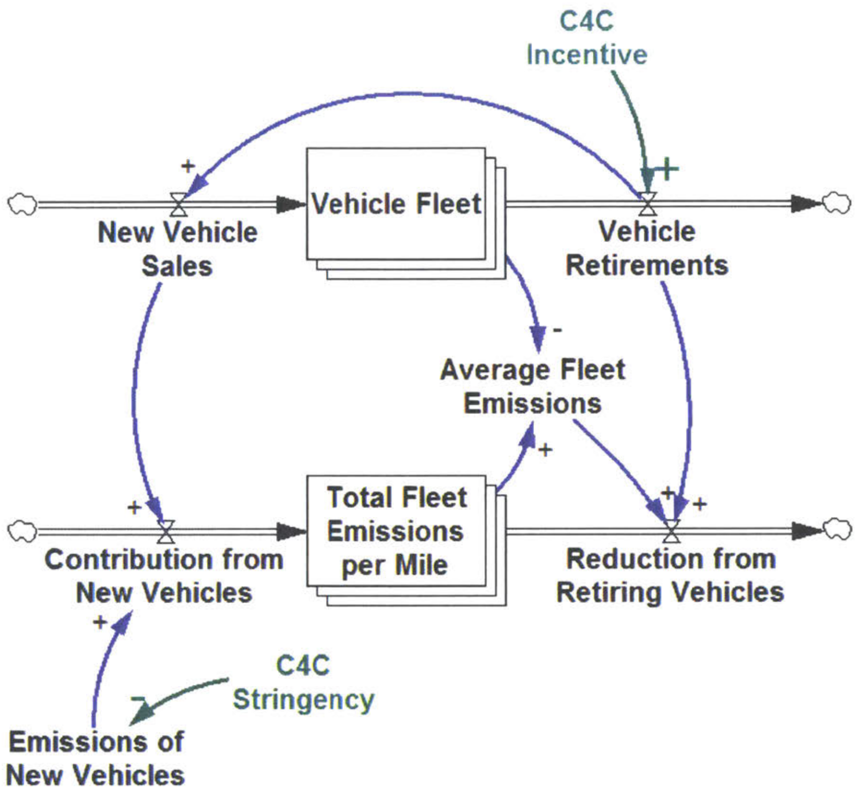

Figure 3. The C4C Policy and Fleet Turnover

The model is calibrated to represent the light duty vehicle fleet of the U.S. and has four platforms: two internal combustion engine (ICE) platforms i, cars and light trucks, as defined by United States Department of Transportation (NHTSA, 2018), and two electric vehicle (EV) platforms e, EV cars and EV light trucks, to reflect potential switch to EV platforms by owners of each current ICE platform. We denote the combined set of platforms as p, such that $e \cup i = p$. Each platform comprises 31 one-year age cohorts, calibrated to reflect the actual cohort-specific rates of vehicle retirement and vehicle-miles traveled in the US light-duty vehicle fleet (Davis, Williams, & Boundy, 2017).

4.1 Vehicle Fleet Turnover

The total installed base of vehicles of platform p sums over N individual age cohorts a:

$$V_p = \sum_{a=1}^{N} V_{pa} \tag{1}$$

In the absence of the C4C program, the total installed base is changed through vehicle retirements r_{pa} from each cohort a of platform p, and the addition of vehicle purchases n_p entering the cohort of new vehicles:

$$\frac{dV_p}{dt} = n_p - \sum_{a=1}^{N} r_{pa} \tag{2}$$

where r_{pa} is a function of the rate of vehicle retirements through natural turnover α_{pa}, increasing with the age of the cohort a, estimated based on the existing data of the U.S. fleet (Davis et al., 2017):

$$r_{pa} = V_{pa}\alpha_{pa} \tag{3}$$

The impact of the C4C policy is captured by adding outflows of discarded vehicles due to the C4C program from qualifying age cohorts d_{pa} and the inflow of mandatory replacement purchases m_p:

$$\frac{dV_p}{dt} = n_p - \sum_{a=1}^{N} r_{pa} + m_p - \sum_{a=Q}^{N} d_{pa} \tag{4}$$

where Q is the minimum age cohort qualifying for the C4C program.

4.2 Changing Vehicle Mix

Vehicles that were discarded are replaced with new vehicles. We consider that people might replace their old ICE vehicle with either a new ICE or a new EV vehicle. We model consumer choice based on the utility of an ICE vs. EV vehicle, u_j, within each platform $j \in \{Car, Light\ Truck\}$. Following the existing literature on new vehicle platform diffusion (Struben & Sterman, 2008; Keith et al., 2017a; Keith, Naumov, et al., 2019), we use discrete consumer choice formulations (e.g. McFadden, 1981a; Ben-Akiva & Lerman, 1985; Brownstone, Bunch, & Train, 2000). We assume the utility of ICE platform as a reference and model the market share of EV platform in replacement sales, within platform j, σ_j, using a binomial logit:

$$\sigma_j = \frac{1}{1 + e^{1-u_j}} \tag{5}$$

We model the utility of an EV platform relative to ICE:

$$u_j = \sum_s \beta_s x_{sj} + \epsilon_j \tag{6}$$

with alternative specific covariates x_{sj} with generic coefficients β and homoscedastic i.i.d. extreme value errors ϵ_j. We include the covariates for the inconvenience of the EV platform (reflecting lower driving range, longer refueling time, and immature market manifested in the lack of recharging infrastructure, low consumer awareness, etc.), price of EV relative to ICE, and relative fuel savings from driving an EV vs. ICE vehicle.

Because the EV market is not yet mature, we assume that the utility of EVs increases with new vehicle sales, aggregating mechanisms including social exposure, learning-by-doing, R&D investment, and the coevolution of recharging infrastructure, which leads to yet more sales, a reinforcing feedback (Figure 4).

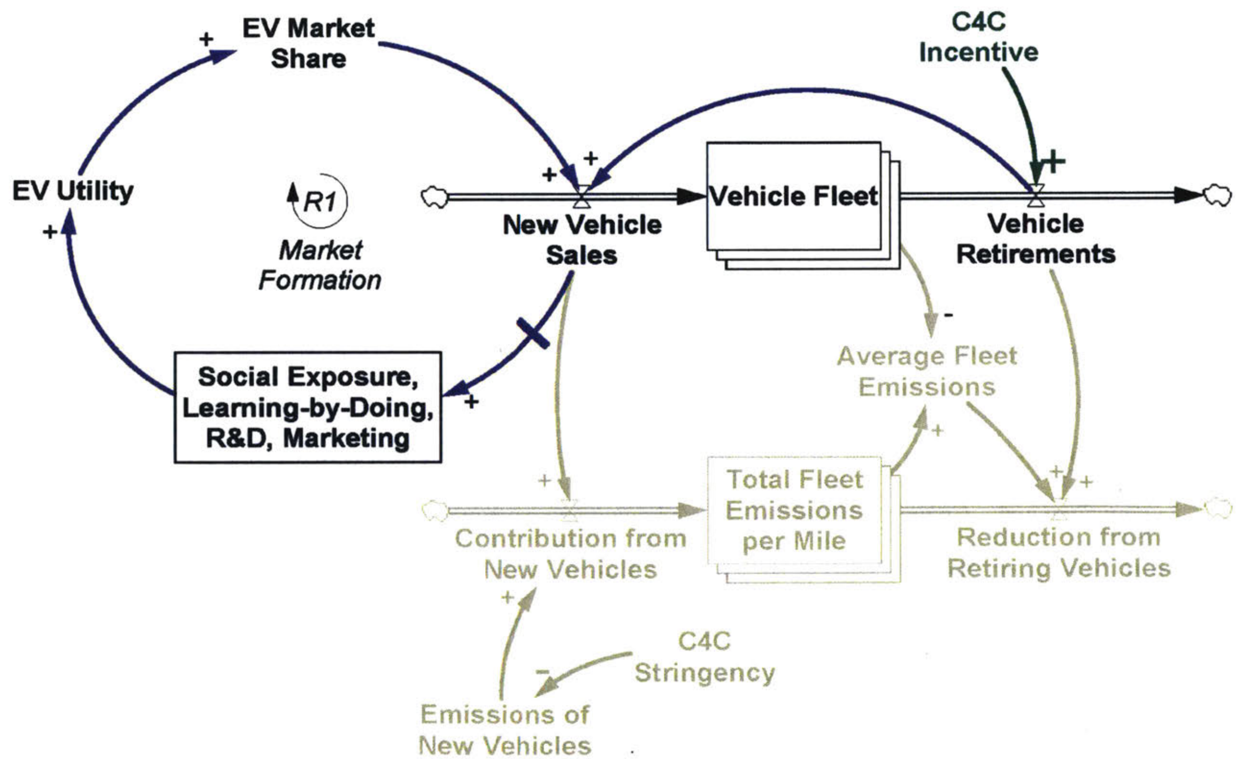

Figure 4. EV Market Formation

We capture these effects as reductions in the price of EVs and the inconvenience of the EV platform. We use a power-law learning curve cumulative in production experience, which serves as a proxy for the aggregate effect of all sources of learning (Argote & Epple, 1990). For the price attribute, we include both cumulative world production W, and local market production L:

$$x_{price,j} = P_0 \left(\frac{W}{W_0}\frac{L}{L_0}\right)^{\gamma_p} \tag{7}$$

where W_0 and L_0 are reference levels of world and local production respectively, P_0 is the price of EV at the reference level of experience, and γ_p is the strength of the learning curve for price.

For the EV market formation, we capture the effect of local market production on market formation dynamics, reflected in consumer acceptance, recharging infrastructure availability, quality of vehicle service, etc.

$$x_{market,j} = I_0 \left(\frac{L}{L_0}\right)^{\gamma_i} \tag{8}$$

where I_0 is the reference inconvenience of EV at the reference level of experience, and γ_i is the strength of the learning curve for market formation.

The relative fuel savings of the EV platform are calculated based on savings that a person might get if they purchased an EV vehicle with the fuel economy FE^{EV} and electricity price p_e vs. the new ICE vehicle with the average fuel economy, determined by the CAFE standard FE_j^{CAFE}:

$$x_{fuel,j} = 1 - \left(\frac{1}{FE^{EV}}\, l'\, p_e\right) \Big/ \left(\frac{1}{FE_i^{CAFE}}\, l\, p_g\right) \tag{9}$$

where l is the average number of miles traveled per vehicle per year, adjusted by the price of gasoline p_g from the baseline number of miles driven l'. It is well documented that people adjust their driving behavior when the fuel price p changes relative to the reference fuel price p', with the elasticity of miles driven to fuel price ε_l (Wang & Chen, 2014):

$$l = l' \left(\frac{p}{p'}\right)^{\varepsilon_l} \tag{10}$$

New vehicle purchases are then modeled as a function of the total amount needed to replace the discarded vehicles, adjusted by the EV market share, and accounting for an increase in market size due to population growth with the rate λ:

$$
\begin{aligned}
n_p &= \delta_p \sum_{a=1}^{N} r_{pa} + V_p\, \lambda \\
\delta_p &= \sigma_p, \forall p \in \{EV\ Car, EV\ Light\ Truck\} \\
\delta_p &= 1 - \sigma_p, \forall p \in \{ICE\ Car, ICE\ Light\ Truck\}
\end{aligned}
\tag{11}
$$

This formulation assumes no change in the mix of light trucks and cars. While it is plausible that some people might decide to purchase a light truck when they trade in an old car, or they might pick a more efficient car when they trade in an old light truck (e.g. the recent shift of consumers from sedans to SUVs (EIA, 2018)), we leave consideration of this mechanism for future studies.

4.3 Vehicle Discards in the C4C Program

We assume that the C4C program doesn't encourage the retirement of EV platforms, therefore $d_{ea} = 0$. The outflow of retiring vehicles of ICE platforms due to C4C program d_{ia} is:

$$d_{ia} = V_{ia}\beta_{ia} \tag{12}$$

where β_{ia} are the hazard rates of vehicle retirement due to the C4C program, calculated as the product of the reference rate β_i', increasing in age a with sensitivity ε_A:

$$\beta_{ia}' = \beta_i'\, a^{\varepsilon_A} \tag{13}$$

and the effect of the C4C policy η_i on hazard rates:

$$\beta_{ia} = \beta_{ia}'\, \eta_i \tag{14}$$

where η_i is the product of three main effects: the effect of C4C incentive θ^I, the effect of C4C stringency θ_i^S, and the effect of additional fuel savings from C4C program θ_i^{FE}:

$$\eta_i = \theta_i^I\, \theta_i^S\, \theta_i^{FE} \tag{15}$$

The incentive effect θ_i^I reflects how much the incentive value of the C4C program I_i relative to the reference value I' affects the propensity of people to participate in the program:

$$\theta_i^I = \left(\frac{I_i}{I'}\right)^{\varepsilon_I} \tag{16}$$

where ε_I is the sensitivity of the incentive effect to the change in the incentive value.

The C4C program mandates the minimum fuel economy that a new vehicle purchased as a replacement for the traded-in vehicle must satisfy, FE_i^{min}. The stringency effect θ_i^S reflects the fact that higher minimum fuel economy standards that a new replacement vehicle has to satisfy relative to the average fuel economy determined by the CAFE standard FE_i^{CAFE} reduces addressable market by providing fewer vehicle options for people to choose from, therefore reducing C4C hazard rate, i.e., probability of participation in the program:

$$\theta_i^S = \left(\frac{FE_i^{min}}{FE_i^{CAFE}}\right)^{\varepsilon_S} \tag{17}$$

where ε_S is the sensitivity of the stringency effect to the ratio of the minimum mandated fuel economy to the average fuel economy of new vehicles.

While the C4C program mandates the minimum fuel economy in miles per gallon for new vehicles purchased as a replacement, people might decide to buy an even more fuel efficient vehicle, especially if the C4C mandated standard is not much higher than the average fuel economy stipulated by CAFE standards. We capture this effect by calculating the average fuel economy of new vehicle sales induced by the C4C program as the product of the minimum mandated fuel economy FE_i^{min} and the effect of C4C stringency on addressable market θ_i^S on the average increase in the fuel economy of purchased vehicles δ_{FE}:

$$FE_i^{C4C} = FE_i^{min}\left(1 + \delta_{FE}\beta_i^S\right) \tag{18}$$

The more stringent the C4C requirement, the fewer vehicle makes and models that satisfy them are likely to be available on the market, with fewer people likely to be willing to purchase those vehicles.

The effect of fuel savings θ_i^{FE} is calculated based on the additional savings that a person might get if they purchased a new vehicle with the high fuel economy FE_i^{C4C} vs. the new vehicle with the average fuel economy, determined by the CAFE standard FE_i^{CAFE}:

$$\theta_i^{FE} = \left(1 - \left(\frac{1}{FE_i^{C4C}}\right) \Big/ \left(\frac{1}{FE_i^{CAFE}}\right)\right)^{\varepsilon_F} \tag{19}$$

where ε_F is the sensitivity of the fuel savings effect to additional fuel savings.

4.4 Vehicle Replacement Purchases under C4C Program

Vehicles that were traded in under the C4C program are replaced with new vehicles. We assume a one-to-one vehicle replacement ratio. Similar to the Eq. (11), we formulate the mandatory replacement of vehicles as a function of discarded vehicles and the market share of EVs.

$$m_p = \delta_p \sum_{a=Q}^{N} d_{pa} \tag{20}$$

While under different realizations of the C4C program it might be possible that people are paid to simply discard their vehicle without buying a new one, the complexity of estimating the resulting change in travel habits is beyond the scope of this paper, so we do not consider this possibility, establishing a lower bound on the potential reduction in greenhouse gases achieved through the program.

4.5 Greenhouse Gas Accounting

We use standard co-flow formulations (Sterman, 2000) to track GHG emissions from the vehicle fleet. The co-flow structure is parallel to the structure of the vehicle fleet described above, but it tracks emissions from each age cohort instead of vehicle counts, representing age-specific fuel-efficiency, improving fuel-efficiency of new vehicles, and changing the mix of vehicle platforms. The total emissions of platform p sum over N individual age cohorts a:

$$E_p = \sum_{a=1}^{N} E_{pa} \tag{21}$$

The emissions accumulate and deplete following vehicle sales and retirements:

$$\frac{dE_p}{dt} = n_p \mu_p^{CAFE} - \sum_{a=1}^{N} r_{pa} \bar{\mu}_{pa} + m_p \mu_p^{C4C} - \sum_{a=Q}^{N} d_{pa} \bar{\mu}_{pa} \tag{22}$$

where μ_p^{CAFE} is vehicle emissions required by the CAFE policy in grams CO_2 per mile, and $\bar{\mu}_{pa}$ is the average emissions of vehicles of platform p in the age cohort a:

$$\bar{\mu}_{pa} = \frac{E_{pa}}{V_{pa}} \tag{23}$$

Average vehicle emissions of new vehicle sales induced by the C4C program μ_p^{C4C} is calculated from the average fuel economy in the Eq. (18):

$$\mu_i^{C4C} = \frac{\nu_{gas}}{FE_i^{C4C}}$$
$$\mu_e^{C4C} = \mu_e^{EV} \tag{24}$$

where ν_{gas} is the emission factor of gasoline vehicles in (EPA, 2019a) in grams CO_2 per gallon, and μ_e^{EV} is the emission from EVs. We assume that the electric grid used to charge EVs becomes 'greener' over time, reflecting increased share $\sigma_t^{renewables}$ of renewable energy in the U.S.:

$$\mu_e^{EV} = \nu_{grid}\,\eta_e\,(1 - \sigma_t^{renewables}) \tag{25}$$

with emission factor of conventional electrical grid ν_{grid} in grams CO_2 per kWh and the energy efficiency of EVs η_e in kWh per mile which also improves over time.

5 Analysis

In the following sections, we use the model of vehicle fleet turnover to first estimate the baseline emissions reduction that might be achieved through natural fleet turnover in the absence of any additional policies, and then consider accelerated vehicle retirements in combination with fossil fuel tax and transition to renewable electricity to evaluate feasibility of reaching intermediate climate goals by 2050.

5.1 Model Initialization

To estimate the parameters of market formation and consumer choice, we use prior analyses and data from similar settings. We use various sources to make plausible assumptions, not exact estimations, because we study the future behavior of the vehicle market where exact prior numbers might not hold, therefore qualitative and directional assumptions are more important. We use the best available data and previous work on vehicle fleet turnover (Keith, Naumov, & Sterman, 2017b; Keith, Houston, et al., 2019), data or scrappage rates and vehicle miles traveled from NHTSA and Oak Ridge National Laboratory (NHTSA, 2006; Davis et al., 2017), and multiple studies of the U.S. CARS program in 2009 (Abrams & Parsons, 2009; Sivak & Schoettle, 2009; Morrison et al., 2010; Lenski et al., 2013; Li et al., 2013; Hoekstra et al., 2017) to estimate the parameters of the model (see Appendix A: Parameterization of the Model for details).

5.2 Baseline (CAFE only)

First, we consider baseline emissions reduction that results from the improvement in the fuel economy of new vehicles along the requirements for ICE vehicle emissions based on CAFE standards. For years until 2025, we assume that CAFE standards follow the proposed Safer Affordable Fuel-Efficient Vehicles Rule, which freezes CAFE standards between 2020 and 2025 at the level of 37 and 25 miles per gallon for cars and light trucks respectively (NHTSA, 2018). Current CAFE policy doesn't mandate specific numbers for fuel economy beyond the year 2025, so we assume a conservative scenario with a linear trajectory from 2025 with 20% reduction in emissions by 2050 from the 2018 level, which is equivalent to adjusted fuel economy of 41.1 and 29.6 miles per gallon for cars and light trucks respectively. Also, unlike actual CAFE policy, we apply CAFE standards to gasoline vehicles only, excluding EVs so that the increasing sales of EVs don't have the unintended consequence of providing some relief for automakers allowing to sell less fuel-efficient vehicles (Jenn, Azevedo, & Michalek, 2019). The trajectories of new vehicle sales and annual emissions of the fleet for the baseline scenario are shown in Figure 5.

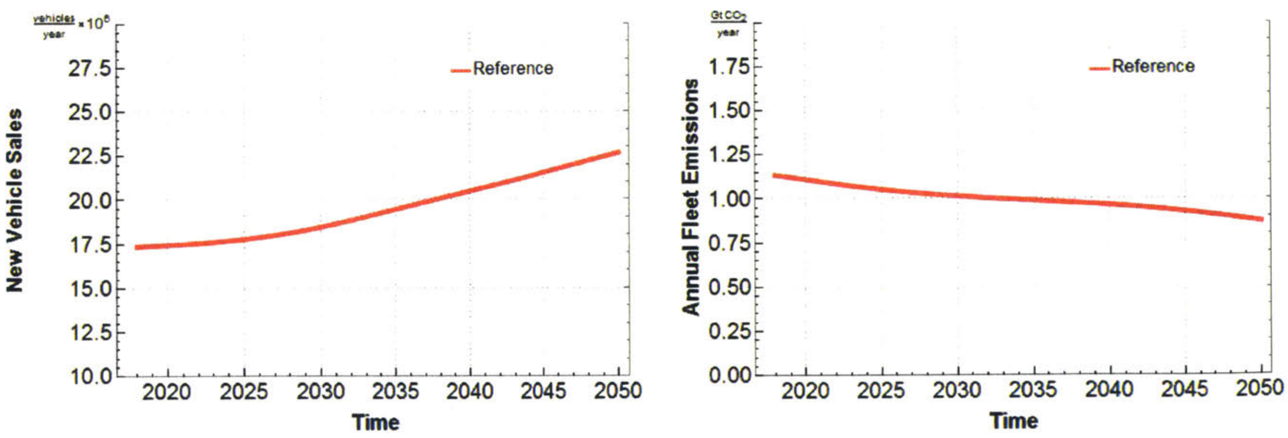

Figure 5 Baseline Scenario (CAFE only)

Relying only on natural fleet turnover, EVs comprise 43% of new vehicle sales by 2050, but the market adoption dynamics are slow, resulting in about 27% installed base share of EVs. The emissions of an average vehicle in the fleet are reduced by about 45%, but this is offset by increasing fleet size due to population growth, so fleet emissions go down by only about 23% (Figure 5, right panel).

5.3 C4C for Efficient Gasoline Vehicles

In order to further reduce vehicle fleet emissions, we now introduce an accelerated vehicle retirements program (C4C) that provides incentives for people to discard older inefficient vehicles, and replace them with new efficient ones, starting in 2020 (Figure 6).

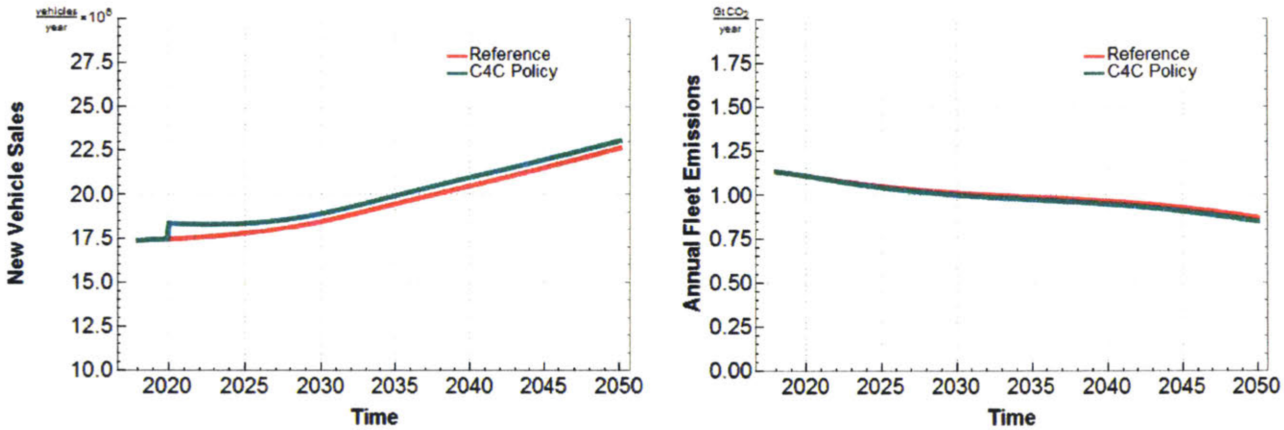

Figure 6. C4C Policy with $4,000 Incentive

We set the incentive at a level of $4,000 per vehicle, roughly equal to the average incentive of the CARS program in 2009 (Li et al., 2013). This policy replaces 29M vehicles by 2050 and gets additional 2% in annual fleet emissions reduction relative to the baseline (Figure 6, right panel), with a unit cost of $254/tonne CO_2. This emission reduction is relatively modest, and is not sufficient to achieve intermediate climate goals by 2050.

The impact of the C4C policy is contingent on two main parameters – C4C stringency, as measured by the multiplier of C4C mandatory minimum fuel economy for replacement vehicles relative to CAFE required fuel economy for all new vehicle sales, and C4C qualifying age, determining the minimum age of vehicles eligible for the C4C program. Our next analysis explores the effect of these parameters on the additional emissions reduction relative to the baseline run, and the unit cost of emissions reduction, two important metrics describing the costs and benefits of the C4C policy (Figure 7).

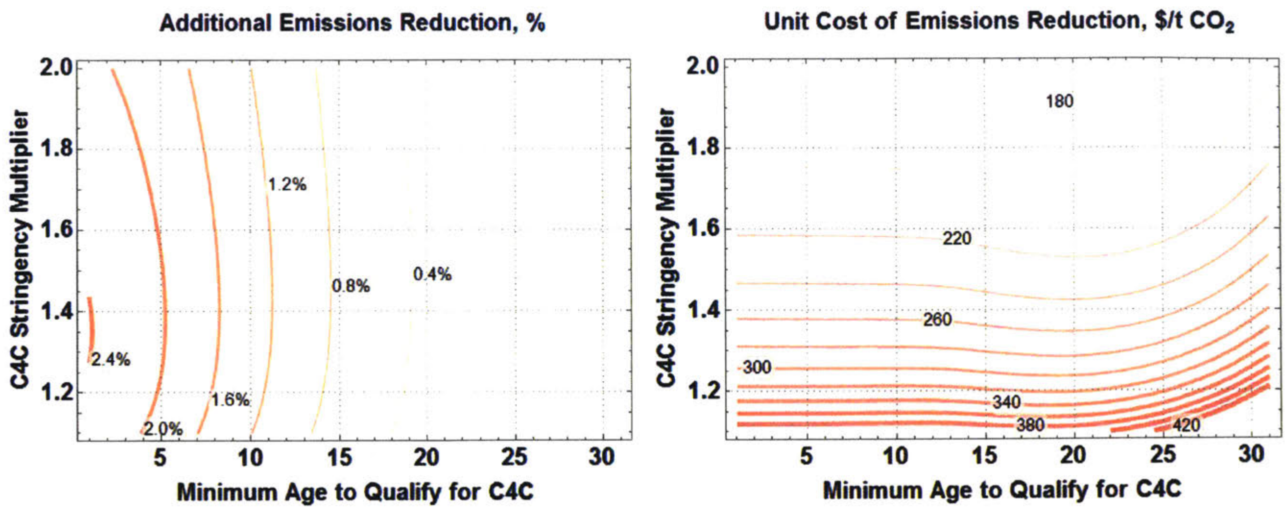

__Figure 7. Effects of C4C Policy Parameters__

Optimal minimum qualifying age exists in terms of additional emission reduction relative to the baseline, given minimum qualifying age (Figure 7, left panel). Emission reduction is the product of reduction per single vehicle and the number of vehicles replaced. Less stringent requirements do not achieve a lot of emission reduction per vehicle, but too stringent requirements negatively affect the propensity of people to participate in the program (because it is harder to find a vehicle that satisfies the requirements, and available vehicles are more expensive), therefore reduce the number of vehicles discarded and replaced.

The unit cost of emission reduction (Figure 7, right panel) is based on the cumulative emission reduction by the year 2050. Given stringency multiplier, there exists a cost-minimizing qualifying age. Including younger vehicles is less optimal, because they are less emission-intensive, therefore additional emissions reduction is insignificant. Limiting the incentive to older vehicles is also more expensive per tonne of CO_2. When younger cohorts are eligible for C4C, the replacement vehicles purchased in lieu of discarded ones will qualify again as they age, and the C4C standards increase, so the emissions reduction accumulates by 2050. When the qualifying age is too high, older cohorts can be replaced fewer times, since it takes time for new replacement vehicles to reach the minimum qualifying cohort, therefore the emission reduction by 2050 does not accumulate as much, making unit costs higher.

The most cost-efficient combination of the two C4C policy parameters is not equal to the most emissions reduction effective combination (see two panels in Figure 7). In the analysis that follows, we use a minimum qualifying age of 5 years, as this is the most intensive vehicle-emission cohort in the current fleet (~2800 vehicle-tonnes CO_2 per mile), and assume the optimal C4C mandated fuel economy multiplier to be 1.4 times more stringent relative to CAFE-based ICE standards to maximize the emissions reduction (Figure 8).

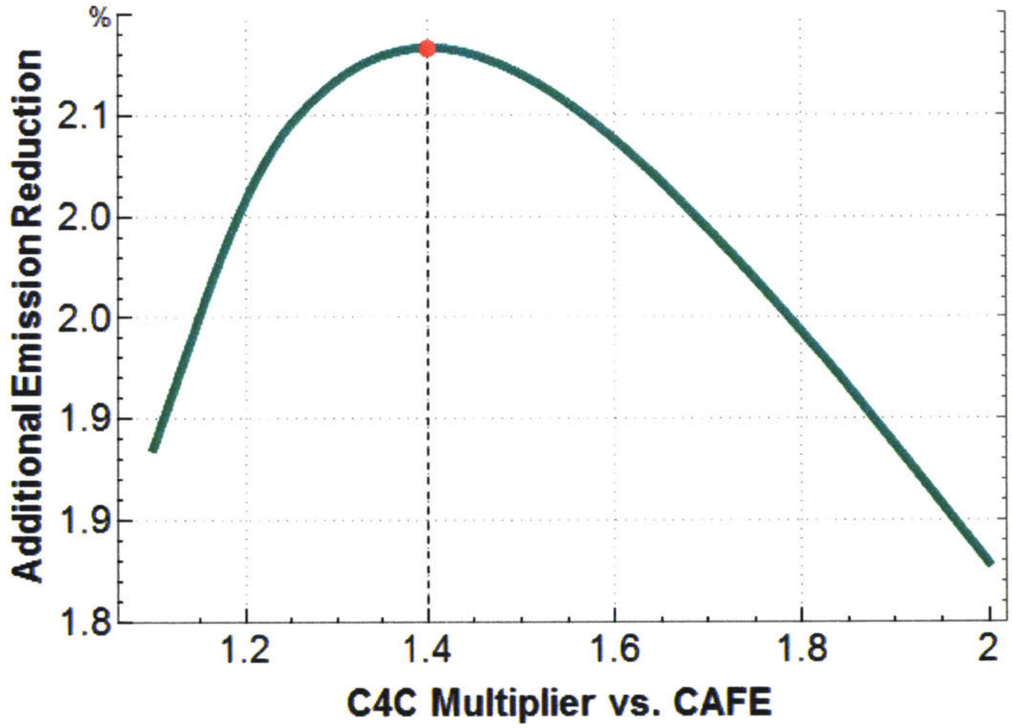

Figure 8. Optimal C4C Stringency Multiplier

Next, we increase the C4C incentive to $8,000 per vehicle (Figure 9).

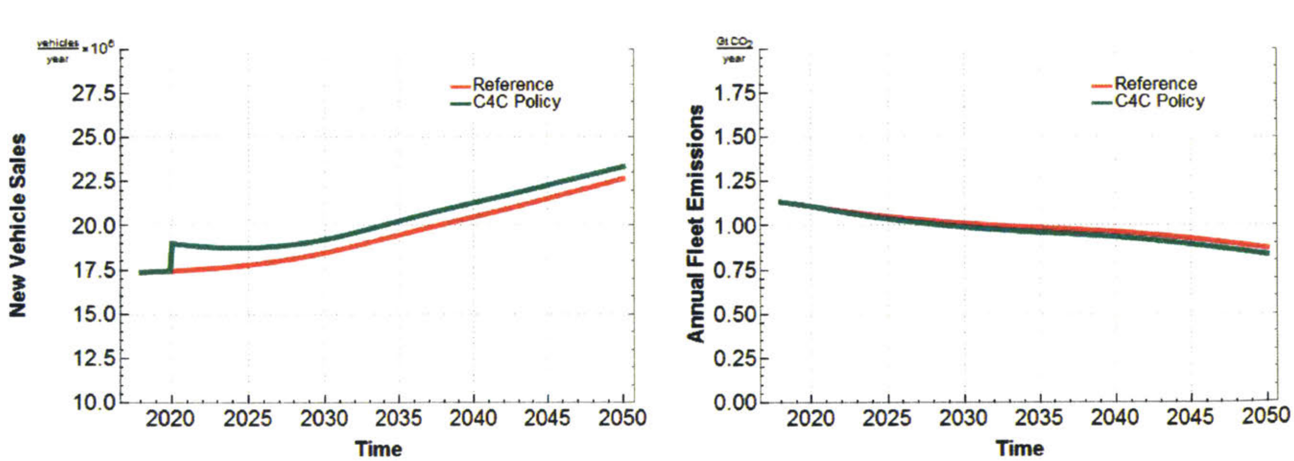

Figure 9. C4C Policy with $8,000 Incentive

This policy replaces 48M vehicles by 2050 and achieves 3.3% reduction in addition to the baseline (Figure 9, right panel), with a unit cost of \$512/tonne CO_2. The emissions reduction remains modest since we are only reducing the emissions of vehicles that people are willing to replace under the C4C program, while the whole fleet keeps emitting CO_2 at the same level as before. The runs above show that there are limits to how much emission reduction can be achieved by simply increasing the incentive within a reasonable range. The higher is the incentive the more people would trade in their old vehicles, but with diminishing marginal returns. Therefore, a very high incentive policy would be uneconomical and not efficient, since the replacement vehicles are still fossil-fuel vehicles, even if with higher fuel-efficiency, therefore unit costs of the emissions reduction would remain very high.

5.4 C4C for Electric Vehicles

We now keep the minimum qualifying age at 5 years and assume that C4C mandates people to buy EVs only ($\sigma_p = 1$ when calculating δ_p in Eq. (11)). This policy not only removes polluting cars from the existing fleet of vehicles, but also helps automakers to reduce manufacturing costs of electric vehicles through learning curves and R&D investment (Argote & Epple, 1990), stimulates market formation by increasing consumer familiarity with EVs and leveraging network effects (Struben & Sterman, 2008), and includes EVs in people's consideration sets (Hauser & Wernerfelt, 1990). Stimulating EV sales also helps resolve a chicken-and-egg issue that exists between EVs and recharging infrastructure (Keith, Naumov, et al., 2019), further promoting sales of EVs, in a virtuous cycle (Figure 4).

We increase the C4C incentive to \$10,000, reflecting the current level of incentives available for buyers of EVs with up to \$7500 tax credits from the federal government and up to additional \$2500 in some states (U.S. DOE, 2019). While the incentive is higher, its level is justified by the expected increase in the emissions reduction due to much more efficient EVs. The results of this policy are shown in Figure 10.

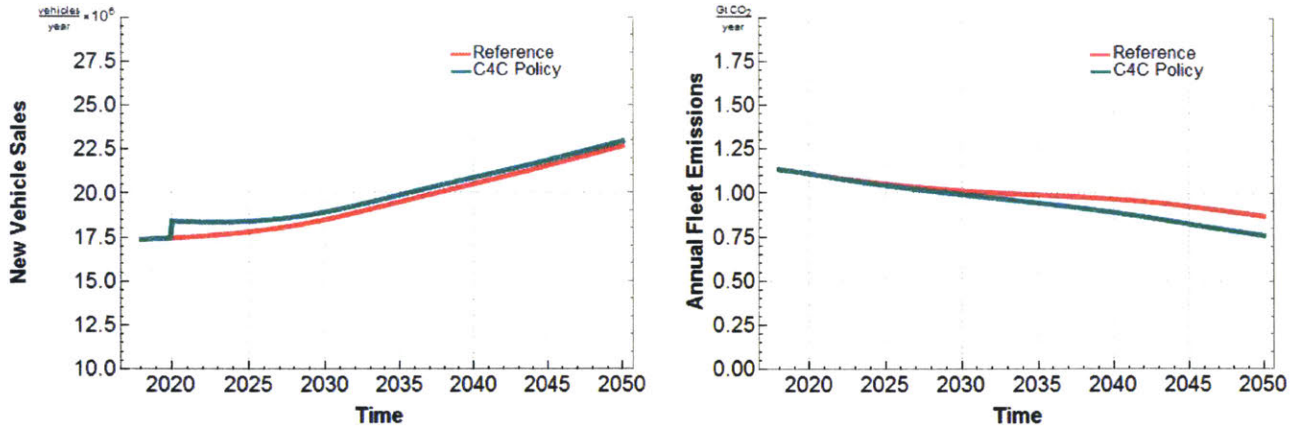

Figure 10. C4C Policy with EVs only and $10,000 Incentive

This policy replaces 27M vehicles by 2050, a much lower number than no-EVs policies above, because of the limited willingness of people to purchase an EV due to its lower utility overall (lower range, limited availability of recharging infrastructure, etc.). However, this policy accomplishes 9.8% emissions reduction in addition to the baseline (Figure 10, right panel), with a unit cost of $176/tonne CO_2, while the share of EVs in new vehicle sales increases to about 53%, and the installed base share of EVs reaches 46% by 2050. Mainly, this is because additional EV sales induced by the C4C policy catalyze the EV market through the market formation loop (Figure 4).

To increase the effectiveness of this policy further, we bring the EV incentive to $15,000 (Figure 11).

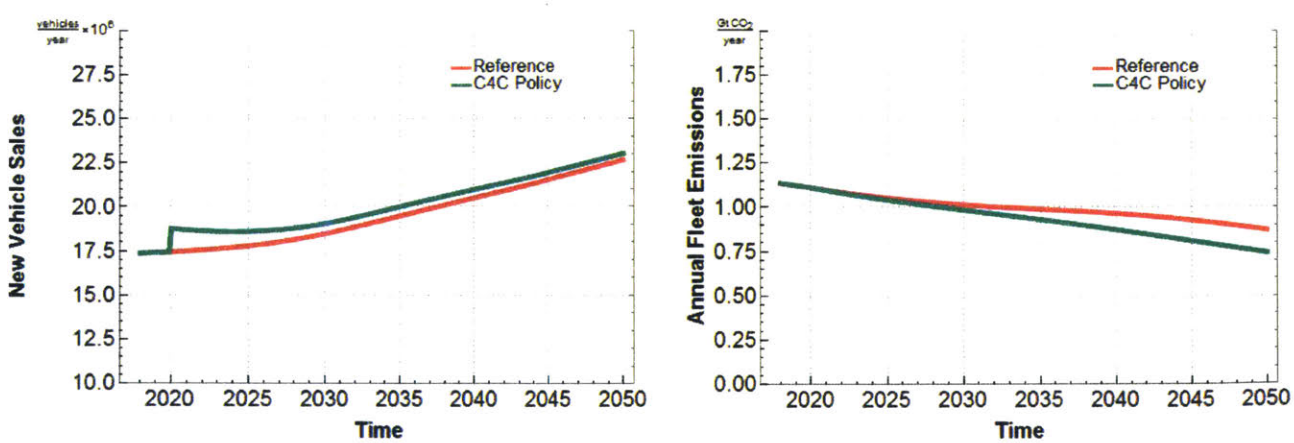

Figure 11. C4C Policy with EVs only and $15,000 Incentive

This policy replaces 36M vehicles by 2050 and achieves 11.5% reduction in addition to the baseline (Figure 11, right panel), with a unit cost of \$282/tonne CO_2. The share of EVs in new vehicle sales increases to about 55%, with the installed base share reaching 49%. Once again, we observe the marginally better aggregate impact, but more expensive, and with the diminishing return, as we exhaust the potential pool of people who would be willing to replace their vehicles.

The results of the C4C policies incentivizing sales of EVs are contingent on the assumptions we have about the learning curve strength of EV technology improvement. It is possible that a technological breakthrough would substantially increase the utility of EVs, promoting their market share further and leading to even lower fleet emissions, but evaluating such possibility is beyond the scope of this paper, therefore our analysis establishes a lower bound on the possible emissions reduction.

5.5 C4C for Electric Vehicles + Gas Tax

A major barrier to the implementation of any of the C4C policies described above is cost, which could render them infeasible from a political perspective. The picture is even more complicated due to the fact that unit emissions reduction is calculated on a cumulative basis, with emissions reductions continue to accrue over decades, but with C4C incentives paid out immediately. Substantial foresight is required to introduce a policy that incurs substantial upfront costs in order to realize long-term emissions reduction. A further limitation is that the benefits of C4C are limited by the number of consumers who choose to participate and purchase a new vehicle, not influencing the behavior of non-participants including owners of newer vehicles that represent the majority of the on-road fleet.

To moderate the cost of C4C implementation, and achieve further emissions reduction, we next consider a policy that combines the C4C program with a gasoline tax in order to correct the unpriced carbon emissions externality. Gas tax increases have historically been politically unpopular in the U.S. (Hammar, Löfgren, & Sterner, 2004). However, combining these policies in this 'carrot and stick' approach allows gas tax revenues to be returned to consumers in the form of C4C incentives, influencing the behavior of the entire population of drivers. We keep the minimum qualifying age at 5 years, and the C4C incentive at \$15,000, and we also introduce a gasoline tax ramping up linearly from 0% in 2020 to 10% of the price of gasoline in 2050 (Figure 12).

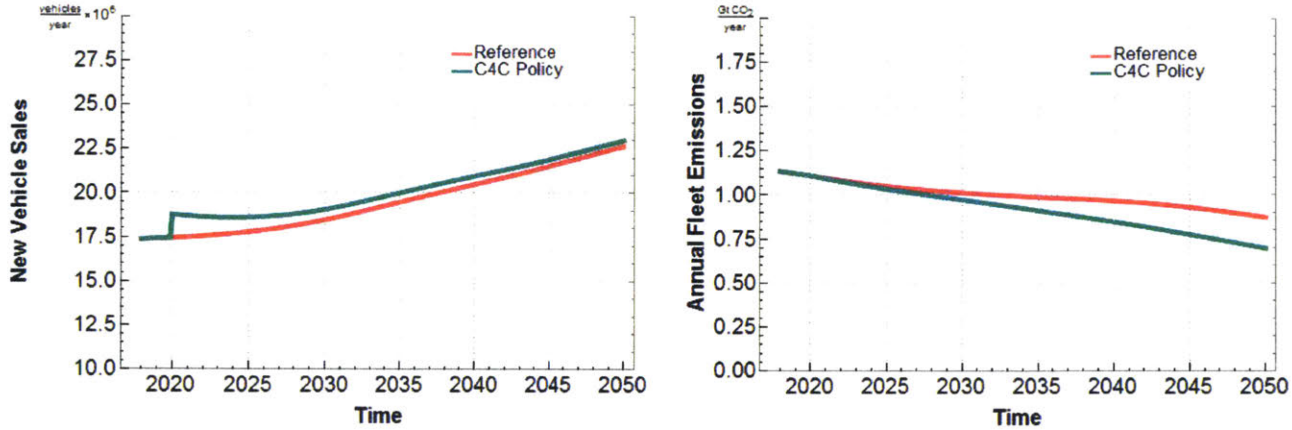

Figure 12. C4C Policy with EV only and Gas Tax

This policy combining both C4C and gas tax achieves 15.6% reduction in GHG in addition to the baseline (Figure 12, right panel), with a unit cost of $79/tonne CO_2, and the share of EVs in new vehicle sales increasing to 61% by 2050, with the fleet share of EVs reaching 54%.

While aversion to the use of gas taxes is understandable from the political perspective, our analysis shows that this combination of policies leads to substantially more emissions reduction, and at significantly lower unit cost (with the possibility of being revenue neutral). The success of this policy might be amplified further if the electricity used to recharge EVs becomes fossil-fuel free.

5.6 C4C for Electric Vehicles + Gas Tax + Renewable Electricity

As long as EVs are recharged using fossil-fuel generated electrons, the absolute reduction in emissions is limited. While 'zero tailpipe emission vehicles' greatly reduce the concentration of greenhouse gases in local urban settings, if the electricity used to recharge them is powered by fossil fuels, there are still emissions of greenhouse gases during power generation. Therefore, it is important to have all EVs charged with renewable electricity. Next, we assume a policy that mandates that all EV charging uses fully renewable electricity starting in 2030. We keep the gas tax policy, to keep internalizing the externalities of fossil-fuel powered vehicles in the fleet (Figure 13).

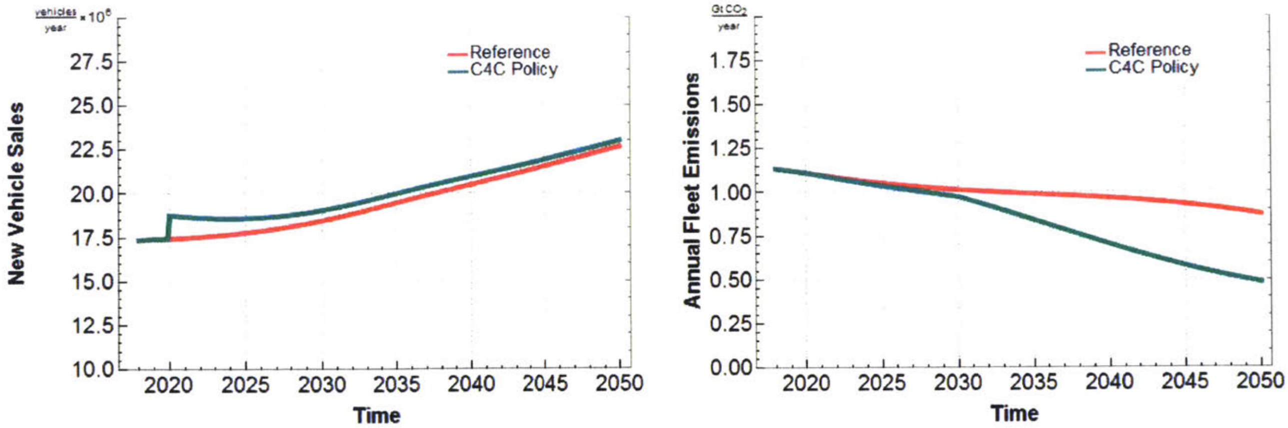

Figure 13. C4C Policy with EVs only, Gas Tax, and Fully Renewable Electricity

This policy achieves 34.2% emissions reduction in addition to the baseline (Figure 13, right panel), and 57.2% reduction in LDV fleet emissions from the 2018 level, with a net unit cost of \$38/tonne CO_2.

5.7 Sensitivity Analysis

The most uncertainty in the model parameterization (Appendix A: Parameterization of the Model) relates to (1) how responsive people are to the incentive of the C4C program (ε_I), (2) how responsive people are to potential fuel savings when replacing a vehicle (ε_F), and (3) how much the probability of participating in the C4C program increases with vehicle age (ε_A). The lower each parameter is, the lower is the response of people to the increasing monetary benefits, or vehicle age respectively, that is the weaker is the increase in the baseline probability of participation in the C4C program. We vary each parameter between 0.1 (not responsive, almost ignoring increasing benefits) and 0.95 (highly responsive, almost proportionally to benefits) in a full factorial sensitivity analysis with 5832 runs (Figure 14).

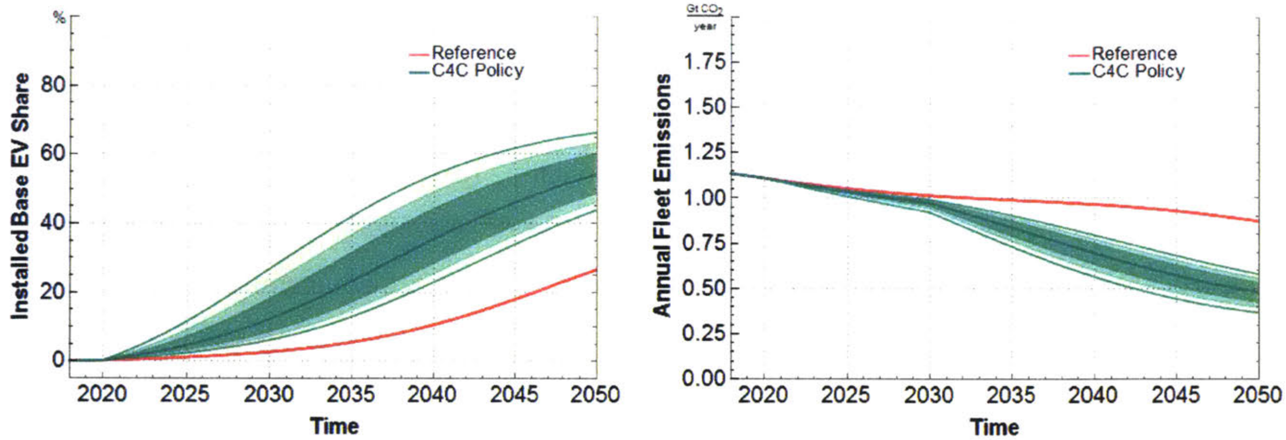

Figure 14. Full Factorial Sensitivity Analysis

The full factorial design explores full parameter space, but in reality, the parameters we are interested in are highly correlated. Sensitivity to the C4C incentive is likely to be highly correlated with sensitivity to fuel savings (both financial incentives), and with sensitivity to vehicle age (older vehicles require more maintenance, with costs not proportional to the residual value of vehicles). A more informative is to explore a fully correlated sensitivity analysis where all sensitivity parameters change together from low to high values (Figure 15).

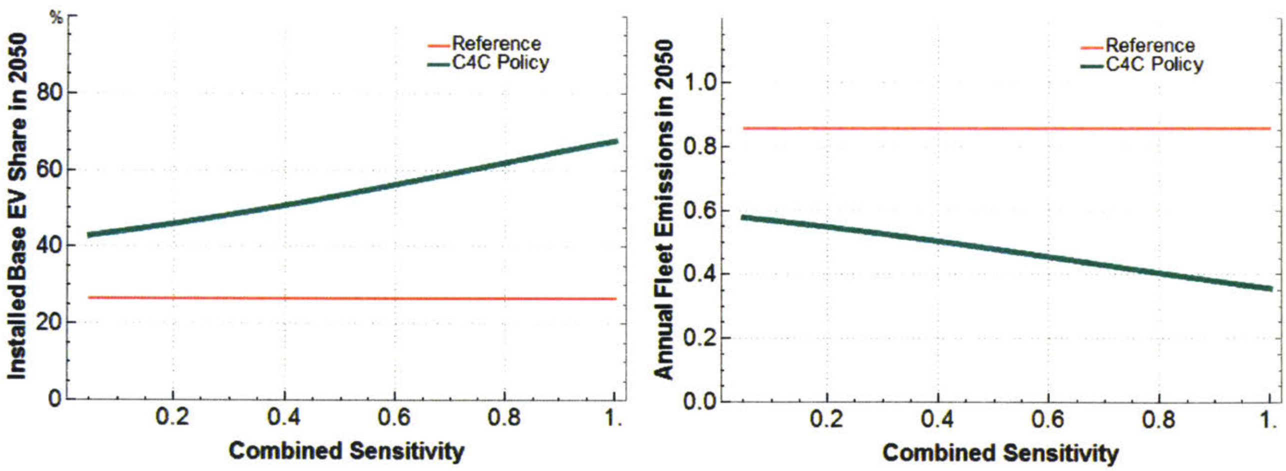

Figure 15. Combined Sensitivity Analysis

We find the results of the combined C4C policy to be relatively robust to the full spectrum of values, achieving 50% to 69% reduction in fleet emissions (Figure 14 and Figure 15, right panel), and the share of the EVs in the on-road vehicle fleet ranging from 44% to 68% (Figure 14 and Figure 15, left panel).

6 Discussion

Reducing greenhouse gas emissions from the transportation sector is important to reach climate goals, as it is the most polluting sector of the U.S. economy. However, automobile transportation is the hardest sector to decarbonize. Unlike decarbonizing the power generation industry, where upstream policies can achieve high effectiveness, reducing emissions from LDV fleet requires dealing with preferences of consumers, which are highly heterogeneous and hard to change.

Boosting fuel economy standards and reducing emissions of new vehicles through policies such as CAFE or promoting sales of new low- and zero-emission vehicles (such as EVs) is not sufficient to bring the US in line with the Paris Agreement on Climate Change. Such policies address the inflow of vehicles, but vehicles are very durable, and stay in the fleet for decades, polluting the environment until they retire. Accelerated retirement of old gas-guzzlers can provide meaningful improvements towards meeting the goals of the Paris Agreement.

Cash-for-clunkers (C4C) policies that incentivize the replacement of old vehicles in the fleet provide levers to reduce fleet emissions and improve the average fuel economy of the whole fleet faster. However, incentivizing more fuel-efficient ICE vehicles is not sufficient to achieve a substantial reduction in emissions by 2050, given the plausible trajectory of the improvement in fuel economy. It is important for C4C policy to require that all the replacement purchases of retired vehicles are EVs to get closer to the climate goals. While the number of vehicles replaced under such policy is lower due to the relatively lower attractiveness of EVs (e.g. due to factor such as range anxiety, recharging time, and recharging infrastructure availability), the unit cost of emissions reduction is ultimately lower due to much better energy efficiency of EVs, and because such policies stimulate market formation for EVs, making them more attractive to all buyers over time.

However, such C4C EV policy comes at a cost that might be prohibitively high to achieve meaningful emissions reduction in time. To offset the costs of the C4C program and internalize the carbon externality of fossil-fuel vehicles, it is reasonable to introduce a gas tax. Such a policy would provide further leverage on emissions reduction, because gas tax reduces fuel consumption across the whole fleet (not just eligible clunkers) by effectively reducing vehicle miles traveled when fuel prices increase. To achieve further reduction in vehicle fleet emissions, greening the electricity used to recharge EVs is important to stop the accumulation of pollutions in the atmosphere from the displaced emissions at the power generation sites that use fossil fuels.

Our study is not without limitations. We present a set of conservative scenarios, as our model assumes that existing modes of car ownership and use continue, therefore it doesn't consider an additional increase in the attractiveness of EVs due to technological breakthroughs, and also change in commuting patterns, e.g., pooling (Naumov & Keith, 2019). Future research can address the potential impact of sharing economy and higher utilization of vehicles on the emissions coming from operations and maintenance of local vehicle fleets.

We assume that the mix between cars and light trucks remains the same throughout the model. It is possible that people might decide to purchase a light truck when they trade in an old car, or they might pick a more efficient car when they trade in an old light truck. We leave consideration of this mechanism for future studies, but we believe that additional insights can be gained from explicitly capturing the endogenous change in consumer preferences, as the result of evolving utility attributes of the EV platform.

Furthermore, our model assumes that every vehicle traded in under the C4C program is replaced by a new vehicle, with a one-to-one ratio. Under different realizations of the C4C program, it might be possible that people are paid to simply discard their vehicle without buying a new one, switching over to car-sharing or public transit. We do not consider this possibility, therefore establishing a lower bound on the potential reduction in greenhouse gases achieved through the program, but future studies could estimate the potential additional gain associated with this behavior.

Designing an effective and efficient mix of policies to stay on track to reduce transportation fleet emissions is hard. While policies that promote sales of low- and zero-emission vehicles look very effective, we show that counting on natural fleet turnover is myopic, and actionable steps that replace the most polluting vehicles in the fleet with EVs that can be recharged with renewable electrons are needed to achieve fleet emissions reductions within a reasonable time frame to meet the climate goals.

Appendix A: Parameterization of the Model

Table 1: Model Parameters

Parameter	*Value*
Initial Price Surcharge of EVs relative to ICE	0.25
Reference Inconvenience of EVs	-2
Weight of Price Surcharge	-2
Weight of Fuel Savings	2
Logit Choice Scaling	2.5
Grid Electricity Cost, $/kWh	0.15
Current Share Renewable Electricity	0.15
Max Share Renewable Electricity	0.9
Learning Curve Strength Price	0.25
Learning Curve Strength Market Formation	0.25
Average VMT, miles/year/vehicle	11,525
Aggregate Market Growth Rate, 1/year	0.01
Hazard Rate of vehicle discards, 1/year	(Davis et al., 2017)
Initial Vehicle Fleet, vehicles	(Keith, Houston, et al., 2019)
Initial Emissions, grams CO_2/mile*vehicles	(Keith, Houston, et al., 2019)
Baseline Fuel Price, $/gallon	3.0
CAFE standards	(Keith, Houston, et al., 2019)
Reference C4C Hazard Rate	0.002
Sensitivity of C4C Hazard Rate to Vehicle Age	0.5
Reference C4C Incentive Value, $/vehicle	$4,000
Reference C4C EV Incentive Value, $/vehicle	$20,000
Sensitivity of Incentive Effect	0.75
C4C Policy Start Year	2020
C4C Qualifying Fuel Economy Start Year, Cars, miles/gallon	35
C4C Qualifying Fuel Economy End Year, Cars, miles/gallon	55
C4C Qualifying Fuel Economy Start Year, Light Trucks, miles/gallon	25
C4C Qualifying Fuel Economy End Year, Light Trucks, miles/gallon	40
Gas Tax Start Year	2020
Fully Renewable Electricity Available in	2030
Sensitivity of Addressable Market to C4C Stringency	-0.75
Sensitivity of C4C Stringency Effect	-1.5
Sensitivity of Fuel Savings Effect	0.75

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Model Documentation

```
"2050 Emissions Target CO2 per mile i"[ICE]= INITIAL(
              Start Point p[ICE]*MAX(0,(1-"2050 reduction of emissions")))
Units: g CO2/mile
Effective vehicle emissions in 2050

"2050 EV Energy Efficiency increase"=
       0
Units: dmnl
Increase in energy efficiency of EVs by 2050

"2050 reduction of emissions"=
       0.2
Units: dmnl [0,0.95,0.05]
Reduction in emissions by 2050 relative to 2018

Actual C4C Fuel Consumption of New Vehicles i[ICE]=
       1 / Actual C4C Fuel Economy of New Vehicles i[ICE]
Units: gallon/mile
Actual fuel consumption of C4C replacement vehicles

Actual C4C Fuel Economy of New Vehicles i[ICE]=
       C4C Required Fuel Economy of New Vehicles i[ICE] *
       (1 + C4C Average FE Shift i[ICE])
Units: mile/gallon
Actual fuel economy of C4C replacement vehicles

Actual C4C Replacement Vehicles Emission p[ICE]=
       ICE CO2 conversion factor / Actual C4C Fuel Economy of New Vehicles i[ICE]
Actual C4C Replacement Vehicles Emission p[EV]=
       GHG Emissions EV Effective e[EV]
Units: grams CO2/mile
Actual emissions of C4C replacement vehicles

"Additional Annual Fuel Savings from trade-in to C4C vs CAFE i"[ICE]=
       Fuel Price Adjusted VMT * Real Fuel Price *
       ("New Vehicle Fuel Consumption CAFE + EV p"[ICE] -
       Actual C4C Fuel Consumption of New Vehicles i[ICE])
Units: $/(vehicle*year)
Annual fuel savings from driving a vehicle with C4C standards
              vs. CAFE standards for fuel economy

Age:
       (a0-a30)->Emissions Cohort

Aggregate Market Growth Rate=
       0.01
Units: dmnl/year [0,0.1,0.01]
Market growth rate

All but first:
       (c1-c30)->All but last

All but last:
       (c0-c29)->All but first

All but oldest:
       (a0-a29)->All but youngest

All but youngest:
```

```
        (a1-a30)->All but first

Annual Cost of C4C Program=
        (SUM(C4C Replacement Sales p[ICE!]) +
        SUM(C4C Replacement Sales p[EV!])) * C4C Incentive Value
Units: $/year
Annual cost of the C4C program

Annual Emissions per Vehicle C4C=
        SUM(Emissions cp[Emissions Cohort!,Platform!]*
        VMT cp[Emissions Cohort!,Platform!]) /
        SUM(Fleet ap[Age!,Platform!]) / Grams CO2 per Tonne CO2
Units: Tonnes CO2/(vehicle*year)
Annual emissions of a vehicle when C4C program is active (using
                VMT by age cohort)

Annual Emissions per Vehicle Reference=
        SUM(Emissions cp 0[Emissions Cohort!,Platform!]*
        VMT cp[Emissions Cohort!,Platform!]) /
        SUM(Fleet ap 0[Age!,Platform!]) / Grams CO2 per Tonne CO2
Units: Tonnes CO2/(vehicle*year)
Annual emissions of a vehicle when C4C program is active (using
                VMT by age cohort), reference

Annual EV Sales=
        SUM(Sales p[EV!]+C4C Replacement Sales p[EV!])
Units: vehicle/year
Annual local sales of EVs

Annual EV Sales 0=
        SUM(Sales p 0[EV!])
Units: vehicle/year
Annual local sales of EVs, reference

"Annual Fuel Savings from trade-in to CAFE ai"[Age,ICE]=
        Fuel Price Adjusted VMT * Real Fuel Price *
        (Average Fuel Consumption ci[Emissions Cohort,ICE] -
        "New Vehicle Fuel Consumption CAFE + EV p"[ICE])
Units: $/(vehicle*year)
Annual fuel savings from driving a vehicle with CAFE standards
                vs. old vehicle that was traded in

Annual Gas Tax Revenue=
        SUM(Total Fuel Consumption ai[Age!,ICE!]) * Gas Tax
Units: $/year
Annual revenue from gas tax

Annual Retirements C4C=
        SUM(C4C Discards ap[Age!,Platform!])
Units: vehicles/year
Annual retirements of all vehicles under C4C program

Annual World EV Sales=
        Cumulative World EV Sales * EV Market Growth Rate
Units: vehicle/year
Annual worldwide sales of EVs

Average Age of Fleet C4C=
        SUM(Total Age ap[Age!,Platform!]) / SUM(Fleet ap[Age!,Platform!])
Units: years
Average age of vehicles in the fleet

Average Age of Fleet Reference=
```

```
       SUM(Total Age ap 0[Age!,Platform!]) / SUM(Fleet ap 0[Age!,Platform!])
Units: years
Average age of vehicles in the fleet, reference

Average Annual Emissions per Vehicle C4C=
       SUM(Emissions cp[Emissions Cohort!,Platform!]) * Fuel Price Adjusted VMT /
       SUM(Fleet ap[Age!,Platform!]) / Grams CO2 per Tonne CO2
Units: Tonnes CO2/(vehicle*year)
Annual emissions of a vehicle when C4C program is active (using
              average VMT)

Average Annual Emissions per Vehicle Reference=
       SUM(Emissions cp 0[Emissions Cohort!,Platform!]) * Average VMT /
       SUM(Fleet ap 0[Age!,Platform!]) / Grams CO2 per Tonne CO2
Units: Tonnes CO2/(vehicle*year)
Annual emissions of a vehicle when C4C program is active (using
              average VMT), reference

Average Emissions cp[Emissions Cohort,Platform]=
       ZIDZ(Emissions cp[Emissions Cohort,Platform],Fleet ap[Age,Platform])
Units: grams CO2/mile
Average emissions by age and platform

Average Emissions cp 0[Emissions Cohort,Platform]=
       ZIDZ(Emissions cp 0[Emissions Cohort,Platform],Fleet ap 0[Age,Platform])
Units: grams CO2/mile
Average emissions by age and platform, reference

Average Fleet Emission Reduction=
       (Initial Average Total Fleet Emissions-Average Total Fleet Emissions) /
       Initial Average Total Fleet Emissions
Units: dmnl
Fleet emissions reduction (using average VMT)

Average Fleet Emission Reduction Improvement=
       Average Fleet Emission Reduction - Average Fleet Emission Reduction Reference
Units: dmnl
Additional fleet emissions reduction (using average VMT)

Average Fleet Emission Reduction Reference=
       (Initial Average Total Fleet Emissions Reference-
       Average Total Fleet Emissions Reference) /
       Initial Average Total Fleet Emissions Reference
Units: dmnl
Fleet emissions reduction (using average VMT), reference

Average Fleet Emissions=
       SUM(Emissions cp[Emissions Cohort!,Platform!])/
       SUM(Fleet ap[Age!,Platform!])
Units: grams CO2/mile
Average emissions of a vehicle

Average Fleet Emissions 0=
       SUM(Emissions cp 0[Emissions Cohort!,Platform!])/
       SUM(Fleet ap 0[Age!,Platform!])
Units: grams CO2/mile
Average emissions of a vehicle, reference

Average Fuel Consumption C4C=
       Average Fleet Emissions/ICE CO2 conversion factor
Units: gallon/mile
Average fuel consumption of a vehicle
```

```
Average Fuel Consumption ci[Emissions Cohort,ICE]=
	Average Emissions cp[Emissions Cohort,ICE] / ICE CO2 conversion factor
Units: gallon/mile
Average fuel consumption of ICE vehicles by age

Average Fuel Consumption Reference=
	Average Fleet Emissions 0/ICE CO2 conversion factor
Units: gallon/mile
Average fuel consumption of a vehicle, reference

Average Fuel Economy C4C=
	1 / Average Fuel Consumption C4C
Units: miles/gallon
Average fuel economy of a vehicle

Average Fuel Economy ci[Emissions Cohort,ICE]=
	ZIDZ(1,Average Fuel Consumption ci[Emissions Cohort,ICE])
Units: mile/gallon
Average fuel economy of ICE vehicles by age

Average Fuel Economy Reference=
	1 / Average Fuel Consumption Reference
Units: miles/gallon
Average fuel economy of a vehicle, reference

Average Miles Driven ai[Age,ICE]=
	Fleet ap[Age,ICE] * Fuel Price Adjusted VMT
Units: mile/year
Average VMT of ICE vehicles

Average Time Per Age[Age]=
	1,1,1,1,1,1,1,1,1,1,
	1,1,1,1,1,1,1,1,1,1,
	1,1,1,1,1,1,1,1,1,5
Units: year
Average tenure of vehicles in each age cohort

Average Total Fleet Emissions=
	SUM(Emissions cp[Emissions Cohort!,Platform!]) * Fuel Price Adjusted VMT /
	Grams CO2 per Gigatonne CO2
Units: Gigatonnes CO2/year
Total emissions of the fleet (using average VMT)

Average Total Fleet Emissions Reference=
	SUM(Emissions cp 0[Emissions Cohort!,Platform!]) * Average VMT /
	Grams CO2 per Gigatonne CO2
Units: Gigatonnes CO2/year
Total emissions of the fleet (using average VMT), reference

Average VMT=
	11525
Units: miles/year/vehicle
Average VMT of a vehicle

Baseline Fuel Price=
	3
Units: $/gallon
Baseline fuel price (before additional gas tax)

C4C Average FE Shift i[ICE]=
	Reference C4C Average FE Shift *
	Effect of C4C Stringency on Addressable Market i[ICE]
Units: dmnl
```

```
Actual increase in fuel economy relative to mandated C4C fuel
              economy (available vehicles can do better)

C4C Discards ap[Age,ICE]=
       Fleet ap[Age,ICE] * C4C Hazard Rate ai[Age,ICE]
C4C Discards ap[Age,EV]=
              0
       Units: vehicles/year
       The outflow of vehicles due to C4C program

C4C End Year=
       2050
Units: year [2018,2050,1]
Stop year of the C4C program

C4C Hazard Rate ai[Age, ICE]=
       IF THEN ELSE
         (Age < Minimum Age to Qualify for C4C :OR: Flag C4C Active = 0,
           0,
           IF THEN ELSE
             (SW C4C must buy EVs = 1,
              MIN(Combined Effect of EV on C4C Hazard Rate i[ICE] *
              Reference C4C Hazard Rate ai[Age,ICE], 1),
              MIN(Combined Effect of ICE on C4C Hazard Rate i[ICE] *
              Reference C4C Hazard Rate ai[Age,ICE], 1)
             )
         )
Units: dmnl/year
Effective propensity of participation in the C4C program

C4C Incentive Value=
       4000
Units: $/vehicle [0,15000,1000]
C4C program incentive

C4C Replacement Sales p[Car]=
       SUM(C4C Discards ap[Age!, Car]) *
       IF THEN ELSE
         (SW C4C must buy EVs = 1,
          0,
          (1-Share of EV i[Car])
         )
             C4C Replacement Sales p[LightTruck]=
             SUM(C4C Discards ap[Age!, LightTruck]) *
             IF THEN ELSE
               (SW C4C must buy EVs = 1,
                0,
                (1-Share of EV i[LightTruck])
               )
             C4C Replacement Sales p[EVCar]=
             SUM(C4C Discards ap[Age!, Car]) *
             IF THEN ELSE
               (SW C4C must buy EVs = 1,
                1,
                Share of EV i[Car]
               )
             C4C Replacement Sales p[EVLightTruck]=
             SUM(C4C Discards ap[Age!, LightTruck]) *
             IF THEN ELSE
               (SW C4C must buy EVs = 1,
                1,
                Share of EV i[LightTruck]
               )
```

```
Units: vehicle/year
The inflow of replacement sales due to C4C program

C4C Required Fuel Economy of New Vehicles i[Car]=
       "New Vehicle Fuel Economy CAFE + EV p"[Car] *

       IF THEN ELSE
         (Time < C4C Start Year :OR: Time > C4C End Year,
          1,
          C4C Stringency Multiplier Cars
         )
              C4C Required Fuel Economy of New Vehicles i[LightTruck]=
              "New Vehicle Fuel Economy CAFE + EV p"[LightTruck] *

              IF THEN ELSE
                (Time < C4C Start Year :OR: Time > C4C End Year,
                 1,
                 C4C Stringency Multiplier Light Trucks
                )
Units: miles/gallon [20,200]
Required fuel economy for C4C replacement purchases

C4C Start Year=
       2020
Units: year [2018,2050,1]
Start year of the C4C program

C4C Stringency Multiplier Light Trucks=
       C4C Stringency Multiplier
Units: dmnl [1,2,0.1]
C4C stringency multiplier of fuel economy vs. CAFE for light
              trucks

C4C Stringency Multiplier=
       1.4
Units: dmnl [1,2,0.1]
C4C stringency multiplier of fuel economy vs. CAFE

C4C Stringency Multiplier Cars=
       C4C Stringency Multiplier
Units: dmnl [1,2,0.1]
C4C stringency multiplier of fuel economy vs. CAFE for cars

Combined Effect of EV on C4C Hazard Rate i[ICE]=
       Effect of C4C EV Incentive on C4C Hazard Rate *
       Effect of Additional Fuel Savings from driving EV vs ICE on C4C Hazard Rate i
       [ICE]
Units: dmnl
Combined effect on propensity to participate in the C4C program
              for EVs

Combined Effect of ICE on C4C Hazard Rate i[ICE]=
       Effect of Additional Fuel Savings from Driving C4C vs CAFE on C4C Hazard Rate i
       [ICE] * Effect of C4C Incentive on C4C Hazard Rate *
       Effect of C4C Stringency on C4C Hazard Rate i[ICE]
Units: dmnl
Combined effect on propensity to participate in the C4C program
              for ICE vehicles

Cost of Driving EV e[EV]=
       Energy Consumption EV e[EV] * Electricity Cost * Average VMT
Units: $/(year*vehicle)
Cost of driving an EV
```

```
Cost of Driving EV e 0[EV]=
       Energy Consumption EV e[EV] * Grid Electricity Cost * Average VMT
Units: $/(year*vehicle)
Cost of driving an EV, reference

Cost of Driving ICE i[ICE]=
       Fuel Price Adjusted VMT * Real Fuel Price *
       New Vehicle ICE Fuel Consumption CAFE i[ICE]
Units: $/(year*vehicle)
Cost of driving an ICE vehicle

Cost of Driving ICE i 0[ICE]=
       Average VMT * Baseline Fuel Price *
       New Vehicle ICE Fuel Consumption CAFE i[ICE]
Units: $/(year*vehicle)
Cost of driving an ICE vehicle, reference

Cumulative Cost of C4C Program= INTEG (
       Annual Cost of C4C Program,
              0)
Units: $
Cumulative cost of the C4C program

Cumulative Emissions= INTEG (
       Increase in Cumulative Emissions,
              0)
Units: Gigatonnes CO2
Cumulative emissions of the fleet

Cumulative Emissions Reduction=
       Cumulative Emissions Reference - Cumulative Emissions
Units: Gigatonnes CO2
Reduction in cumulative emissions relative to reference

Cumulative Emissions Reference= INTEG (
       Increase in Cumulative Emissions Reference,
              0)
Units: Gigatonnes CO2
Cumulative emissions of the fleet, reference

Cumulative EV Sales= INTEG (
       Annual EV Sales,
              Reference Cumulative EV Sales)
Units: vehicle
Cumulative local sales of EVs

Cumulative EV Sales 0= INTEG (
       Annual EV Sales 0,
              Reference Cumulative EV Sales)
Units: vehicle
Cumulative local sales of EVs, reference

Cumulative Gas Tax Revenue= INTEG (
       Annual Gas Tax Revenue,
              0)
Units: $
Cumulative revenue from gas tax

Cumulative Retirements C4C= INTEG (
       Annual Retirements C4C,
              0)
Units: vehicles
```

Cumulative retirements of all vehicles under C4C program

```
Cumulative World EV Sales= INTEG (
       Annual World EV Sales,
              Reference Cumulative World EV Sales)
Units: vehicle
Cumulative worldwide sales of EVs

Current Share Renewables=
       0.15
Units: dmnl
Initial share of renewable power generation

Custom 2nd Point i[ICE]=
       230, 330
Units: grams CO2/mile [0,500,1]
Vehicle emissions at the second point of the piecewise function
              that describes custom CAFE policy

Custom 2nd Point Year=
       2025
Units: year [2018,2050,1]
Year of the second point of the piecewise function that
              describes custom CAFE policy

Custom 3rd Point i[ICE]=
       230, 330
Units: grams CO2/mile [0,500,1]
Vehicle emissions at the third point of the piecewise function
              that describes custom CAFE policy

Custom 3rd Point Year=
       2035
Units: year [2018,2050,1]
Year of the third point of the piecewise function that describes
              custom CAFE policy

Effect of Additional Fuel Savings from Driving C4C vs CAFE on C4C Hazard Rate i
[ICE]=
       (1+Relative Fuel Savings from Driving C4C vs CAFE i[ICE]) ^
       Sensitivity of Fuel Savings Effect
Units: dmnl
Effect of fuel savings on propensity to participate in the C4C
              program for ICE vehicles

Effect of Additional Fuel Savings from driving EV vs ICE on C4C Hazard Rate i
[ICE]=
       (1+Relative Fuel Savings from Driving EV e[EV]) ^
       Sensitivity of Fuel Savings Effect
Units: dmnl
Effect of fuel savings on propensity to participate in the C4C
              program for EVs

Effect of C4C EV Incentive on C4C Hazard Rate=
       (C4C Incentive Value / Reference C4C EV Incentive Value) ^
       Sensitivity of Incentive Effect
Units: dmnl
Effect of C4C incentive on propensity to participate in the C4C
              program for EVs

Effect of C4C Incentive on C4C Hazard Rate=
       (C4C Incentive Value / Reference C4C Incentive Value) ^
       Sensitivity of Incentive Effect
```

```
Units: dmnl
Effect of C4C incentive on propensity to participate in the C4C
             program for ICE vehicles

Effect of C4C Stringency on Addressable Market i[ICE]=
       (C4C Required Fuel Economy of New Vehicles i[ICE] /
       "New Vehicle Fuel Economy CAFE + EV p"[ICE]) ^
       Sensitivity of Addressable Market to C4C Stringency
Units: dmnl
Effect of addressable market (available makes and models)
             satisfying C4C standard stringency

Effect of C4C Stringency on C4C Hazard Rate i[ICE]=
       (C4C Required Fuel Economy of New Vehicles i[ICE] /
       "New Vehicle Fuel Economy CAFE + EV p"[ICE]) ^
       Sensitivity of C4C Stringency Effect
Units: dmnl
Effect of C4C stringency standards on propensity to participate
             in the C4C program (more stringent standards mean it is harder
             to find a car)

Effect of Learning on Market Formation=
       (Cumulative EV Sales / Reference Cumulative EV Sales)^
       LOG(1-Learning Curve Strength Market Formation, 2)
Units: dmnl
Effect of learning on EV market formation

Effect of Learning on Market Formation 0=
       (Cumulative EV Sales 0 / Reference Cumulative EV Sales)^
       LOG(1-Learning Curve Strength Market Formation, 2)
Units: dmnl
Effect of learning on EV market formation, reference

Effect of Learning on Price=
       (Cumulative EV Sales / Reference Cumulative EV Sales)^
       LOG(1-Learning Curve Strength Price, 2)
Units: dmnl
Effect of local learning on EV price

Effect of Learning on Price 0=
       (Cumulative EV Sales 0 / Reference Cumulative EV Sales)^
       LOG(1-Learning Curve Strength Price, 2)
Units: dmnl
Effect of local learning on EV price, reference

Effect of World Learning on Price=
       (Cumulative World EV Sales / Reference Cumulative World EV Sales)^
       LOG(1-Learning Curve Strength Price, 2)
Units: dmnl
Effect of worldwide learning on EV price

Elasticity of VMT to Fuel Price=
       -0.3
Units: dmnl
Elasticity of VMT to fuel price

Electricity Cost=
       Grid Electricity Cost +

       Renewable Electricity Surcharge *
       IF THEN ELSE
         (SW EV Renewable Electricity = 1 :AND:
          Time >= Year of Fully Renewable Electricity
```

```
          ,
          1,
          Green Electricity Share
         )
Units: $/(kW*hour)
Effective cost of electricity used for recharging EVs

Emission Introduction from C4C Replacement p[Platform]=
       C4C Replacement Sales p[Platform] *
       Actual C4C Replacement Vehicles Emission p[Platform]
Units: grams CO2*vehicle/(mile*year)
The increase in emissions due to replacement vehicles from C4C
              program

Emissions Cohort:
       (c0-c30)->Age

Emissions Cohort Progression cp[Emissions Cohort,Platform]=
       Fleet Aging ap[Age,Platform]*
       Average Emissions cp[Emissions Cohort,Platform]
Units: grams CO2/mile*vehicles/year
Change in emissions due to vehicle aging

Emissions Cohort Progression cp 0[Emissions Cohort,Platform]=
       Fleet Aging ap 0[Age,Platform]*
       Average Emissions cp 0[Emissions Cohort,Platform]
Units: grams CO2/mile*vehicles/year
Change in emissions due to vehicle aging, reference

Emissions cp[c0,Platform]= INTEG (
       Emissions Introduction p[Platform]+
       Emission Introduction from C4C Replacement p[Platform]-
       Emissions Cohort Progression cp[c0,Platform]-
       Emissions Phase Out cp[c0,Platform] -
       Emissions out due to C4C cp[c0,Platform],
              Initial Emissions cp[c0,Platform])
Emissions cp[All but first,Platform]= INTEG (
       Emissions Cohort Progression cp[All but last,Platform]-
       Emissions Cohort Progression cp[All but first,Platform]-
       Emissions Phase Out cp[All but first,Platform] -
       Emissions out due to C4C cp[All but first,Platform],
              Initial Emissions cp[All but first,Platform])
Units: vehicles*grams CO2/mile
The emissions of vehicles by age cohort

Emissions cp 0[c0,Platform]= INTEG (
       Emissions Introduction p 0[Platform]-
       Emissions Cohort Progression cp 0[c0,Platform]-
       Emissions Phase Out cp 0[c0,Platform],
              Initial Emissions cp[c0,Platform])
Emissions cp 0[All but first,Platform]= INTEG (
       Emissions Cohort Progression cp 0[All but last,Platform]-
       Emissions Cohort Progression cp 0 [All but first,Platform]-
       Emissions Phase Out cp 0[All but first,Platform],
              Initial Emissions cp[All but first,Platform])
Units: vehicles*grams CO2/mile
The emissions of vehicles by age cohort, reference

Emissions Introduction p[Platform]=
       Sales p[Platform]*"New Vehicle Emissions CAFE + EV p"[Platform]
Units: grams CO2/mile*vehicles/year
The increase in emissions due to new vehicle sales
```

```
Emissions Introduction p 0[ICE]=
	Sales p 0[ICE] * "New Vehicle Emissions CAFE + EV p"[ICE]
Emissions Introduction p 0[EV]=
		Sales p 0[EV] * GHG Emissions EV e[EV]
Units: grams CO2/mile*vehicles/year
The increase in emissions due to new vehicle sales, reference

Emissions out due to C4C cp[Emissions Cohort,Platform]=
	C4C Discards ap[Age,Platform] *
	Average Emissions cp[Emissions Cohort,Platform]
Units: grams CO2/mile*vehicles/year
The reduction in fleet emissions due to discards from C4C program

Emissions Phase Out cp[Emissions Cohort,Platform]=
	Retirements ap[Age,Platform]*
	Average Emissions cp[Emissions Cohort,Platform]
Units: grams CO2/mile*vehicles/year
The reduction in fleet emissions due to retirements of vehicles

Emissions Phase Out cp 0[Emissions Cohort,Platform]=
	Retirements ap 0[Age,Platform]*
	Average Emissions cp 0[Emissions Cohort,Platform]
Units: grams CO2/mile*vehicles/year
The reduction in fleet emissions due to retirements of vehicles,
		reference

Energy Consumption EV e[EV]=
	Fuel Consumption of EV e[EV] * Native units to GGE Electricity
Units: kW*hour/mile
Energy consumption of EVs

EV:
	EVCar,EVLightTruck->ICE

EV Energy Efficiency e[EV]=
	Initial EV Energy Efficiency e[EV] *
	(1-RAMP("2050 EV Energy Efficiency increase"/(FINAL TIME-INITIAL TIME),
	INITIAL TIME , FINAL TIME ))
Units: kW*hour/miles
Energy efficiency of EVs

EV Market Growth Rate=
	0.05
Units: dmnl/year
Worldwide EV market growth rate

Excel Input:IS:
	'Fleet Model Inputs - Oak Ridge data v8 c4c.xlsx'
The input file name

FINAL TIME  = 2050
Units: year
The final time for the simulation.

Finish Point p[ICE]=
	"2050 Emissions Target CO2 per mile i"[ICE]
Units: grams CO2/mile
Vehicle emissions at the end point of the piecewise function
		that describes effective CAFE policy

Flag C4C Active=
	IF THEN ELSE
	  (SW C4C Active = 0 :OR: Time < C4C Start Year :OR: Time > C4C End Year,
```

```
          0,
          1
         )
Units: dmnl
Flag to indicate that C4C program is in effect

Fleet Aging ap[Age,Platform]=
       Fleet ap[Age,Platform]/Average Time Per Age[Age]
Units: vehicles/year
The flow of vehicles between age cohorts

Fleet Aging ap 0[Age,Platform]=
       Fleet ap 0[Age,Platform]/Average Time Per Age[Age]
Units: vehicles/year
The flow of vehicles between age cohorts, reference

Fleet ap[a0,Platform]= INTEG (
       Sales p[Platform]+C4C Replacement Sales p[Platform]-
       Fleet Aging ap[a0,Platform]-Retirements ap[a0,Platform]-
       C4C Discards ap[a0,Platform],
              Initial Fleet ap[a0,Platform])
Fleet ap[All but youngest,Platform]= INTEG (
       Fleet Aging ap[All but oldest,Platform]-
       Fleet Aging ap[All but youngest,Platform]-
       Retirements ap[All but youngest,Platform] -
       C4C Discards ap[All but youngest ,Platform],
              Initial Fleet ap[All but youngest,Platform])
Units: vehicles
The stock of vehicles in the fleet

Fleet ap 0[a0,Platform]= INTEG (
       Sales p 0[Platform]-Fleet Aging ap 0[a0,Platform]-
       Retirements ap 0[a0,Platform],
              Initial Fleet ap[a0,Platform])
Fleet ap 0[All but youngest,Platform]= INTEG (
       Fleet Aging ap 0[All but oldest,Platform]-
       Fleet Aging ap 0[All but youngest ,Platform]-
       Retirements ap 0[All but youngest ,Platform],
              Initial Fleet ap[All but youngest,Platform])
Units: vehicles
The stock of vehicles in the fleet, reference

Fleet Average New Vehicles Fuel Economy=
       (SUM(Sales p[Platform!]*
       "New Vehicle Fuel Economy CAFE + EV p"[Platform!]) +
       SUM(C4C Replacement Sales p[ICE!]*
       Actual C4C Fuel Economy of New Vehicles i[ICE!]) +
       SUM(C4C Replacement Sales p[EV!]*"New Vehicle Fuel Economy CAFE +
       EV p"[EV!])) /
       (SUM(Sales p[Platform!]) + SUM(C4C Replacement Sales p[Platform!]))
Units: mile/gallon
Average fuel economy of new vehicles

Fleet Average New Vehicles Fuel Economy Reference=
       SUM("New Vehicle Fuel Economy CAFE + EV p"[Platform!] *
       Sales p 0[Platform!]) / SUM(Sales p 0[Platform!])
Units: mile/gallon
Average fuel economy of new vehicles, reference

Fuel Consumption ai[Age,ICE]=
       ZIDZ(Emissions cp[Emissions Cohort,ICE],Fleet ap[Age,ICE]) /
       ICE CO2 conversion factor
Units: gallon/mile
```

```
Fuel consumption of an ICE vehicle by age and platform

Fuel Consumption of EV e[EV]=
	1 / "New Vehicle Fuel Economy CAFE + EV p"[EV]
Units: gallon/mile
Energy consumption of EVs in GGE

Fuel Price Adjusted VMT=
	Average VMT * Fuel Price Adjusted VMT Multiplier
Units: mile/(year*vehicle)
Average VMT adjusted by real fuel price

Fuel Price Adjusted VMT Multiplier=
	(Real Fuel Price / Baseline Fuel Price) ^ Elasticity of VMT to Fuel Price
Units: dmnl
Effect of fuel price on VMT

Fuel Savings from Driving EV e[EV]=
	Cost of Driving ICE i[ICE] - Cost of Driving EV e[EV]
Units: $/(year*vehicle)
Fuel savings from driving EV vs ICE vehicle

Fuel Savings from Driving EV e 0[EV]=
	Cost of Driving ICE i 0[ICE] - Cost of Driving EV e 0[EV]
Units: $/(year*vehicle)
Fuel savings from driving EV vs ICE vehicle, reference

Gas Tax=
	IF THEN ELSE
	  (Time < Gas Tax Ramp Start Year :OR: SW Gas Tax Active = 0,
	   0,
	   IF THEN ELSE
	     (Time > Gas Tax Ramp End Year,
	      Gas Tax End Value,
	      Gas Tax Start Value + (Time-Gas Tax Ramp Start Year) *
	       (Gas Tax End Value - Gas Tax Start Value) /
	       (Gas Tax Ramp End Year - Gas Tax Ramp Start Year)
	     )
	  )
Units: $/gallon
Gas tax

Gas Tax End Value=
	0.3
Units: $/gallon [0,2,0.05]
Gas tax in end year

Gas Tax Ramp End Year=
	2050
Units: year [2018,2050,1]
End year of gas tax

Gas Tax Ramp Start Year=
	2020
Units: year [2018,2050,1]
Start year of gas tax

Gas Tax Start Value=
	0
Units: $/gallon [0,2,0.05]
Gas tax in start year

GHG Emissions EV e[EV]=
```

```
	("GHG Emissions Factor - Renewables"*Green Electricity Share +
	"GHG Emissions Factor - Grid Mix"*(1-Green Electricity Share)) *
	EV Energy Efficiency e[EV]
Units: grams CO2/mile
Emissions factor of electricity mix

GHG Emissions EV Effective e[EV]=
	IF THEN ELSE
	  (SW EV Renewable Electricity = 1 :AND:
	      Time >= Year of Fully Renewable Electricity,
	   0,
	   GHG Emissions EV e[EV]
	  )
Units: grams CO2/mile
Effective emissions factor of electricity mix

"GHG Emissions Factor - Grid Mix"=
	689.27
Units: grams CO2/(kW*hour)
Emissions factor of grid electricity

"GHG Emissions Factor - Renewables"=
	0
Units: grams CO2/(kW*hour)
Emissions factor of renewable electricity

Grams CO2 per Gigatonne CO2=
	1e+15
Units: grams CO2/Gigatonne CO2
Conversion from grams to gigatonnes

Grams CO2 per Tonne CO2=
	1e+06
Units: grams CO2/Tonne CO2
Conversion from grams to tonnes

Green Electricity Share=
	RAMP((Max Share Renewables-Current Share Renewables)/
	(FINAL TIME-INITIAL TIME), INITIAL TIME , FINAL TIME)
Units: dmnl
Share of renewable power generation in the electricity mix

Grid Electricity Cost=
	0.15
Units: $/(kW*hour)
Grid cost of electricity used for recharging EVs

Hazard Rate ap[Age,Car]=
	GET XLS CONSTANTS(Excel Input,'Cars','D2*')
Hazard Rate ap[Age,LightTruck]=
	GET XLS CONSTANTS(Excel Input,'LightTrucks','D2*')
Hazard Rate ap[Age,EVCar]=
	GET XLS CONSTANTS(Excel Input,'Cars','D2*')
Hazard Rate ap[Age,EVLightTruck]=
	GET XLS CONSTANTS(Excel Input,'LightTrucks','D2*')
Units: dmnl/year
Year to year hazard rate of discards for cars and light trucks

ICE:
	Car,LightTruck->EV

ICE CO2 conversion factor=
	8887
```

Units: grams CO2/gallon
Carbon content in a gallon of gasoline

Inconvenience of EV e[EV]=
Ref Inconvenience of EV e[EV] * Effect of Learning on Market Formation
Units: dmnl
Inconvenience of EVs (short range, long recharging time, lack if recharging infrastructure etc.)

Inconvenience of EV e 0[EV]=
Ref Inconvenience of EV e[EV] * Effect of Learning on Market Formation 0
Units: dmnl
Inconvenience of EVs (short range, long recharging time, lack if recharging infrastructure etc.), reference

Increase in Cumulative Emissions=
Average Total Fleet Emissions
Units: Gigatonnes CO2/year
Increase in the cumulative emissions of the fleet

Increase in Cumulative Emissions Reference=
Average Total Fleet Emissions Reference
Units: Gigatonnes CO2/year
Increase in the cumulative emissions of the fleet, reference

Initial Average Total Fleet Emissions= INITIAL(
Average Total Fleet Emissions)
Units: Gigatonne CO2/year

Initial Average Total Fleet Emissions Reference= INITIAL(
Average Total Fleet Emissions Reference)
Units: Gigatonne CO2/year
Initial total emissions of the fleet (using average VMT)

Initial Emissions cp[Emissions Cohort,Car]=
GET XLS CONSTANTS(Excel Input,'Cars','Q2*')
Initial Emissions cp[Emissions Cohort,LightTruck]=
GET XLS CONSTANTS(Excel Input,'LightTrucks','Q2*')
Initial Emissions cp[Emissions Cohort,EVCar]=
GHG Emissions EV Effective e[EVCar]*Vehicle
Initial Emissions cp[Emissions Cohort,EVLightTruck]=
GHG Emissions EV Effective e[EVLightTruck]*Vehicle
Units: grams CO2/mile*vehicles
Initial emissions of vehicles by age cohort

Initial EV Energy Efficiency e[EV]=
0.32, 0.45
Units: kW*hour/miles
Initial energy efficiency of EVs

Initial Fleet ap[Age,Car]=
GET XLS CONSTANTS(Excel Input,'Cars','G2*')
Initial Fleet ap[Age,LightTruck]=
GET XLS CONSTANTS(Excel Input,'LightTrucks','G2*')
Initial Fleet ap[Age,EVCar]=
0
Initial Fleet ap[Age,EVLightTruck]=
0
Units: vehicles
The initial level of vehicles in each age cohort

Initial Price Surcharge of EVs relative to ICE=
0.25

```
Units: dmnl
Initial price multiplier of EV vs. ICE vehicle

INITIAL TIME  = 2018
Units: year
The initial time for the simulation.

Learning Curve Strength Market Formation=
       0.25
Units: dmnl
Strength of the learning curve for market formation

Learning Curve Strength Price=
       0.25
Units: dmnl
Strength of the learning curve for price

Logit Choice Scaling=
       2.5
Units: dmnl
Sensitivity of the logit model to a difference in utilities

Max Share Renewables=
       0.9
Units: dmnl
Max share of renewable power generation by 2050

Minimum Age to Qualify for C4C=
       5
Units: years [1,31,1]
Minimum vehicle age to qualify for the C4C program

Native units to GGE Electricity=
       33.7
Units: kW*hour/gallon
Conversion from kWh to GGE

New Customer Sales i[Car]=
       Total fleet * Aggregate Market Growth Rate * Share of Cars in the Fleet
New Customer Sales i[LightTruck]=
       Total fleet * Aggregate Market Growth Rate *
       (1-Share of Cars in the Fleet)
Units: vehicle/year
Additional sales of new vehicles due to market growth

New Customer Sales i 0[Car]=
       Total fleet 0 * Aggregate Market Growth Rate * share of cars in the fleet 0
New Customer Sales i 0[LightTruck]=
       Total fleet 0 * Aggregate Market Growth Rate *
       (1-share of cars in the fleet 0)
Units: vehicle/year
Additional sales of new vehicles due to market growth, reference

"New Vehicle Emissions CAFE + EV p"[Car]=
       IF THEN ELSE
         (Time <= Point 2 Year,
          Start Point p[Car] + (Time-INITIAL TIME) *
              (Point 2 i[Car]-Start Point p[Car]) / (Point 2 Year-INITIAL TIME),
              IF THEN ELSE
                (Time <= Point 3 Year,
                     Point 2 i[Car] + (Time-Point 2 Year) *
                     (Point 3 i[Car]-Point 2 i[Car]) / (Point 3 Year-Point 2 Year),
                     Point 3 i[Car] + (Time-Point 3 Year) *
```

```
                    (Finish Point p[Car]-Point 3 i[Car]) / (FINAL TIME-Point 3 Year)
            )
         )
"New Vehicle Emissions CAFE + EV p"[LightTruck]=
             IF THEN ELSE
               (Time <= Point 2 Year,
                Start Point p[LightTruck] + (Time-INITIAL TIME) *
                    (Point 2 i[LightTruck]-Start Point p[LightTruck]) /
                    (Point 2 Year-INITIAL TIME),
                IF THEN ELSE
                  (Time <= Point 3 Year,
                  Point 2 i[LightTruck] + (Time-Point 2 Year) *
                    (Point 3 i[LightTruck]-Point 2 i[LightTruck]) /
                    (Point 3 Year-Point 2 Year),
                  Point 3 i[LightTruck] + (Time-Point 3 Year) *
                    (Finish Point p[LightTruck]-Point 3 i[LightTruck]) /
                    (FINAL TIME-Point 3 Year)
                  )
               )
"New Vehicle Emissions CAFE + EV p"[EVCar]=
             GHG Emissions EV Effective e[EVCar]
"New Vehicle Emissions CAFE + EV p"[EVLightTruck]=
             GHG Emissions EV Effective e[EVLightTruck]
Units: grams CO2/mile
New vehicle emissions according to CAFE policy and EV learning

New Vehicle Emissions Fleet Average p[Car]=
       ZIDZ((Actual C4C Replacement Vehicles Emission p[Car]*
       C4C Replacement Sales p[Car] +
       Actual C4C Replacement Vehicles Emission p[EVCar]*
       C4C Replacement Sales p[EVCar] + "New Vehicle Emissions CAFE +
       EV p"[Car]*Sales p[Car] + "New Vehicle Emissions CAFE +
       EV p"[EVCar]*Sales p[EVCar]),
       (C4C Replacement Sales p[Car] + C4C Replacement Sales p[EVCar] +
       Sales p[Car] + Sales p[EVCar]))
New Vehicle Emissions Fleet Average p[LightTruck]=
       ZIDZ((Actual C4C Replacement Vehicles Emission p[LightTruck]*
       C4C Replacement Sales p[LightTruck] +
       Actual C4C Replacement Vehicles Emission p[EVLightTruck]*
       C4C Replacement Sales p[EVLightTruck] +
       "New Vehicle Emissions CAFE + EV p"[LightTruck]*Sales p[LightTruck] +
       "New Vehicle Emissions CAFE + EV p"[EVLightTruck]*Sales p[EVLightTruck]),
       (C4C Replacement Sales p[LightTruck] + C4C Replacement Sales p[EVLightTruck] +
       Sales p[LightTruck] + Sales p[EVLightTruck]))
Units: grams CO2/mile
Average emissions of a new vehicle

"New Vehicle Fuel Consumption CAFE + EV p"[Car]=
       "New Vehicle Emissions CAFE + EV p"[Car]/ICE CO2 conversion factor
"New Vehicle Fuel Consumption CAFE + EV p"[LightTruck]=
       "New Vehicle Emissions CAFE + EV p"[LightTruck]/ICE CO2 conversion factor
"New Vehicle Fuel Consumption CAFE + EV p"[EVCar]=
       EV Energy Efficiency e[EVCar] / Native units to GGE Electricity
"New Vehicle Fuel Consumption CAFE + EV p"[EVLightTruck]=
       EV Energy Efficiency e[EVLightTruck] / Native units to GGE Electricity
Units: gallon/mile
New vehicle fuel consumption according to CAFE policy and EV
                    learning

"New Vehicle Fuel Economy CAFE + EV p"[Platform]=
       1 / "New Vehicle Fuel Consumption CAFE + EV p"[Platform]
Units: miles/gallon
New vehicle fuel economy according to CAFE policy and EV learning
```

```
New Vehicle ICE Fuel Consumption CAFE i[Car]=
       "New Vehicle Fuel Consumption CAFE + EV p"[Car]
New Vehicle ICE Fuel Consumption CAFE i[LightTruck]=
       "New Vehicle Fuel Consumption CAFE + EV p"[LightTruck]
Units: gallon/mile
New vehicle emissions according to CAFE policy for ICE vehicles

Obama 2nd Point i[ICE]=
       201,283
Units: grams CO2/mile
Vehicle emissions at the second point of the piecewise function
             that describes CAFE policy under Obama rule

Obama 2nd Point Year=
       2025
Units: year
Year of the second point of the piecewise function that
             describes CAFE policy under Obama rule

Obama 3rd Point i[ICE]=
       201,283
Units: grams CO2/mile
Vehicle emissions at the third point of the piecewise function
             that describes CAFE policy under Obama rule

Obama 3rd Point Year=
       2025
Units: year
Year of the third point of the piecewise function that describes
             CAFE policy under Obama rule

Platform:
       Car, LightTruck, EVCar, EVLightTruck

Point 2 i[ICE]=
       IF THEN ELSE
         (SW Scenario = 1,
          Obama 2nd Point i[ICE],
          IF THEN ELSE
            (SW Scenario = 2,
             Trump 2nd Point i[ICE],
             Custom 2nd Point i[ICE]
            )
         )
Units: grams CO2/mile
Vehicle emissions at the second point of the piecewise function
             that describes effective CAFE policy

Point 2 Year=
       IF THEN ELSE
         (SW Scenario = 1,
          Obama 2nd Point Year,
          IF THEN ELSE
            (SW Scenario = 2,
             Trump 2nd Point Year,
             Custom 2nd Point Year
            )
         )
Units: year
Year of the second point of the piecewise function that
             describes effective CAFE policy
```

```
Point 3 i[ICE]=
       IF THEN ELSE
         (SW Scenario = 1,
          Obama 3rd Point i[ICE],
          IF THEN ELSE
            (SW Scenario = 2,
             Trump 3rd Point i[ICE],
             Custom 3rd Point i[ICE]
            )
         )
Units: grams CO2/mile
Vehicle emissions at the third point of the piecewise function
             that describes effective CAFE policy

Point 3 Year=
       IF THEN ELSE
         (SW Scenario = 1,
          Obama 3rd Point Year,
          IF THEN ELSE
            (SW Scenario = 2,
             Trump 3rd Point Year,
             Custom 3rd Point Year
            )
         )
Units: year
Year of the third point of the piecewise function that describes
             effective CAFE policy

Price Surcharge of EVs relative to ICE=
       Initial Price Surcharge of EVs relative to ICE *
       Effect of Learning on Price * Effect of World Learning on Price
Units: dmnl
Price multiplier of EV vs. ICE vehicle

Price Surcharge of EVs relative to ICE 0=
       Initial Price Surcharge of EVs relative to ICE *
       Effect of World Learning on Price * Effect of Learning on Price 0
Units: dmnl
Price multiplier of EV vs. ICE vehicle, reference

Real Fuel Price=
       Baseline Fuel Price + Gas Tax
Units: $/gallon [0,10,0.1]
Actual fuel price

Ref Inconvenience of EV e[EV]=
       -2
Units: dmnl
Initial inconvenience of EVs (short range, long recharging time,
             lack if recharging infrastructure etc.)

Reference C4C Average FE Shift=
       0.05
Units: dmnl
Reference increase in fuel economy relative to mandated C4C fuel
             economy (available vehicles can do better)

Reference C4C EV Incentive Value=
       20000
Units: $/vehicle
Reference value of C4C incentive for EVs

Reference C4C Hazard Rate ai[Age,ICE]=
```

```
        Reference Hazard Rate i[ICE] * (Age^Sensitivity of Hazard Rate to Age)
Units: dmnl/year
Propensity to participate in the C4C program

Reference C4C Incentive Value=
        4000
Units: $/vehicle
Reference value of C4C incentive for ICE vehicles

Reference Cumulative EV Sales=
        1e+07
Units: vehicles
Reference local sales of EVs

Reference Cumulative World EV Sales=
        1e+07
Units: vehicles
Reference worldwide sales of EVs

Reference Hazard Rate i[ICE]=
        0.002,0.002
Units: dmnl/year
Reference propensity to participate in the C4C program

Relative Fuel Savings from Driving C4C vs CAFE i[ICE]=
        1 - (Actual C4C Fuel Consumption of New Vehicles i[ICE]/
        "New Vehicle Fuel Consumption CAFE + EV p"[ICE])
Units: dmnl
Annual fuel savings from driving a vehicle with C4C standards
                relative to CAFE standards for fuel economy

Relative Fuel Savings from Driving EV e[EV]=
        Fuel Savings from Driving EV e[EV] / Cost of Driving ICE i[ICE]
Units: dmnl
Fuel savings from driving EV relative to ICE

Relative Fuel Savings from Driving EV e 0[EV]=
        Fuel Savings from Driving EV e 0[EV] / Cost of Driving ICE i 0[ICE]
Units: dmnl
Fuel savings from driving EV relative to ICE, reference

Renewable Electricity Surcharge=
        0
Units: $/(kW*hour) [0,1,0.01]
Additional surcharge for renewable electricity used for
                recharging EVs

Retirements ap[Age,Platform]=
        Fleet ap[Age,Platform]*Hazard Rate ap[Age,Platform]
Units: vehicles/year
The outflow of retirements from the fleet

Retirements ap 0[Age,Platform]=
        Fleet ap 0[Age,Platform]*Hazard Rate ap[Age,Platform]
Units: vehicles/year
The outflow of retirements from the fleet, reference

Sales p[Car]=
        (Total outflow p[Car]+Total outflow p[EVCar] + New Customer Sales i[Car]) *
        (1-Share of EV i[Car])
Sales p[LightTruck]=
        (Total outflow p[LightTruck]+Total outflow p[EVLightTruck] +
        New Customer Sales i[LightTruck]) * (1-Share of EV i[LightTruck])
```

```
Sales p[EVCar]=
       (Total outflow p[Car]+Total outflow p[EVCar] + New Customer Sales i[Car])*
       Share of EV i[Car]
Sales p[EVLightTruck]=
       (Total outflow p[LightTruck]+Total outflow p[EVLightTruck] +
       New Customer Sales i[LightTruck]) * Share of EV i[LightTruck]
Units: vehicles/year
Sales of new vehicles

Sales p 0[Car]=
       (Total outflow p 0[Car]+Total outflow p 0[EVCar] + New Customer Sales i 0[
Car]) * (1-Share of EV i 0[Car])
Sales p 0[LightTruck]=
              (Total outflow p 0[LightTruck]+Total outflow p 0[EVLightTruck] + New
Customer Sales i 0
       [LightTruck]) * (1-Share of EV i 0[LightTruck])
Sales p 0[EVCar]=
       (Total outflow p 0[Car]+Total outflow p 0[EVCar] +
       New Customer Sales i 0[Car]) * Share of EV i 0[Car]
Sales p 0[EVLightTruck]=
       (Total outflow p 0[LightTruck]+Total outflow p 0[EVLightTruck] +
       New Customer Sales i 0[LightTruck]) * Share of EV i 0[LightTruck]
Units: vehicles/year
Sales of new vehicles, reference

SAVEPER  =
        TIME STEP
Units: year [0,?]
The frequency with which output is stored.

Sensitivity of Addressable Market to C4C Stringency=
       -0.75
Units: dmnl
Sensitivity of the effect of addressable market (available makes
              and models) satisfying C4C standard stringency

Sensitivity of C4C Stringency Effect=
       -1.5
Units: dmnl [-2,0,0.1]
Sensitivity of the effect of C4C stringency standards on
              propensity to participate in the C4C program (more stringent
              standards mean it is harder to find a car)

Sensitivity of Fuel Savings Effect=
       0.75
Units: dmnl [0,2,0.1]
Sensitivity of additional fuel savings from C4C program

Sensitivity of Hazard Rate to Age=
       0.5
Units: dmnl [0,3,0.1]
Sensitivity of the propensity to participate in the C4C program
              to vehicle age

Sensitivity of Incentive Effect=
       0.75
Units: dmnl [0,2,0.1]
Sensitivity of C4C incentive

Share of Cars in the Fleet=
       (Total fleet p[Car]+Total fleet p[EVCar]) / SUM(Total fleet p[Platform!])
Units: dmnl
Share of cars vs. light trucks in the fleet
```

```
share of cars in the fleet 0=
       (Total fleet p 0[Car]+Total fleet p 0[EVCar]) /
       SUM(Total fleet p 0[Platform!])
Units: dmnl

Share of EV i[ICE]=
       EXP(Utility of EV e[EV]*Logit Choice Scaling) /
       (EXP(Utility of EV e[EV]*Logit Choice Scaling)+
       EXP(Utility of ICE i[ICE]*Logit Choice Scaling))
Units: dmnl
Share of EVs in new vehicle sales

Share of EV i 0[ICE]=
       EXP(Utility of EV e 0[EV]*Logit Choice Scaling) /
       (EXP(Utility of EV e 0[EV]*Logit Choice Scaling)+
       EXP(Utility of ICE i[ICE]*Logit Choice Scaling))
Units: dmnl
Share of EVs in new vehicle sales, reference

Share of EVs in Fleet=
       SUM(Fleet ap[Age!,EV!]) / SUM(Fleet ap[Age!,Platform!])
Units: dmnl
Share of EVs in the fleet

Share of EVs in Fleet Reference=
       SUM(Fleet ap 0[Age!,EV!]) / SUM(Fleet ap 0[Age!,Platform!])
Units: dmnl
Share of EVs in the fleet, reference

Start Point p[ICE]=
       270,375
Units: g CO2/mile
Vehicle emissions at the start point of the piecewise function
             that describes effective CAFE policy

SW C4C Active=
       0
Units: dmnl [0,1,1]
Switch to activate the C4C program

SW C4C must buy EVs=
       0
Units: dmnl [0,1,1]
Switch to mandate that replacements under C4C program must be EVs

SW EV Renewable Electricity=
       0
Units: dmnl [0,1,1]
Switch to mandate fully renewable electricity for EV recharging

SW Gas Tax Active=
       0
Units: dmnl [0,1,1]
Switch to activate gas tax

SW Scenario=
       2
Units: dmnl [1,3,1]
Switch to control CAFE scenarios 1 - Obama, 2 - Trump, 3 - Custom

TIME STEP  = 0.125
Units: year [0,?]
```

The time step for the simulation.

```
Tonnes per Billion Tonnes=
      1e+09
Units: Tonnes CO2/Gigatonne CO2
Conversion from tonnes to gigatonnes

Total Age ap[Age,Platform]=
      Fleet ap[Age,Platform]*Age*Year
Units: vehicle*year
Total age of all vehicles in the fleet

Total Age ap 0[Age,Platform]=
      Fleet ap 0[Age,Platform]*Age*Year
Units: vehicle*year
Total age of all vehicles in the fleet, reference

Total fleet=
      SUM(Total fleet p[Platform!])
Units: vehicles
Total fleet of vehicles

Total fleet 0=
      SUM(Total fleet p 0[Platform!])
Units: vehicles

Total Fleet Emissions C4C=
      SUM(Emissions cp[Emissions Cohort!,Platform!]*
      VMT cp[Emissions Cohort!,Platform!]) / Grams CO2 per Gigatonne CO2
Units: Gigatonnes CO2/year
Total emissions of the fleet (using VMT by age cohort)

Total Fleet Emissions Reference=
      SUM(Emissions cp 0[Emissions Cohort!,Platform!]*
      VMT cp[Emissions Cohort!,Car]) / Grams CO2 per Gigatonne CO2
Units: Gigatonnes CO2/year
Total emissions of the fleet (using VMT by age cohort), reference

Total fleet p[Platform]=
      SUM(Fleet ap[Age!,Platform])
Units: vehicles
Total fleet of vehicles by platform

Total fleet p 0[Platform]=
      SUM(Fleet ap 0[Age!,Platform])
Units: vehicles

Total Fuel Consumption ai[Age,ICE]=
      Average Miles Driven ai[Age,ICE] * Fuel Consumption ai[Age,ICE]
Units: gallon/year
Total fuel consumption of ICE vehicles

Total New Vehicle Sales C4C=
      SUM(Sales p[Platform!]+C4C Replacement Sales p[Platform!])
Units: vehicles/year
Total sales of new vehicles

Total New Vehicle Sales Reference=
      SUM(Sales p 0[Platform!])
Units: vehicles/year
Total sales of new vehicles, reference

Total outflow p[Platform]=
```

```
       SUM(Retirements ap[Age!,Platform])+Fleet Aging ap[a30,Platform]
Units: vehicles/year
Total outflow from the fleet that needs to be replaced

Total outflow p 0[Platform]=
       SUM(Retirements ap 0[Age!,Platform])+Fleet Aging ap 0[a30,Platform]
Units: vehicles/year
Total outflow from the fleet that needs to be replaced, reference

Trump 2nd Point i[ICE]=
       251,363
Units: grams CO2/mile
Vehicle emissions at the second point of the piecewise function
              that describes CAFE policy under Trump proposal

Trump 2nd Point Year=
       2020
Units: year
Year of the second point of the piecewise function that
              describes CAFE policy under Trump proposal

Trump 3rd Point i[ICE]=
       251,363
Units: grams CO2/mile
Vehicle emissions at the third point of the piecewise function
              that describes CAFE policy under Trump proposal

Trump 3rd Point Year=
       2026
Units: year
Year of the third point of the piecewise function that describes
              CAFE policy under Trump proposal

Unit Cost of Emissions Reduction=
       ZIDZ(Cumulative Cost of C4C Program-Cumulative Gas Tax Revenue,
       Cumulative Emissions Reduction*Tonnes per Billion Tonnes)
Units: $/Tonne CO2
Unit cost of emissions reduction

Utility of EV e[EV]=
       Inconvenience of EV e[EV] + Relative Fuel Savings from Driving EV e[EV]*
       Weight of Fuel Savings + Price Surcharge of EVs relative to ICE*
       Weight of Price Surcharge
Units: dmnl
Utility of EV

Utility of EV e 0[EV]=
       Inconvenience of EV e 0[EV] +
       Relative Fuel Savings from Driving EV e 0[EV]*
       Weight of Fuel Savings + Price Surcharge of EVs relative to ICE 0*
       Weight of Price Surcharge
Units: dmnl
Utility of EV, reference

Utility of ICE i[ICE]=
       0,0
Units: dmnl
Utility of an ICE vehicle

Vehicle=
       1
Units: vehicle
A unit of one vehicle
```

```
VMT cp[Emissions Cohort,Car]=
       GET XLS CONSTANTS(Excel Input,'Cars','E2*')
VMT cp[Emissions Cohort,LightTruck]=
       GET XLS CONSTANTS(Excel Input,'LightTrucks','E2*')
VMT cp[Emissions Cohort,EVCar]=
       GET XLS CONSTANTS(Excel Input,'Cars','E2*')
VMT cp[Emissions Cohort,EVLightTruck]=
       GET XLS CONSTANTS(Excel Input,'LightTrucks','E2*')
Units: miles/year/vehicle
VMT of vehicles by age cohort

Weight of Fuel Savings=
       2
Units: dmnl
Weight of fuel savings in the utility

Weight of Price Surcharge=
       -2
Units: dmnl
weight of price in the utility

Year=
       1
Units: year
A unit of one year

Year of Fully Renewable Electricity=
       2030
Units: year [2019,2050,1]
Year when the EV recharging can be 100% renewable
```