Fuel Economy, Electric Vehicles, and the Future of US Infrastructure Funding

by

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ABSTRACT

This paper examines how fuel tax policies affect the generation of revenue to maintain the US road infrastructure. Currently, deferred maintenance and outdated policies have led to a budget deficit to both finance new projects and maintain the existing infrastructure at the state and national levels. Gas taxes are the main source of tax revenue currently, but improvements in fuel efficiency and the introduction of electric vehicles (EVs) will exacerbate this problem in the coming years. In this thesis, I develop a model to simulate tax revenues over time as a function of vehicle fleet turnover, consumer vehicle choice, and the design of policies such as fuel taxes and registration fees. Using data from the Ohio Department of Transportation, I simulate the effect of a range of tax policies including gas taxes, and vehicle miles traveled (VMT) taxes relative to the baseline set of policies recently adopted in the state of Ohio. My analysis shows the tradeoffs and complexities between different policy structures seeking to satisfy both infrastructure funding and emissions reduction policies concurrently. The best policies combine taxes to both gasoline vehicles and EVs, but balances taxes to sustain the relative attractiveness of EVs to achieve long-term greenhouse emissions reduction.

Keywords: Gas Tax, Tax Policy, Infrastructure Funding, Electric Vehicles, System Dynamics

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I look forward to the next challenge.

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List of Acronyms

CAFE	Corporate Average Fuel Economy
CARS	Car Allowance Rebate System
DOT	Department of Transportation
EV	Electric Vehicles
GHG	Greenhouse Gases
HEV	Hybrid Electric Vehicles
HTF	Highway Trust Fund
ICE	Internal Combustion Engine
ICEV	Internal Combustion Engine Vehicle
LDV	Light-duty Vehicle
ODOT	Ohio Department of Transportation
OTIC	Ohio Turnpike and Infrastructure Commission
VMT	Vehicle Miles Traveled
US	United States
USD	United States Dollars

1 Introduction

Deferred maintenance on US roads and bridges has left the system in a heavily degraded state. According to the US Department of Transportation (2013), clearing the backlog of necessary system improvements would cost an estimated $189 billion. The average annual capital investment required to maintain all US roads and bridge conditions at 2010 levels is estimated between $65 and $87 billion. However, the Department of Transportation (DOT) estimated the costs are $145 billion a year to improve the system performance to meet taxpayers' expectations. Currently, the US spends less than two-thirds of that amount and maintenance, leading to an ever-increasing backlog in road and bridge maintenance.

Lyneis and Sterman (2016) refer to this problem as the maintenance capability trap, where poor infrastructure is a result of dynamics between reactive and proactive maintenance to eliminate infrastructure defects. The essential trap dynamics are that poor performance prevented investments in win-win opportunities and capabilities needed to realize them, perpetuating poor performance. This result is consistent with research from both Sargent (2015) and the US DOT (2013), who mentions that the building of new road and bridges is not prioritized over the maintenance and fixing existing road infrastructure.

As mentioned in TRIP (2018), the Federal Highway Administration estimates that for every dollar spent in maintenance of roads, bridged or infrastructure, results in an average of $5.20 in the form of reduced vehicle maintenance costs, reduced maintenance cost of roads and bridges, and fewer emissions, among others. Failure in making the right decision is discussed in Landry and Sterman (2018) that hypothesize the prevalence of the capability trap in social systems. They propose several cases where the capability trap dynamics appear, including infrastructure maintenance.

The consequence of the maintenance backlog is that the failure to invest in proactive maintenance leads to a reactive mode that gets successively worse, costing more to repair and maintain. As it gets more expensive to repair, resources directed to solve the problems are used at the expense of future projects or maintenance, increasing the revenue requirements and therefore, the revenue gap.

While managers are prone to underinvest in preventative maintenance, the US situation is exacerbated by the way the road funding is generated from the gas tax. The Highway Trust Fund (HTF) is the primary source of revenue for interstate highways, local roads, bridges, and transit systems. As stated by Sargent (2015), revenues entering into the Highway Trust Fund come almost exclusively from motor fuel taxes (18.4 cents per gallon for gasoline and 24.4 cents per gallon for diesel fuel).

The fundamental problem with this system is that federal motor fuel taxes are not indexed for inflation and have not updated since 1993. Though all states have similar fuel taxes over-and-above the federal gas tax to fund their infrastructure, most of them have not updated their policies to meet current requirements. Many research papers have stated that existing fuel tax levels are lower than economically efficient levels (e.g., Parry and Small (2005), Lin and Prince (2009), Tscharaktschiew (2014)). Coady et al. (2017) calculated an optimal tax level for fuel vehicles in the US as $2.23 per gallon decomposed in 60 cents per gallon for environmental externalities and $1.63 per gallon for congestion and accidents as first-best policies and to equal all negative externalities of driving.

As a consequence of the fuel tax fixed at a level far below the optimal value, the Highway Trusting Fund has been insufficient to pay for federal spending in highways and had shortfalls in the last decade. According to the US Congressional Budget (2016), lawmakers have transferred $143 billion to fund the HTF to maintain a positive balance of the fund since 2008.

However, this situation is likely to get worse still in the coming years. Improvements in gasoline fuel economy and the introduction of alternative fuel vehicles are likely to result in a reduction in gasoline consumption and associated gas tax revenues, further exacerbating these problems (US Department of Transportation (2013), Advisory Committee on Transportation Infrastructure (2019), Sargent (2015)). The continued adoption of these low gasoline-consuming vehicle technologies presents an interesting dilemma for policymakers seeking to balance infrastructure funding and environmental policy goals. Increasing gas taxes to compensate for falling gasoline consumption will serve to make driving gasoline vehicles even less attractive. However, imposing taxes on fuel-efficient and electric vehicles that contribute equally to the wear and tear of the road system will discourage their adoption, making it harder to meet greenhouse gases (GHG) emissions reduction targets.

In this thesis, I develop a model of light-duty vehicle fleet turnover to analyze how fuel tax policies can be designed to close the infrastructure funding gap while also maximizing the reduction of GHG emissions. Using the US state of as a case study, I show that current policies implementing high fees on electric vehicles (EVs) have strong effects on the market formation and are counterproductive to revenue generation as they stagnate the growth of the market. As a consequence, this type of policies contributes to slow down the reduction of greenhouse emissions. I further show that the revenue gap closes while emissions are reduced if policies that impose lighter conditions to electric cars in comparison to fuel based vehicles are introduced. The previous, in order to keep the attractiveness of electric vehicles high and contribute to the market formation. This thesis contributes to the research on tax optimization and EV market formation, presenting the tradeoffs of different tax policy structures to reach to sustainable policies that can both meet the revenue requirements and greenhouse emissions goals.

The structure of this thesis is divided as follows: Chapter 2 presents an overview of the model, the pieces of the sub-model, the relationships between them, and defining the main feedback loops. It is an explanatory chapter of the model and how it works while referencing the literature that provides the base for the model. In Chapter 3, a study case based on the Ohio Department of Transportation (ODOT) is presented by introducing the context of the ODOT, including the current legislation and revenue requirements. Immediately after, the parametrization of the model is presented, and the ODOT model is introduced. The purpose of the chapter is to present a specific instance to test the model, test the current motor fuel tax policies of the state of Ohio, and test different tax policies to illustrate the tradeoffs of the problem. Finally, in Chapter 4, conclusions and insights obtained from testing the model are presented. The chapter also includes the limitations of the model, the possible extensions, and the further research that can be done upon this work.

2 Model

This chapter presents the model used to simulate the transportation system described earlier. It contains an overview and general description of the model, the description of the sub-models, presents the main feedbacks operating within, and also describes its limitations.

2.1 General Model Description

To simulate the dynamics of the composition and use of the light-duty vehicle fleet in the presence of fuel tax policies, an extension of the U.S. Light-duty Vehicle (LDV) fleet model developed by (Keith, Houston, et al. 2019) was used. The extended model considers how fuel consumption and tax revenue generation is a function of consumer choice of new vehicles entering the fleet, and the extent to which these vehicles are driven while in operation. As mentioned by (Naumov, Keith, et al. 2019), "*the model is behaviorally robust and incorporates established formulations from fleet diffusion models* (Struben & Sterman, 2008; Naumov, Keith, & Sterman, 2017a; Naumov, Keith, & 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)".

The model captures the multiple ways in which fuel taxes influence the generation of tax revenue: i) the amount of tax generated per unit of fuel consumption; ii) the effect of fuel taxes on vehicle miles traveled; iii) the amount of fuel economy that consumers purchase when buying a gasoline vehicle; and iv) the likelihood that a consumer chooses to purchase an electric vehicle. A range of possible policies is considered, including gas taxes, electricity taxes, vehicle miles traveled (VMT) taxes, and annual registration fees.

The model consists of 4 sub-models:

- **Vehicle Fleet Model:** Simulates the current vehicle fleet and separates it by age cohorts. Vehicles move through the stock of cohorts considering an average time rate of one year and move out of the system considering a hazard rate.

- **Emissions Co-flow Model:** Simulates the current vehicle fleet emissions as a co-flow to the vehicle model. Incorporates Corporate Average Fuel Economy Standards to establish a maximum value for vehicle emissions per cohort.

- **Consumer Behavior Model:** The consumer behavior model considers two pieces related to the adoption of vehicles and the vehicle miles traveled by car. The vehicle adoption model has as its output the market share for internal combustion engine vehicles (ICEV) and electric vehicles for cars and light trucks based on the relative utilities of each powertrain. The vehicle miles traveled considers the elasticity of demand for driving based on fuel price or the cost of electricity.

- **World Learning Model:** Vehicles sales drive production learning, which reduces the prices of electric vehicles in comparison to gasoline vehicles. These variables and the annual cost of ownership increases the utility of electric vehicles and lead to an increase in market share. EV market share is the main output of the model that affects the composition of the vehicle introduction rate into the system.

- **Tax Revenue Model:** The tax revenue model calculates the amount of revenue collected by the Department of Transportation based on the attributes of tax policies, including from the gas tax and registration fees, among others. The main output is the revenue gap of the DOT to meet the requirements.

The relationships between the sub-model consider the following interactions:

From / To	Vehicle Fleet Co-flow	Emission Co-flow	Consumer Behavior	World Learning	Tax Revenue
Vehicle Fleet Co-flow	-	Vehicle Sales contribute to the introduction of new Emissions. Vehicle retirement contributes to the reduction of Emissions.	Vehicle Sales affect the Market Formation and therefore, the price and inconvenience of EV.	Vehicle Sales improve the Local Learning Effect.	The number of vehicles affects the tax revenue collected.
Emission Co-flow		-			Emissions and Fuel Efficiency affect the gas used and therefore, the tax collected by the ODOT.
Consumer Behavior	Adoption affects the market share of new vehicles purchased.		-		Elasticity affects the VMT and therefore, revenue collected by tax policies.
World Learning			World learning affects the relative price and inconvenience of EVs compared to ICEVs.	-	
Tax Revenue	None		Tax policies affect the annual cost of a vehicle and the adoption of technology. Tax policies affect the cost of driving and therefore, the Average VMT.		-

Table 1 Interaction between sub-models

Model variables, parameters, and others

In the following lines, the different sets, ranges, parameters, and variables that the model uses are presented. They have been organized according to the different sub-models for better understanding.

<u>**Set and ranges:**</u>

a: set of age cohorts of vehicles
p: set of platforms
j: set of technologies
i: set of ICE platforms
e: set of EV platforms
s: set of alternatives covariates

a = { 1, 2, … , N }
p = { Car, EV Car, Light-Truck, EV Light-Truck }
j = { i, e }
i = { Car, Light-Truck}
e = { EV Car, EV Light-Truck }
s = { price, market, cost }

Parameters:

Vehicle Fleet Model

α_{pa}: Rate of vehicle retirements through natural turnover
FE_j^{CAFE}: CAFE standard of j
FE^{EV}: Fuel economy of EV vehicle

Consumer Behavior

σ_j: Market share
β_s: Alternative specific covariates coefficient
p_g: Price of gasoline
l' : Baseline number of miles driven
p': Reference fuel price
ε_l: Elasticity of miles driven to fuel price

World Learning Sub-model

W_0 : Reference Levels of World Production
L_0: Reference Levels of Local Production
P_0 : Price of EV at the reference level of experience
γ_p : Strength of the learning curve for price
I_0 : Reference inconvenience of EV

GHG Emissions Co-flow

μ_p^{CAFE}: Vehicle emissions required by the CAFE policy in grams CO2 per mile
$\bar{\mu}_{pa}$: Average emissions of vehicles of platform p in the age cohort a:

Variables:

Vehicle Fleet and Emission Co-flow Model

V_{pa}: Number of vehicles in the fleet from cohort a of platform p
r_{pa}: Vehicle retirements from each cohort a of platform p
n_p: Vehicle purchases entering the cohort of new vehicles
λ : Population growth with the rate

Consumer Behavior

x_{sj}: Alternative specific covariates
l : Average number of miles traveled per vehicle per year

World Learning Sub-model

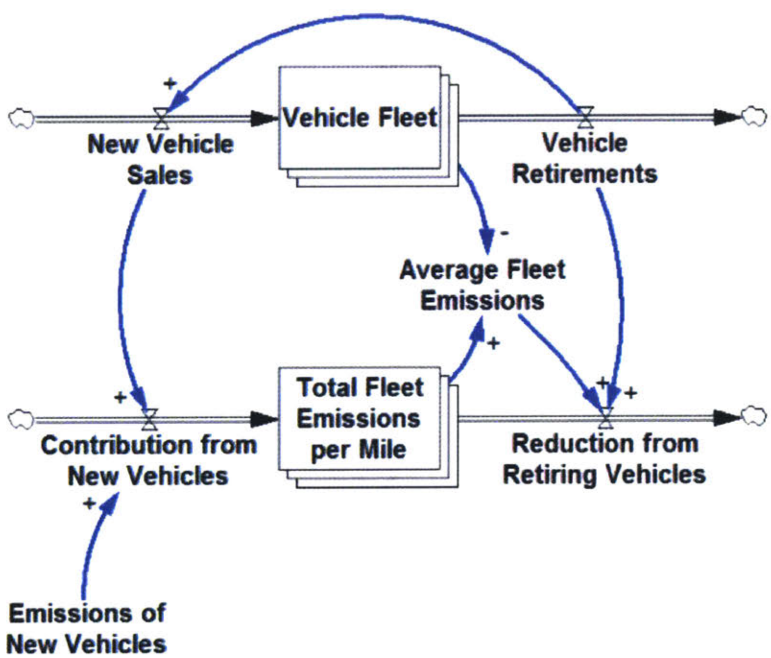
W: World market production
L: Local market production

GHG Emissions Co-flow

E_{pa}: Vehicle emissions from age cohort a of platform p

2.2 Vehicle Fleet Co-flow Sub-model

To simulate the dynamics of the vehicle fleet in the presence of specific vehicle tax policies, we used as base the U.S. LDV fleet model (Keith, Houston, et al. 2019). The following equations. Figure 1 represents the stock and flow diagram of the vehicle and GHG emission co-flow sub-models.



Source: Naumov, Keith, et al. (2019)

Figure 1 Vehicle Fleet and Emissions Co-flow Model

The explanation of the model is based on the paper of Naumov, Keith, and Sterman (2019). In the following paragraphs ranges, parameters and variables will be defined, and equations of the model will be described and presented.

As stated by Naumov, Keith et al. (2019): "*The model is calibrated to represent the light-duty vehicle (LDV) 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)."

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

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

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):

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

2.3 Consumer Behavior and Technology Adoption Model

Vehicles that are discarded are replaced with new vehicles. However, these new replacements can either be an internal ICEV or EV, meaning that the share of fuel and electric vehicles can change in time. The model used is adapted from Naumov, Keith, et al. (2019) considering the introduction of an annual operating cost as an extension to the relative savings from driving EVs.

As the authors, model consumer choice is based on the utility of an ICEV vs. EV, u_j, within each platform $j \in \{Car, Light\ Truck\}$. The modeling follows the existing literature on new vehicle platform diffusion (Struben & Sterman, 2008; Keith et al., 2017a; Naumov, Keith, et al., 2019) and uses discrete consumer choice formulations (e.g. McFadden, 1981a; Ben-Akiva & Lerman, 1985; Brownstone, Bunch, & Train, 2000).

The utility of ICE platform is considered as a reference and model the market share of EV platform in replacement sales, within platform j, σ_j, using a binomial logit:

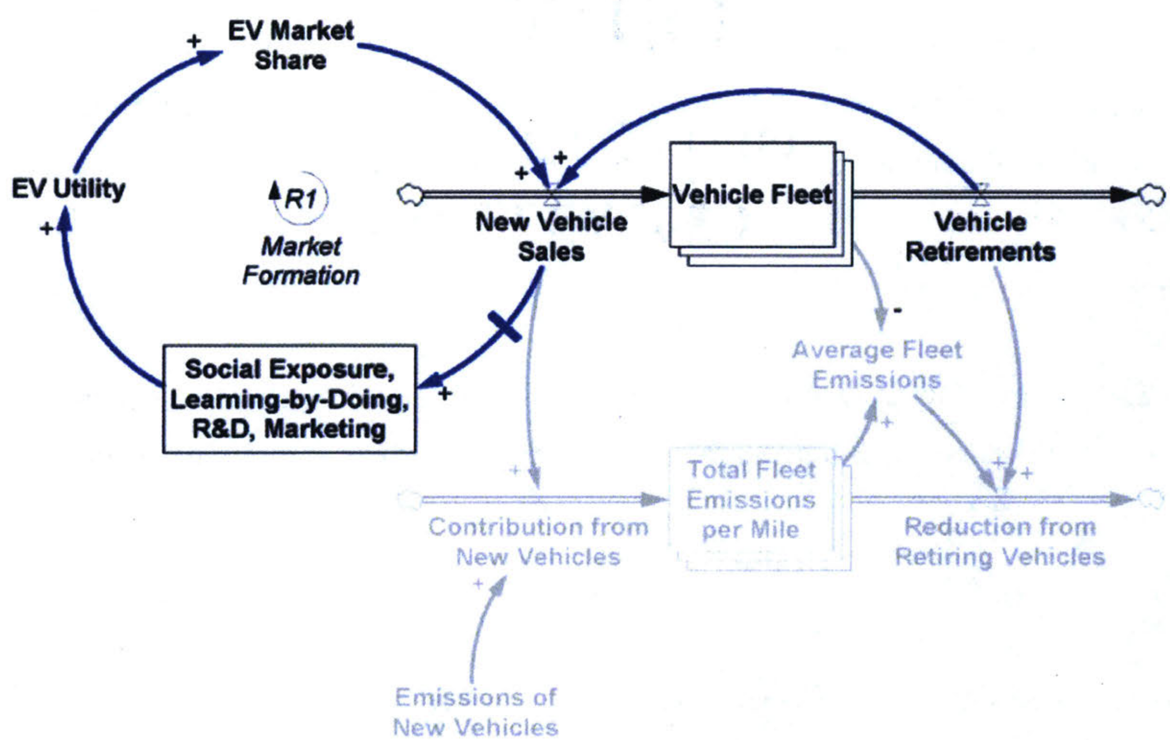
$$\sigma_j = \frac{1}{1 + e^{1-u_j}} \tag{4}$$

The utility of an EV platform is modeled relative to ICE:

$$u_j = \sum_s \beta_s x_{sj} + \epsilon_j \tag{5}$$

with alternative specific covariates x_{sj} with generic coefficients β and homoscedastic i.i.d. extreme value errors ϵ_j. As stated by Naumov, Keith et al. (2019) "*the covariates are included 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*".

As the EV market is not yet mature, the utility of EVs is assumed to increase 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, and reinforcing feedback" (**Error! Reference source not found.**).



Source: Naumov, Keith, et al. (2019)

Figure 2 EV Market Formation

These effects are captured as reductions in the price of EVs and the inconvenience of the EV platform. The model uses a power-law learning curve cumulative in production experience. This serves as a proxy for the aggregate effect of all sources of learning (Argote & Epple, 1990). For the price attribute, the model includes both cumulative world production W and local market production L:

$$x_{price,j} = P_0 \left(\frac{W}{W_0}\frac{L}{L_0}\right)^{\gamma_p} \tag{6}$$

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, the effect of local market production on market formation dynamics. In real life, this is reflected in consumer acceptance, recharging infrastructure availability, quality of vehicle service, among others.

$$x_{market,j} = I_0 \left(\frac{L}{L_0}\right)^{\gamma_i} \tag{7}$$

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}":

$$x_{fuel,j} = 1 - \left(\frac{1}{FE^{EV}}\, l'\, p_e\right) \Big/ \left(\frac{1}{FE_i^{CAFE}}\, l\, p_g\right) \tag{8}$$

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):

$$l = l' \left(\frac{p}{p'}\right)^{\varepsilon_l} \tag{9}$$

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:

$$
\begin{aligned}
n_p &= \delta_p \sum_{a=1}^{N} r_{pa} + V_p \lambda \\
\delta_p &= \sigma_p, \forall p \in \{EV\ Car, EV\ Light\ Truck\} \\
\delta_p &= 1 - \sigma_p, \forall p \in \{ICE\ Car, ICE\ Light\ Truck\}
\end{aligned}
\tag{10}
$$

This formulation assumes no change in the mix of light trucks and cars. While 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, the mechanism was not implemented by Naumov et al. (2019) and not extended by this thesis.

2.4 GHG Emissions Co-flow Sub-model

The GHG sub-model uses 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:

$$
E_p = \sum_{a=1}^{N} E_{pa} \tag{11}
$$

The emissions accumulate and deplete following vehicle sales and retirements:

$$\frac{dE_p}{dt} = n_p \mu_p^{CAFE} - \sum_{a=1}^{N} r_{pa} \bar{\mu}_{pa} \tag{12}$$

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:

$$\bar{\mu}_{pa} = \frac{E_{pa}}{V_{pa}} \tag{13}$$

2.5 Tax revenue Sub-Model

The tax revenue model simulates the revenue generated based on fuel taxes, VMT taxes, and registration fees for both ICEVs and EVs. It also includes the revenue requirements to maintain the roads and bridges as an input to the sub-model. It compares the tax revenue generated against the requirements to calculate the revenue gap. The cumulative revenue gap is one of the measures that could be optimized to fit the purpose of establishing a policy that can meet the revenue requirements.

Tax revenue is calculated as the sum of gas tax revenues, registration fee tax revenues, and VMT taxes collected.

$$\begin{aligned} GT_{Rev} = GT * \sum_{p \epsilon I} \sum_{a}^{N} \frac{E_{pa} * l_{pa}}{ICF} * \left(\frac{l}{l'}\right) \; + \; \sum_{p \epsilon P} \left(RFT_p * \sum_{a=1}^{N} V_{pa} \right) \\ + \sum_{p \epsilon P} \left(VT_p * \sum_{a=1}^{N} V_{pa} * l_{pa} * \left(\frac{l}{l'}\right) \right) \end{aligned} \tag{14}$$

Gas tax revenue is calculated as the product of total fleet fuel consumption (gallons) and the gas tax (cents/gallon). Total fuel consumption is calculated as the sum across all platforms and cohorts of fuel consumption and miles driven. Registration fee revenue is calculated as the sum across all platforms and cohorts of the vehicle fleet and the registration fee applied to each platform. VMT tax revenue is calculated as the VMT tax per mile multiplied by the sum in all platforms and cohorts of the vehicle fleet and the miles driven per vehicle.

Fuel consumption of cohort a from platform p is calculated as the division of the average fuel consumption per vehicle (E_{pa}/ICF) and the number of vehicles.

$$\left(\frac{E_{pa}}{ICF * V_{pa}}\right) \tag{15}$$

Total miles driven a from platform p is calculated as the multiplication of the average vehicle miles driven and the number of vehicles. The average vehicle miles driven is calculated using the cohort average VMT adjusted to elasticity.

$$V_{pa} * l_{pa} * \left(\frac{l}{l'}\right) \tag{16}$$

2.6 Model Analysis

Feedback Loops

As mentioned previously and summarized in table 1, the sub-models interact and affect the outputs of each other. For example, the vehicle fleet model affects the tax revenue through the number of vehicles in the system and at the same time, the tax revenue affects the annual cost of operation of a vehicle. This interaction between sub-models creates feedback loops, either reinforcing or balancing, that drive the behavior of the system in time, and that should be considered in order to understand it and to create stronger policies.

Another example is when one of the key reinforcing loops of the system is related to the gas tax increase to close the gap revenue: the greater the gas tax, the greater the cost of driving, which leads to less attractiveness of fuel-based vehicles. The previous leads to a smaller market share of fuel-based-vehicles, which leads to fewer fuel-based vehicles in the system; thus, to less tax revenue, which increases the gap revenue that we aimed to close. If the behavior of the policymaker repeats and thinks of a new increase of the gas tax as the solution to close the revenue gap, it will face the same reinforcing behavior or the system and will not address the issue properly.

However, we must consider that the system is complex and that many feedback loops are acting at the same time but sometimes in different directions. For example, exactly as in the previous case, let the gas tax value increase again: this will reduce the vehicle miles traveled by vehicles, therefore increasing the average duration of the road infrastructure, which will reduce the yearly revenue requirements of the DOT, which will reduce the revenue gap.

Therefore, though increasing the gas tax has the direct consequence of an increase in the tax revenue, when model boundaries are expanded, other dynamics come to play and affect the results. In the previous case, when the tax revenue structure was interconnected with the other sub-models, feedback structures such as the revenue reinforcing loop or the VMT road maintenance balancing loop arise.

The strength of each feedback loop and the outcome of this encounter of forces depends entirely on the state of the system. In other words, the behavior of the system in time and therefore, the outcome of any given tax policy depends on the initial conditions of the system. These conditions are expressed in terms of stock variables of the system and will be addressed in the next section.

As mentioned already in the previous paragraphs, the main feedback structures that are acting in the system are:

- **Technology Adoption:** Taxes increase the annual cost of owning a car, which is one of the considerations when purchasing one. The previous leads to a lower relative attractiveness compared to other vehicles affecting the market share of the platform. The decrease in the number of vehicles results in a decrease in tax revenue, which may lead to an increase in motor taxes.
- **VMT Elasticity:** Taxes increase the cost of driving a vehicle, leading to a decrease in VMT and therefore in fuel or electricity. This increase will lead to lower revenues related to fuel or electricity, which will decrease the tax revenue generated.
- **World Learning through sales:** The production of vehicles leads to more knowledge on vehicle manufacturing, which leads to improvements in the production process, which is reflected in cost savings and price reduction, which lead to greater sales, and therefore greater production size. Vehicle sales represent the learning curve and improvement cycle.

Stock and Flows

As mentioned by Sterman (2000), the state of systems is characterized by its stock variables. Stock variables accumulate a quantity over time and are the basis upon which decisions and actions within the model are made. An example of a stock is the vehicle fleet, defining how many of each type of vehicles are in the system at any point in time. Failure to understand the difference between stocks and flows often leads to an underestimation of time delays, a short-term focus, and policy resistance (Sterman, 2000).

Regarding the model presented, the stock variables that characterize the state of the system are:

- **Vehicle Fleet:** The number of vehicles for each platform and age cohort is the key stock variable of the model. It defines the revenue collected by the government, the rate of GHG emissions, and other variables.
- **Vehicle Emissions:** The emission potential for each platform and age cohort.
- **Cumulative Sales:** Cumulative world sales and local sales in our model represent the amount of knowledge cumulated in the industry to manufacture vehicles.
- **Cumulative Tax Revenue:** is the difference between cumulative revenue requirements and cumulative tax revenue. It defines the financial position of the government to fund transportation infrastructure.

The combination of these four stock variables define the state of the system at any point in time, and any behavior of the model can be traced back to these four variables. Policymakers should keep in mind the state variables to address properly the issues that they want to solve: for example, a policy could have different outcomes if the EV fleet (stock variable) has a large market share compared to the scenario where the market is in an early stage.

Other variables that could extend the model formulation are the state of the road infrastructure and the extent of the road infrastructure. While the state of the road could represent the quality and conditions of the road and bridge infrastructure to define better maintenance practices, the extent of the infrastructure could represent the capacity of transportation.

Boundaries of the Model

The model presented extends the scope of the existing gas tax literature by considering the development of the EV market. Nonetheless, it presents boundaries that must be recognized when analyzing tax policies.

Regarding the vehicle fleet, the existing model simplifies the existing types of vehicles to consider just four platforms, excluding drivers of motorbikes from the equation, for example. Also, all ICE vehicles use gasoline as fuel and not diesel. Though the replacement of ICEV to EV (and vice versa) is allowed within the model, the of a car to a light truck (SUV) is not. In terms of policies, the model does not address other policies such as CARS, incentives to acquire EVs, or the effect of charging stations in the development of the EV market.

Learning both local and global is modeled and simplified through cumulative sales. Real development could be completely exogenous to the model, or the specific market addressed within.

Regarding the tax revenue, the model currently compares revenue requirements with tax revenue generated from state policies. The introduction of other sources of revenue (such as federal funds) or the allocation of existing ones to other budgets (cycle roads) will modify the existing model and depends on the specific instance modeled.

Finally, as mentioned before, the capacity and state/performance of the road infrastructure is not included in the model. If included, interesting non-linearities could appear and highlight even more the importance of preventive maintenance as an investment and its economic effect on the DOT.

3 Case Study: The Ohio Department of Transportation

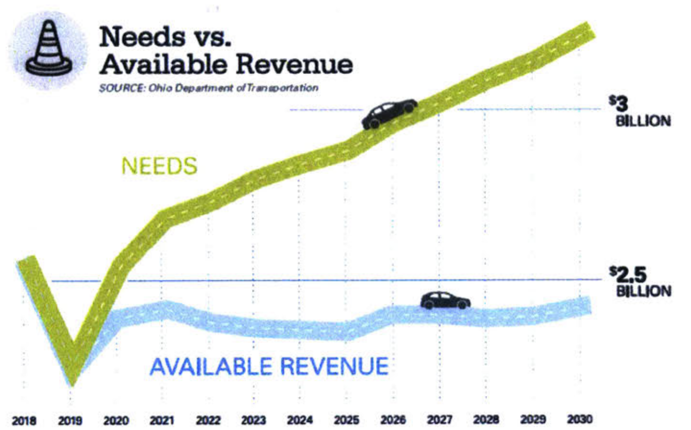
In this chapter, I present a case study analyzing the application of the model to the state of Ohio, a jurisdiction that has recently undertaken a public conversation about raising the gas tax. The purpose of the case study is twofold: first, to exhibit the dynamics and tradeoffs of the model using Ohio as an example, and second, to analyze different tax policies to close the revenue gap in the state. The case study is structured as follows: (i) introduce the context of ODOT and the problem; (ii) present the baseline simulations based on the former and recently approved tax policies in the state; (iii) simulate alternative tax policies to evaluate their performance; (iv) analyze the results and present recommendations.

The selection of Ohio as the state to create a study case follows the relevance of the topic and the discussion: In February 2019, the governor of Ohio proposed a motor fuel tax reform to address the revenue needs of the ODOT. The tax reform was modified and approved during April 2019. Given these conditions, updated data is available to be used as parameters of the model and test its robustness in a real-life and up-to-date scenario.

3.1 The Ohio Department of Transportation

The Ohio Department of Transportation is the organization responsible for developing and maintaining all state and federal roads in the state of Ohio, except for the Ohio Turnpike which is owned and maintained by the Ohio Turnpike and Infrastructure Commission. It manages the fourth-largest transportation network in the United States and depends on funding from the Ohio state government. The value of transportation infrastructure managed by ODOT totals $115 billion, including $65 billion in pavement and $22 billion in bridges. The maintenance of those assets is critical to Ohio's economic vitality (Advisory Committee on Transportation Infrastructure, 2019).

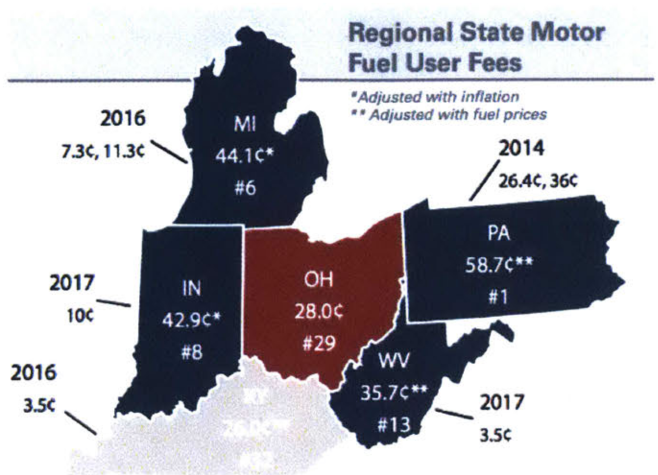
According to the Advisory Committee on Transportation Infrastructure (2019), the ODOT will run out of money for new projects and fall behind regular maintenance and preservation of the existing infrastructure in the coming years. Even though ODOT was able to invest $2 billion and $2.35 billion in the state transportation system in years 2017 and 2018 respectively, the investment will drop to $ 1.89 billion in 2019 and to $1.7 billion in 2021 (TRIP 2018). The total funding gap each year for ODOT out to 2030 is estimated in $1 billion, which includes $500 million in maintenance projects, $250 million in safety projects, and $250 million for new projects (Advisory Committee on Transportation Infrastructure, 2019). Figure 3 displays the current needs of ODOT and estimated revenue until 2030.



Source: Advisory Committee on Transportation Infrastructure (2019) [28]
Figure 3 Needs and available revenue of Ohio's Department of Transportation until 2030

As the US Department of Transportation, the financial problems of ODOT is related to the current outdated tax policies in place and the technological context: the value of the fuel tax has decreased due to both inflation and the increase of fuel-efficient cars (Advisory Committee on Transportation Infrastructure, 2019). Although the miles that people are driving have not decreased, fuel-efficiency improvements have caused motorists to use relatively less gas, and therefore, revenue generated is not covering the cost of infrastructure maintenance.

To give context to the current state motor fuel policy, Ohio's motor fuel tax rate was last increased in 2005 to the value of 28 cents per gallon, ranking Ohio 29th among all US states. In comparison to the states surrounding Ohio, every state has increased their motor fuel taxes since 2014, all of them have indexed their fuel taxes to either inflation or fuel prices, and all of them but Kentucky have higher fees. Figure 4 exhibits the regional state motor fuel taxes scenario.



Source: (Advisory Committee on Transportation Infrastructure, 2019)

Figure 4 Regional State Motor Fuel User Fees surrounding Ohio

In contrast to the motor fuel taxes, which has remained the same since 2005, construction cost has risen dramatically: the value of a dollar in 2003 is only 58 cents today according to ODOT (2019). As the taxes are not indexed and not been updated in the previous administrations, the revenue gap has increased over the years to the point of no return: by July 1, 2019, ODOT will run out of money to meet its short-term commitments and will fall behind regular maintenance.

The Governor of Ohio proposed by February 2019 an increase of 18 cents per gallon to motor fuel tax to be adjusted yearly according to inflation to close the state revenue gap. However, the final tax bill approved by Ohio Senate approved in March 2019 comprised:

- Increment of 10.5 cents per gallon of gas to the value of 38.5 cents per gallon.
- Increment of 20 cents per gallon of diesel to the value of 47 cents per gallon.
- Establishes a registration fee to hybrid vehicles of 100 USD a year.
- Establishes a registration fee to electric vehicles of 200 USD a year.
- Maintains registration fee to ICE vehicles in 34.5 UD a year.

All of these changes will act from July 1st, 2019.

This approved tax reform bill differs to the one proposed initially by the Governor of Ohio as it increases the gas and diesel taxes by smaller amounts, establishes high registration fees to new technologies, and does not consider the indexation of the gas tax. Questions that naturally arise of the newly approved tax reform is whether the policy will close the revenue gap of ODOT, and how will the registration fee affect the adoption of new alternative fuel technologies such as HEVs and EVs.

3.2 Model Parametrization

Using the model introduced in the previous chapter, a baseline has been created considering two cases: the value of the taxes before and after the tax reform recently approved. These two cases will serve as a comparison point to other policies.

3.2.1 Time horizon

For all cases, the time horizon for simulations is between 2019 and 2050. All tax policies proposed will start by July 1st, 2019. The start date resembles the actual case of Ohio, where the new policy approved will act from that date. Though the requirements and implementation of the policy done by ODOT frame the problem until 2030, the specific end-date of the simulation period is defined as 2050 to explore the full dynamics of the system.

3.2.2 Parameter Selection

The parameters used for the model are replicated from Naumov, Keith & Sterman (2019). Table 2 displays the description and value of all parameters.

Sub-model	Parameter	Description	Value	Units
Fleet Co-flow	Initial Fleet Value	Value of the initial fleet in the system per age cohort and platform. Values for Ohio calculated as a percentage of the total Ohio fleet. Source: NHTS (2001), DOT (2016).	Multiple	Vehicles
	Initial Emissions	Information adapted to Ohio State from NHTS (2001).	Multiple	Vehicles * (CO2 grams) / miles
	Hazard Rate	Rate at which vehicles fail and are taken out of the system. Source: NHTS (2001)	Multiple	Dimensionless
	Average Time per Age	Average time in each one of the cohorts. The last cohort of cars considers all car from 30 to 35 years.	Multiple	Year
	Aggregate Market Growth	Aggregate market growth of the vehicle fleet.	0.01	Dimensionless
Market Share	Logit Choice Scaling	Logit model scaling parameter.	2.5	Dimensionless
	Weight of Price Surcharge	Weight of the price surcharge of EV relative to ICE.	-2	Dimensionless
	Initial Price Surcharge of EV relative to ICE	How much more expensive is an EV compared to an ICE vehicle.	0.25	Dimensionless
	Weight of Annual Savings	Weight of the savings from driving an EV relative to ICE.	0.001	Dimensionless
	Reference inconvenience of EV	Reference inconvenience of driving an EV	-2	Dimensionless
	Ohio Market Factor	Market Formation Factor for Ohio's Market. The factor accounts for the formation of the market, accounting Ohio's market size. This is calculated as the total fleet of cars in the US, divided by the number of cars in Ohio.	24	Dimensionless
Effect of Learning	Reference Cumulative World EV Sales	The reference level of sales to increase the world learning to produce EVs	10^7	Vehicles
	Reference Cumulative EV Sales	The reference level of sales to increase the learning to produce EVs	10^7	Vehicles
	Learning Curve Strength Market Formation	Strength of the curve of Market Formation related to Ohio.	0.25	Dimensionless
	Learning Curve Strength Price	Strength of the learning curve related to the World EV Market.	0.25	Dimensionless
	EV Market growth	EV Market growth worldwide.	0.05	Dimensionless
Annual Cost of Driving and Maintenance	Average Cost of Maintenance	Cost of maintaining an ICE Car or EV Car. ICE = 1,186 USD, EV= 982 USD.	Multiple	Dollars/year
	Registration Fee Tax	ICE = 34.5, EV= 200	Multiple	Dollars/year
	Gas Tax	Gas Tax for Ohio State	38.5	cents/gallon
	Baseline Fuel Price	Price of gas.	3	USD/Gallon
	Average VMT	Average VMT calculated using (NHTS, 2001) information.	11525	Miles/(Year*Vehicle)
	Grid Electricity Cost	Grid Electricity Cost.	0.15	USD/ KWH
	Native Units to GGE Electricity	Conversion from Native Units to CGE Electricity.	33.7	KWH /gallon
Elasticity of VMT	Elasticity of VMT to Fuel Price	Elasticity of Vehicle Miles traveled as compared to Fuel Price.	-0.3	Dimensionless

Table 2 Parameters of the Model

3.2.3 Revenue Requirements Parameters

Additionally, the revenue requirements of Ohio are included in the model as a function of revenue over time calculated as a quadratic polynomial regression based on the yearly requirements presented in table 3.

Year	Requirements (USD Billions)
2018	2.6
2021	2.7
2022	2.75
2023	2.8
2024	2.85
2025	2.9
2026	2.95
2027	3
2028	3.1
2029	3.2
2030	3.3

Source: Advisory Committee on Transportation Infrastructure (2019)

Table 3 Estimated ODOT Revenue Requirements

Equation (17) is the quadratic function that represents the revenue requirements:

$$\text{Revenue} = 0.0029958\,(year)^2 - 12.0711\,(\text{year}) + 12162.2 \tag{17}$$

Figure 5 displays the annual requirements of the ODOT from table 3 and the function obtained from the quadratic regression.

3.2.4 Software

The model was simulated in Vensim simulation software with a time step of 0.125 years. Policy optimization was performed using Vensim's optimization tool.

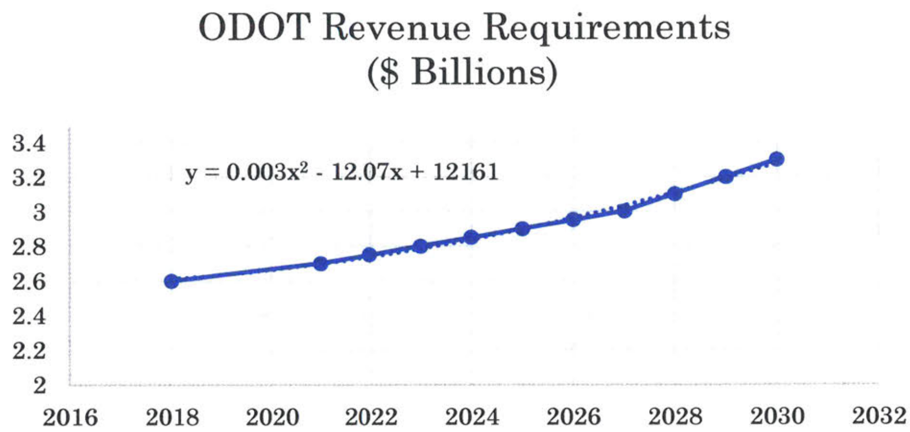


Figure 5 Regression of Required Tax Revenue by ODOT

3.3 Baseline Case Scenarios

As mentioned before, the Ohio Department of Transportation of Ohio has gone through a tax reform that aims to close the current revenue gap to maintain roads and bridges. This revenue gap is estimated at $1 billion per year. To close this revenue gap, the new tax reform was approved by Ohio in March of 2019 to increase tax to gas and diesel, as well as the registration fees to electric vehicles.

In this section, two baseline cases are created based on the current situation: the first one, refers to the initial case before the approval of the tax reform, and the second one, considers the actual case where the tax reform for light duty vehicles has been approved to tax gas with 38.5 cents per gallon and electric vehicles with a $200 registration fee.

3.3.1 Pre-Tax-Reform Case

The present case exhibits the dynamics of the system before the approval of the tax reform. Its purpose is to compare and validate the model results with the analysis available from the Governor's Office and ODOT as well as to provide a base to compare other potential policies. The case considers a tax of 28 cents per gallon of gas and diesel and a registration fee of $34.50 per vehicle per year for all vehicles. Both the gas tax and registration fee do not change over simulation time.

Regarding the total vehicle fleet numbers in Ohio, the total fleet size is simulated to expand from 10,695 million vehicles in the year 2018 to 14,579 million in the year 2050 due to population growth. The result is as expected as the aggregate growth parameter was set to increase the fleet size by 1% a year. In terms of vehicle platforms, the total number of ICE cars decreases while the size of the fleet of the other platforms grows. Figure 6 shows the increase in the total fleet size and the average fuel economy of the fleet, while figure 7 shows the decomposition for each platform considered. Also, tables 4 and 5 display the evolution of the vehicle fleet.

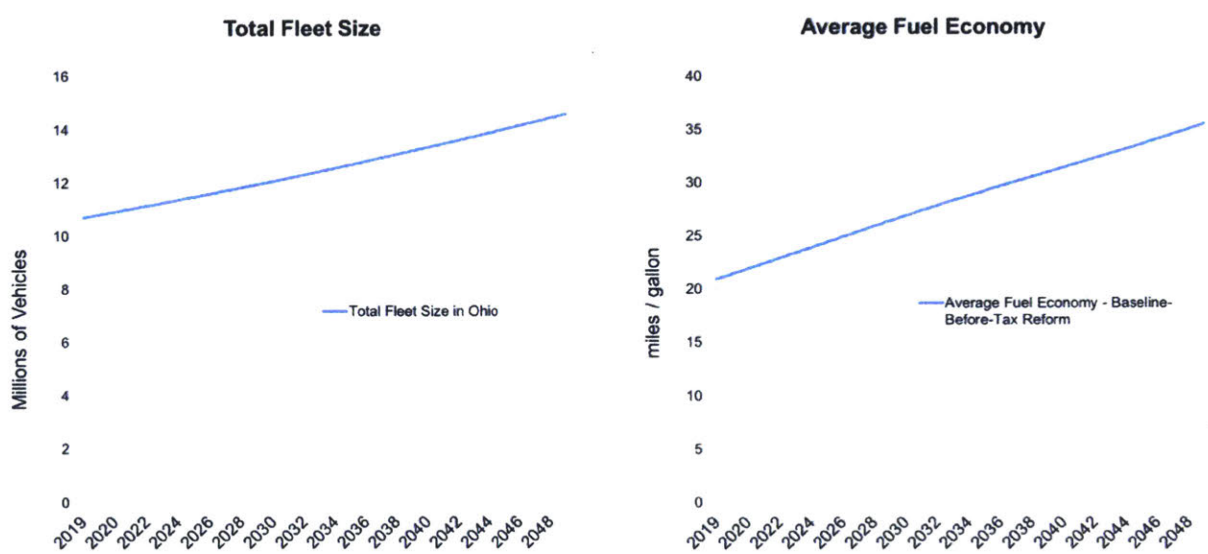


Figure 6 Total Fleet and Average Fuel Economy - Baseline Scenario Before Tax Reform

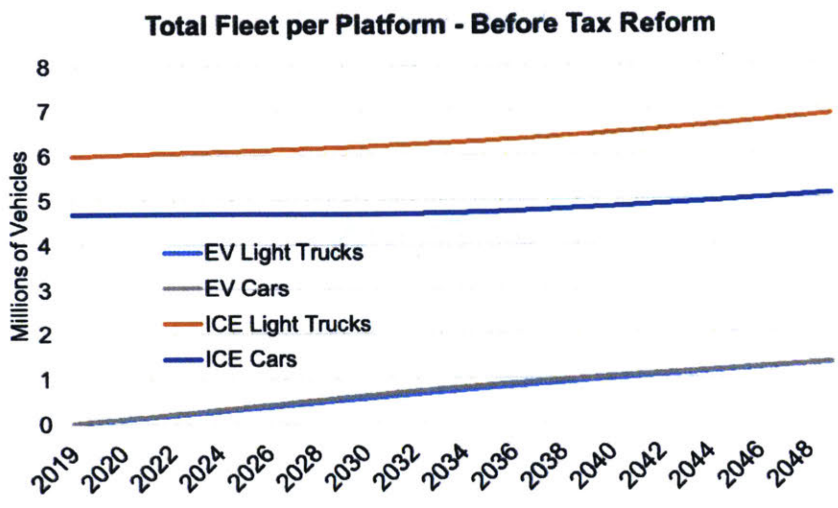


Figure 7 Total Fleet Size per Platform - Baseline Scenario Before Tax Reform

Platform	Year 2018 [Million of vehicles]	Year 2018 [Percentage of Total Fleet]	Year 2050 [Million of vehicles]	Year 2050 [Percentage of Total Fleet]	Absolute Difference [Million of vehicles]
ICE cars	4.694	43.89%	4.86	33.3%	0.17
ICE Light-trucks	5.992	56.03%	6.62	45.4%	0.63
EV cars	0.009	0.08%	1.54	10.6%	1.53
EV Light-trucks	0.000	0.00%	1.54	10.5%	1.54
Total Vehicles	**10.695**	**100.00%**	**14.57**	**100.00%**	**3.88**

Table 4 Total Fleet Size per Platform - Baseline Scenario Before Tax Reform

Platform	Year 2018 [Million of vehicles]	Year 2018 [Percentage of Total Fleet]	Year 2050 [Million of vehicles]	Year 2050 [Percentage of Total Fleet]	Absolute Difference [Million of vehicles]
Total ICE Vehicles	10.69	99.92%	11.49	78.81%	0.80
Total EV Vehicles	0.009	0.08%	3.09	21.19%	3.08
Total Vehicles	**10.70**	**100.00%**	**14.58**	**100.00%**	**3.88**

Table 5 Total Fleet Size per Technology - Baseline Scenario Before Tax Reform

Regarding revenue generated of the DOT, results obtained show that tax revenues decrease while revenue requirements increase over time (Figure 8). Despite the growth of the total vehicle fleet, tax revenue generated decreases over the simulation period, and the revenue gap increases at a higher rate until 2050. This situation arises due to the introduction of EVs to the market and improvements in the fuel economy (Figures 6 and 7).

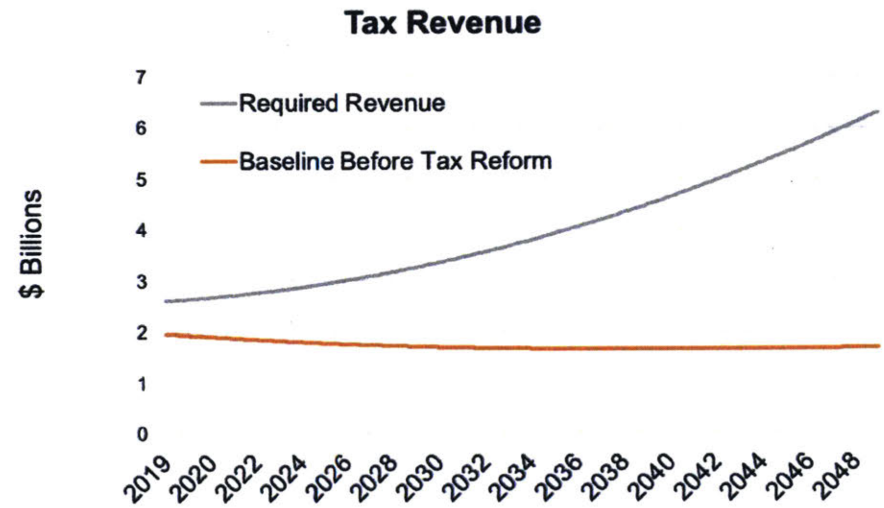


Figure 8 Tax Revenue Generated - Baseline Scenario Before Tax Reform

As a consequence of the introduction of EVs into the vehicle fleet, total fleet GHG emissions are reduced from 0.5092 to 0.4193 gigatons of CO2 per year by 2050 (17,66%). Figure 9 offers a view of the decrease in total fleet emissions by the year 2050.

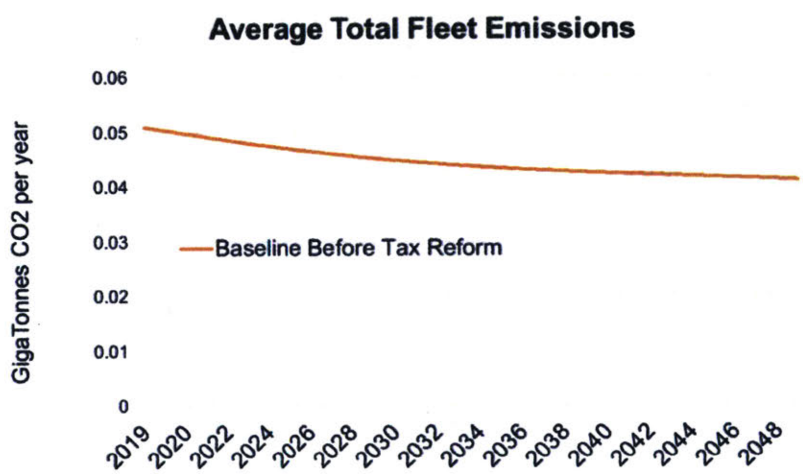


Figure 9 Total Fleet Emissions - Baseline Scenario Before Tax Reform

3.3.2 Baseline Case - After Tax Reform

The present case is based on the recently approved tax reform and simulated the system under the approved conditions. It considers a gas tax of 38.5 cents per gallon to gas, a registration fee of $34.50 per year for ICE vehicles, a registration fee of $100 per year hybrid vehicles and a registration fee of $200 per year for electric vehicles. Figure 10 offers a comparison between the before-tax-reform and after-tax-reform scenario.

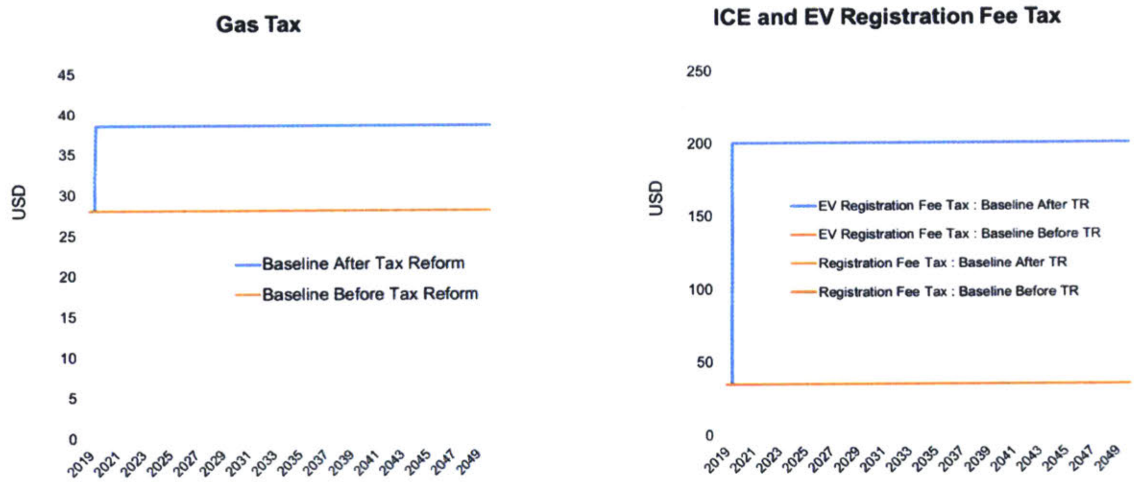


Figure 10 Motor Fuel Tax for Ohio State – Before and After Tax Reform

In terms of the vehicle fleet size, the aggregated growth has remained the same given the fixed growth rate, and therefore, total vehicle fleet size by the year 2050 is equal to the previous case. However, in terms of platform share, the effect of the higher registration fee imposed on EVs discourages vehicle buyers from making the transition to the new technology. The tax effect means a reduction of approximately 480,000 electric vehicles between the period of 2018 and 2050. Figure 11 captures the dynamics of the present scenario for each platform and make a comparison between them. Tables 6 to 7, exhibit the numbers of this scenario as well, and finally, table 8 makes a comparison between both tax policies.

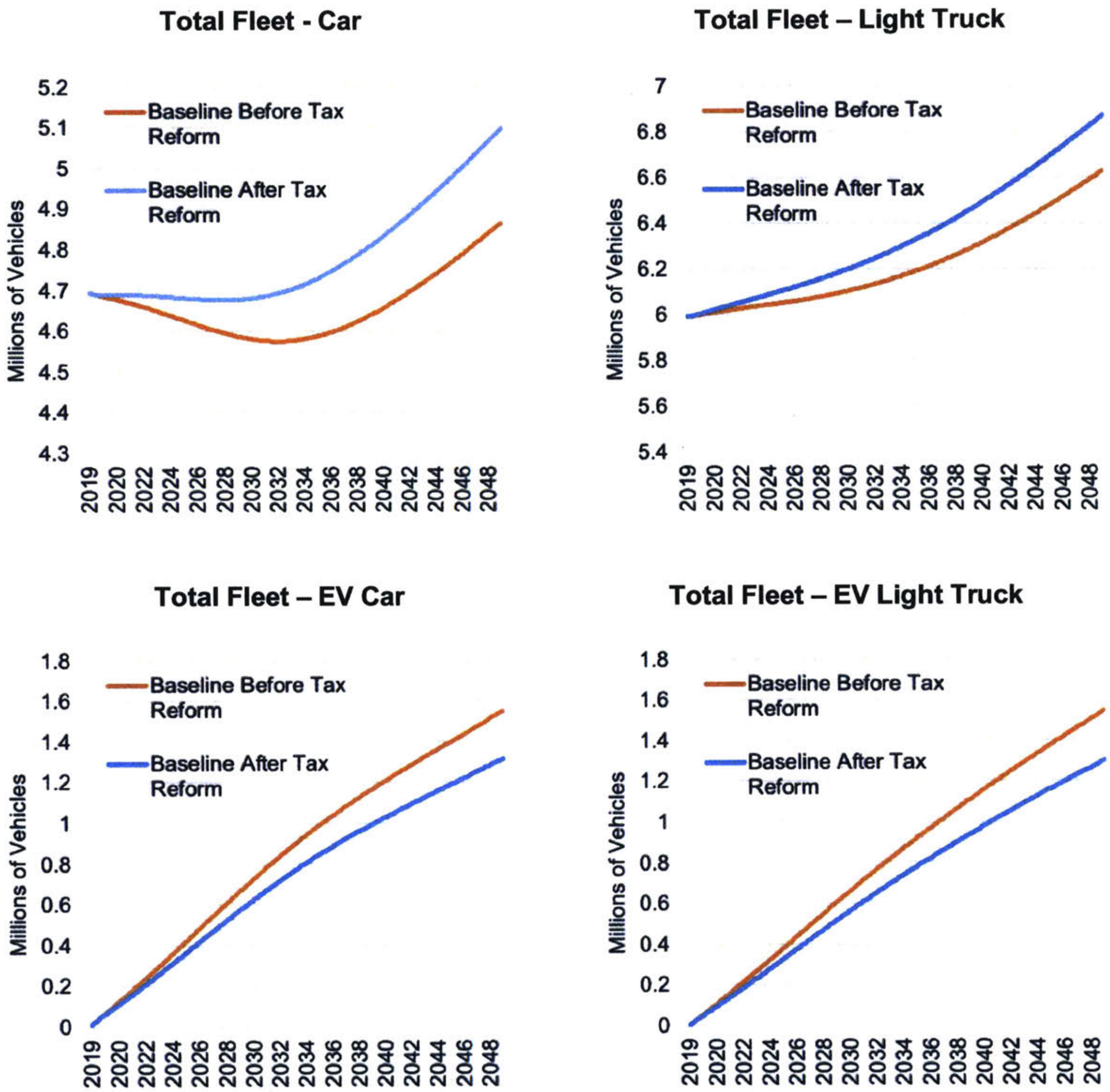


Figure 11 Total Fleet Size per Platform Comparison - Before and After the Tax Reform

Platform	Year 2018 [Million of vehicles]	Year 2018 [Percentage of Total Fleet]	Year 2050 [Million of vehicles]	Year 2050 [Percentage of Total Fleet]	Absolute Difference [Million of vehicles]	Percentage Increase
ICE cars	4.69	43.89%	5.10	34.96%	0.40	8.57%
ICE Light-trucks	5.99	56.03%	6.87	47.11%	0.87	14.63%
EV cars	0.01	0.08%	1.31	9.02%	1.30	14507.67%
EV Light-trucks	0	0.00%	1.30	8.91%	1.30	N/A
Total Vehicles	**10.69**	**100.00%**	**14.58**	**100.00%**	**3.88**	**36.32%**

Table 6 Total Fleet Size per Platform - Baseline Scenario After Tax Reform

Platform	Year 2018 [Million of vehicles]	Year 2018 [Percentage of Total Fleet]	Year 2050 [Million of vehicles]	Year 2050 [Percentage of Total Fleet]	Absolute Difference [Million of vehicles]	Percentage Increase
Total ICE Vehicles	10.68	99.92%	11.96	82.07%	1.28	11.97%
Total EV Vehicles	0.01	0.08%	2.61	17.93%	2.60	28946.22%
Total Vehicles	**10.69**	**100.00%**	**14.57**	**100.00%**	**3.88**	**36.32%**

Table 7 Total Fleet Size per Technology - Baseline Scenario After Tax Reform

Platform	Year 2050 [Million of vehicles]		
	Before Tax Reform	**After Tax Reform**	**Difference**
Total ICE Vehicles	11.5	12.0	0.48
Total EV Vehicles	3.1	2.6	-0.48
Total Vehicles	14.6	14.6	0

Table 8 Total Fleet Size per Technology - Scenario Comparison

With respect to revenue, the current after-tax-reform policy in place improves the scenario by securing an additional amount of $600 million a year in tax revenue. Figure 12 exhibits the tax revenue, the revenue gap, and the cumulative revenue gap after the tax reform is implemented. However, the new policy in place never gets to close the cumulative revenue gap, which increases at an exponential rate until 2050 accumulating almost $50 billion in debt.

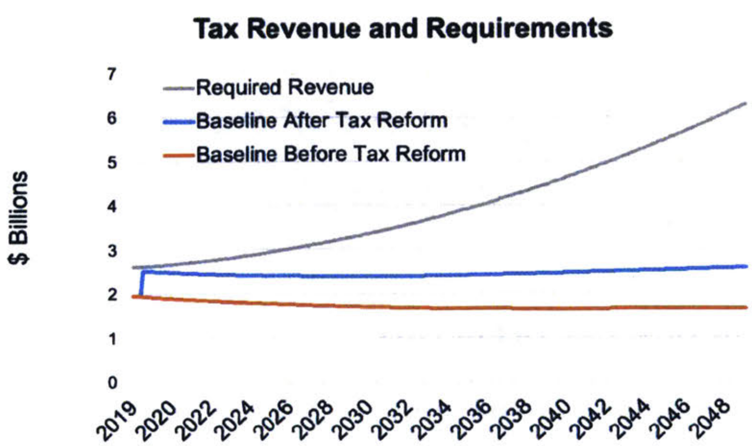


Figure 12 Tax Revenue and Requirements Comparison - Before and After the Tax Reform

As expected, this policy is not able to generate the revenues to meet the requirements as the gas tax requirements are lower than the ones originally proposed by Ohio's governor. Therefore, though a new state policy was approved, the discussion about closing the revenue gap and about creating a sustainable policy is still open.

In terms of GHG emissions, the new policy in place does not materially change the magnitude of the current situation: though it increases the gas tax for gasoline vehicles, it also increases the cost of electric vehicles through the $200 EV registration fee. Figure 13 exhibits the dynamics of total fleet emissions showing a similar behavior when comparing the before and after scenarios.

As the registration fee increases the annual cost of ownership for EVs, the relative attractiveness of EV decreases. By the year 2050, the after-tax-reform policy accounts for a reduction of around 480.000 electric vehicles when compared to the initial baseline, and an increment of 0.01 Gigatons of CO2 per year by 2050.

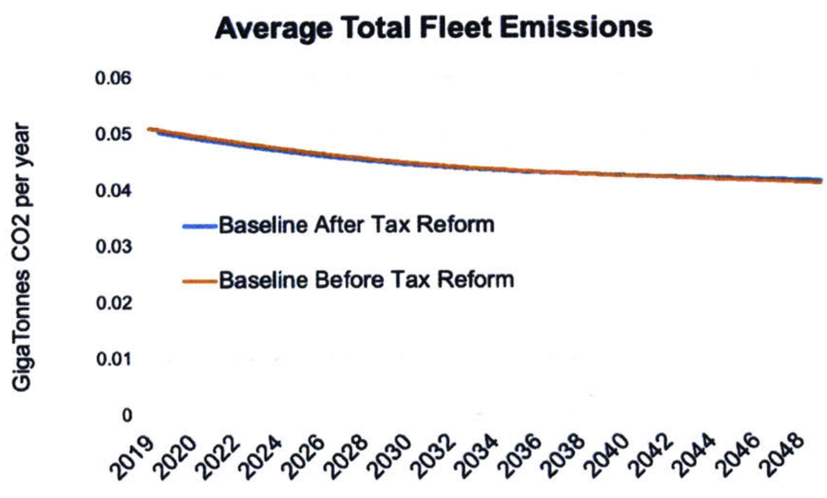


Figure 13 Fleet Emissions Comparison – Before and After the Tax Reform

3.3.3. Summary of Baseline Scenarios

As previously exhibited in the previous section, there is a tradeoff between the vehicle fleet size, the amount of tax revenue generated, the policy adopted and the emission gases: while EV adoption reduces the amount of GHG emissions, it also reduces the tax revenue generated by the ODOT. After the tax reform, though revenue increases and reduces the revenue gap, the new registration fee to electric vehicles disincentivizes EV adoption, thus, reducing the fleet size of EVs and slightly increasing GHG emissions per year. This tension between variables is inherent in the system and must be addressed by policymakers.

The creation of a good policy to tackle the problem must encompass a holistic view of the current problem to understand how main variables affect other outcomes, and what are the possible scenarios that may arise. Clear definition of the problem being solved is key for decision-makers to choose the best scenario among all possibilities.

In the following subsection, alternative policies will be tested to understand how the system responds to them and what are the outcomes from the policy. Given that the current problem statement has been framed in the context of Ohio's Department of Transportation, the analysis focuses first on optimizing the parameters to close the revenue gap, then to understand what the other outcomes are.

3.4 Policy Testing and Results

The current section presents two sets of policies related to the implementation of a new gas tax policy and the implementation of a VMT tax. The policies are tested, and their results are evaluated and compared.

3.4.1 Gas Tax Policy

The current section simulates two functions to increase the gas tax policy: a linear function and an exponential function. Both cases are built on top of the after-tax-reform policy, meaning that the initial value of the gas tax is 38.5 cents per gallon, the registration fee for ICEVs is $34.50, and the registration fee for EVs is $200.

Gas Tax Policy – Linear Function

The gas tax linear policy implementation considers the implementation of a ramp to increase the current gas tax value to one that can close the revenue gap by 2050. This implies that every year, the gas tax should increase by a fixed amount up to the end year, where it will get to the end value that closes the cumulative revenue gap in this period. To calculate the end value of the gas tax policy, the optimization tool of Vensim was set to minimize the cumulative revenue gap at the end of the simulation period by 2050.

The optimization process led to the results of a ramp with an end value of $1.15 per gallon by the end of the year 2050. This policy translates to an increase of approximately 2.5 cents per gallon per year. Figure 14 presents an overview of the gas tax linear policy adopted, including the specific policy, the tax revenue generated, the share of the EV market, and the average emission of the total fleet.

As shown in figure 14, the linear gas tax policy adopted closes the revenue gap considering positive cash flow during most of the simulation period and also presents reduction in GHG emissions when compared to the baseline scenarios. This is explained by two mechanisms: the reduction in the attractiveness of ICEVs, and the reduction of VMT due to the increase in the driving cost. Nonetheless, the adoption of a high registration fee for EVs constraints growth of the EV market, and therefore presents worse results in term of EV market share compared to the first before tax reform scenario.

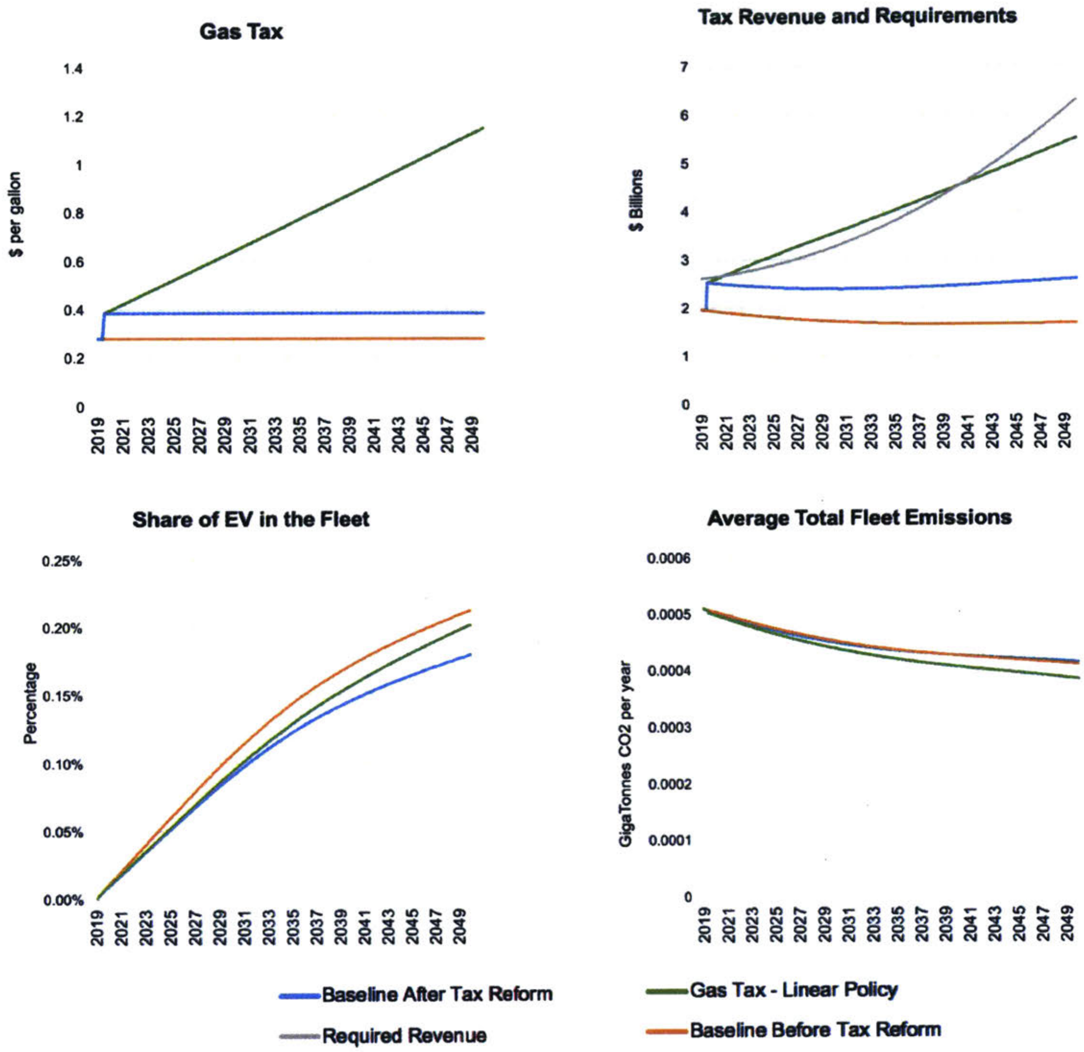


Figure 14 Overview of Gas Tax Linear Policy

Gas Tax Policy – Exponential Function

The gas tax exponential policy implementation considers the implementation of a percentile increment to the current gas tax value to close the revenue gap by 2050. This implies that every year, the gas tax should increase in a specific percentage to the end year, where it will get to the end value that closes the cumulative revenue gap. To calculate the percentage that will increase the value of the gas tax policy, the optimization tool of Vensim was set to minimize the cumulative revenue gap at the end of the simulation period by year 2050.

The optimization process led to the results of a percentage increase of 4.2% a year. Figure 15 presents an overview of the gas tax exponential policy adopted, including the specific policy, the tax revenue generated, the share of the EV market, and the average emissions of the total fleet. For this case, the plots also reference to the previous gas tax linear policy in order to make a comparison.

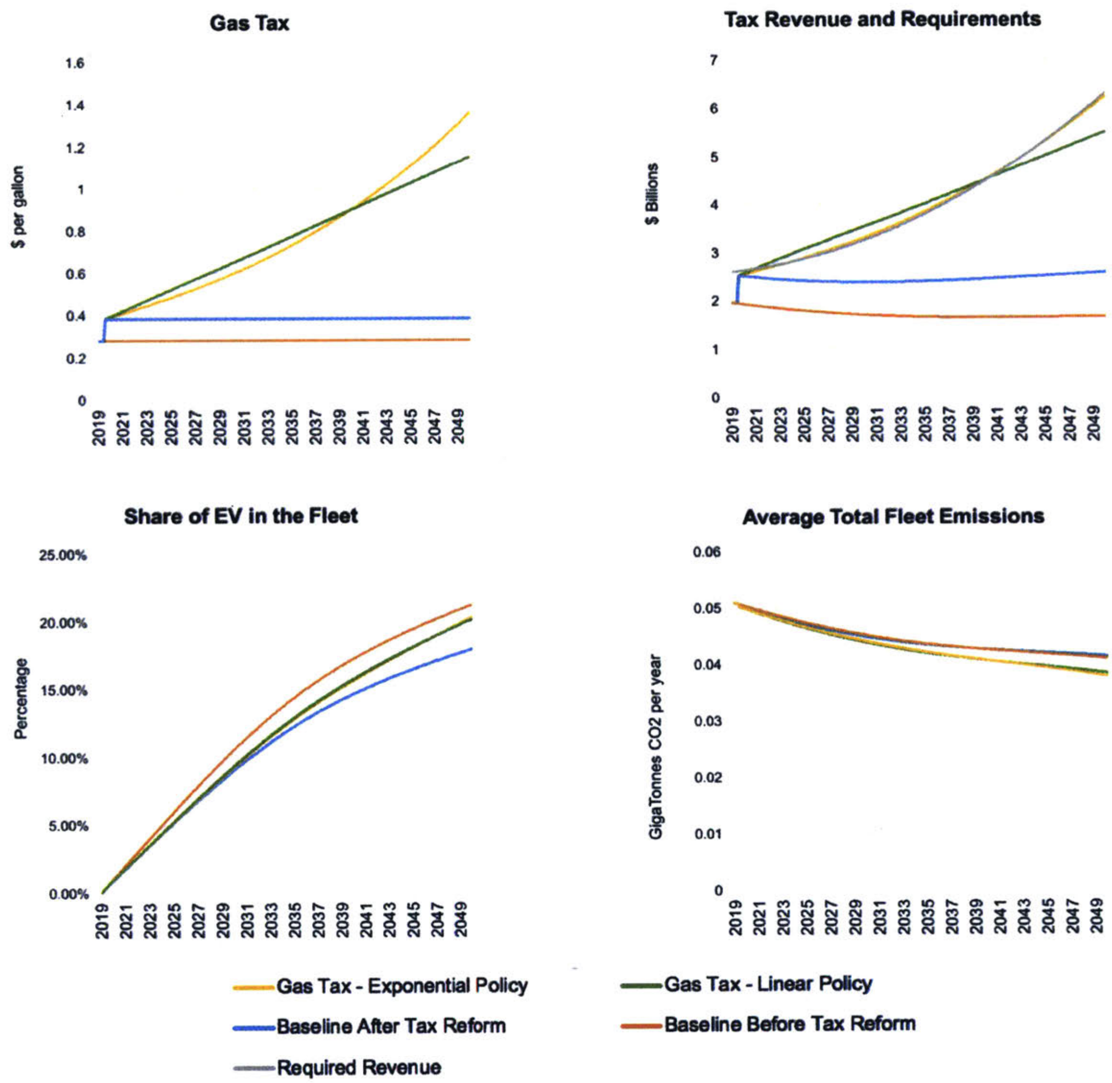


Figure 15 Comparison of the Gas Tax Policies

The results of the exponential policy are in the same order of magnitude compared to the linear policy in terms of the GHG emissions and market share of the fleet. This is explained by the fact that the period is not long enough for the exponential curve to demonstrate any behavior that could be extremely different from a linear curve.

Nonetheless, in terms of revenue generated, the difference between the optimized policies relies on the fact that the exponential policy captures most of the revenue during the last years of the period evaluated. This difference means that the linear policy collects the tax revenue during the earlier years, leading to positive cash flow during most of the simulation period.

3.4.2 VMT Tax Policy

The VMT Tax Policy introduces a new policy structure to tax both types of vehicles, ICE and EV, according to the vehicle miles driven. The initial VMT tax value of 1.65 cents per mile is equivalent to the initial gas tax value after the tax reform. This is calculated as the division between the gas tax value (38.5 cents per gallons) by the average fuel efficiency (23.6 miles per gallon). Also, to provide a fair comparison between the results, the registration fee has been fixed to $34.50 USD for all vehicles.

In implementation the VMT Tax, I consider three different structures for the linear function: the first considers a coupled policy for the EV and ICEV to pay the same VMT tax; the second provides an advantage to EVs that closes over time; the third provides the EV VMT tax an advantage, and maintains that advantage over time. The results for each policy are presented first, followed by the comparison of the three cases in relation to the baseline.

VMT Tax Policy 01 - Coupled Policy

The implementation of VMT tax policy 01 considers a VMT tax value of 1.65 cents per mile to all vehicles driven and a ramp to the year 2050 to meet revenue requirements. This tax structure brings equality to drivers by charging the same amount per mile driven to any vehicle. To calculate the end value of the linear function, the optimization tool of Vensim was set to minimize the cumulative revenue gap at the end of the simulation period by 2050.

The optimization process led to the results of a ramp with an end value of 3.41 cents per mile by the end of the year 2050 to close the revenue gap. The value is exhibited in figure 16, where both ICE and EV have the same value. The results in terms of EV market share and emissions will be exhibited and analyzed in further sections (Figure 19).

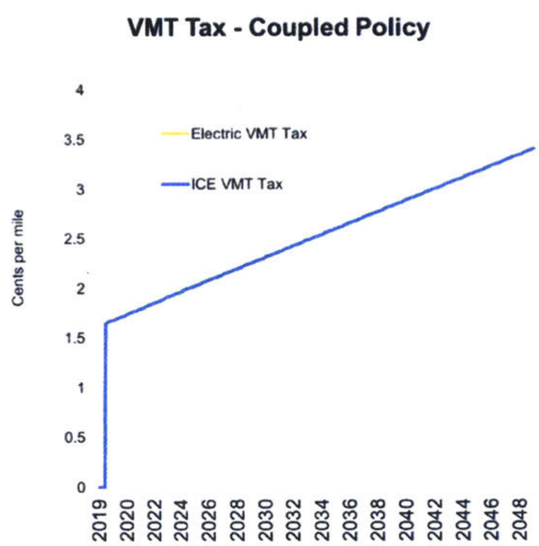


Figure 16 VMT Tax Policy 01 – ICE VMT Tax and EV VMT Tax

VMT Tax Policy 02 – Decoupled Policy (a)

The implementation of a second VMT Tax Policy considers the implementation of different linear functions for ICEVs and EVs, respectively. The function for ICEV will start at 1.65 cents a mile, while the function for EV will start in 0 cents per mile. The end value for both policies will be the same by the year 2050. This will mean that both linear functions will have a different slope and intercept. Also, to provide a fair comparison between the results, the registration fee has been fixed to $34.50 USD for all vehicles. Optimization is set to minimize the cumulative revenue gap.

The results of this optimization found an end value of 3.62 cents per mile to close the revenue gap. Figure 17 displays the value of the ICE and EV VMT tax. As expected, the end value of VMT policy 2 is higher than the previous given that the policy must compensate for the revenue that the EV VMT Tax is not collecting.

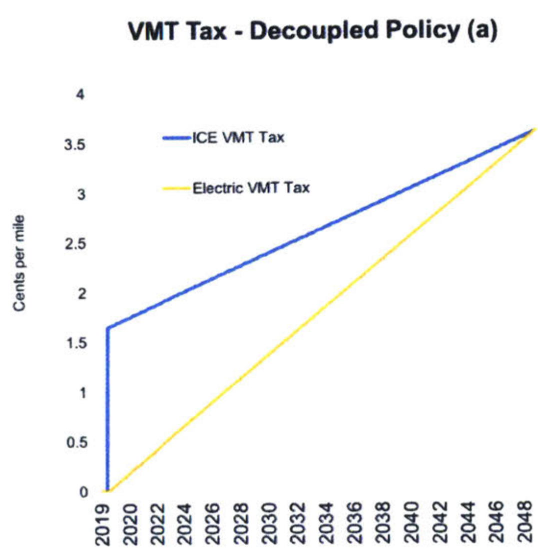


Figure 17 VMT Tax Policy 02 – ICE VMT Tax and EV VMT Tax

VMT Tax Policy 03 – Decoupled with different intercept

The implementation of a third VMT Tax Policy considers the implementation of different linear functions for ICEVs and EVs again. Here, the function for ICEV will start at 1.65 cents a mile, while the function for EV will start in 0 cents per mile. The slope of both functions will remain the same until the year 2050, meaning that both linear functions will maintain the gap of 1.65 cents per mile over the simulation period. This gap will maintain the relative attractiveness of EVs over ICEVs. Also, to provide a fair comparison between the results and as in the previous cases, the registration fee has been fixed to $34.50 USD for all vehicles. Optimization is set to minimize the cumulative revenue gap.

The results of this optimization experiment show that the revenue is closed by the year 2050 with an end value of 4.03 cents per mile for ICEV VMT and 2.39 cents per mile for EV VMT. Figure 18 displays the value of both taxes from 2019 to 2050.

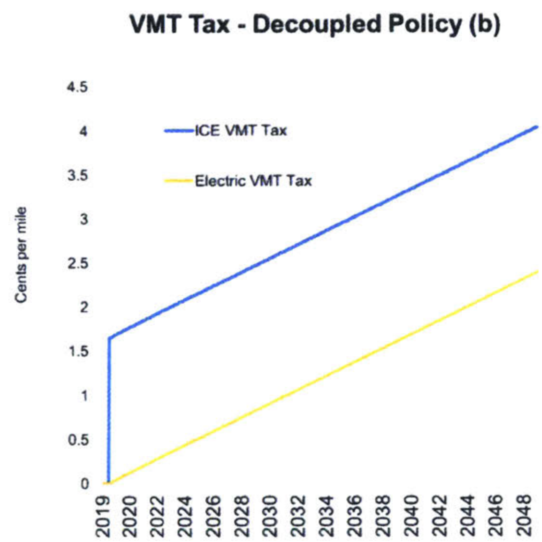


Figure 18 VMT Tax Policy 03 – ICE VMT Tax and EV VMT Tax

Comparison of VMT Tax Policies

Each of the policies simulated in this section are variants of a VMT tax for both EVs and ICEVs. Though all of them close the revenue gap of ODOT successfully, they balance taxes between EVs and ICEs in different ways. This difference in the structure of the policy affects the development of the EV market share and the GHG emissions, as displayed in figure 19.

With regard to revenue generated, all policies present a similar result in terms of shape and magnitude despite their different taxing structure. Regarding the development of the EV market share and emissions, VMT Tax policy 03 outperforms the other two policies, improving the market share by more than 50% and reducing total fleet emissions by more than 10% in comparison to the current policy (baseline after tax reform).

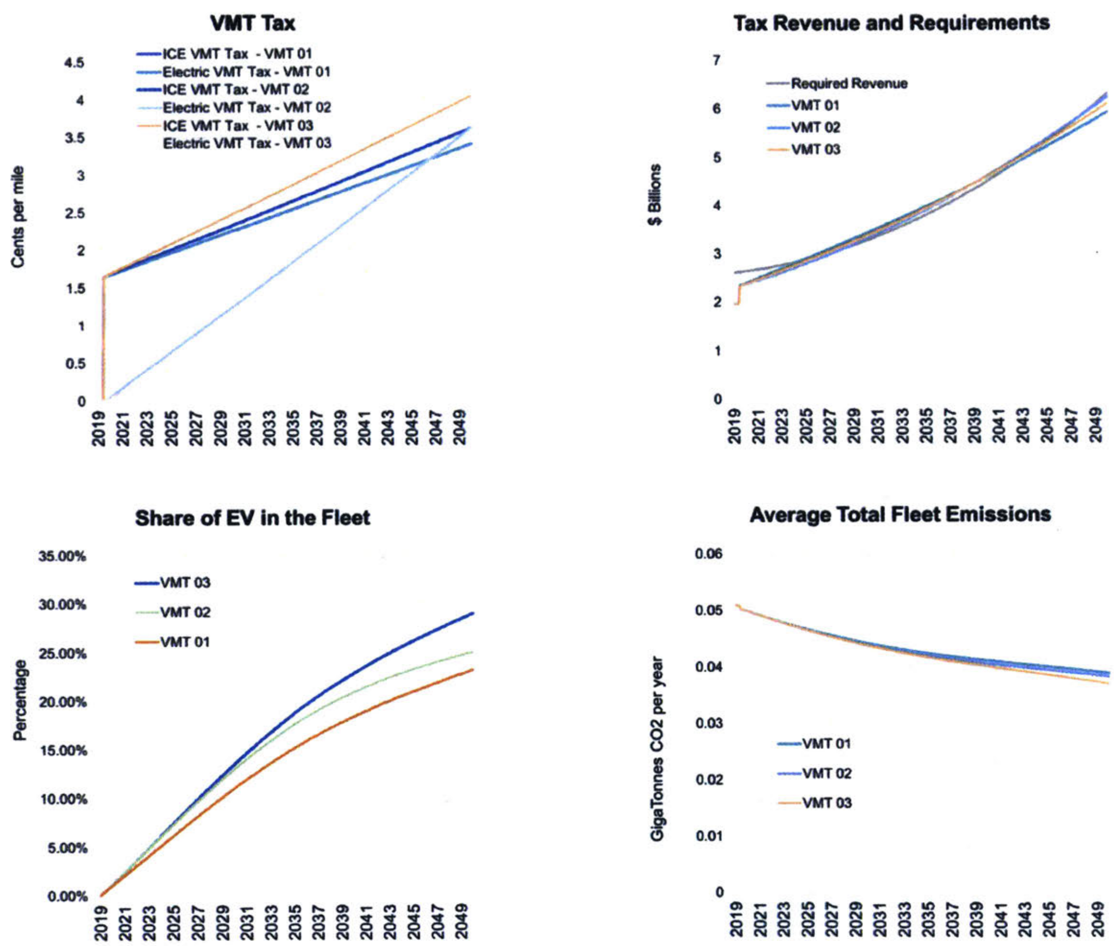


Figure 19 Comparison of the VMT Tax Policies

This comparison illustrates that it is possible to create sustainable policies that can close the revenue gap requirements while balancing the development of the EV market and reducing GHG emissions.

3.4.3 Summary of Policies Tested

In the previous sections, different policies were tested and compared to the baseline scenarios in the context of the Ohio study case. Though all policies displayed were successful in term of closing the revenue, they have differential impacts on the adoption of EVs and the resulting reduction in GHG emissions.

The results of these policies are summarized in figures 20, 21 and 22, highlighting that policy VMT 03 is the best performing in terms of EV market development and emissions: it reduces greenhouse emissions by 10,8% and increases market share with respect to the baseline scenario after the tax reform.

The results of policy VMT 03 are especially interesting when compared to the gas tax linear policy: though the later extends the policy approved recently through a linear ramp until 2050, VMT 03 does the same but replaces the registration fee to a ramp with same slope but lower intercept leading to better results. This shows that, with the parameters used in this analysis, the high EV registration fee imposed was a counterproductive policy for ODOT from an environmental perspective.

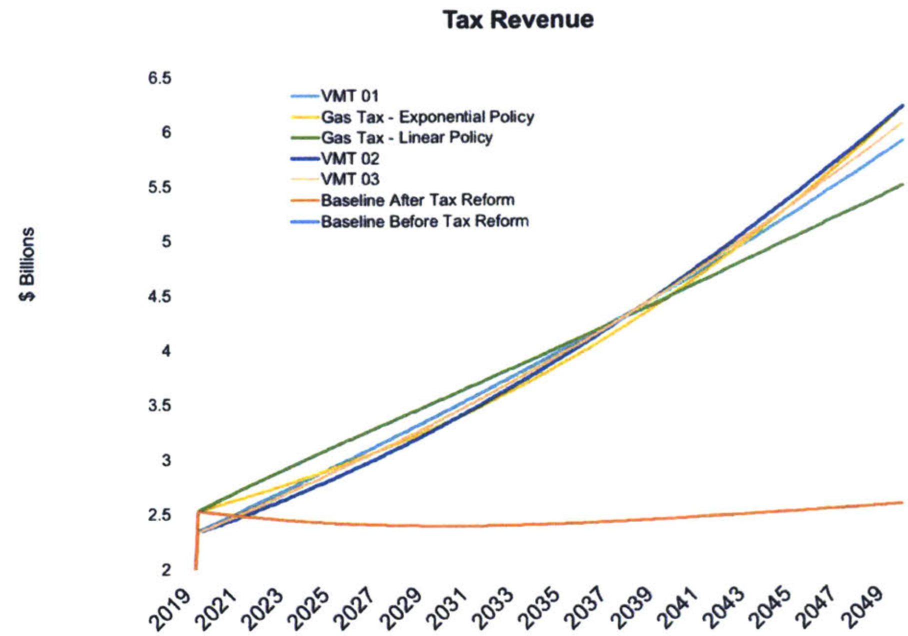


Figure 20 Tax Revenue – All policies comparison

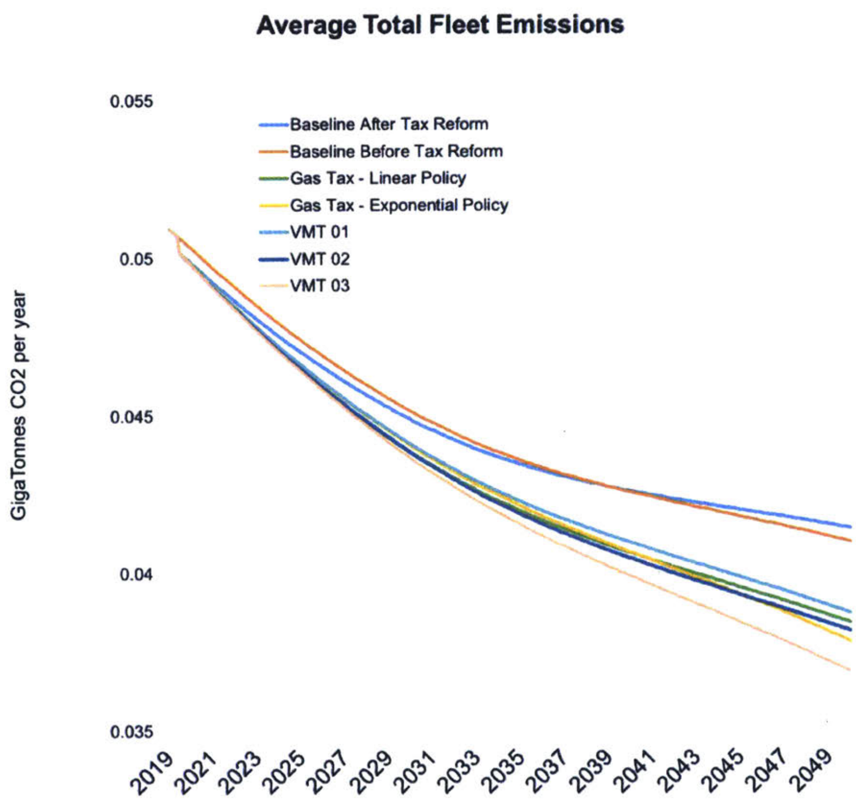


Figure 21 Average Total Fleet Emissions – All policies comparison

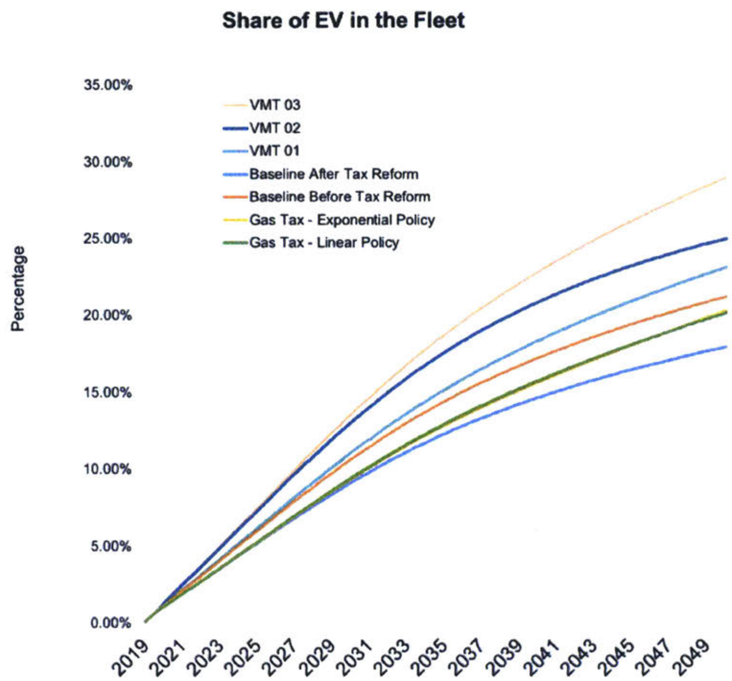


Figure 22 EV Market Share – All policies comparison

4 Conclusion

The analysis I undertake in this thesis explores the effect of different tax policies on infrastructure funding, considering the ongoing introduction of fuel-efficient and electric vehicles into the market. My goal is to understand the tradeoffs that policymakers face when establishing specific motor fuel policies to close the revenue gap and at the same time, reduce greenhouse emissions.

Using a broad-boundary model to analyze this system highlights that important feedback structures exist in the macro system relating to technology adoption, VMT elasticity, and vehicle sales. Policies do not only have a direct effect in tax revenue generated for the DOT but also affect indirectly other dimensions such as consumer behavior, vehicle sales, and VMT. Though researchers and policymakers might acknowledge this indirect impact of policies, the full effect of these feedbacks has not been quantified until now.

The results of my policy analysis show that most policies tested can secure enough tax to close the revenue gap, however important trade-offs exist in many tax designs, limiting the growth of the EV market, or increasing GHG emissions in relative terms. Policies that only tax gasoline vehicles might be signaled as an easy solution to the problem, however, they will become ineffective in time as they accelerate the replacement rate and decrease the gasoline vehicle fleet that generates the revenue taxes. Moreover, a reduction in VMT reduction contributes slightly to maintain the revenue gap, and the measure of not taxing EVs could be contrary to the public opinion and cataloged as a regressive tax. I find that the best policies close the revenue gap while deliberately balancing issues around greenhouse emissions and the development of the EV market in the short-term and the long-term. I find that the implementation of a mixed policy that taxes the use of both ICEVs and EVs but maintains a difference between them was the best policy. This gap maintains the policy attractiveness of EVs relate to ICEVs, allowing the EV market to develop in the next 30 years.

Another key insight from the analysis is related to time delays: changing the vehicle fleet composition takes time. Even if EV technology and prices can be superior, ICEV vehicles will not exit the on-road vehicle fleet for multiple decades due to the durable nature of these vehicles. This insight reinforces the conclusions presented by Naumov, Keith & Sterman (2019). Achieving aggressive GHG reductions from the light-duty vehicle fleet in the next few decades is likely to require a suite of policies, including scrappage policies that accelerate the rate of fleet turnover to be put in place.

The research addressed in this master thesis can be expanded in 3 directions: improving the current work, extending the model presented, and creating other study cases and moving to other platforms to create more impact. First, regarding the analysis, sensitivity analysis of the main parameters of the model, and further explanation of parameter selection is needed. Second, the various model limitations addressed in previous sections could be addressed: including a model that considers the capacity and the capability of the road infrastructure. This sub-model could define the needs for maintenance and incorporate some feedback structure related to the deterioration rate of the road infrastructure when periodic maintenance is not performed. Moreover, a direct consequence of this extension would make the decisions of the model to affect the amount of taxes motorist are paying: as the revenue requirements is a function that depends on infrastructure maintenance, deciding the maintenance periodicity or incorporating proactive maintenance could lead to a decrease in the requirements. Also, including the social cost of carbon in the estimation of required revenue will bring further insight into the relative merit of these policy designs. Future work could also undertake case studies on other jurisdictions. This could be meaningful to validate the model and to incorporate and test other structures such as the indexation of the policies.

Finally, the model could be exported to a web platform and be open to policymakers and researchers. This could provide feedback and ideas on how to improve and extend the model, and at the same time used as a tool to understand the tradeoffs and complexity of the system. Furthermore, this could enhance the impact of the research on a larger community, including researchers, policymakers, and drivers. This could be used a way to educate taxpayers about the complexities and importance of road infrastructure maintenance and would bridge the gap between undertaking research and having a real impact in the world.

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