WCTR 2013 RIO

SELECTED PROCEEDINGS

THE EFFECTIVENESS OF FUEL TAXATION AND MILEAGE TAXATION TO REDUCE TRUCKING SECTOR GHG EMISSIONS

SEBASTIAN E. GUERRERO, SAMER MADANAT AND ROBERT LEACHMAN,
SEBASTIAN.GUERRERO@BERKELEY.EDU, UNIVERSITY OF CALIFORNIA, BERKELEY, CA 94720, USA

This is an abridged version of the paper presented at the conference. The full version is being submitted elsewhere. Details on the full paper can be obtained from the author.

ISBN: 978-85-285-0232-9

13th World Conference on Transport Research

www.wctr2013rio.com

15-18 JULY 2013

Rio de Janeiro, Brazil

THE EFFECTIVENESS OF FUEL TAXATION AND MILEAGE TAXATION TO REDUCE TRUCKING SECTOR GHG EMISSIONS

Sebastian E. Guerrero[1], Samer Madanat[2] and Robert Leachman[3]

[1]Sebastian.guerrero@berkeley.edu

[1,2,3]University of California, Berkeley, CA 94720, USA

ABSTRACT: A policy debate is currently taking place in California about the best ways to achieve the GHG emission reduction goals set by the *Global Warming Solutions Act of* 2006 (Assembly Bill 32). This paper studies how fuel taxation and mileage taxation can be used in California to reduce the GHG emissions of the trucking sector, which is a large and growing contributor of emissions in the state. While it is widely known that fuel taxation is theoretically a more efficient way to internalize the externalities of fuel combustion, in many cases mileage taxation is a more politically palatable substitute. The Trucking Sector Optimization Model (TSO) was developed to study the responses of California's trucking industry to these strategies, and to estimate the corresponding changes in life-cycle GHG emissions. This model consists of a supply-demand equilibrium between carriers and shippers, where carriers' decisions about the management of their vehicle fleets are modeled dynamically throughout time. Results indicate that mileage taxation needs to increases trucking costs by 9-11% more than fuel taxation to achieve the same GHG emission reductions. It is also found that there presently exist significant economic incentives for carriers to invest in Fuel Saving Technologies (FSTs) beyond what is currently commonplace in the industry. The correction of the market mechanisms that are responsible for this apparently suboptimal behavior would lead to significant reductions in emissions, and would also allow for incentive-based mitigation strategies to have their first-best efficiency outcomes predicted by theory.

1 INTRODUCTION

One of the most critical challenges facing our generation is the need to reduce Greenhouse Gas (GHG) emissions to improve the sustainability of our economy. Multiple studies have concluded that anthropogenic GHG emissions lead to global climate change, which can impact humanity negatively in many ways. The freight transportation sector is important in meeting this challenge because it is responsible for a share of emissions that is significant and growing. However, policy makers should be careful in selecting GHG mitigation strategies for this sector because the costs of freight transportation are a key determinant of trade and economic activity. A thorough analysis of various strategies is needed to ensure that this environmental goal can be achieved as effectively as possible.

In California, the *Global Warming Solutions Act of 2006* (Assembly Bill 32) instructed the California Air Resources Board (CARB) to find ways to reduce economy-wide GHG emissions to 1990 levels by 2020.

To help meet this objective it is necessary to consider the trucking sector because it alone was responsible for 15.5% of the growth in GHG emissions in the US from 1990 to 2005 (Davies *et al.* 2007) and because its activity is broadly expected to double by 2035 (US-GAO 2008). This rapid growth can be partially attributed to supply chains becoming more responsive to inventory costs and the demands of customers. As such, governmental agencies in the US should intervene in this industry so that supply chains are designed with consideration of their environmental externalities.

Even though conventional economic thinking (Calthop *et al.* 2007; Parry 2008) indicates that fuel taxation is the best approach to reduce GHG emissions from the transportation sector because it prices the externality most directly, this strategy is not being considered by policy makers in California or elsewhere in the US. Most of the strategies implemented, or being considered, seek to regulate improvements in the fuel efficiency of trucks. In California, CARB recently implemented a requirement that Class-8 tractor-trailers need to meet EPA's SmartWay certification to operate in the state, which requires certain investments in Fuel Saving Technologies (FSTs), such as low rolling resistance tires and some aerodynamic improvements.

The present paper studies the responses of the heavy-duty truck fleet in California to the incentives-based mitigation strategies of fuel taxation and mileage taxation. For simplicity, this truck fleet is called "Core T7" in the remainder of the paper. This fleet is composed by combination trucks with Gross Vehicle Weight Rating (GVWR) of Class-8 that operate at least some portion of their mileage within California. This fleet includes trucks that provide intercity service as well as urban and non-port drayage services. The Core T7 truck fleet was designed to encompass the following truck types found in the EMFAC2011 mobile sources emissions model (CARB 2011): Heavy-Heavy Duty Diesel, Non-Neighboring Out-of-state Trucks (NNOOS), Heavy-Heavy Duty Diesel Neighboring Out-of-state Trucks (NOOS), Heavy-Heavy Duty Diesel Tractor Trucks (Tractor) and Heavy-Heavy Duty Diesel CA International Registration Plan Trucks (CAIRP). Combined, they are estimated to account for around 60% of trucking GHG emissions in California (4.8% of total California emissions) in 2020 (CARB 2012).

First, an analysis framework is introduced that can be used to conceptualize the responses of the trucking sector to various types of governmental interventions. A background section then presents a brief summary of the literature in each of the areas introduced in this framework. Then, a methodology section describes the Trucking Sector Optimization Model (TSO) and briefly explains how the model was applied to study California's Core T7 truck fleet. The final sections present the results of running the model under different levels of fuel taxation and mileage taxation, and then provide some discussion and conclusions.

2 ANALYSIS FRAMEWORK

The trucking sector is conceptualized as being composed of three different agents. **Shippers** are the agents that demand transportation service because of the spatial nature of their businesses. These include wholesalers, importers, retailers, etc. **Carriers** are the agents that supply transportation service, and in this case they are the truck owners and operators. The **infrastructure** provides the platform on which carriers can supply transportation, which in this case consists mainly of highways. This is a convenient conceptualization as in reality the trucking industry is more complex, with many shippers owning truck fleets or relying on third-party logistics companies (3PL). However, these definitions facilitate the following discussion.

Governments can influence shippers, carriers and the infrastructure in order to reduce GHG emissions. Carriers and shippers interact in the transportation services market, which is brought to equilibrium by a prevailing market price. In consideration of this price for trucking, shippers optimize their Logistical Distribution System (LDS), making decisions about the transportation modes used, the size of shipments and the location of warehouses, for example.

On the other hand, carriers optimize their Fleet Management and Operations (FMO) in order to supply transportation services demanded by shippers. This includes decisions about truck purchases, truck retirements and truck utilization. Carriers also optimize their investments in FSTs to control fuel costs. The combination of FMO and FST decisions determines the market price of trucking observed by shippers and the level of GHG emissions from the industry. Emissions from the combustion and upstream production of the fuel are closely linked to the level of FSTs implemented, while FMO decisions determine the emissions from vehicle manufacturing.

It is also important to consider the interactions between carriers and the infrastructure. An increase in trucking mileage, or in their axle loads, will speed up the deterioration of the infrastructure. This increases the costs and GHG emissions from its rehabilitation and maintenance. Carriers are also affected by the capacity and quality of the infrastructure. The prevalence of congestion and the free flow speeds of the road affect time-costs that are observed by carriers and subsequently by shippers. Also, the roughness of the pavement can affect vehicle wear and tear.

Finally, the implementation of mitigation strategies should be reconsidered insofar as reductions in life-cycle GHG emissions from this sector meet policy targets.

Using this framework, a wide range of GHG mitigation strategies can be classified based on who they target and what types of responses they elicit. An objective of this research is to contribute towards the understanding of how mitigation strategies lead to desired outcomes in the trucking sector.

3 BACKGROUND

The state-of-the-art in freight transportation modeling is limited in its ability to evaluate a wide range of GHG mitigation strategies because the carrier responses of FMO and FSTs and the shipper responses of LDS are not modeled simultaneously. Many methodological gaps exist in the literature that prevent policy analysts and planners from taking this more comprehensive modeling approach.

The majority of studies on the mitigation of GHG emissions in the freight transportation sector have only considered strategies that regulate the level of FSTs in truck fleets (Ang-Olson & Schroeer 2002; Cooper *et al.* 2009; Frey & Po-Yao 2007; Vyas *et al.* 2002). These studies assumed that the LDS and FMO remain unchanged, while carriers are *forced* to implement different FSTs. They also do not account for the fact that increasing the level of FSTs in the truck fleet will incentivize carriers to change their FMO, to retire trucks later in life, and also incentivize shippers to change their LDS in response to changes in the market price for trucking.

The freight transportation literature is rich with models of shippers' LDS decisions. Many papers (Harker 1985; Pendyala *et al.* 2000; Chow *et al.* 2010; Samimi *et al.* 2010) have surveyed the large variety of modeling approaches that have been developed, ranging from network models to behavioral models. A common theme throughout these surveys is how LDS models fundamentally limited by the availability of shipment data. This has been recognized to be a critical constraint on the research into the determinant of freight transportation demand, and it is in fact a main factor shaping the development of the TSO model. However, another common theme in this literature is that the carriers are typically not considered in LDS models. This means that the costs and technology of the transportation system are not modeled endogenously when determining how shippers make LDS decisions.

A separate literature has focused primarily on making recommendations about how individual firms should manage their vehicle fleets and make FMO decisions. This forms part of a larger literature in Operations Research that investigates the optimal utilization and replacement of machines under varying types of assumptions, conditions and objectives (Simms *et al.* 1982, Hartman 2004, Stasko and Gao 2010, Figliozzi *et al.* 2011). A separate but smaller set of literature has sought to model the behavior of vehicle fleets in the aggregate (Chen and Lin 2006; Greenspan and Cohen 1996). The focus of this research has been to estimate survival functions for vehicle fleets based on exogenous factors. The main limitation of using these models to describe truck fleets is that they require extensive time series data that are not publically available. Additionally, it can be shown that treating truck retirement as a probabilistic event is not necessary for this research because the average truck retirement contains enough information to approximate total costs well.

An additional approach used to model aggregate vehicle fleets can be found in the National Energy Modeling System (NEMS) developed by EIA (2012) and in the EMFAC2011 model developed by CARB (2011). However, both of these models make the assumption that FMO responses are exogenous, and that the LDS is constant. Essentially, an exogenous truck survival function is used to update the fleet of trucks from year to year, and truck purchases are determined exogenously by a separate macroeconomic model. In addition to considering FMO responses (albeit indirectly), the NEMS model also considers FST responses because they matter greatly to the energy consumption of the industry. However, the penetration of FSTs in the truck fleet is assumed to follow an ad-hoc function of their break-even fuel price. FST responses are therefore imposed on the model, as opposed to resulting from a cost minimization objective. Another limitation is that FMO decisions are assumed to be independent of FST decisions.

There has been much research into FMO, FST and LDS responses individually, but very little effort has been placed in modeling them jointly, in theory or in practice. Some researchers (Calthop *et al.* 2007; Parry 2008) have used simplified economic models to evaluate the implantation of incentives-based strategies in the trucking industry, considering both FST and LDS responses. However, these responses have been modeled by assuming the values of various elasticities. While these models are conceptually a step in the right direction, they don't consider FMO, FST and LDS responses jointly, which is the objective of the TSO model.

4 METHODOLOGY

The first step of the TSO model is to segment trucks into *fleets* that can be modeled independently from each other. Each of these fleets should be composed of similar trucks that compete for the same type of service from shippers. Trucks remain in the same fleet they were purchased in throughout their lives, therefore there are no interactions between truck fleets. For example, one fleet might be composed of Class-8 trucks that are purchased into intercity service and another can be composed by Class-8 drayage trucks at ports. The segmentation of truck fleets should be consistent with the data availability and scope of the study. The remainder of this paper assumes that the Core T7 truck fleet is being studied; however, the methodologies could be also applied to study other truck fleets as well. In this paper, the term *trucking industry* refers to the interactions between shippers and carriers in this particular truck fleet.

The TSO model considers the supply-demand equilibrium between carriers and shippers. The carriers' supply of transportation is modeled by assuming that they continuously optimize their operations to provide service at the lowest average cost. This is consistent with the market assumption that the industry operates competitively in the long-run, which has been found to be a reasonable representation of the industry. Carriers have also been found to have constant returns to scale (Friedlaender and Spady 1981), which allows the trucking industry can be modeled as if all trucks are operated by a single carrier. Firms with *constant returns to scale* have average costs that do not change significantly with the size of the firm. The trucking industry fits this description well because the trucks and types of service provided by small firms are fundamentally the same as those provided by large firms. Trucking service is essentially modeled as a commodity.

The FMO and FST decisions that carriers make throughout time are modeled as the minimization of discounted costs from operations, maintenance activities, fuel consumption and capital investments. This minimization is subject to the constraint that enough trucking miles are supplied to meet the transportation demanded by shippers at the market clearing price.

Shippers' demand for transportation is modeled through response elasticities found in the literature, obtained from the estimation of behavioral models. The difficulty of this approach is ensuring that the elasticities obtained from previous studies reflect the LDS responses of interest. To cope with this uncertainty a large number of studies was surveyed and a sensitivity analysis was conducted.

Mitigation strategies are evaluated insofar as they affect the economic environment of shippers (shifting demand) and/or carriers (shifting supply), establishing a new market equilibrium that hopefully achieves reductions in GHG emissions. Modeling the dynamics of this equilibrium throughout time is important because (1) mitigation strategies are likely to be phased in over long periods of time and because (2) the composition of the existing truck fleet will influence how carriers respond to certain strategies.

4.1 Carrier Model

Carriers are modeled as seeking to minimize the discounted costs of supplying trucking demand $D(t)$ [miles] in a finite time horizon $t \in [t_0, t_f]$. In each year t carriers make FMO decisions about: the number of trucks purchased $P(t)$, the level of FST investment in trucks purchased that year $\gamma(t)$ and the planned retirement age of the trucks $S(t)$. However, because the present formulation is non-convex and has a relatively large state-space, a quasi-optimal solution was obtained using a two-stage heuristic described in *Section 4*.

The notation of the model is the following:

Indices

i	index of time
j	index of truck cohorts (all trucks purchased in the same time period belong to the same cohort)

Variables

γ_j	level of investment in FSTs in truck cohort j [0,1]

P_j quantity of trucks purchased into cohort j
S_j age of retirement of trucks in cohort j

Parameters
β effective discount factor
$A_j(\gamma)$ purchase costs of trucks with technology γ into cohort j (see *Appendix A*)
$O_{ij}(\gamma)$ operating costs per mile of trucks of technology γ in cohort j at time i
M_{ij} maintenance costs per mile of trucks in cohort j at time i
$V_{ij}(\gamma)$ salvage value of trucks with technology γ in cohort j if retired at time i
u_{ij} utilization rate [miles/year] of trucks in cohort j at time i.

Three sets of the indices of i and j were used to express the mathematical program succinctly. Set $\mathbb{K}$ identifies the indices of truck cohorts j that are active at i given their retirement age S_j. Set $\mathbb{S}$ identifies the indices of truck cohort retirements. Set $\mathbb{T}$ identifies the analysis time horizon $i \in [t_0, t_f]$. Note that S_j needs to be an integer variable with intervals consistent with i and j, which can be determined based on the desired precision of the results.

$$\mathbb{K} = \{ i,j \mid i - j \leq S_j, j \leq t_f \} \tag{1}$$

$$\mathbb{S} = \{ i,j \mid i = j + S_j \} \tag{2}$$

$$\mathbb{T} = \{ i \mid t_o \leq i \leq t_f \} \tag{3}$$

$$j, i \in \mathbb{Z} \qquad P_j \in \mathbb{R}^+ \qquad S_j \in \mathbb{Z}^+ \qquad \gamma_j \in \{0,1\} \tag{4}$$

The existing truck fleet at t_o, where $\{j + S_j \geq t_o, j < t_o\}$, represents the initial conditions of the model, and is considered by the predetermination of P_j and γ_j.

Carriers face the constraint of meeting the demand for trucking mileage in each time period D_i, which can be formulated as

$$\sum_{j \in \mathbb{K}|i} P_j u_{ij} \geq D_i \quad for \quad i = t_0, t_0 + 1, \ldots, t_f \tag{5}$$

Carriers face the objective of satisfying (5) by minimizing discounted costs

$$\min \sum_{i \in \mathbb{T}} \beta^i P_i A_i(\gamma_i) + \sum_{ij \in \mathbb{K} \cap \mathbb{T}} \beta^i P_j u_{ij} O_{ij}(\gamma_j) + \sum_{ij \in \mathbb{K} \cap \mathbb{T}} \beta^i P_j u_{ij} M_{ij} - \sum_{ij \in \mathbb{S} \cap \mathbb{T}} \beta^i P_j V_{ij}(\gamma_j) \tag{6}$$

The first term in (6) sums the discounted costs associated with truck purchases, the second term sums operational costs, the third term sums maintenance costs and the fourth term subtracts the salvage value of retired trucks.

Optimization (6) can be modified trivially to capture additional realism, such as: investment of FSTs in existing trucks, technological progress where $A_i\ \gamma\ \ > A_k\ \gamma$ for $k > i$ and time varying discounting β_i.

Note that $A_i\ \cdot\ ,\ O_{ij}\ \cdot$ and M_{ij} represent the primary inputs through which governmental strategies can impact the trucking industry in this model. These inputs can evolve throughout time to reflect the gradual implementation of strategies.

Truck utilization enters (6) in two ways. First, the exogenous parameters u_{ij} indicate the miles that a truck in cohort j supplies in time period i. The modeler could allow truck utilization to change exogenously with time. The second place where truck utilization enters into the formulation is in M_{ij}, which is derived from $M_{ij} = k_m u_{ij}$, such that maintenance costs vary linearly with truck odometer by k_m.

While in this section the optimization model was formulated as a discrete problem, and it was in fact solved as a discrete problem, in the remainder of the paper continuous notation is used instead to simplify the discussions. The optimal FMO decisions are represented by $S(t)$ and $P(t)$, while the optimal FST decisions are represented by $\gamma(t)$. The economic environment faced by carriers, which summarizes the cost inputs of the model, is represented by a vector $E(t)$. The minimized nominal cost per year for carriers to supply a trucking mileage $D(t)$ is defined as $C\ \ t$.

4.2 Shipper Model

A simple shipper model was constructed to capture the LDS responses of interest. Unlike the carrier model, this model does not depend on a cost optimization. Instead, the shipper model relies on own-price elasticities that have been estimated in previous literature. Equation (7) shows the effect of changes in the market price, from a baseline level of $y_B(t)$ to $y(t)$, on the time-series of baseline demand $D_B(t)$, through the elasticity parameter e_D.

$$D\ \ t, y\ \ = D_B(t, y_B)\ \ \frac{y(t)}{y_B(t)}^{\ e_D} \qquad (7)$$

Model (7)**Error! Reference source not found.** makes some assumptions that can be relaxed in future research. These assumptions are necessary given that trucks within the same truck category can operate in very different types of service. For example, an old truck might work on urban tours while a new truck might operate intercity routes. This model also implies that all of these types of service observe the same trucking rate y and elasticity e_D. Or alternatively, that these variables have been defined specifically to represent the truck fleet being studied.

4.3 Equilibrium

The equilibrium between carriers and shippers can be specified in different ways depending on the assumptions made about the relationship between these two agents. A carrier's ability to foresee changes in trucking demand and a shipper's ability to foresee changes in the market rate (potentially caused by mitigation strategies) will affect how a medium-term equilibrium is reached. If both sides in this market have complete information about each other, a fixed long-run market rate could be agreed upon. In such a situation however the carrier may need short-term borrowing and lending given that the underlying costs of the trucking business might not be fixed over time. Profits and losses would need to add to zero in the long run. Because of this, the ability of carriers to borrow money also affects how market equilibrium is reached. Depending on the assumptions made about the industry, the model can be specified at either of the following extremes.

4.3.1 Long-Run Equilibrium

Under a *long-run equilibrium* carriers and shippers have perfect information about each other's operations and have complete financial instruments. This allows both parties to negotiate a market rate that is fixed in real terms for the period of analysis. Mathematically, carriers estimate their real long-run transportation cost y using (8) to meet a certain demand $D(t,y)$ for analysis time period $t \in [t_0, t_f]$.

$$\int_{t_0}^{tf} \beta^t C(t)dt \quad \int_{t_0}^{tf} \beta^t D(t) \, dt = y \tag{8}$$

Shippers observe this single market rate and adjust $D(t,y)$ per (9) until equilibrium is reached.

$$D(t,y) = D_B(t, y_B) \left(\frac{y}{y_B}\right)^{e_D} \tag{9}$$

This equilibrium assumes that shippers demand for transportation in all time periods is affected in the same proportion by changes in $\frac{y}{y_B}$. On the other hand, carriers are assumed to charge the same rate in all time periods, absorbing supply shocks to an extent. If a mitigation strategy is implemented that increases near-term costs but decreased far-term costs then carriers would charge shippers a fixed rate for all time periods so that they end up with zero profits.

These equilibrium assumptions make the model easy to solve (single supply and demand curves identify equilibrium), but are somewhat unrealistic in modeling real world transportation markets. Also, this approach does not lend itself for modeling transitional effects.

4.3.2 Short-Run Equilibrium

Under a *short-run equilibrium* carriers possess information about future transportation demand, but do not have the financial capacity to operate losses or profits. Carriers charge shippers their minimized transportation costs in every time period, and shippers adjust their demand accordingly.

$$C(t)\ D\ t\ = y(t) \quad (10)$$

This equilibrium assumption leads the model to be more difficult to solve as there will exist as many equilibria as time periods, where each time period is essentially assumed to be independent from each other. To obtain a solution we iteratively solve (10) and (11) until convergence is achieved.

$$D\ t, y\ = D_B(t, y_B)\ \frac{y(t)}{y_B(t)}^{e_D} \quad (11)$$

4.4 Solution Heuristic

Because of the relatively large state-space of the problem (6), and the fact that it is non-convex, it was necessary to use a two-stage heuristic to solve the problem approximately. Without delving into the details, which are covered elsewhere, the optimal S_j are determined first by solving an infinite-time version of the problem for each time period. These values are then inputted into (6) where the rest of the variables can be solved easily because the problem becomes convex. Also, the equilibrium between carriers and shippers was solved by iteration.

4.5 Model Parameters

Parameter values used in the TSO model are summarized in *Table 1*. These values were obtained from California specific data sources when possible.

Table 1: Summary of cost parameters for Core T7 trucks in California

Parameter	Notation	Value	Units	Source
Fixed Operation Cost	k_o	0.647	$/mile	Fender & Pierce 2011
Fuel Price	p_F	3.15, 4.0, 4.87	$/gallon	CEC 2011
Base-line Fuel Efficiency	f	0.169	gallons/mile	EMFAC 2011
Truck Purchase Costs	A_p	120,000	$/truck	CARB 2008
Maintenance Costs Parameter	k_m	$1.85*10^{-7}$-7	$/odometer-mile	CARBb 2008
Baseline Toll	θ_M	0	$/mile	
Baseline Fuel Tax	θ_F	0	$/gallon	

The assumptions and data used to determine the effectiveness and costs of various FSTs can be found in *Appendix A*. This was used to develop the abatement curve $A\ \gamma$ which indicates the lowest possible capital invest required to achieve γ reduction in fuel consumption. By construction $A'(\gamma) > 0$, $A''(\gamma) > 0$, and $A(0) = A_p$.

LDS responses are modeled using elasticities that have been estimated in the literature. A review of the literature found that these estimates elasticities vary significantly with the type of model used, location of study, type of data used (aggregate vs. disaggregate), commodity grouping, demand specification (tons or ton-miles), trip type segmentation, etc. Given these difficulties, three elasticity scenarios were used for the analysis. Graham and Glaister (2004) surveyed studies that estimated 143 elasticities under various types of assumptions and found an average of -1.07 (ton-miles) with a standard deviation of 0.84. Therefore, for this paper the analysis scenarios where set at $e_Q = \{-0.65, -1.07, -1.49\}$, which correspond to $\pm$ half a standard deviation of Graham and Glaister's (2004) survey findings. This corresponds well with FHWA's estimate of -0.97 (TRB 2010), Fiedlaender and Spady (1981) estimate of -1.12, and Chiang *et al.*'s (1981) estimate of -1.143, which are frequently cited studies in the literature.

4.6 GHG Emission Accounting

The life-cycle GHG emissions of the trucking industry were estimated using results from Facanha and Horvath (2007). Tailpipe emissions and pre-combustion emissions were estimated directly from fuel consumption calculations. Vehicle manufacturing emissions were estimated assuming that they increase linearly with truck purchases. Infrastructure emissions were estimated using methodologies from Sathaye *et al*. (2010), which essentially involved tracking how the interval between pavement overlays is affected by increasing or decreasing trucking mileage.

While it might not be critical to consider sources of emissions other than tailpipes when comparing fuel taxation to mileage taxation, these other sources become more important for other strategies that could also be analyzed with the approach presented in this paper. For example, increasing the weight limit of trucks will reduce the mileage driven on road (consolidation of loads) but also increase the deterioration resulting from any single truck trip. In this case measuring the reduction in tailpipe emissions against the increases in infrastructure emissions is critical to make a determination about whether this strategy indeed mitigates total GHG emissions.

5 RESULTS

Increases in fuel taxation and mileage taxation were analyzed in their effectiveness to reduce tailpipe, precombustion, infrastructure and vehicle manufacturing GHG emissions in 2020 in California. The FMO and FST decisions of carriers and LDS decisions of shippers were modeled from 2011 to 2035, with the existing truck fleet in 2010 as the initial condition of the model. Results are presented with an *uncertainty* range obtained by using the best-case and worse-case scenarios of fuel prices and shipper response elasticity. A discount rate of 3% was selected based on forecasts of inflation and the US prime rate.

The analysis assumed that the strategies are phased in starting in 2013 and will be fully implemented by 2019. This is defined as the *standard phase in* schedule. Phasing in onerous strategies is necessary because in reality firms take time to re-optimize their operations. The details of the phase-in schedules are important because they will impact emissions in 2020. Future research should consider this policy variable more closely.

It is important to note that the phase-in schedule and levels of strategy implementation were determined based on engineering judgment, and not from the consideration of the political and practical realities present in California. These represent inputs into the analysis rather than recommendations.

The fuel taxation and mileage taxation strategies will only affect the miles that trucks drive within California. Therefore, modeling Core T7 trucks homogenously represents an approximation because the fleet is composed of sub-fleets that each drives a different percentage of their mileage within California. At the extremes, the T7 Non-Neighboring-Out-of-State (NNOOS) truck fleet only drives 9.88% of its miles in California while the T7 Tractor fleet drives 100% of its mileage in California. Even though these truck fleets are very similar, it would be ideal to model them separately as mitigation strategies affect them differently. However, such a model would take significantly longer to solve (approaching several days). Instead, it was decided to model them jointly. This represents a reasonable approximation because it can be shown that modeling an average truck fleet provides results that are not significantly different from those obtained by averaging the models of several fleets that only differ in their proportion of instate travel. The main reason for this is that the rate of change of the convexity of the abatement curve $A''' \ \gamma$ is small.

Given the varying proportions of instate travel, it is also necessary to assume that the mitigation strategies do not affects the proportion of mileage driven in California by out-of-state trucks. In other words, mitigation strategies are assumed not to dissuade the demand for California trucking specifically.

5.1 Reference Scenarios

GHG mitigation strategies are compared against two important reference scenarios in which no strategies are implemented. The ***Continuation no Technology*** (**CNT**) scenario assumes that carriers do not make any investments in FSTs, but do optimize their FMO in meeting the forecasted trucking demand. This represents a continuation of current operations, as carriers are currently not observed to make investments to improve the fuel economy of their truck fleets. The *mid* assumption for fuel price and shipper response elasticity of this scenario provides identical VMT and emissions estimates as the EMFAC2011 inventory model in California. It does not however provide similar estimates of FMO (service life and truck purchases) as the EMFAC2011 model because the methodologies used are very different.

On the other hand, the ***No Action Optimal Baseline*** **(NAOB)** scenario assumes that carriers optimize their investment in FSTs in addition to their FMO in meeting the trucking demanded by shippers, who then optimize their LDS through e_D. The FST, FMO and LDS responses observed in this scenario identify the shipper-carrier equilibrium that is optimal according to the cost data found in the literature.

In 2020 the optimal level of investment in FSTs in the NAOB scenario is $\gamma = 0.29$, which corresponds to investing in most of the FSTs listed in *Appendix A*. This large difference between the NAOB and CNT scenarios can be explained by: (1) the model incompletely capturing the costs and incentives faced by carriers and/or (2) carriers in real life do not fully optimize their operations. Either way, this difference suggests that there currently exist strong economic incentives for improving the fuel economy of trucks.

Many reasons could explain why carriers are not acting on these perceived incentives more vigorously, such as a present bias, imperfect information, budgetary constraints, operational constraints, principal-agent problems, and the negative incentives of the fuel surcharge program (discussed below). Theory suggests that all of these market mechanisms could be preventing trucking companies from fully observing fuel costs, and making investments that would reduce their costs and reduce their emissions.

Removing or mitigating these perverse mechanisms would not only lead to significant reductions in emissions, as evidenced by the difference between the CNT and the NAOB scenarios, but it would also allow incentive-based strategies to have their first-best outcomes predicted by theory. However, an assessment of these market mechanisms lies beyond the scope of this research.

The increased investment in FSTs in the NAOB scenario leads the trucking rate to fall and the quantity of trucking mileage demanded to increase compared to the CNT scenario. Also, greater use of FSTs increases the capital costs of the trucks, resulting in truck being used 47% longer in the NAOB scenario than the CNT scenario. Using trucks until an older age in the NAOB scenario implies that fewer new trucks need to be purchased to meet the demand of shippers.

5.2 Fuel Taxation

Fuel taxation is widely recognized theoretically as the most efficient way to reduce GHG emissions from the transportation sector because it prices the externality directly. However, fuel taxation in the US and in Europe has been used primarily to collect revenues for the transportation system, not to mitigate its externalities. Presently fuel taxes in California are among the highest in the US, therefore further increases could incentivize leakage of economic activity to neighboring states that have lower energy costs.

In the analysis of this strategy it was assumed that carrier observe the full impact of the fuel tax and are incentivized to make more sustainable decisions about their FSTs and FMO. In reality there exists a nationwide fuel surcharge program that allows carriers to bill shippers separately for their fuel costs above a certain threshold. Given that we are currently above that threshold, additional fuel taxes would simply be passed onto shippers and will not incentivize carriers to change their operations. For fuel tax increases to be an effective GHG mitigation strategy they need to be partially absorbed by carriers. In the analysis it was assumed that institutional and regulatory changes are made such that carriers absorb the fuel tax fully.

Taxes on diesel fuel are assumed to be implemented in California following the standard phase-in schedule. Different levels of fuel taxation result in the reductions of GHG emissions shown in *Figure 3a*. As seen in Figure 4, the tailpipe source accounts for about 84% of the reductions. This fraction remains roughly constant for different levels of taxation. Infrastructure related emissions account for 8.5% of these reductions, precombustion accounts for 4.4% of these reductions and the remaining 3.1% of the reductions come from vehicle manufacturing.

A fuel tax of $1/gallon causes GHG emissions reductions in 2020 relative to the NAOB scenario of 0.51 MMTCO2e from the Core T7 truck fleet in California, and an additional 1.67 MMTCO2e of reductions elsewhere in the US. In the low scenario for fuel prices and LDS elasticity the total amount of GHG emissions under this strategy decreases by 9.2%, while under the high scenario it increases by 8.3%. These changes are roughly constant for the different sources of emissions from the trucking sector.

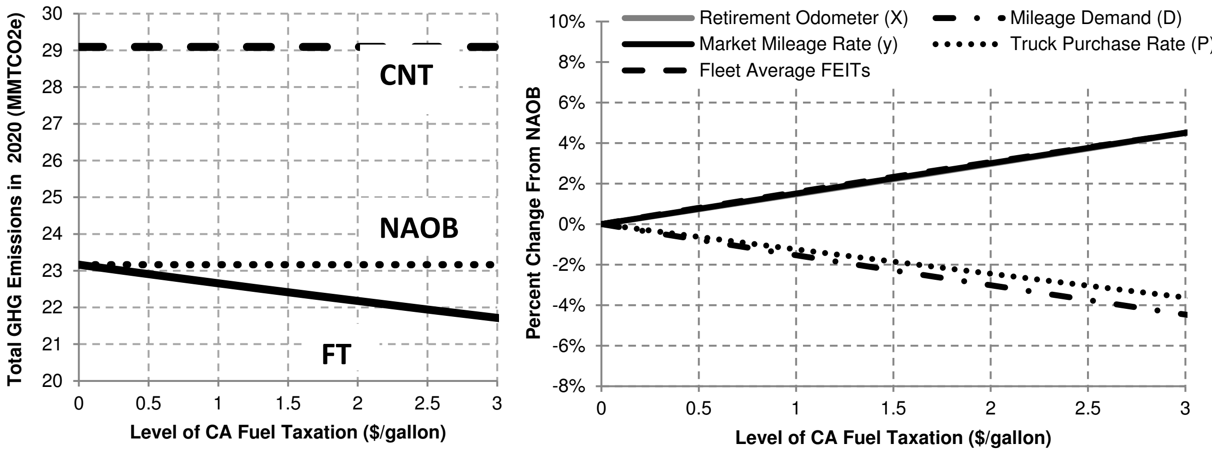
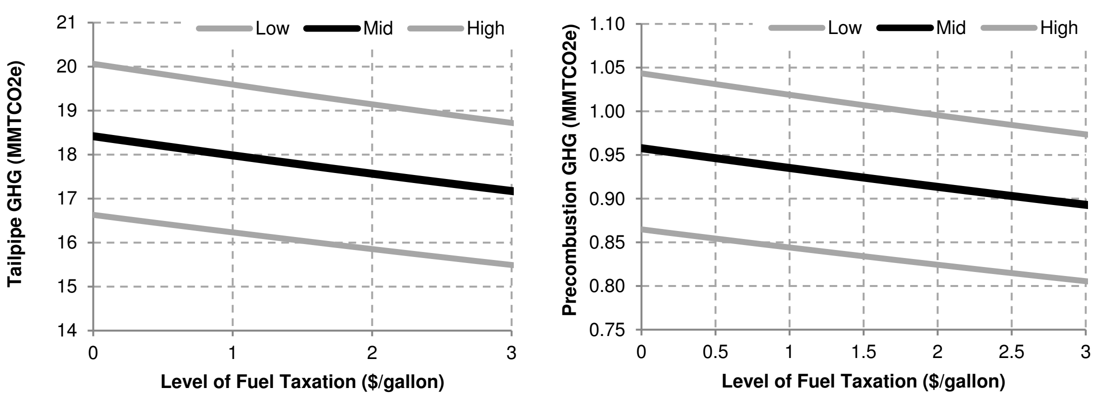


Figure 3: Effect of fuel taxation on (a) GHG emissions and (b) truck fleet characteristics in 2020

Figure 3b shows that increasing fuel taxation has the predictable effect of increasing the market rate and decreases mileage demanded by shippers. On the carrier side, the level of FSTs increases to mitigate the higher fuel prices, which has the effect of increasing the average age of the fleet and decreasing truck purchases.

The model predicts the response of the Core T7 truck fleet to these large and unprecedented (in the US) fuel taxes to be modest. The reason for this is that fuel taxes only affect the portion of the mileage driven within California. A fuel tax of $1.3/gallon implemented in California will have an average effect of $0.3/gallon for the whole Core T7 fleet. This represents an increase in mileage costs of only 2.1%. Even though the fuel tax seems large at face value, its effect on the costs of the Core T7 fleet is not very large.



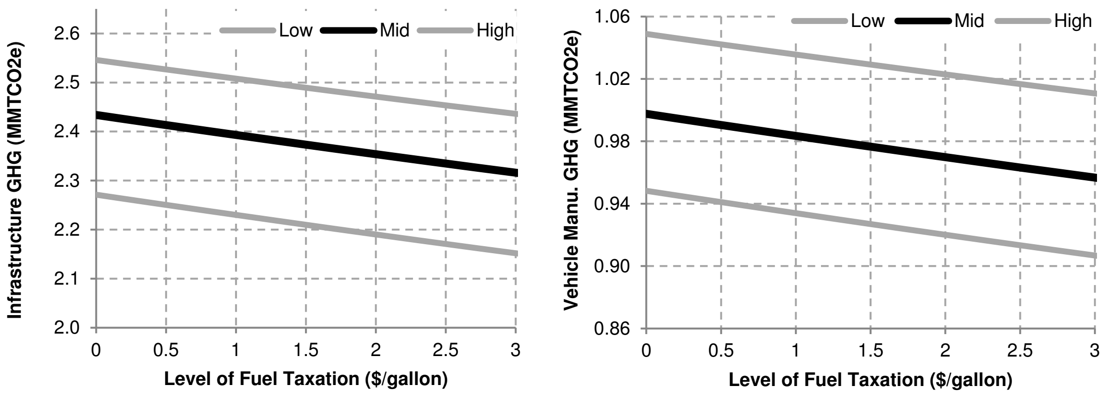


Figure 4: 2020 Core T7 GHG emissions with fuel taxation in CA

Another reason for the modest FST response is that under the NAOB scenario it is already optimal to invest significantly in FSTs at $\gamma = 0.29$, which lies in a domain of the abatement curve $c(\gamma)$ that has a high $c'(\gamma)$. The diminishing returns of the FSTs make achieving fuel economy improvements relative to the NAOB scenario expensive. Given that the trucking industry does not operate near NAOB conditions, fuel tax increases implemented currently should have a larger impact on γ.

A key factor driving the average fuel economy of the fleet throughout time is the proportion of trucks purchased before the strategy is implemented. Even though carriers can invest in the FSTs for the old trucks, it is not optimal for them to do so at the same level as for new trucks because the old trucks have fewer miles left on which to accrue fuel savings. As new trucks replace old trucks the average fuel economy of the fleet increases. This continues until the point where all of the trucks in the fleet were purchased after the strategy is fully implemented, which does not occur until after the 2020 emissions target. This reemphasizes the importance of tracking the dynamics of the truck fleet for this analysis.

5.3 Mileage Taxation

Mileage taxation can be implemented in a variety of ways. In the US the states of Oregon, Kentucky, New York and New Mexico require trucking companies to report the mileage driven in their states and pay a mileage tax accordingly. In Oregon for example, the tax increases with the weight of the vehicle so that a truck with a maximum Gross Vehicle Weight (GVW) of 74,000 lbs has to pay a tax of $0.147/mile, which is equivalent to a comparatively large fuel tax of $0.82/gallon for the average truck.

Tolls also represent another way that mileage taxes can be implemented. Fender & Pierce (2011) estimated that the highest tolls in the US are found in the Midwest and Northeast, averaging $0.047/mile in these two regions, while the lowest are in the West and Southwest with an average of $0.011/mile. Therefore there exists some room for expanding tolls in California.

In Europe trucks are tolled more extensively than in the US. Germany has a GSM/GPS system that charges trucks a mileage fee that exceeds $0.5/mile for the largest trucks. In Switzerland mileage taxes were increased five-fold from 1998 to 2005 to almost $1/mile, while truck weight limits were increase by 42% (McKinnon 2006). The combination of these two changes has been estimated to reduce the GHG emissions of the industry by 6% (SFOSD 2007).

In the analysis of mileage taxation it is assumed that a system is put into place that charges a uniform tax on the Core T7 truck fleet for mileage driven within in California. Mileage taxes are assumed to be implemented following the standard phase-in schedule. This strategy reduces GHG emissions primarily by decreasing the demand for trucking by shippers, and therefore it is theoretically inferior to fuel taxation because it does not incentivize additional investment in FSTs. This implies that trucking costs need to increase more with this strategy than with fuel taxation to achieve the same level of GHG reductions. However there are reasons for mileage taxation to be more desirable, leading to its wide utilization in Europe.

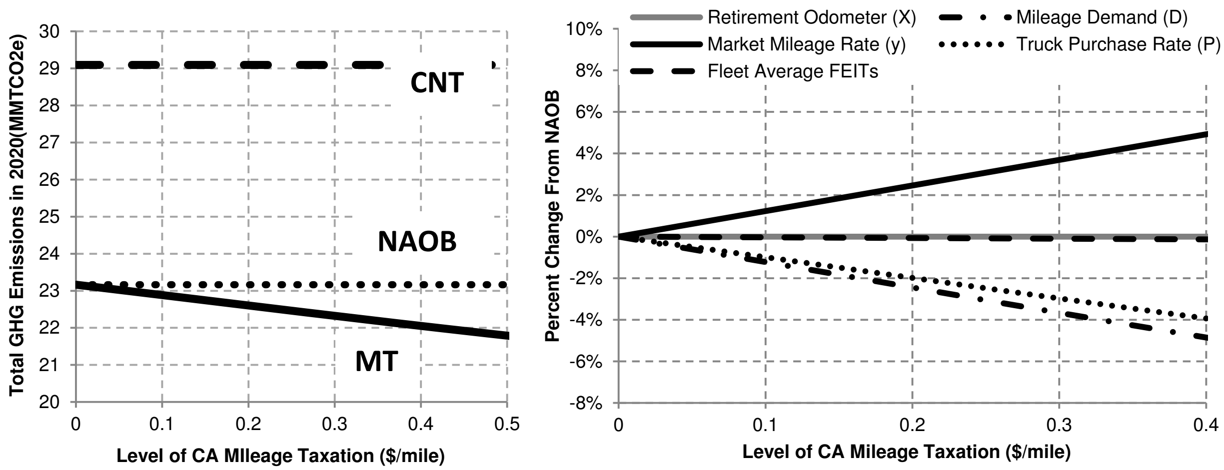


Figure 5: Effect of mileage taxation on (a) GHG emissions and (b) truck fleet characteristics in 2020

The results of the analysis are shown in *Figure 5a*. Note that a mileage tax of $0.3/mile is equivalent to a fuel tax of $2.6/gallon. Therefore, the levels of strategy implementation shown in this figure are quite large and unprecedented in the US, but in line with some of the European examples. A mileage tax of $0.3/mile should result in GHG reductions relative to the NAOB scenario in California of about 0.9 MMTCO2eq, with an additional reduction of about 2.9 MMTCO2eq elsewhere in the US. In the low scenario for fuel prices and LDS elasticity the total amount of GHG emissions under this strategy decreases by 10.2%, while under the high scenario it increases by 10.1%.

As seen in *Figure 6* for this strategy about 81% of the GHG reductions come from the tailpipe source, 10.5% from the infrastructure source, 4.2% from the precombustion source and 4.3% from the vehicle manufacturing source.

Figure 5b shows that the changes in GHG emissions are primarily caused by reductions in the demand for trucking as the market rate increases substantially. It is also observed, as expected, that carriers are not incentivized to increase the technology of their truck fleets or use trucks for longer. This can be changed with the use of differentiated mileage taxation that creates similar incentives as fuel taxation. If a mileage tax of $\theta_M = \theta(1-\gamma)f$ is implemented, such that as the level of γ increases the mileage tax decreases, then effectively a fuel tax of θ is being charged. In practice, a certification process could be created that classifies trucks in discrete ranges of γ, similar to the EPA's SmartWay program, and a different mileage tax could be charged to each range. The analysis of this would be identical to the analysis of fuel taxation already performed.

Another type of differentiated mileage taxation that has been described in the literature involves taxing older trucks. However, this is not worthwhile from a GHG emissions perspective because in the previous discussion it was shown that the fuel efficiency of trucks has not improved significantly in the last couple of decades (EMFAC2011 corroborates this finding). The overall technology of trucks has improved in dimensions other than fuel efficiency. Also, properly maintained trucks have roughly the same fuel efficiency throughout their service life. Therefore, decreasing the average age of the fleet will not reduce tailpipe emissions, and will actually increase vehicle manufacturing emissions as the purchasing rate would have to increase. This type of differentiated mileage tax is not likely to be beneficial to reduce GHG emissions. A similar finding is also found in Kim et al. (2004) which concludes that programs that seek to incentivize the scrappage of old personal vehicles will likely reduce CO, NMHC and NOx emissions, but might actually increase CO2 emissions.

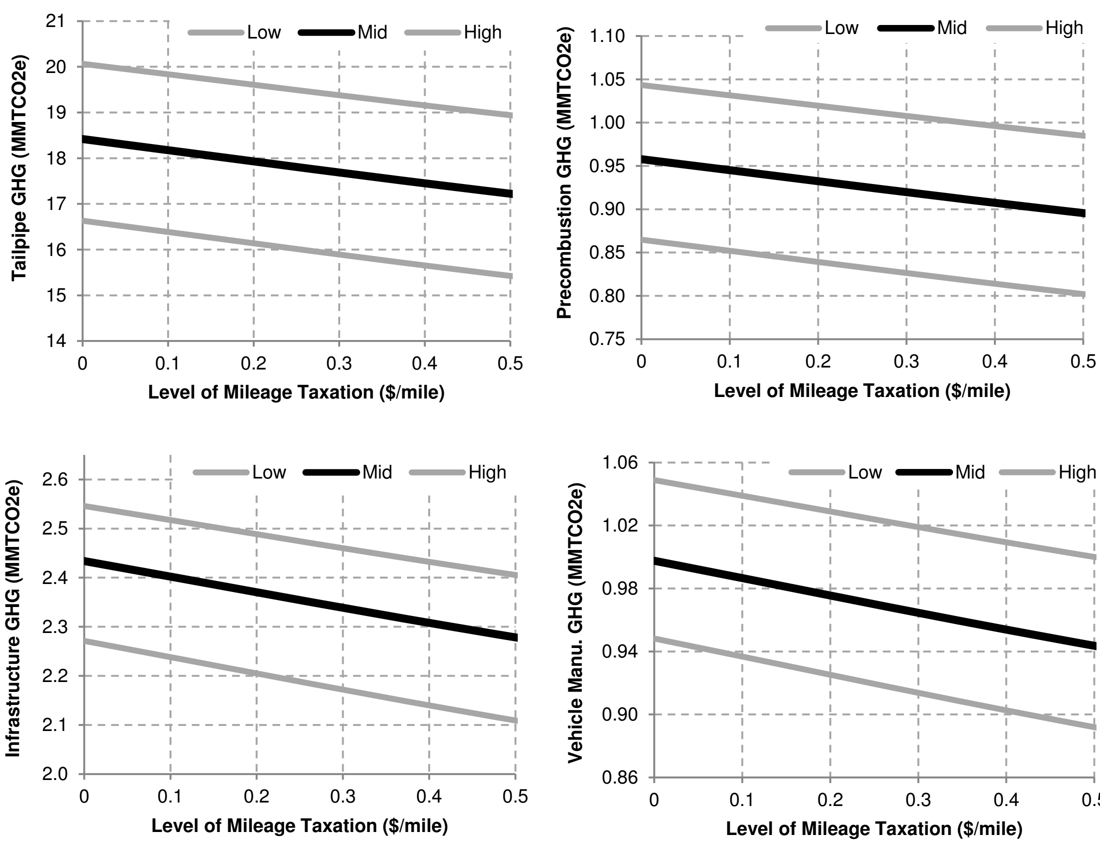


Figure 6: 2020 GHG Emissions with Mileage Taxation in CA

6 DISCUSSION

Mitigation strategies can be analyzed in either the idealistic NAOB scenario or in the realistic CNT scenario. As explained above, the main difference between these two is that in the NAOB scenario trucking companies are assumed to make optimal investments in FSTs, while in the CNT scenario they are assumed to continue not to make these investments. The CNT scenario is described as *realistic* because currently most truck owners do not make these types of investments.

In the results shown in the previous section, strategies were implemented in the idealized NAOB scenario, and not on the CNT scenario, because incentivizing investments in FSTs represents the main difference between fuel taxation and mileage taxation. Fuel taxation incentivizes additional investments in FSTs, while mileage taxation does not. Consequently, if fuel taxation and mileage taxation were implemented in the CNT scenario, the results would be identical because in this scenario FST investments are assumed not to take place. In other words, the fact that we see little investment in FSTs in the real-world implies that fuel taxes will likely be unsuccessful at incentivizing investments in FSTs, and the industry would respond similarly to fuel taxation as mileage taxation. Therefore, studying fuel taxation and mileage taxation in the CNT scenario is uninformative.

So, if the strategies are only analyzed in the idealized NAOB scenario, and therefore the results cannot be interpreted as predictions, what insights can be drawn from this analysis? Basically, insights can be obtained from the following. (1) The results of the strategy evaluation are best interpreted when comparing between strategies. The differences in the responses of the industry to different strategies will be driven more by the nature of the strategy than by the assumptions of the analysis scenario. This, of course, depends on the details of the strategies being analyzed, but it is likely to be true in most cases. (2) Analyzing strategies in the NAOB scenario provides us an upper bound for the responses of the industry because carriers are acting optimally and fully in response to incentives. (3) Understanding how the industry would operate in the NAOB scenario provides governments a benchmark for what policy should strive to achieve.

In this paper we focus more on (1), as (2) and (3) are discussed in other papers. *Table 2* compares the level of fuel taxation and mileage taxation required to achieve a certain amount of GHG reductions in the NAOB scenario. The fuel taxation results were converted to a mileage basis so that a direct comparison can be made with the mileage taxation strategy. The results consistently indicate that mileage taxation would have to increase trucking costs by 11-9% more than fuel taxation to achieve the same level of reduction in emissions. This is because fuel taxation incentives investments in FSTs while mileage taxation does not. Therefore, trucking costs need to be increased by a greater amount with mileage taxation to achieve the same reduction in emissions. However, everything considered the difference between both of this strategy is not that large. If increasing fuel taxation is politically unpalatable or difficult in a state with already high fuel taxes such as California, mileage taxation offers a viable alternative that can achieve the same environmental goals at a manageable premium in costs.

Table 2: Effectiveness fuel taxation and mileage taxation in CA in 2020 relative to NAOB reference scenario

Core T7 GHG Emission Reductions (MMTCO2eq)	Fuel Taxation ($/gallon)	Fuel Taxation (equivalent $/mile)	Mileage Taxation ($/mile)
0.2	0.39	0.06	0.07
0.4	0.79	0.13	0.14

0.6	1.19	0.19	0.22
0.8	1.61	0.26	0.29
1.0	2.03	0.33	0.36
1.2	2.46	0.39	0.43

7 CONCLUSIONS

This paper presented a conceptual and analytical framework for evaluating the effectiveness of GHG mitigating strategies in the trucking sector. The analytical framework consists of an optimization model, termed TSO model, that tracks key FST, FMO and LDS responses throughout time. The impacts of these responses on the life-cycle GHG emissions of the sector were also estimated. These methodologies were used to evaluate the effectiveness of fuel taxation and mileage taxation to reduce the GHG emissions of Core T7 trucks in California.

The analysis primarily found that the current cost structure of trucking creates a strong incentive for carriers to invest significantly in FSTs beyond what is currently observed in the industry. There are various reasons that could explain this apparently suboptimal market outcome. These are not discussed in this paper beyond simply stating that governmental strategies that increase the investment in FSTs are desirable.

From the analysis it was also clear that mileage taxation needs to increase trucking costs by a larger proportion that fuel taxation to achieve the same level of GHG emission reductions. This result was anticipated because mileage taxation does not incentivize investments in FSTs while fuel taxation does. However, it was unexpected that the difference in cost between these two strategies is not that large at 9-11%. This could be a worthwhile price to pay to avoid the political impossibilities of increasing fuel taxes in California.

Overall it was found that 81-84% of emission reductions come from the tailpipe source, 8-12% come from the infrastructure source, 4-5% come from the precombustion source, and 2-4% come from the vehicle manufacturing source. The sensitivity analysis conducted indicates that assuming optimistic or pessimistic values for fuel price and shipper response elasticity changes emission estimates in 2020 by $\pm$10%.

Now that the responses of the trucking industry can be quantified using the TSO model, a welfare analysis can be performed to inform how governments should implement strategies to maximize some measure of aggregate social welfare. This should consider other emission sources, tax revenue recycling, infrastructure costs and economic activity deadweight loss.

8 ACKNOWLEDGEMENTS

The authors are grateful to the California Air Resources Board (CARB) for their sponsorship of this research and valuable feedback on preliminary drafts.

9 REFERENCES

Ang-Olson, J. and Schroeer, W., 2002. Energy Efficiency Strategies for Freight Trucking, Potential Impact on Fuel Use and Greenhouse Gas Emissions. *Transportation Research Record: Journal of the Transportation Research Board* 1815, 11-18.

Calthrop, E., Borger, B. and Proost, S., 2007. Externalities and partial tax reform: Does it make sense to tax road freight (But Not Passenger Transport)? *Journal of Regional Science 47(4)*, 721 – 752.

CARB, 2008. Technical support document: Proposed regulation for in-use on-road diesel Vehicles: Appendix J, Mobile Sources Control Division, Heavy-Duty Diesel In-Use Strategies Branch, October 2008.

CARB, 2008b, Rulemaking to consider adoption of a regulation to reduce greenhouse gas emissions from heavy-duty vehicles, http://www.arb.ca.gov/regact/2008/ghghdv08/ghghdv08.htm (Accessed 7/2012)

CARB, 2011. EMFAC2011 Technical Documentation, http://www.arb.ca.gov/msei/modeling.htm (Accessed 04/2011)

CARB, 2012. Greenhouse Gas Inventory – 2020 Emissions Forecast, http://www.arb.ca.gov/cc/inventory/data/forecast.htm (Accessed 04/2012)

CEC, 2011. California Energy Commission: Transportation Energy Forecasts and Analyses for the 2011 integrated Energy Policy Report, August 2011.

Chen, C. and Lin, J., 2006. Making an informed vehicle scrapping decision. *Transport Reviews* 26(6), 731-748.

Chow, Y. J., Yang, C. H. and Regan, A. C., 2010. State-of-the art of freight forecast modeling: lessons learned and the road ahead. *Transportation* 37, 1011-1030.

Cooper, C., Kamakate, F., Reinhart, T., Kromer, M. and Wilson, R., 2009. Reducing heavy-duty long haul combination truck fuel consumption and CO2 emissions, Final Report.

Davies, J., Facanha, C. and Aamidor, J., 2007. Greenhouse gas emissions from U.S. freight sources: using activity data to interpret trends and reduce uncertainty, Proceedings from the 87th Annual Meeting of the Transportation Research Board, Washington DC.

EIA, 2012. Transportation Sector Module of the National Energy Modeling System: Model Documentation 2011, Office of Energy Analysis, Energy Information Administration, Washington DC.

Facanha, C. and Horvath, A., 2007. *Environmental Science & Technology 41*. 7138-7144.

Fender, K. J. and Pierce, D. A., 2011. An Analysis of the Operational Costs of Trucking: A 2011 Update, American Transportation Research Institute, June.

Figliozzi, M. A., Boudart, J. A. and Feng, W., 2011. Economic and environmental optimization of vehicle fleets. *Transportation Research Record: Journal of the Transportation Research Board No. 2252*, 1-6.

Frey, C., Po-Yao, K., 2007. Best practices guidebook for greenhouse gas reductions in freight transportation, Prepared for USDOT, NC State.

Friedlaender, A. and Spady, R., 1980. A derived demand function for freight transportation. *Review of Economics and Statistics 62*, 432–441.

Greenspan, A. and Cohen, D., 1996. Motor vehicle stocks, scrappage, and sales. *Review of Economics and Statistics 81,* 369-383.

Harker, P., 1985. The state of the art in the predictive analysis of freight transport systems. *Transport Review 5(2)*, 143-164.

Hartman, J. C., 2004. Multiple asset replacement analysis under variable utilization and stochastic demand. *European Journal of Operational Research 159*, 145-165.

Kim, H. C., Ross, M. H and Keoleian, G. A., 2004. Optimal fleet conversion policy from a life cycle perspective. *Transportation Research Part D 9*, 229-249.

McKinnon, A. C., 2006. A review of European truck tolling schemes and assessment of their possible impacts on logistics systems, *International Journal of Logistics: Research and Application 9(3)*, 191-205.

Parry, I. W.H., 2008. How should heavy Duty Trucks be Taxed? *Journal of Urban Economics* 63, 651 – 668.

Pendyala, R.M., Shankar, V.N., and R.G. McCullough, 2000. Freight travel demand modeling: synthesis of approaches and development of a framework. *Transportation Research Record: Journal of the Transportation Research Board No. 1725*, 9-16.

Sathaye, N., Horvath, A. and Madanat, S., 2010. Unintended impacts of increased truck loads on pavement supply-chain emissions. *Transportation Research Part A 44,* 1-15.

SFOSD: Swiss Federal Office for Spatial Development, (2007), Fair and Efficient: The Distance-related Heavy Vehicle Fee (HVF) in Switzerland.

Smith, V. L., 1957. Economic equipment policies: an evaluation. *Management Science 4(1)*, 20-37.

Stasko, T. H. and Gao, H. O., 2010. Reducing transit fleet emissions through vehicle retrofits, replacement, and usage changes over multiple time periods. *Transportation Research Part D 15*, 254 – 262.

US-GAO, 2008. Freight Transportation: National Policy and Strategies Can Help Improve Freight Mobility, United States Government Accountability Office 08-287.

Vyas, A., Saricks, C. and Stodosky, F., 2002. The Potential Effect of Future Energy-Efficiency and Emissions-Improving Technologies on Fuel Consumption of Heavy Trucks, ANL/ESD/02-4/, Argonne National laboratory, Argonne, IL, August.

APPENDIX A: FUEL SAVING TECHNOLOGIES (FSTs)

Type of System	*Fuel Efficiency Improving Technology (FST)*	No. of Purchases in Lifetime of 800k miles	Average Capital Costs to Trucker Above Standard Truck	% Reduction in Fuel Consumption	Source	% of CoreT7 Miles Affected	% Core T7 Reduction	Benefit/ Costs	Cumulative Costs	Cumulative % Reductions in Fuel Consumption γ
Transmission	Turbocharged, Direct Injection to Improved Thermal Management	*2*	$1,576	4.70%	*MSMC*	1.00	4.70%	0.34	**$1,576**	**4.7%**
Transmission	Increased Peak Cylinder Pressures	2	$2,251	4.00%	*MSMC*	1.00	4.00%	0.20	**$3,827**	**8.5%**
Aerodynamic	Closing and Covering of Gap	1	$735	2.00%	*MSMC*	0.55	1.10%	0.17	**$4,561**	**9.5%**
Aerodynamic	Aerodynamic Bumpers	2	$1,351	3.00%	*MSMC*	0.55	1.64%	0.14	**$5,912**	**11.0%**
Rolling Resistance	Wide-base Tires	5	$6,431	6.98%	*MSMC*	1.00	6.98%	0.12	**$12,343**	**17.2%**
Rolling Resistance	Automatic Tire Inflation Systems	1	$760	0.80%	*MSMC*	1.00	0.80%	0.12	**$13,103**	**17.9%**
Aerodynamic	Pneumatic Aerodynamic Drag Reduction	1	$4,361	6.54%	*MSMC*	0.55	3.58%	0.09	**$17,464**	**20.8%**
Aerodynamic	Wheel Well Covers	4	$1,891	2.00%	*MSMC*	0.55	1.10%	0.07	**$19,355**	**21.7%**
Aerodynamic	Trailer Leading and Trailing Edge Curvatures	1	$1,407	1.26%	*MSMC*	0.55	0.69%	0.06	**$20,762**	**22.2%**

Aerodynamic	Planar Boat Tail Plates on a Tractor-Trailer	2	$5,628	5.00%	*MSMC*	0.55	2.74%	0.05	**$26,390**	**24.4%**
Aerodynamic	Trailer side skirts	2	$5,988	5.00%	*MSMC*	0.55	2.74%	0.05	**$32,377**	**26.4%**
Weight Reduction	Lightweight Materials (2,500lbs)	1	$11,396	7.46%	*NAS*	0.55	4.08%	0.04	**$43,773**	**29.4%**
Hybrid Propulsion	Hybrid Trucks	1	$28,138	5.66%	*NAS*	1.00	5.66%	0.02	**$71,911**	**33.4%**
Rolling Resistance	Pneumatic Blowing to Reducing Rolling Resistance	1	$4,924	0.99%	*NAS*	1.00	0.99%	0.02	**$76,835**	**34.1%**
Transmission	Transmission Friction Reduction through Low-Viscosity Transmission Lubricants	8	$9,724	1.00%	*MSMC*	1.00	1.00%	0.01	**$86,560**	**34.7%**

Methodology: Most of the estimates for GHG reductions come from MSMC: Madanat, Shaheen, Martin and Camel (2010). Gaps in the information were supplemented with NAS: National Academies of Science by TRB (2010). The fuel economy improvements were scaled down if they would only reduce fuel consumption in rural highway operations vs. urban operations, because Core T7 trucks operate in both settings and we want the abatement curve to be representative of both of them. From Battelle (1999) we know that 55% of miles driven by class-8 trucks in California occur in rural highways. Also, the cumulative benefit from technologies was calculated using the methodology in TRB (2010) as:

$$1 - P_{overall} = \quad 1 - P_1 \quad 1 - P_2 \quad 1 - P_3 \quad \ldots (1 - P_n)$$

The costs of the different FSTs were brought to the year 2010 using an inflation rate of 3% per year. These costs also include the fact that there are 2.5 trailers per tractor on average (Schubert and Kromer 2008).