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by

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Abstract

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In response to the growing climate change problem, many governments around the world are seeking ways to reduce the greenhouse gas (GHG) emissions of various sectors of the economy. The trucking sector is important in meeting this challenge in the US because it is responsible for a share of emissions that is significant and rapidly growing. For governments to intervene in this sector smartly, they need models that capture its key incentives, constraints and dynamics, while making the most out of the limited data available. However, existing models fall short of this ideal. This dissertation first introduces the Trucking Sector Optimization Model (TSO) as a tool for studying the decisions that carriers and shippers make within a short-run time horizon—modeling the dynamics of truck fleets, penetration rate of Fuel Saving Technologies (FSTs) such as aerodynamic improvements and low rolling resistance tires, and changes in the demand of trucking. In addition to estimating tailpipe GHG emissions, the model also estimates emissions from upstream fuel production sources, vehicle manufacturing, and pavement rehabilitation activities.

This model is then used to evaluate the effectiveness of various incentives-based and regulation-based strategies that California's government could implement in the trucking sector to help achieve the objectives of the *Global Warming Solutions Act of 2006* (AB 32). The strategies analyzed are: fuel taxation, mileage taxation, truck purchase taxation, FST subsidies, FST regulations, increases in the allowed weight of trucks, and the Low Carbon Fuel Standard recently introduced in California. Results indicate that there presently exist significant economic incentives for carriers to invest in FSTs beyond what is currently commonplace. The correction of market mechanisms that are responsible for this apparently suboptimal behavior, would lead to significant reductions in emissions, and would also allow for incentive-based strategies to have their first-best outcomes. Without making these corrections, the regulation approach currently adopted in California, of mandating certain investments in FSTs, serves as a reasonable first-step in meeting AB 32's medium-term emissions target. However, moving forward, the correction of these market mechanisms and subsequent implementation of incentives-based strategies, particularly those that are complementary with each other, should be a priority. Based on their estimated effectiveness, these and other recommendations are articulated in a seven-step plan for reducing trucking related emissions in the state.

The remaining chapters of this work study some long-run factors that affect how carriers manage their fleets and invest in FSTs, in particular considering that they often discount heavily the future because of the existence of various market failures, hidden costs and uncertainties in the industry. The nature of these issues is not investigated deeply in this research, but their effect on carriers is captured by parameterizing the level of discounting in an improved model called the Trucking Sector Trip Segmentation Model (TSTS). This model represents the long-term decisions made in this sector better than the TSO model by: (i) modeling endogenously how trucks are utilized throughout their service-lives, and (ii) capturing some heterogeneity in truck retirements. The first of these improvements is made possible by incorporating information on the performance of trucking (the ability of carriers to complete shipments) and on the spatial distribution of shipment demand. The second of these improvements is made possible by assuming that truck retirements follow a log-logistic function. Combining both of these methodological improvements with a parameterized discount rate provides analysts a more flexible model for studying the long-term decisions made in the trucking sector, especially regarding FST investments, which impact greatly emissions and costs.

The TSTS model is then used to evaluate the effectiveness of three additional governmental interventions that reduce GHG emissions, which could not have been studied with the TSO model. Improvements in trucking performance—by reducing congestion or shipment waiting times for example—were found to significantly incentivize investments in FSTs and reduce GHG emissions. However, 40 – 50% of these reductions were offset in the aggregate by increases in the demand for shipments precipitated by the lower market prices of trucking. Mode-shifts were also found to incentivize investments in FSTs because they distort the spatial distribution of shipments in ways that favor making greater capital investments because trucks are used more intensely and retired quicker. And finally, implementing FST regulations that only apply to a subset of the truck fleet (as in California currently) also reduces emissions, but incentivizes other changes in how the industry operates.

The TSO model is best suited for studying the dynamics and transitions of truck fleets in response to governmental interventions, while the TSTS model is best suited for studying long-run responses. Together, they allow policy makers and researchers to study a wide range of issues in the trucking sector, considering many interactions and responses that had not been adequately explored previously. They also share a rich theoretical framework that can be used in future research to develop better models of this sector, especially to help design interventions that have environmental objectives.

To my parents Maria Victoria and Livano,

for sacrificing so that I could get the best possible education.

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1 Introduction

1.1 Problem Statement

One of the most critical challenges facing our generation is the need to improve the sustainability of our economy by reducing its Greenhouse Gas (GHG) emissions. Multiple studies have concluded that anthropogenic GHG emissions lead to global climate change, which impacts humanity negatively in many ways (IPCC 2007). The trucking sector is important in meeting this challenge because its GHG emissions have been growing relatively rapidly over the past two decades (Davies *et al.* 2007), and now account for over 7% of all emissions in the US (EPA 2013). Much of this growth has been driven by increases in the demand for tucking, as supply chains have become more responsive to inventory costs and customer demands (Kamakate and Schipper 2009).

This growth trend was interrupted by the economic crisis of 2008, which caused trucking emissions to decrease by 12.4% from 2007 to 2009 (EPA 2013). However, this sector has bounced back since, with emissions increases of 3.1% between 2009 and 2011 (EPA 2013). Even though these are the last years for which these emissions data are available, there are indications from the Freight Transportation Services Index—which is a measure of freight transportation activity reported every month—that the demand for goods movement has continued to increase past 2011, and in fact has already matched its pre-recession peak (BTS 2013). Therefore, the GHG emissions outlook of this sector is still worrisome.

As such, governments in the US, and around the world, should intervene in the trucking sector to ensure that its market participants observe the environmental externalities of their actions. Theoretically, governments should intervene up to the point where the marginal societal benefit of emission reductions equals the marginal economy-wide cost of these reductions, because it leads to an allocation of resources that maximizes total classical welfare. Therefore, it can be strongly argued that governments should implement pricing and/or regulation strategies to correct this market failure.

In addition, governments should also intervene in this sector to correct other sources of market failures that might be causing suboptimal outcomes. It has been found that many industries operate less efficiently than is privately optimal for a variety of reasons (Gillingham *et al.* 2009), resulting in greater energy consumption and higher costs. Recent research has found that many of these market failures are also present in the trucking industry (Aarnink *et al.* 2012; Vernon and Meier 2012), decreasing the incentives for trucking companies improve the fuel economy of their operations. These market failures include: principal-agent problems in who bares fuel costs, information asymmetries in the contracting of trucking services, and financial constraints on long-term investments. Some reasons for these problems are discussed in the body of this dissertation. For now, it suffices to point that strong arguments can also be made that—in addition to internalizing the costs of GHG emissions—governments should also intervene to reduce these other types of market failures, in order to improve the operations of the industry while reducing its emissions.

However, governments should be careful when intervening in this sector because the quality and efficiency of freight transportation has fundamental impacts on our economy (Hummels 2007). Over the years, the lowering of transportation costs has expanded the reach of markets, empowering more buyers and sellers throughout the world, and increasingly from more remote areas, to engage in the modern economy. Advances in freight transportation have been instrumental in driving urbanization, specialization, and globalization; all of which have increased aggregate productivity and improved our quality of life.

Today, trucking is the most important freight transportation mode in the US. It moves 1/3 of all ton-miles and lifts 2/3 of all the value of trade (ATA 2013). In 2013, the trucking industry had revenues close to $642B, representing around 40% of all transportation related expenditures in the US (ATA 2013)[1]. This industry employed directly or indirectly 1 out of every 13 Americans working in the private sector. Because of its size, this industry interphases significantly with the public sector, contributing to 36% of all fuel tax revenues (ATA 2008) and causing around 40% of all pavement deterioration on US highways (March 1998). Furthermore, not only is this industry a significant contributor of GHG emissions, but it is proportionally an even greater emitter of other criteria pollutants in urban centers, such as particulate matter (PM) and NOx.

The current approach taken by governments in the US to reduce GHG emissions from the freight transportation sector consists of requiring trucks to be retrofitted with certain Fuel Saving Technologies (FSTs). The FSTs that are currently market-ready include, for example: low rolling resistance tires, technologies that reduce the aerodynamic drag of vehicles, and low viscosity transmission fluids, among others (National Research Council 2010). Targeting the trucking industry represents a reasonable way to reduce GHG emissions from freight transportation because it is the largest and fastest growing source of emissions in this sector (Nealer *et al.* 2012). Emission reductions from other freight transportation modes are possible, but they will be likely smaller and costlier to achieve. Therefore, this dissertation—as well as the present policy debate—focuses on studying the mitigation of GHG emissions from trucking.

To accomplish this goal, there are other incentives-based interventions might be more desirable than the current regulatory approach. Additional investments in the FSTs can also be incentivized through: fuel taxes, differentiated mileage taxes, technology subsidies, cheap financing, etc. In contemplating these, governments should also keep in mind that changes in use of FSTs will likely lead to unintended impacts in how trucking companies

[1] However, somewhat less than 40% of transportation research focuses on the trucking sector.

manage their vehicle fleets. There will be pressure on truck owners to retire trucks later in life to accrue additional fuel savings that justify the capital costs of the FSTs. This in turn will put downward pressure on the number of trucks that need to be purchased to supply a given demand from shippers (because existing trucks are used longer), reducing emissions from the manufacturing of those trucks. This often overlooked source of GHG emissions has been estimated to account for 11% of total trucking related emission in the US (Facanha and Horvath 2007).

Governments should also consider that trucking companies cannot optimize their operations in a vacuum because they have to remain responsive to the demands of shippers. The quality and price of trucking will affect significantly how shippers design their supply-chains, and therefore their demand for transportation services. Modeling these decisions and interactions in the aggregate is generally difficult, and requires very detailed datasets that are not publically available in the US. However, it is clear that neglecting to represent shippers in models of the trucking sector is short-sighted, and will lead to large biases in the estimation of changes in emissions.

Another reason why governments should consider shippers is that they can be targeted directly with strategies that reduce their demand for transportation and/or incentivize them to use more sustainable modes. Some of these strategies include: time-of-day pricing, land-use zoning changes, packaging reduction, intermodal infrastructure investment, etc. Strategies that target shippers might be desirable because many trucking are often constrained in responding to governmental interventions because of their low and volatile profits.

Finally, governments should also consider the important role that the infrastructure plays in the trucking sector. Governmental interventions that improve highways and reduce congestion can help truck owners operate more efficiently and reduce fuel combustion. On the flipside, maintaining and rehabilitating highway infrastructure represents a large cost to the public sector, and is also a significant source of GHG emissions. This other often overlooked source of emissions has been estimated to account for 9% of all trucking related emissions in the US (Facanha and Horvath 2007).

It is clear that the trucking sector has very important impacts on our economy and environment, and that the way this sector reacts to governmental interventions can be quite complex. To study and evaluate these interventions, governments need to have comprehensive models of this sector that consider the key incentives, constraints and tradeoffs underpinning the responses of trucking companies and shippers. These models should also account for various sources of GHG emissions (including those from vehicle manufacturing and pavement rehabilitation), and of other environmental externalities, such that unintended impacts can be foreseen and mitigated. This comprehensive modeling approach would allow governments to consider a wide-range of incentives-based and regulation-based strategies so that the most effective ones are pursued. It would also allow the government to identify and mitigate market failures in this sector by gaining an understanding of the how the current operations of the industry can be improved. However, as *Section 1.3* details, models that permit this type of analysis presently do not exist, mostly because of limitations in the data that is publically available about the costs and operations of this sector, and also because of gaps in the methodologies for modeling this sector comprehensively.

The inadequacy of trucking sector models has limited the ability of policy makers to analyze more complex and sophisticated GHG mitigation strategies; which, in my opinion, has steered them towards preferring blunter regulation-based strategies that are likely less efficient. This dissertation seeks to provide policy makers with better methodologies for modeling this sector—that make the most out of the scarce data that is available—so that the best policies can be pursued in this critically important component of our economy.

1.2 Research Framework

The trucking sector can be conceptualized as having three key distinct components. **Shippers** are the agents that demand transportation services because of the spatial dimensions of their businesses. These include wholesalers, importers, exporters, retailers, etc. **Carriers** are the agents that supply transportation services. In this case they are the truck owners and operators. The final component is the **Infrastructure**, which provides a platform on which carriers can supply transportation. In this case it consists not just of highways and urban roads, but also of ports, intermodal yards and Intelligent Transportation Systems. Of course, in reality the trucking industry is more complex, with many shippers owning trucks fleets or hiring third-party logistics companies, however these convenient definitions presented above help facilitate the following discussion.

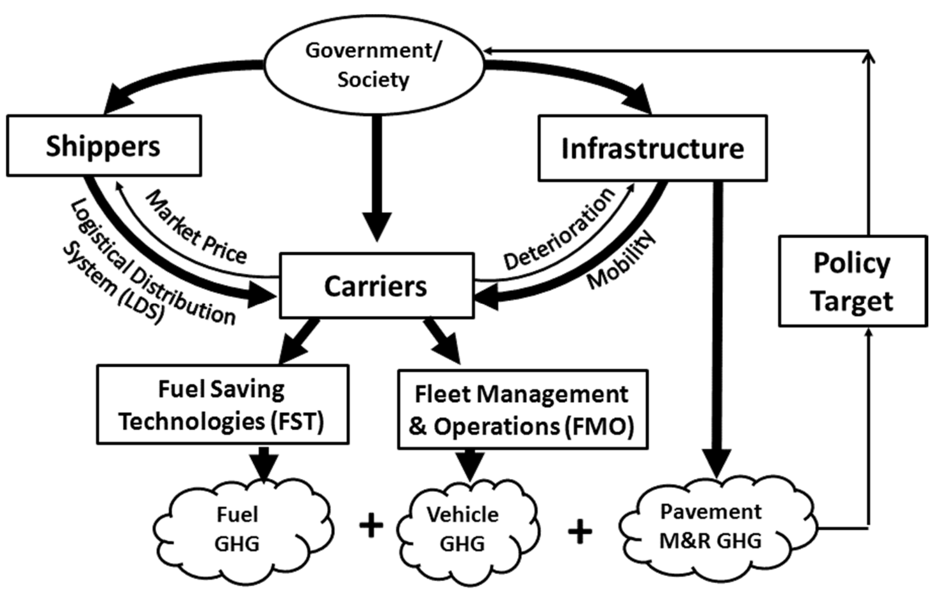

Figure 1: Framework of GHG mitigation in the trucking sector

As seen in *Figure 1,* the government can target shippers, carriers and the infrastructure in order to reduce GHG emissions of this sector. Carriers and shippers interact in a market for transportation services, which is brought to equilibrium by a prevailing market price. In consideration of these transportation costs, shippers optimize their Logistical Distribution System (LDS) by 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 the quantity of transportations services demanded in the market. 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 this sector. Emissions from the combustion and upstream production of the fuel are closely linked to the technology of the trucks (influenced by investments in FSTs), while FMO decisions affect the emissions from vehicle manufacturing.

It is also important to consider the interactions between carriers and the infrastructure. An increase in trucking vehicle miles traveled (VMT), 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.

While *Figure 1* was developed with the trucking industry in mind, it can be generalized to describe how governmental intervention can reduce GHG emissions in other transportation sectors. In future work this figure can also be expanded to include emissions from shippers' supply-chains, such as warehousing, manufacturing, retailing, etc.

Using this framework a wide range of GHG mitigation strategies can be classified as shown in *Figure 2*. A long-term objective of this research is to develop methodologies for evaluating how a promising subset of these strategies can lead to the desired outcomes on the right side of the figure.

The strategies that are bolded represent those that have been implemented already.

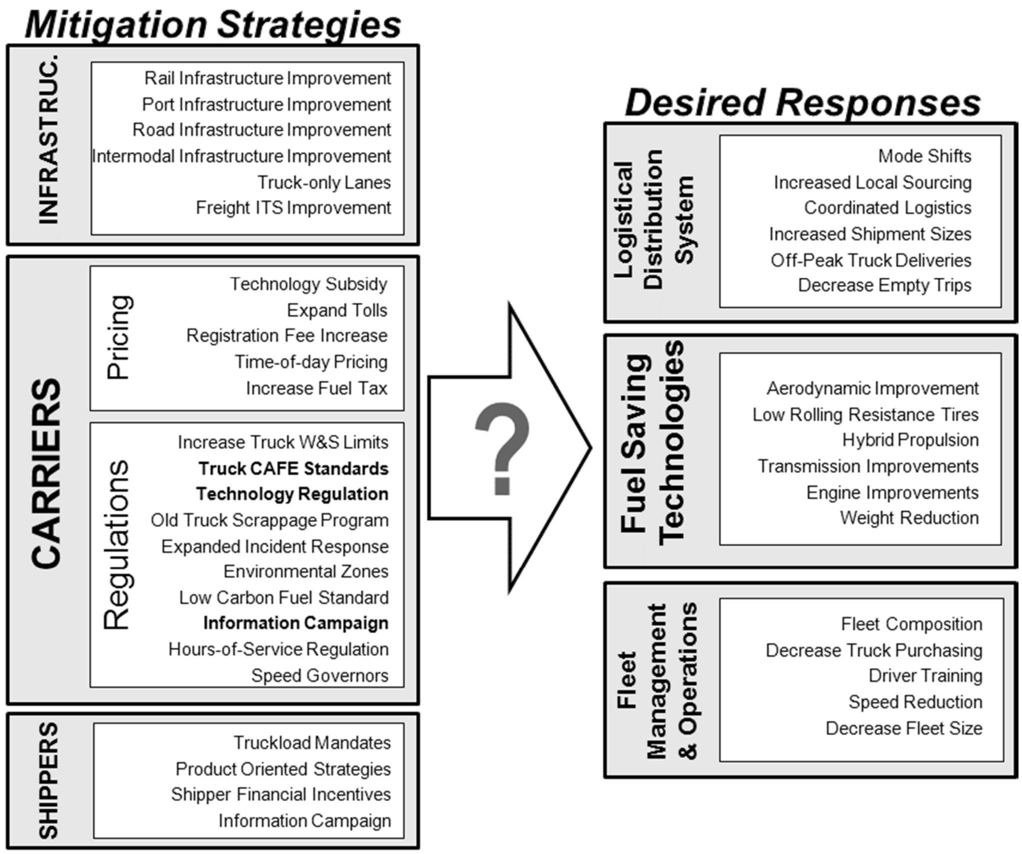

Figure 2: Universe of GHG mitigation strategies and desired responses

1.3 Literature Review

The state-of-the-art in modeling of the trucking sector 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 have not been studied simultaneously. Many methodological gaps exist in the literature that prevent policy analysts from taking this more comprehensive modeling approach. Not much effort has been placed in the past on bridging these gaps because there have not been many instances of analysts wanting to simultaneously study the responses of shippers and carriers to a wide range of mitigation strategies. Past analyses of governmental interventions in this industry have focused on a single strategy (such as fuel taxation or infrastructure improvements) and thus could make various simplifying assumptions about the responses of the industry. However, to address the problem statement described in the previous section we need a model that does not make these simplifying assumptions, so that the analyses of different strategies are performed with consistent methodologies, leading their results to be comparable.

1.3.1 Modeling of FST Responses

The majority of the studies on GHG emissions mitigation in the freight transportation sector have only considered strategies that regulate the level of FSTs in truck fleets (Ang-Olson and Schroeer 2002; Cooper *et al.* 2009; Frey and Po-Yao 2007;Vyas *et al.* 2002). These studies assumed that LDS and FMO remain unchanged, while carriers are *forced* to implement different FSTs. The effectiveness of each FST is found either through experimental tests, information from the manufacturers, computer simulation of engine loads or simply from previous studies. The results are presented as percent-increases in fuel efficiency for an average truck from the implementation of certain FSTs. Then, using aggregate measures of Vehicle Miles Traveled (VMT) by truck type, these studies calculate industry wide GHG emission reductions from the implementation of combinations of FSTs. Governments have used these results with activity forecasts to determine the amount of FSTs needed to be implemented to achieve certain emissions targets (CARB 2008b).

While this approach is common in many studies and provides a useful first-order analysis of FST regulation strategies, it has several critical limitations. Foremost, the implementation of FSTs will affect the optimal FMO and LDS. Greater implementation of FSTs incentivizes carriers to change their FMO to retire trucks later in life. This occurs because carriers prefer to accrue more fuel savings throughout the life of the trucks (relative to the less fuel efficient trucks) to offset the higher capital costs of the FSTs. Having a fleet of older trucks will also affect the number of trucks that need to be purchased to meet the demands of the shippers. These responses of the trucking industry are interrelated in ways that have not been quantified in past research.

An additional limitation of this common analysis approach is that the LDS is assumed to be fixed. Changes in the implementation of FSTs will affect the market rate for trucking (fuel accounts for 1/3 to 1/4 of trucking costs), and thus influence how shippers optimize their LDS. Important responses such as mode-shifts and shipment size changes are not considered in the existing analysis of FST regulations.

Besides not capturing the responses of the industry fully, this basic analysis approach is also limited in not being able to evaluate incentive-based strategies. These strategies seek to tilt the economic tradeoffs that carriers and shippers face so that more sustainable decisions about FMO, FSTs or LDS are made at the margin. For example, increasing the tax on fuel or providing direct subsidies will incentivize greater investment in FSTs, and also change the optimal FMO and LDS. Modeling all these responses would allow the comparison of the effectiveness of regulations and incentives in reducing GHG emissions. There are also other strategies that affect FMO and LDS directly that would have secondary effects on the level of FSTs of truck fleets. These relationships have not been researched in the past.

1.3.2 Modeling of LDS Responses

Several synthesis of research in freight transportation demand modeling have been performed (Chow *et al.* 2010; Harker 1985; Pendyala *et al.* 2000; Samimi *et al.* 2010) that categorized and highlighted the strengths and weaknesses of different modeling approaches. The different approaches taken can be generally classified into: early **spatial-price equilibrium models**, cost minimization **network models** and econometric **behavioral models**.

One of the main limitations of these models as they apply to this present research is that they consider transportation costs to be fixed and exogenous. The LDS responses captured in these models needs to be combined with a model of carriers that considers FST and FMO responses as well. A second limitation is that there currently does not exist any publically available dataset in the US to estimate any of the disaggregate behavioral models that capture logistical decisions explicitly (de Jong and Ben-Akiva 2007). Current LDS models can be useful to study the trucking industry in European countries that collect detailed data on individual shipments, but not to study the trucking industry in the US. Aggregate models of freight transportation demand have been used in some cases in the US, but they have not modeled logistical tradeoffs explicitly (NCHRP Report 606). One of these models that has received much attention is the Commercial Transport (CT) module of the Oregon Statewide Integrated Model (SWIM2) developed by Parsons Brinckerhoff *et al. (*2010). This model estimates truck flows in Oregon by simulating over many decisions made by carriers and shippers given the observed distribution of these decisions. While decisions are simulated about mode choice, carrier type (private vs. for-hire), vehicle type and transshipment location, these represent exogenous inputs into the model and not results of the model. Such an approach can be useful in some circumstances, but it cannot be used to characterize the LDS responses of interest.

1.3.3 Modeling of FMO Responses

FMO modeling in the literature has focused primarily on making recommendations about how individual firms should manage their vehicle fleets. 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. Some of the phenomena studied includes: stochastic fluctuations of trucking demand (Hartman 2004), deterministic daily fluctuations in bus transit demand (Simms *et al.* 1982), random machine breakdowns (Christer and Scarf 1994; Scarf and Bouamra 1995; Suzuki and Pautsch 2005), stochastic deterioration of machines (Childress and Durango-Cohen 2005; Morse and Bean 1998) and technological progress (Bethuyne 1998). The resulting optimization problems have been solved using dynamic programming with Bellman recursion (Stasko and Gao 2012), two-stage approximate dynamic programming (Simms *et al.* 1982), network linear programming (Vemuganti *et al.* 2007) and integer programming (Karabakal *et al.* 1994). Even though most of the recent literature has focused on studying the effect of uncertainty on time-varying FMO decisions, some earlier work has considered steady-state solutions as a way of understanding the forces driving optimality (Smith 1957).

To our knowledge only two papers have used these types of models to evaluate the effect of environmental policies on vehicle fleets. Stasko and Gao (2010) used an integer program to determine the optimal management of a bus fleet as a transit agency considers the purchase of buses with more energy efficient propulsion technologies in response to governmental regulations. The second of these papers was written by Figliozzi *et al.* (2011)

and used an integer programming model to find the composition of the personal vehicle fleet (considering cars with different propulsion technologies) that minimizes total costs that include the costs of GHG emissions.

These Operations Research models have been designed to be used by single decision making units (such as a carrier or transit agency for example) to develop an optimal machine management strategy. Emphasis has been usually placed on providing a detailed accounting of costs under different uncertainties. However, for this research we are interested in modeling a whole trucking industry, which is composed of many firms, therefore the models need to be focused differently. Also, with a couple of exceptions, the approaches used rely primarily on numerical optimization techniques that do not provide many insights about the nature of the results because of the large dimensionality of the problems studied.

A separate but much 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 for this industry. Additionally, in following sections it is shown that treating truck retirement as a probabilistic event is not necessary for this research because the average retirement odometer of trucks contains enough information to approximate total costs well.

Another 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 (2011b). The objective of the freight module of the NEMS model is to investigate how changes in macroeconomic conditions affect the energy consumption in the sector, while the objective of the EMFAC2011 model is to forecast the environmental impacts of the trucking sector in California. However, both of these models make the same assumption that FMO responses are exogenous. 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. Treating both of these variables exogenously and independently of each other represents a larger limitation in the NEMS model as it seeks to model the responses of the industry, not just forecast current operations. Another limitation of the NEMS and EMFAC2011 model is that they do not consider LDS responses.

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.

1.3.4 Comprehensive Modeling of FMO, FSTs and LDS

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 through assumed elasticity parameters. While these models are conceptually a step in the right direction, they are inadequate for policy analysis.

Theoretically, the FST and FMO responses of carriers and the LDS responses of shippers can be modeled either by (1) an econometric analysis of industry data, or (2) as an aggregate optimization problem.

Econometric models are used often in many research fields to quantify the behavioral responses of agents from data about their past decisions. In freight transportation, this approach has been used to model the LDS decisions that shippers make (see *Section 1.3.2*), although in the last couple of decades there has not been enough publicly available data (especially of the disaggregate kind) to estimate this type of model in the US. Econometric models have also been used to represent some of the FMO decisions that carriers make by estimating survivability curves for truck fleets (see *Section 1.3.3*). However, these models also require datasets that are not publically available, and their results have not been very informative for policy making because they omit important variables such as the investment in FSTs and the amount of truck purchases.

On the other hand, optimization models reduce significantly the data that the analyst must have access to by requiring her greater use of her judgment and expertise to formulate the model. In these models the market conditions are conjectured from economic theory and empirical evidence, and firms are assumed to seek to maximize profits. The profits are calculated using data obtained from the literature on the average costs and operations of the industry.

Using aggregate average data to characterize an industry is easier and more defensible for trucking companies than for shippers because they are significantly more homogeneous. Companies that ship commodities come from all sectors of the economy and their shipment decisions result from the managing of supply chains that in many cases can be quite complex. As seen in previous sections, econometric models have been preferred to model shippers because they can capture a greater degree of heterogeneity than optimization models. On the other hand, trucking companies all operate essentially the same trucks, on the same infrastructure, and with similar objectives. The costs and operational constraints they face can be well characterized with industry wide averages. This is why optimization models have been used more often to represent the responses of carriers.

In order to achieve the objectives of this dissertation, new modeling methodologies need to be developed that smartly combine econometric models and optimization models in order to provide the best representation of the trucking sector from the little empirical evidence available.

1.4 Research Contributions and Dissertation Organization

This dissertation develops of a comprehensive modeling framework for studying the responses of the trucking sector to various governmental interventions that skirts some of the data limitations that have restricted past research. The modeling approach is described as being *comprehensive* because it considers simultaneously the FMO and FST responses of carriers and LDS responses of shippers, and because it accounts for changes in life-cycle emissions from various sources, including: tailpipes, precombustion, vehicle manufacturing and infrastructure rehabilitation.

Section 2 describes the Trucking Sector Optimization Model (TSO). This model considers the optimal decisions that carriers and shippers make throughout time, essentially modeling the transitional dynamics of today's trucking sector in responses to time-dependent governmental interventions and changes in the business environment. As its name suggests, carrier's decisions are modeled through the optimization of a dynamic mathematical program that is specified on the average costs observed for this industry. The costs considered includes: labor costs, fuel costs, capital costs, FST costs, salvage value, etc. Shipper's decisions are represented with response elasticities obtained from the literature. The model is solved using a two-stage heuristic that provides satisfactory approximate results. The GHG emissions of the sector are then determined using methodologies from the life-cycle assessment literature. The main methodological contributions of this model are: (1) the simultaneous consideration of FST, FMO and LDS responses, (2) the modeling the transitional dynamics of aggregate truck fleets, and (3) the consideration of life-cycle GHG emissions.

Because at the heart of the TSO model lays an optimization problem, its results can provide both normative and positive insights. The responses of the industry predicted by the TSO model give policy makers a sense of the magnitude and direction of the economic incentives caused by their interventions. This answers questions such as: by how much are average costs going to increase? how will the average truck be operated differently? and, most importantly, what will be the impact on life-cycle emissions? The predictive accuracy with which these questions are answered depends on how well the observed average costs represent the circumstances in the industry, and how well these are tweaked by the analyst according to her experience and judgment. The TSO model can also be used to identify inefficiencies in the trucking industry by proposing alternative ways of doing business that could lead to lower costs. Market failures can explain why carriers provide services at a higher cost than the TSO model suggests. In that case, governments should intervene to make sure that this industry operates closer to optimality, either by correcting the market failures at their root cause or by introducing corrective regulations.

Section 3 then uses the TSO model to evaluate the effectiveness of seven different types of governmental interventions to achieve the GHG emissions target set in California by the Global Warming Solutions act of 2006. The strategies analyzed are: fuel taxation, mileage taxation, truck purchase taxation, FST subsidies, increases in truck size and weight limits, Low Carbon Fuel Standard and FST regulations. This case study demonstrates the usefulness of the TSO model in: (1) evaluating the responses of the sector to meet policy targets in the near-term, (2) comparing regulation-based strategies against incentives-based strategies, (3) evaluating the impact of the phase-in schedule of strategies on the trajectory of emissions, (4) evaluating the impact of the existing truck fleet on the optimal decisions of carriers moving forward, (5) evaluating the penetration rates of FSTs, (6) evaluating the tradeoffs between different emission sources, and (7) finding ways to mitigate market failures in this industry. These insights are used in *Section 3.4* to propose seven consecutive steps that policy makers in California should take to reduce emissions from this sector.

The GHG mitigation strategies studied in *Section 3* go a long way in realizing the vision presented in *Figure 2.* However, there are other important strategies that cannot be analyzed with the TSO model because of its simplifying assumptions. This limitation is addressed by the Trucking Sector Trip Segmentation Model (TSTS) introduced in *Section 4*. The TSTS model improves on the TSO model in two key ways. First, truck retirements are modeled as probabilistic events such that the distribution of truck ages in the model matches better real-world observations. Secondly, the TSTS model represents endogenously the utilization of trucks throughout their service-lives, based on the spatial distribution of the demand for trucking and the mileage supply performance of the truck fleet. In contrast, in the TSO model trucks were assumed to follow an exogenous utilization function, where at a given age trucks provide a fixed and exogenous amount of miles per year. The introduction of these additional variables comes at a cost. The state-space of the dynamic optimization problem is increased significantly, making the solution approach used for the TSO model unworkable. Therefore, for now, only a stationary version of the TSTS model is presented, where all of the variables are assumed to be fixed throughout time. This essentially represents a long-run model that can be used to study the responses of the trucking sector once its operations have converged to optimality.

Section 5 uses the TSTS model to evaluate how California's heavy-duty truck fleet would respond to: improvements in the performance of trucking, mode shifts, and FST regulation to a subset of the truck fleet. These three interventions are demonstrated to reduce GHG emissions, but also affect other dimensions of how the sector operates.

The ground-level understanding of the trucking sector provided by the TSO and TSTS models has the potential to significantly improve future research in this field in three key dimensions. (1) As mentioned in *Section 1.3.4,* welfare studies into the optimal level of implementation of FSTs have represented the responses of the trucking industry using elasticity parameters that are largely assumed, which detracts considerably from the weight of their conclusions. The models presented in this dissertation would allow future work on the economic efficiency of trucking sector interventions to be based on more realistic representations of industry responses. (2) The modeling of various sources of emissions is even more important for studying ways to mitigate Particulate Matter (PM) and NOx emissions, because these other pollutants are emitted more intensely in the manufacturing of vehicles and rehabilitation of pavements than for GHGs. The models presented in this dissertation are especially salient for understanding these types of tradeoffs. (3) With little modifications, the TSO model can be also applied to study the responses of other sectors, such as railroad, air or waterborne transportation. The economic tradeoffs faced in managing fleets of trains, airplanes and ships are not fundamentally different than those of managing fleets of trucks. In summary, there are many ways in which future research can benefit from the methodological contributions of this dissertation.

2 Trucking Sector Optimization Model (TSO)

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 demand from shippers (at one point or another in their service life). Trucks should always belong to the same fleet such that there are no interactions between fleets. For example, one fleet can be composed of Class-8 trucks that are purchased into intercity service and another one can be composed of Class-8 trucks that are purchased to provide drayage services at ports. The segmentation of truck fleets should be consistent with the data availability and scope of the study. Given that our objective is to model GHG emissions, the remainder of chapter assumes that the truck fleet being modeled is composed of Class-8 trucks purchased into intercity service, because they contribute to the bulk of emissions from trucking. However, other truck fleets could be studied as well in future research. In this dissertation, the terms *trucking industry* and *trucking sector* are used interchangeably to refer to shippers and carriers.

The schematic shown in *Figure 3* summarizes the different components of the TSO model. At its core, the 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 assumption that the industry operates competitively in the long-run, which has been found to be a reasonable representation of this industry. Carriers have also been found to have constant returns to scale (Friedlaender and Spady 1981), which allows the trucking industry to 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 their size. The trucking industry fits this description well because the physical 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.

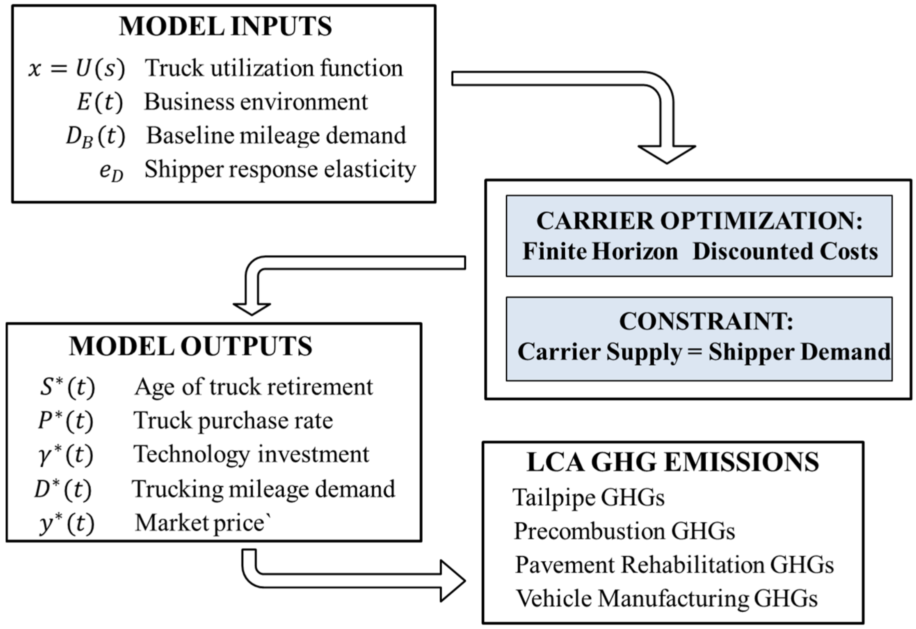

Figure 3: Schematic of TSO Model

The FMO and FST decisions that carriers make throughout time (age of truck retirements, truck purchase rate and technology investments) are modeled through the minimization of discounted costs over the study time horizon 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. The inputs used in this model are obtained from industry averages found in the literature; their selection and components are discussed in detail later in this section.

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

Government's interventions 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 produces less GHG emissions.

The TSO model considers the decisions that carriers and shippers make at every time-step of the analysis. This is important because the trucking industry will not respond to governmental interventions from a clean slate; the characteristics of the present truck fleet will influence the responses of carriers. Over time, the decisions that carriers make will converge to a long-run optimal, but this could take many fleet turnover cycles. If policy objectives are set in the short-term or medium-term (as occurs in the case study explored in *Section 3*), then modeling the transitional dynamics of the truck fleet is important.

Additionally, governmental interventions are likely to be phased in over significant periods of time; modeling this transition is of interest to policy makers.

The TSO model is labeled as *time-dynamic* because all of the variables have to be defined at every time-step. However, before this model is described formally, this chapter introduces a simplified version of the TSO model where the operations of the trucking industry are assumed to be constant throughout time. This idealized model, which is labeled as *time-stationary,* allows us to gain several key insights about the mechanisms governing the decisions of carriers and shippers, by expressing the optimality conditions succinctly. Additionally, as explained in *Section 4.3*, the results of this model were used to reduce the dimensionality of the time-dynamic model so that solutions can be obtained more computationally efficiently.

The time-dynamic model can be interpreted as a short-run model while the time-stationary model can be interpreted as a long-run model.

2.1 Time-Stationary Model

This section presents the analytical framework used to model the trucking industry. First, truck fleet utilization curves are introduced as a tool to describe the operations of a truck fleet. These curves are then analyzed analytically to derive a cost-minimization model that captures FST and FMO responses.

2.1.1 Truck Fleet Utilization Curves

Truck fleet utilization curves describe how carriers manage their trucks in the supply of transportation services to shippers. Each curve represents the operations of an individual truck. In *Figure 4* we see an example of these curves (for the non-stationary case), where on the horizontal axis plots time t and on the vertical axis plots the truck odometer x (cumulative mileage since purchase).

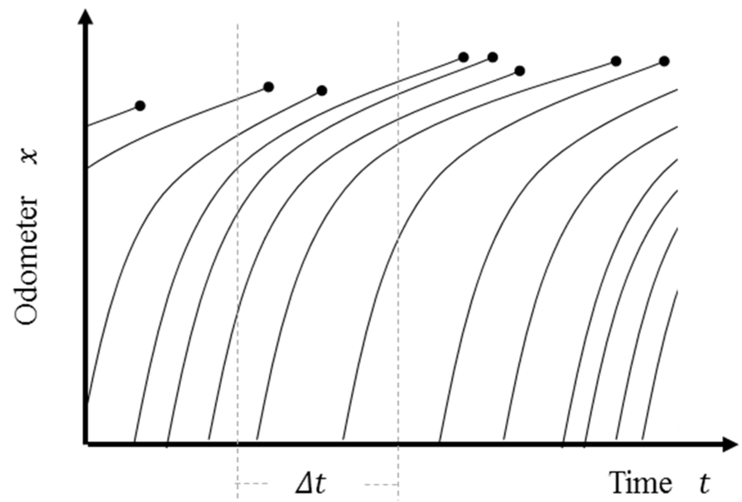

Figure 4: Truck fleet utilization curves

From these curves we can read the FMO information:

1. *Truck Purchase Rate:* The start of each curve at $x = 0$ represents the time at which each truck is purchased and put into service. The rate at which trucks are being purchased (trucks/year) is defined as $P(t)$. The time between two truck purchases at t can be approximated by $1/P(t)$.
2. *Truck Utilization:* From the time of purchase trucks are driven at a certain rate (that can vary with age and time) that is described by the curves in the figure. Each of these curve is represented by a function $x = U_t(s)$, where s is the age of the truck and t is the time of purchase.
3. *Service Lifetime:* The maximum odometer reached by each curve is the point where the truck is scrapped. This is defined as $X(t)$, the retirement odometer of trucks at time t. Note that trucks retiring at $X(t)$ were purchased at $t - S$, where S is the retirement age.
4. *Mileage Supply:* The aggregate supply miles by a truck fleet in any time interval Δt is the summation of the vertical distance covered by all truck utilization curves in that time interval. The instantaneous rate of aggregate mileage supply is defined as $\psi(t)$.

2.1.2 Carrier Model

By assuming time-stationary conditions we can exploit several analytical features of truck utilization curves to specify the trucking model succinctly. *Figure 5* depicts a stationary truck fleet in which trucks are purchased at a rate P, utilized according to $x = U(s)$, and retired at X.

From *Figure 5* it is clear that in a time interval $1/P$ the truck fleet will supply X miles in the aggregate. This result can be rearranged into

$$\psi = PX \tag{2.1}$$

where the aggregate mileage supply ψ can be found in the time units of P [in years] and distance units of X [in miles]. It can also be written alternatively as $\psi = U(S)P$. A consequence of (2.1) is that the aggregate mileage supply is independent of the functional form $U(s)$, and only depends on the retirement odometer and purchase rate of trucks.

Underpinning the truck fleet utilization curves observed in *Figure 5* is the assumption that all trucks face the same economic conditions and therefore will be managed identically. This leads to the model to assume that truck retirements that are deterministic. However, data of real life operations show that trucks retire at different ages in the same time period. This reflects the fact that carriers are somewhat heterogeneous and use trucks to provide different types of service. The approach in Chen and Lin (2006) could be used to model this heterogeneity, but it would require significantly more data than is publically available.

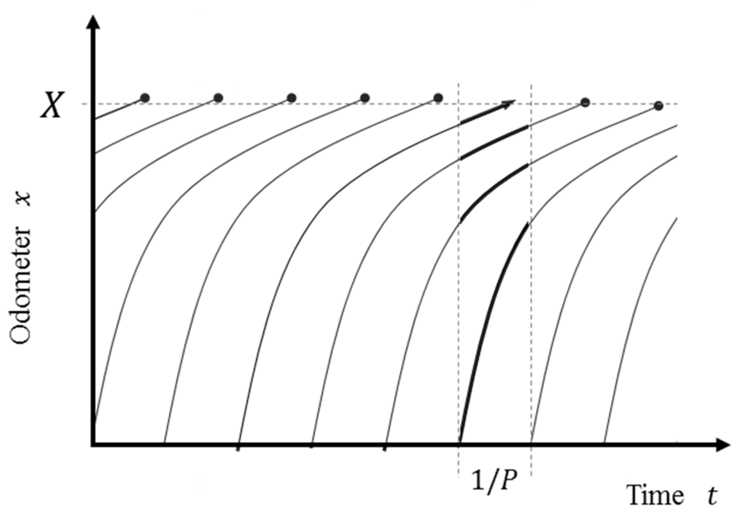

Figure 5: Stationary truck utilization curves

To deal with this limitation, truck utilization curves are treated in this research as describing the average operations of a truck fleet, where the average itself is modeled deterministically. It can be shown analytically that if trucks retire at a random X, along the same $U(S) = X$, then the supply of miles of the truck fleet is exactly equal to $\psi = P\bar{X}$ where $\bar{X}$ is the average retirement odometer. This implies that modeling truck retirements randomly does not provide any additional information with regards to the supply of trucking mileage than modeling the average truck retirement. However, because truck costs are a function of truck age, modeling the average truck retirement will result in a bias over modeling truck retirements as random events. This bias is likely to be small because, as will be seen, the bulk of trucking costs vary linearly with trucking mileage and because the bias both decrease and increase total costs, potentially canceling out much of the effect (maintenance costs increase with truck age but costs incurred by older trucks are discounted more heavily).

Stationary truck fleets can be described further. The size of the truck fleet F [number of trucks] can be found from

$$F = PS \tag{2.2}$$

when P and S have consistent time units. Dividing (2.1) by (2.2) provides a calculation of the average miles driven by each truck per year $\psi/F = X/S$. While (2.1) shows that truck mileage supply is insensitive to truck utilization, the size of the truck fleet is not because of S in (2.2).

Now, suppose that trucking carriers need to supply in aggregate ψ_0 miles per time period. Carriers will select an optimal FMO strategy by selecting P and X to meet this demand at the lowest average costs. In addition, carriers also choose to invest in FSTs to reduce the lifecycle costs of their truck fleet. Investing in FSTs reduces fuel costs throughout the life of the truck at the expense of higher capital costs. This investment decision is modeled using a variable $\gamma \in [0,1)$, representing the proportion of fuel saved by a cumulative investment in FSTs. It is assumed that carriers invest in the most cost-effective FSTs first. Details about the FSTs presently available and their cost effectiveness are included in *Table 2* in *Section 3.1.5*.

The costs of a truck fleet can be divided into maintenance costs, operation costs, purchase costs and salvage value. The maintenance costs per mile are defined as $M(x)$ such that $M'(x) > 0$ and $M''(x) \geq 0$. This captures the reality that trucks become more costly to maintain as they get older. It is assumed that by incurring these maintenance costs the truck is kept at original operating conditions. Operational costs per mile are defined as $O(\gamma)$ such that $O'(\gamma) < 0$. These are costs that increase linearly with truck mileage, and include driver wages, insurance, tolls, etc. A very reasonable assumption that can be made is that $O''(\gamma) = 0$, because γ affects fuel costs linearly by definition. However, operational costs can also include the additional expenses associated with operating a truck with FSTs, such as training and new loading equipment. These are omitted from the model because they are comparatively not very large.

The purchase cost of trucks is defined as $A(\gamma)$, with $A'(\gamma) > 0$ and $A''(\gamma) > 0$, such that there are diminishing returns to investing in additional FSTs. Note that the definition of γ it implies that $\lim_{\gamma \to 1} A(\gamma) = \infty$ and $A(0) = A_p$, the purchase price of a truck. The salvage value of a truck is defined as $V(\gamma, X)$ such that it is a non-increasing function of retirement odometer X and a non-decreasing function of level of investment in FSTs corresponding to their worth at salvage.

Independent of whether stationary conditions are assumed, it is necessary to discount costs throughout time because they are accrued in different time periods. The effective discount factor β can be used by the modeler to capture the subjective time preferences of firms, which are determined by the economic environment surrounding them. In the literature it is common to assume that there are two main forces driving this economic environment. First, the prices of the inputs, such as fuel and driver wages, increase according to some inflationary rate $r_i(t)$. For simplicity, in this model it is assumed that this rate is fixed throughout time at r_i. The second driving force, which acts in the opposite direction, results from the ability of firms to make investments in external assets that provide some rate of return $r_l(t)$. This represents the reality that firms can cover a future cost of \$10 by investing less than \$10 today in safe assets. For simplicity, this rate is also assumed to be constant at r_l, and is often assumed in the literature to be the US prime rate. The effective discount factor can be found to be $\beta = (1 + r_i)/(1 + r_l)$, where $\beta = 1$ implies no time discounting of money (Christer and Scarf 1994).

While the financial decisions of firms can be modeled in more detail, the model described above is used because it constitutes the most common approach taken in the equipment replacement literature. Alternatively, previous researchers have not assumed an interest rate because of the short time horizons analyzed (Vemuganti *et al.* 2007), assumed a discount factor of unity by forcing the internal rate of return to equal the rate of inflation (Stasko and Gao 2010), assumed different rates of price inflation for different inputs (Simms *et al.* 1982), and allowed the discount factor to vary with time (Kobbacy and Nicol 1994). Future work could consider the implications of these other assumptions on the results of this research.

Returning to the stationary trucking model, if the revenue per mile is defined as y, then the discounted lifetime profit of a single truck can be found by

$$\int_0^S \beta^s U'(s) y\,ds - \int_0^S \beta^s U'(s)\left[M\big(U(s)\big) + O(\gamma)\right]ds - A(\gamma) + \beta^S V\big(\gamma, U(S)\big) \tag{2.3}$$

where the first term sums the lifetime revenue, the second term subtracts the lifetime operating and maintenance costs, the third term subtracts the purchase cost of the truck and the fourth term adds a salvage value. Note that the substitution $x = U(s)$ is used to express the integrals more succinctly.

To obtain a steady state solution now the discounted stream of profits of trucks purchased in $t \in [0, \infty)$ are summed as

$$\pi = \int_0^\infty \beta^t P\left(\int_0^S \beta^s U'(s) y\,ds - \int_0^S \beta^s U'(s)\left[M\big(U(s)\big) + O(\gamma)\right]ds - A(\gamma) + \beta^S V\big(\gamma, U(S)\big)\right)dt \tag{2.4}$$

The assumption that the trucking industry faces perfect competition in the long run implies that $\pi = 0$. In other words, unlimited market entry and competition forces the market rate

y [$/mile] to be minimized at $dy/dS = 0$ and $dy/d\gamma = 0$. The first of these conditions can be expressed as

$$\frac{d}{dS}\left(\frac{\int_0^{S^*} \beta^s U'(s)\left[M\big(U(s)\big) + O(\gamma)\right]ds + A(\gamma) - \beta^{S^*} V\big(\gamma, U(S^*)\big)}{\int_0^{S^*} \beta^s U'(s)ds}\right) = 0 \tag{2.5}$$

which does not have a closed form solution for various functional forms tested, but it can be solved numerically easily. This expression indicates that trucks should be retired once the average cost of replacement (all lifetime purchase and operational costs divided by lifetime mileage output) equals the marginal cost of operating trucks an additional mile. This point is reached when it makes sense economically to purchase trucks more often and retire them more quickly to save on the more expensive maintenance costs of older trucks. Note that this way of deriving the optimality conditions produces (2.5) where the denominator, lifetime output, is discounted to the present. This is necessary to obtain a measure of average costs that is time consistent. Other researchers however have not taken this approach (Redmer 2009).

Notice that P cancels out of the expression because the model is constructed with constant returns to scale. The optimal P^* can be found using (2.1) as

$$P^* = \psi_0 / U(S^*) \tag{2.6}$$

The optimal level of investment in FSTs can be found through $dy/d\gamma = 0$ as

$$-\int_0^S \beta^s U'(s) O'(\gamma^*) ds = A'(\gamma^*) - \beta^S \frac{dV\big(\gamma^*, U(S)\big)}{d\gamma} \tag{2.7}$$

Indicating that FSTs should be implemented until the marginal benefit of reducing fuel consumption equals the marginal cost of the investment.

Equations (2.5), (2.6) and (2.7) represent the first order conditions of the stationary model.

One of the key intuitions that can be derived from this model is that if $\beta = 1$ the truck utilization function $U(s)$ drops out of the cost expression. This can be seen by substituting $U'(s)ds = dx$ in (2.3), obtaining

$$yX + \int_0^X [M(x) + O(\gamma)]dx + A(\gamma) - V(\gamma, X) \tag{2.8}$$

Therefore in the situation where the β is close to unity the optimal FMO and FST decisions are insensitive to $U(s)$.

Some convenient functional forms are

$$V(\gamma, X) = A(\gamma)k_d(1 - k_x X) \tag{2.9}$$

$$O(\gamma) = pf_M + k_o + (\theta_F + p_F)(1 - \gamma)f \tag{2.10}$$

$$M(x) = k_m x \tag{2.11}$$

where the salvage value is assumed to be a linear decreasing function of odometer reading by k_x and starts with an instantaneous depreciation k_d. The operational costs are a function of the mileage taxation θ_M, a fixed cost per mile k_o (driver wages, overhead, etc), the fuel tax plus fuel price $\theta_F + p_F$, and the after-FSTs fuel economy $(1 - \gamma)f$. Maintenance costs are assumed to increase linearly based on data from CARB (2008a).

Using cost functions (2.9), (2.10) and (2.11), and assuming $\beta = 1$, the first order conditions can be simplified to

$$A'(\gamma^*) = (\theta_F + p_F)fX^* \tag{2.12}$$

$$X^* = \sqrt{2A(\gamma^*)/k_m} \tag{2.13}$$

$$P^* = \psi_0 \,/\, X^* \tag{2.14}$$

2.1.3 Shipper Model

A simple shipper model was developed to capture the LDS responses of interest. Unlike the carrier model, the shipper model does not utilize on a cost optimization approach, instead it relies on own-price elasticities that have been estimated previously in the literature. However, the literature contains many estimates of the elasticity of tons shipped *w.r.t.* trucking cost and ton-miles shipped *w.r.t.* to trucking cost, but not many for estimates for the elasticity of truck mileage *w.r.t* trucking costs, which is the key parameter input in the TSO model that captures LDS responses. This section discusses the assumptions that are necessary to obtain a reasonable approximation of this key parameter from the types of data found in the literature.

Equation (2.15) represents a fundamental identity in freight transportation. For a particular commodity flow in an origin-destination pair s, the demand for trucking D_s [miles/year] depends on the quantity of goods shipped by truck Q_s [tons/year], the length of the truck trips L_s [miles/trip] and the size of the shipments v_s [tons/trip]. Here the variables Q, L and v represent the LDS decisions made by shippers.

$$D_s = \frac{Q_s L_s}{v_s} \tag{2.15}$$

Changes in the RHS variables of (2.15) resulting from changes in trucking costs can be modeled with the own-price elasticities e_Q, e_L and e_v. The notation $e_v = \frac{dv}{dy}\frac{y}{v}$ is used to indicate the elasticity of variable v with respect to market price y. The elasticity e_Q captures the responsiveness of mode-shifts and final demand changes. The elasticity e_L captures the spatial redistribution of demand. And the elasticity e_v captures changes in the management of inventories. In the literature there are many estimations of e_Q, but not of e_v and e_L. There are also several estimations of the elasticity of ton-miles K *w.r.t.* trucking costs, which we define as e_K, where $K = Q\,L$. Note that using the definition of elasticities it can be shown that $e_K = e_Q + e_L$.

From the literature we have good sense of the magnitude of e_Q and e_K, but we do not find any studies that estimated e_v. Therefore we used a simple Economic Order Quantity (EOQ) model of inventories to provide a reasonable estimate of e_v. By minimizing per-ton transportation plus inventory costs the optimal shipment size in each segment s can be derived as $v_s^* = \sqrt{y L_s 2 Q_s / \phi_s}$, where ϕ_s [$/year] is a measure of the time-costs of holding inventories. Using v_s^* yearly trucking mileage across all segments D can be expressed as

$$D = \sum_{\forall s} D_s = \sum_{\forall s} \left(\frac{Q_s L_s \phi_s}{2y}\right)^{1/2}$$

Solving for $e_D = \frac{dD}{dy}\frac{y}{D}$, noting that $\frac{dQ_s}{dy} \neq 0$, $\frac{dL_s}{dy} \neq 0$, and using e_Q and e_L results in

$$e_D = -\frac{1}{2} + \frac{1}{2}\left(e_Q + e_L\right) = -\frac{1}{2} + \frac{1}{2} e_K \qquad (2.16)$$

Expression (2.16) indicates that it is possible to obtain an approximation of e_D from e_K for heterogeneous truck fleets if y is the same throughout all segments s and v is assumed to be determined through an EOQ model. While this represents a rough approximation of e_D, it allows us to gain a sense of its magnitude and better understand its determinants.

Using (2.16) the demand function for trucking mileage can be derived as

$$D(y) = D_B \left(\frac{y}{y_B}\right)^{e_D} \qquad (2.17)$$

2.1.4 Equilibrium

Market equilibrium in the stationary model can be presented with a simple microeconomic framework. The shipper demand for transportation service is downward-sloping to reflect the disutility of the market rate. The carrier supply curve is horizontal because the industry is modeled as having *constant returns to scale*. This means that for any level of demand D, the trucking rate will be the same at y^*. This occurs because there are no economies of scale in the trucking industry. Governmental strategies that change y^* will also lead to changes in latent demand in $D(y^*)$.

2.2 Time-Dynamic Model

The stationary trucking model provides useful insights into the key mechanisms governing optimal truck fleets; however its usefulness in modeling GHG mitigation strategies is limited in practical applications. In many circumstances an emissions target is placed in the medium-term, which does not allow enough time for the truck fleet to reach the steady state conditions required in the simplified stationary model. Additionally, the stationary model cannot be used to analyze the transition of the existing truck fleet or the phase-in of mitigation strategies. Steady state assumptions are also violated if the demand for trucking increases over time. To overcome these limitations a time-dynamic model is introduced in this section that considers how carrier and shipper optimize their operations throughout time in response to changes in the economic environment.

2.2.1 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 $S(t)$. The optimal FMO decisions are found by discretizing the problem and formulating it as an integer program that can be solved numerically. However, because the present formulation is non-convex and has a relatively large state-space, a solution was obtained using the heuristic described in *Section 2.2.4*.

To reasonably reduce the state-space of the discretized mathematical program two assumptions from Jones *et al.* (1991) were used. First, the "no-splitting" assumption implies that trucks purchased in the same year (part of the same cohort) can be treated identically. It is not optimal to manage trucks in the same cohort differently. Second, the "old cluster replacement rule" implies that it is never optimal to retire a certain cohort of trucks without retiring all older cohorts first. Both of these assumptions where investigated by Jones *et al.* (1991) as they apply to the management of truck fleets owned by individual firms, but in this model they are invoked as a reasonable representation of the trucking industry.

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

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. This can be approximated from $u_{ij} = U'(i-j)$.

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.

$$\mathbb{K} = \left\{ (i,j) \mid i - j \leq S_j, j \leq t_f \right\} \tag{2.18}$$

$$\mathbb{S} = \{ (i,j) \mid i = j + S_j \} \tag{2.19}$$

$$\mathbb{T} = \{ (i) \mid t_o \leq i \leq t_f \} \tag{2.20}$$

$$(j,i) \in \mathbb{Z} \qquad P_j \in \mathbb{R}^+ \qquad S_j \in \mathbb{Z}^+ \qquad \gamma_j \in [0,1) \tag{2.21}$$

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

$$\sum_{j \in \mathbb{K}|i} P_j u_{ij} \geq D_i \quad for \quad i = t_0, t_0 + 1, \dots, t_f \tag{2.22}$$

Carriers face the objective of satisfying (2.22) by minimizing discounted costs

$$\min \sum_{i \in \mathbb{T}} \beta^i P_i A_i(\gamma_i) + \sum_{ij \in \mathbb{K} \cap \mathbb{T}} \beta^i P_j u_{ij} O_{ij}(\gamma_j) + \sum_{ij \in \mathbb{K} \cap \mathbb{T}} \beta^i P_j u_{ij} M_{ij} - \sum_{ij \in \mathbb{S} \cap \mathbb{T}} \beta^i P_j V_{ij}(\gamma_j) \tag{2.23}$$

The first term in (2.23) 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 (2.23) 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 (2.23) in two ways. First, the exogenous parameters u_{ij} indicate the miles that a truck in cohort j supplies in time period i. Noting that $s = i - j$, this can also be expressed as $u_{ij} = U'(i - j)$. However, the modeler could allow truck utilization to change exogenously with time such that $u_{ij} = U_j'(i - j)$. The second place where truck utilization enters into the formulation is in the construction of M_{ij}, which is derived as $M_{ij} = k_m U_j(i - j)$ using (2.11).

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 chapter 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 $C(t)$.

Note that $S(t)$ represents the retirement age of trucks purchased in t, which can be mapped to the retirement odometer of trucks at t by $X\big(t + S(t)\big) = U(S(t))$.

2.2.2 Shipper Model

The time-dynamic shipper model represents a generalization of the stationary model where the demand is observed at every time step. Equation (2.24) shows the effect of market rate changes from a baseline level of $y_B(t)$ to $y(t)$ on the time-series of baseline demand D_B.

$$D(t, y) = D_B(t, y_B) \left(\frac{y(t)}{y_B(t)} \right)^{e_D} \tag{2.24}$$

Model (2.24) makes several assumptions on the time dependent equilibrium that occurs between carriers and shippers, which are discussed in the following section.

2.2.3 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.

2.2.3.1 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 $\bar{y}$ using (2.25) to meet a certain demand $D(t,y)$ for analysis time period $t \in [t_0, t_f]$.

$$\int_{t_0}^{tf} \beta^t C(t)dt \bigg/ \int_{t_0}^{tf} \beta^t D(t)dt = \bar{y} \tag{2.25}$$

Shippers observe this single market rate and adjust $D(t,y)$ per (2.26) until equilibrium is reached.

$$D(t,\bar{y}) = D_B(t,y_B)\left(\frac{\bar{y}}{y_B}\right)^{e_D} \tag{2.26}$$

This equilibrium assumes that shippers demand for transportation in all time periods is affected in the same proportion by changes in $\frac{\bar{y}}{y_B}$. 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.

2.2.3.2 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.

$$C(t)/D(t) = y(t) \tag{2.27}$$

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 (2.27) and (2.28) until convergence is achieved.

$$D(t, y) = D_B(t, y_B)\left(\frac{y(t)}{y_B(t)}\right)^{e_D} \tag{2.28}$$

2.2.4 Solution Heuristic

This section describes the procedure used to solve the dynamic TSO model to optimality. The time-stationary carrier model is represented by $\widetilde{M_C}(D; E) = [\tilde{S}, \tilde{P}, \tilde{\gamma}, \tilde{y}]$, such that given a business environment E and shipper demand D, carriers will make FMO decisions ($\tilde{S}$ and $\tilde{P}$) and FSTs decisions ($\tilde{\gamma}$) in order to provide trucking service at minimized rate $\tilde{y}$. The time-stationary shipper model is represented by $\widetilde{M_S}(\tilde{y}; D_B,\ y_B, E) = \widetilde{D}$. Mitigation strategies affect the equilibrium, between carriers and shippers by changing the economic environment E. The time-dynamic model is represented by $M_C(D\,(t); E(t)) = [S(t),\ P(t),\ \gamma(t),\ y(t)\,]$ and the shipper model is represented by $M_s\big(y(t)\,; D_B(t),\ y_B, E(t)\big) = D\,(t)$.

The main complication in solving $M_C(\cdot)$, as formulated in (2.23) is that the problem is non-convex because $S(t)$ because appears in the limits of the summations. Therefore gradient-descent approaches cannot be used to find the global minimum. Several non-convex optimization tools were tried, including genetic algorithms and branch-and-bound algorithms, but because of the "curse of dimensionality" in dynamic optimization problems none of these other approaches worked. To bypass this limitation, the optimal retirement ages obtained from the stationary model $\tilde{S}$ were used as exogenous inputs in the time-dynamic model. This reduced the state-space of the problem and made the problem convex so that the optimal values of the other variables can be found easily. Breaking down these type of problems into several stages is a common approach taken in the literature (Jin and Kite-Powell 2000; Simms *et al.* 1982). This process is illustrated in the pseudo-code below.

Step1. no-action business environment $E_0(t)$
Step2. obtain baseline demand trucking $D_B(t)$
Step3. **for** t iterating in analysis horizon
Step4. solve stationary carrier model $\widetilde{M_C}(D_B(t); E_0(t)) = [\tilde{S}, \tilde{P}, \tilde{\gamma}, \tilde{y}]$
Step5. save approximate retirement ages $\tilde{S}(t) = \tilde{S}$
Step6. **end for**
Step7. $M_C(D\,(t); E_0(t)|\tilde{S}(t)) = [\,P(t),\ \gamma(t),\ y(t)\,]$ solve dynamic carrier model given approximate retirement age $\tilde{S}(t)$
Step8. $y_B(t) = y(t)$ save no-action baseline trucking rate
Step9. implement governmental strategy $E_1(t)$
Step10. **for** t iterating in analysis horizon
Step11. $\widetilde{M_C}(D_B(t); E_1(t)) = [\tilde{S}, \tilde{P}, \tilde{\gamma}, \tilde{y}]$
Step12. $\tilde{S}(t) = \tilde{S}$ save approximate retirement ages
Step13. **end for**
Step14. select equilibrium assumption
Step15. **for** number of iterations until convergence of $y(t)$
Step16. $M_C(D\,(t); E_0(t)|\tilde{S}(t)) = [\,P(t),\ \gamma(t),\ y(t)\,]$
Step17. $M_s(y(t)\,; D_B(t),\ y_B, E_1(t)) = D\,(t)$
Step18. **end for**
Step19. $\tilde{X}\left(t + \tilde{S}(t)\right) = U(\tilde{S}(t))$
Step20. save equilibrium $D\,(t)$ and $y(t)$ and optimal $P(t), \gamma\,(t), \tilde{X}(t)$ and $\tilde{S}(t)$ for $E_1(t)$

2.3 Life-cycle GHG Emissions Accounting

Research into the life-cycle GHG emissions of the trucking industry indicates that tailpipe emissions are responsible for roughly 70% - 80% of total emissions (Spielmann and Scholz 2005; Facanha and Horvath 2007). The remainder comes from the manufacturing of trucks, upstream fuel emissions (pre-combustion) and infrastructure related emissions. This research tracks how mitigation strategies affect all of these emission sources, which is important because for some strategies the reductions of emissions from one source can be tempered by increases from another. For example, increasing the size of trucks will reduce the mileage of weight constrained trucks but increase loading on the infrastructure. Both of these responses will affect total GHG emissions in opposite directions, and it is unclear from the literature that one of them always dominates.

The mathematical accounting of GHG emissions is shown for the time-stationary model for notational simplicity, but it can be generalized trivially for the time-dynamic model. Also, the parameter values are found assuming that the Class-8 intercity trucks fleet in California is being analyzed.

2.3.1 Tailpipe Emissions

Tailpipe GHG emissions are easy to calculate with a high degree of certainty directly from fuel consumption calculations. The tailpipe emissions per year g_x are given by (29). The coefficient R_x is the stoichiometric equivalence between gallons of diesel combusted and GHGs emitted. This is found in the literature to be 22.2 [lbs CO2eq/gallon-diesel] (USEPA 2005). The term $\left(1-\gamma\right)f$ is the post-FST fuel efficiency of the trucks and XP is the amount of miles driven by the truck fleet per year.

$$g_x = R_x\left(1-\gamma\right)fXP \tag{2.29}$$

2.3.2 Precombustion Emissions

Precombustion emissions consider upstream fuel processes such as oil exploration, refining, fuel distribution, etc. Estimates of these emissions are obtained from a process-based LCA performed by Facanha and Horvath (2007), which found that precombustion emissions are roughly 5.2% of tailpipe emissions.

$$g_{pc} = 0.052 g_X \tag{2.30}$$

2.3.3 Vehicle Manufacturing Emissions

Facanha and Horvath (2007) used an EIO-LCA to estimate that the manufacturing of Class-8 trucks produces emissions of 20.6g/ton-mile of shipments. That study assumed that truck are salvaged at 290,000 miles and carry an average payload of 22.3 tons. With this information we can calculate the GHG emissions per truck purchase to be R_P =7.5*10^{-5} MMTCO2eq/truck, and use this value to calculate these GHG emissions of the industry g_P as

$$g_P = R_P P \tag{2.31}$$

2.3.4 Infrastructure Emissions

Facanha and Horvath (2007) estimated that pavement maintenance and rehabilitation activities account for 9% of total GHG emissions from trucking activities. In fact, trucks' high axle loads cause at least 40% of the damage on highways (March 1998). Therefore, it is important to consider how changes in the weight of the vehicles and miles driven affect this significant source of emissions. In this analysis infrastructure emissions only consider those from highway pavement and rehabilitation.

Sathaye *et al*. (2010) provide a description of the standard model of how truck mileage and weight affect pavement overlays. In this model a *pavement structural number* SN is defined by the American Association of Highway Officials (AASHO) as a function of the engineered design of the pavement, including surface thickness, base thickness and subbase thickness. The SN parameter, which captures the structural qualities of the roadway, is then used according to Madanat *et al.* (2002) to estimate the number of Equivalent Single Axle Loadings (ESALs) between pavement overlays.

The average ESALs per mile driven by a truck fleet is defined as $\bar{E}$ and can be calculated using (2.32). This expression sums across different segments of the truck fleet that operate at different combinations of gross vehicle weight GVW_k and number of load-bearing axles a_k. Each of these segments supplies a fraction f_k of the total highway mileage supplied by the fleet. Because deterioration occurs predominantly from loaded axles, the tractor weight TW is subtracted from the total vehicle weight. Also, there is no need to distinguish between loaded axles because in a combination truck the load is roughly distributed equally among all 4 loaded axles (Sathaye *et al.* 2010).

$$\bar{E} = \sum_{\forall k} f_k \left(\frac{GVW_k - TW}{a_k \, 18000 \, lbs} \right)^4 a_k \tag{2.32}$$

Infrastructure emissions from pavement maintenance and rehabilitation increase linearly with $\bar{E}$ (Sathaye *et al.* 2010). This occurs because the time between pavement resurfacings is inversely related to $\bar{E}$. This insight allows us to bypass the pavement failure calculations and use equation (2.33). In this expression an average emissions rate K_I (gramsCO2e/lane mile) found in the literature is scaled by the average ESALs of a truck fleet before governmental intervention $\bar{E}^0$ and after $\bar{E}^1$. The emissions rate was estimated by Facanha and Horvath (2007) to be $R_I = 210.4\text{gCO2eq/lane} - \text{mile}$ for highway infrastructure related emissions caused by Class-8 trucks. The scaled emissions rate is then multiplied by the amount of miles driven on rural highways by the truck fleet XPr_h, where $r_h$was estimated by Battelle (1999) to be 54.8% in California.

$$g_I = R_I \left(\frac{\bar{E}^1}{\bar{E}^0} \right) XPr_h = \frac{R_I XPr_h}{\bar{E}^0} \sum_{\forall k} f_k \left(\frac{GVW_k - TW}{a_k \, 18000 \, lbs} \right)^4 a_k \tag{2.33}$$

Figure 6 shows different scenarios for how the distribution of truck weights on California's highways would change with increases in the weight limits. The scenarios have been constructed such that the amount of goods shipped is the same between them. By assuming that the distances of the trips performed by trucks that weigh over 65,000lbs are the same (at this vehicle weight the scenarios differ from the baseline), the curves in this figure can be used as proxies for f_k and f_k^0, where each k is a range of truck weights. This approximation is necessary given that there exists no data about the weights of individual shipments in the US.

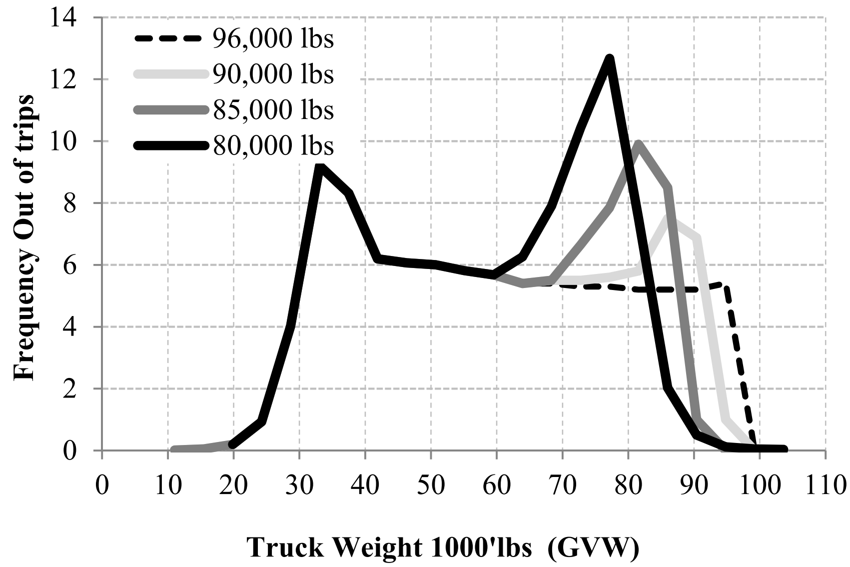

Figure 6: Truck weight distribution under different weight limits (baseline data from Caltrans 2008)

As the truck weight limit is increased the heavier trucks will cause higher infrastructure related emissions per trip, but it will also reduce the amount of trips required to transport weight constrained loads. The reduction in mileage demand is modeled by introducing a variable W into the shipper demand function that scales down the amount of mileage demanded as seen in (2.34). By assuming that the average length of shipments does not change much with truck weight *Figure 7* can be derived. Equation (2.35) provides a model for W, where $GVWL$ is the vehicle weight limit and $k_w = 0.00042$.

$$D(y) = D_B W \left(\frac{y}{y_B}\right)^{e_D} \tag{2.34}$$

$$W = 1 - k_w(GVWL - 80{,}000)^{\frac{1}{2}} \tag{2.35}$$

The methodology used to analyze the impacts of increasing truck weight limits represents the most detailed approach possible given that the basic unit of analysis is truck miles. If the unit of analysis is taken as quantity of goods shipped, then the differences between weight constrained and volume constrained shipments can be considered. This would allow for more detailed shipment weight distribution scenarios to be constructed.

Finally, it is assumed that trucks have the same baseline fuel efficiency as the weight limit increases and the number of axles increases. This could be relaxed in future research. It is unclear how spreading the load over more axles affects fuel economy. If the weight limit would be increased substantially to permit the operation of Turnpike Doubles or Triples then this would be a much more important consideration.

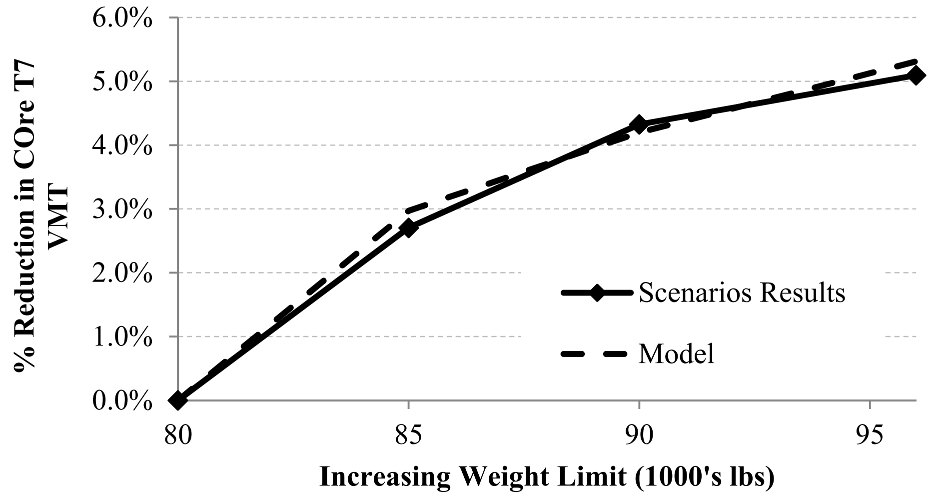

Figure 7: Effect of increasing truck weight limit on VMT

3 California Case Study: TSO Model

In California, the *Global Warming Solutions Act of 2006* (AB 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 CARB seeks to intervene in the trucking transportation industry because it is expected to account for 8.1% of GHG emissions in the state in 2020 (see *Figure 8*).

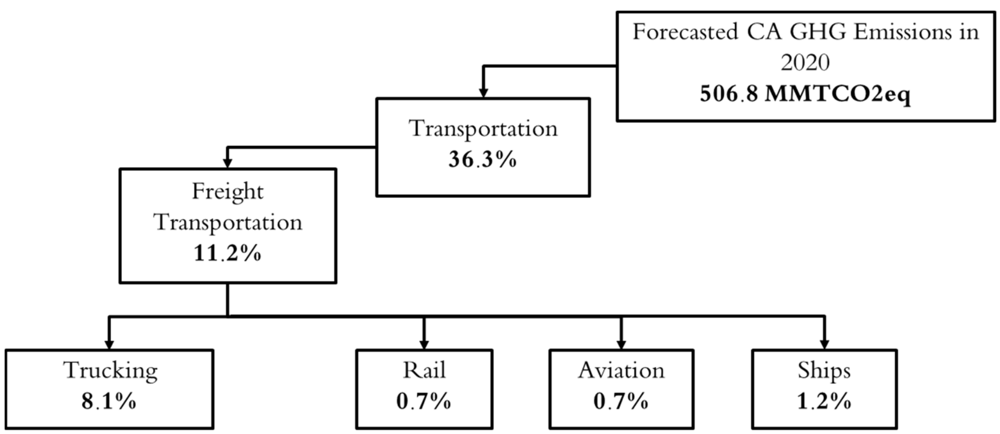

Figure 8: Forecasted CA GHG emissions in 2020 (CARB 2012)

The Climate Change Scoping Plan prepared by CARB (2008c) identified some sources of economy-wide GHG emission reductions that achieve the target set by AB 32. The measures that affect the trucking sector are T-6 (goods movement system-wide efficiency improvements), T-7 (aerodynamic improvement of trucks) and T-8 (medium-duty truck hybridization). In 2020, measure T-6 is expected to achieve reductions of 3.5 MMTCO2eq, measure T-7 is expected to achieve reductions of 0.9 MMTCO2eq and measure T-8 is expected to achieve reductions of 0.5 MMTCO2eq. It is unclear how different freight transportation modes need to contribute to achieve the T-6 reductions, but it is probably safe to assume that most of them will have to come from the trucking sector because as seen in *Figure 1* it is the largest emitter of GHGs. The measures outlined in the Climate Change Scoping Plan do not represent a policy roadmap, but rather a reasonable scenario under which the goals of AB 32 can be accomplished. Therefore, it is reasonable to infer from these figures that the heavy-duty trucking sector should contribute to 3 - 4

MMTCO2eq in emission reductions in 2020, regardless of how the reductions are achieved. This case study evaluates several ways of achieving this policy objective.

In California and in the US most of the strategies considered to reduce freight transportation GHG emissions involve the regulation of truck fuel efficiency. 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. In addition, the federal government recently introduced a heavy-duty truck fuel economy standard that starts in 2014 (EIA 2011). This regulation is similar to the CAFE standard currently in place for automobiles. Additional GHG mitigation strategies could be implemented in California that target carriers, shippers or the infrastructure (see *Figure 1*).

The present chapter studies the responses of the heavy-duty truck fleet in California to the following mitigation strategies: fuel taxation, mileage taxation, truck purchase taxation, FST subsidies, FST regulations, increases in the allowed weight of trucks, and the Low Carbon Fuel Standard recently introduced in California. For simplicity, this truck fleet is called "Core T7" in the remainder of the chapter. 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 2011b): 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). Other truck fleets that operate in California could also be modeled with the TSO model, but this case study focuses on this group of trucks because they account for the bulk of trucking emissions in the state.

The mitigation strategies analyzed are fuel taxation, mileage taxation, truck purchase taxation, FST subsidies, truck weight limit increases, Low Carbon Fuel Standard (LCFS) and SmartWay FST regulation. In addition to analyzing these strategies, this case study also quantifies the economic incentives that carriers face presently without the implementation of any strategy.

Because only 23.5% of Core T7 mileage is driven within California, some of the strategies implemented in California will affect only a fraction of the trucking costs, and also a significant amount of GHG emission reductions will occur outside California. This case study accounts for both of these effects. Issues relating to the political boundaries climate change mitigation have become more common and important in the US because of the decentralized of the policies adopted (Lutsey and Sperling 2008).

3.1 Data Sources

3.1.1 Trucking Costs

The costs carriers face in operating trucks are a key input in the model. However, this type of data has been unavailable in a disaggregated basis since the deregulation of the trucking industry in the 1980s. Before this, carriers were required to supply detailed data about their operations to governmental agencies for regulatory reasons. Many studies used this data to estimate behavioral models of the industry, but after deregulation this data become confidential in order to encourage price competition.

Present efforts to collect trucking cost data have seen mixed results. Samimi *et. al* (2011) used an online survey to obtain information about the latest shipment made by companies in the US, but found the response rate to be very small. Fender and Pierce (2011) conduct an ongoing survey of trucking companies in the US to estimates their marginal costs. Their latest results (found in *Table 1*) were used to approximate the fixed costs of trucking to be \$0.647/mile, which includes costs that are assumed to increase linearly with the supply of truck miles such as: truck insurance, permits/licenses, tires, driver wages/benefits and overhead. The other values in *Table 1* were used to corroborate the assumptions and other data sources used to estimate maintenance costs, fuel costs and capital costs.

Table 1: Marginal trucking costs (Fender & Pierce 2011)

	Dollars/Mile		
Motor Carrier Marginal Expenses	**2008**	**2009**	**Q1 2010**
Truck Insurance Premiums	0.055	0.054	0.052
Permits and Licenses	0.016	0.029	0.023
Tires	0.03	0.029	0.026
Driver Wages	0.435	0.403	0.404
Driver Benefits	0.144	0.128	0.142
Fuel & Oil Costs	0.633	0.405	0.465
Truck/Trailer Lease or Purchase Payments	0.213	0.257	0.235
Repair & Maintenance	0.103	0.123	0.12
Tolls	0.024	0.024	0.024
TOTAL	***1.653***	***1.452***	***1.491***

3.1.2 Fuel Costs

From *Table 1* it can be seen that fuel costs account for a large portion of trucking costs. Three diesel fuel price scenarios were set at \$5.08/gallon, \$4.21/gallon and \$3.36/gallon based on forecasts made by CEC (2011). These values include a federal excise tax of \$0.244, a state excise tax of \$0.156, a state sales tax of 9% and a local sales tax of 1%. It is not clear from the forecasts that the price of diesel fuel is expected to increase in real terms over time, each fuel price scenario is held constant throughout time. These scenarios were adjusted by the fact that Core T7 trucks drive 76.5% of their mileage outside California, where diesel fuel is typically cheaper. The scenarios of the effective diesel fuel price observed by the Core T7 truck fleet are $4.87/gallon, $4.0/gallon and $3.15/gallon.

Fuel costs also depend on the fuel efficiency of the trucks, which is expressed in the model as $(1-\gamma)f$. The parameter f is the baseline fuel efficiency of trucks (in gallons per mile) and γ is a decision variable indicating the level of investment in FSTs. The value of f was determined based on the assumptions of the EMFAC2011 inventory as detailed in CARB (2008a). Here it can be found that the Core T7 truck fleet had a fuel efficiency of 5.61mpg in 2007 and that it is projected to change slightly throughout time with the tightening particulate emissions regulations.

The EMFAC 2011 inventory agrees with Davis and Diegel (2007) in that Class-8 truck fuel economy has not changed much in the last 20 years. For example, from 1988 to 1995 the average fuel economy averaged 5.8mpg while from 2000 to 2005 it averaged 5.6mpg. This data suggests that there does not to exist an organic upward trend in truck fuel economy. Other reasons could explain this observation, such as increased congestion or the operation of heavier trucks, but the effect would not be large over the medium-term.

3.1.3 Maintenance Costs

Based on *Figure 9* maintenance costs were assumed to increase linearly with truck odometer. The proportionality constant was found to be 1.852×10^{-7} [$/mile-odometer] for the Core T7 truck fleet. It was assumed that maintenance expenses keep trucks operating at their original fuel economy, which is also assumed in the EMFAC2011 inventory.

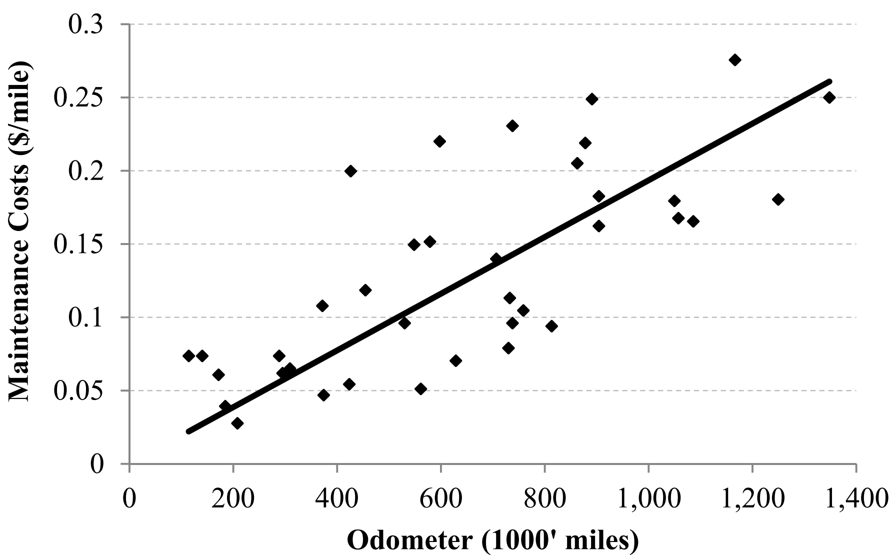

Figure 9: Maintenance cost data (CARB 2008a)

The analysis could be improved by having access to more detailed data about truck maintenance costs. *Figure 9* contains too few data points, and they show a wide variability in costs. Also, it is also not clear what maintenance procedures are included in these costs. A more detailed study of truck maintenance is required to specify this part of the model with more confidence, however in the absence of such study the data in *Figure 9* was used instead. Also, this value agrees with the estimates provided in *Table 1* for common truck retirement odometers.

3.1.4 Capital Costs

CARB (2008a) estimates that the price A_p of a new tractor in 2008 with sleeper cab was around \$130,000, and the price of a new tractor without sleeper cab was around \$100,000. These are after tax prices. Note that $A(0) = A_p$. From the Vehicle Inventory Use Survey (VIUS 2002) it was found that 27% of all miles traveled by trucks registered in California in 2002 are driven by trucks with sleeper cabs, therefore the miles-weighted average capital cost of a Core T7 truck was calculated to be \$108,000/truck. This value was then compounded at 5% yearly inflation to be \$120,000 in 2010.

At retirement trucks have a salvage value $V(X)$ that was modeled using the convenient function (3.1), where k_d is the instantaneous depreciation of the truck at purchase and k_x is the incremental depreciation of retiring a truck at a later odometer. The values of $k_d = 0.75$ and $k_x = 8 * 10^{-7}$ approximate well the salvage value data found in CARB (2008a).

$$V(\gamma, X) = A(\gamma)k_d(1 - k_x X) \tag{3.1}$$

Assuming a linear salvage value leads the model to have properties that are useful in the numerical optimization while reasonably modeling the observed behavior. If trucks are assumed to depreciate exponentially, under some conditions, the model will predict that trucks should be used indefinitely. This problem is avoided by using (3).

3.1.5 FST Costs

In order to achieve a certain level of fuel efficiency improvement γ (proportion of fuel saved) carriers need to invest in FSTs. The cost of these technologies is modeled through an abatement curve shown in *Figure 10* that indicates the smallest capital expenditure required to achieve a given level of γ. The abatement curve is constructed using data about various FSTs found in *Table 2* and theoretically represents the sequence of FST investments that a cost minimizing carrier should make. Most of these estimates of GHG reductions come from MSMC: Madanat, Shaheen, Martin and Camel (2010). Gaps in the information were supplemented with NAS: National Academies of Science by National Research Council (2010). 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. Battelle (1999) estimated 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 National Research Council (2010) as

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

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

The resulting abatement curve is plotted in *Figure 10,* and function (3.2) is used to model it. The parameters k_1 and k_2 have been estimated as $180{,}000$ and 0.6 respectively.

$$A(\gamma) - A_p = \frac{k_1\,\gamma^2}{(k_2 - \gamma)} \tag{3.2}$$

The main assumption that allows truck technology to be modeled in this way is that carriers have perfect information of all of the FSTs available and decide to invest in those that are most cost effective first. In reality it is likely that carriers do not have this type of information, skewing investment decisions. As the sequence of FST investments becomes less optimal the concavity of the abatement curve will decrease. Therefore governmental agencies should engage in an information dissemination campaign to ensure that carriers undertake optimal FST investments.

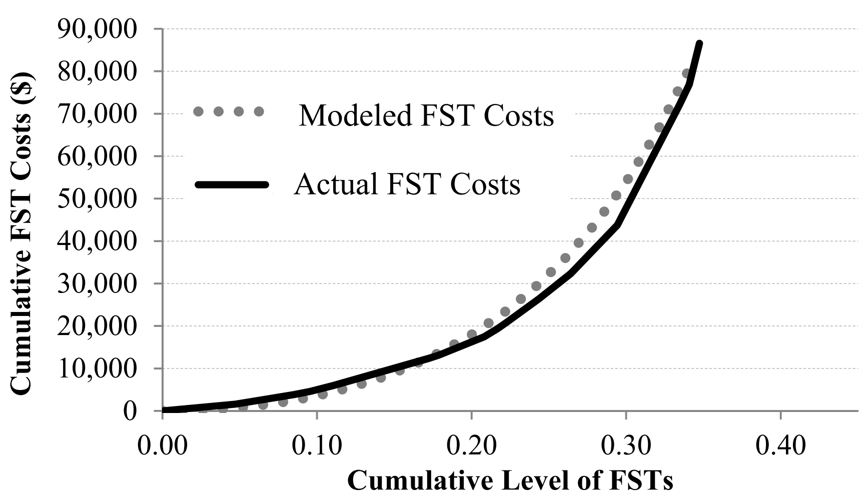

Figure 10: Fuel consumption abatement curve $c(\gamma)$

It was assumed in the time-dynamic model that the abatement curve does not change in real terms over time. In other words, it is assumed that the costs of FSTs do not decrease or increase once discounted. This is reasonable because FSTs are unlikely to benefit significantly from improvements in manufacturing (with the exception of hybrid propulsion) and be sold at lower prices in the future.

Table 2: Fuel Saving Technologies

Type of System	*Fuel Saving Technologies (FST)*	No. of Purchases in Lifetime of 800k miles	Average Capital Costs to Trucker Above Standard Truck	% Reduction in Fuel Consumption	% of CoreT7 Miles Affected	% Core T7 Reduction	Cumulative Costs	% Reductions in Fuel Consumption γ
Transmission	Turbocharged, Direct Injection to Improved Thermal Management	*2*	\$1,576	4.70%	1.00	4.70%	**\$1,576**	**4.7%**
Transmission	Increased Peak Cylinder Pressures	2	\$2,251	4.00%	1.00	4.00%	**\$3,827**	**8.5%**
Aerodynamic	Closing and Covering of Gap	1	\$735	2.00%	0.55	1.10%	**\$4,561**	**9.5%**
Aerodynamic	Aerodynamic Bumpers	2	\$1,351	3.00%	0.55	1.64%	**\$5,912**	**11.0%**
Rolling Resistance	Wide-base Tires	5	\$6,431	6.98%	1.00	6.98%	**\$12,343**	**17.2%**
Rolling Resistance	Automatic Tire Inflation Systems	1	\$760	0.80%	1.00	0.80%	**\$13,103**	**17.9%**
Aerodynamic	Pneumatic Aerodynamic Drag Reduction	1	\$4,361	6.54%	0.55	3.58%	**\$17,464**	**20.8%**
Aerodynamic	Wheel Well Covers	4	\$1,891	2.00%	0.55	1.10%	**\$19,355**	**21.7%**
Aerodynamic	Trailer Leading and Trailing Edge Curvatures	1	\$1,407	1.26%	0.55	0.69%	**\$20,762**	**22.2%**
Aerodynamic	Planar Boat Tail Plates on a Tractor-Trailer	2	\$5,628	5.00%	0.55	2.74%	**\$26,390**	**24.4%**
Aerodynamic	Trailer side skirts	2	\$5,988	5.00%	0.55	2.74%	**\$32,377**	**26.4%**
Weight Reduction	Lightweight Materials (2,500lbs)	1	\$11,396	7.46%	0.55	4.08%	**\$43,773**	**29.4%**
Hybrid Propulsion	Hybrid Trucks	1	\$28,138	5.66%	1.00	5.66%	**\$71,911**	**33.4%**
Rolling Resistance	Pneumatic Blowing to Reducing Rolling Resistance	1	\$4,924	0.99%	1.00	0.99%	**\$76,835**	**34.1%**
Transmission	Transmission Friction Reduction through Low-Viscosity Transmission Lubricants	8	\$9,724	1.00%	1.00	1.00%	**\$86,560**	**34.7%**

3.1.6 Truck Utilization

Truck utilization functions $x = U(s)$ describe how trucks are driven throughout their service lives, where x is the odometer reading of the truck and s is the age. The functional form (3.3) was used to model these curves where its parameters were calibrated on data shown in *Figure 3* to be $k_3 = 1.4 * 10^{-11}$ and $k_4 = 0.5$. Truck utilization is assumed to be exogenous and invariant throughout time (this is also an assumption made in the EMFAC 2011 inventory model).

$$x = U(s) = \left(\frac{s - k_4}{k_3}\right)^{\frac{1}{2}} \tag{3.3}$$

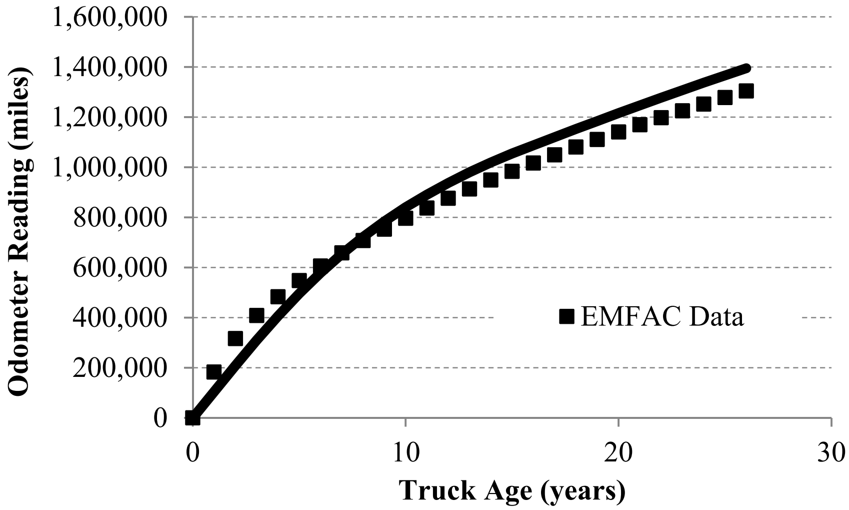

Figure 11: Core T7 truck utilization curve (observed from EMFAC 2011)[2]

3.1.7 Existing Truck Fleet

The time dynamic model considers the response of the existing fleet of trucks as governmental GHG mitigation strategies are phased in. The initial conditions for this transition are provided in *Figure 12,* which shows the age distribution of the truck population of the Core T7 fleet in the year 2010.

[2] Even though a better fitting model of $U(s)$ could have been used, it was found that the shape of this curve is not an important factor in modeling truck fleets.

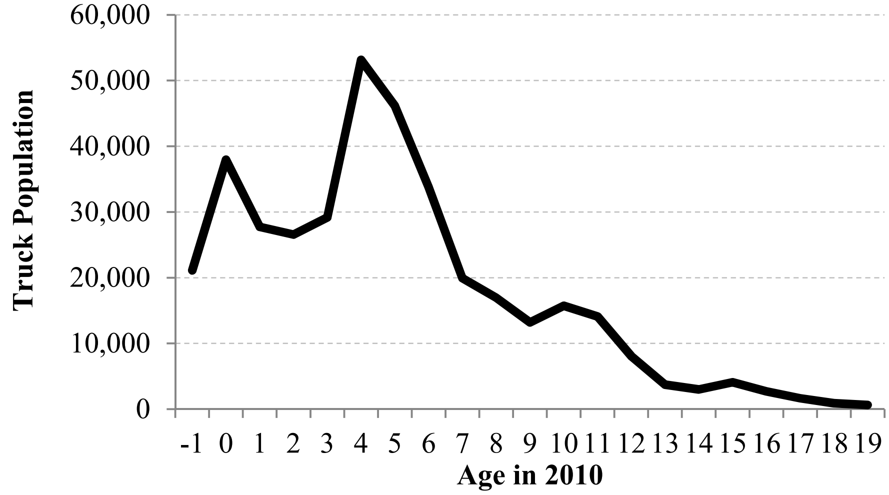

Figure 12: Core T7 truck age distribution (EMFAC 2011)

3.1.8 Baseline Trucking Demand

Figure 13 shows the forecasted baseline trucking demand $D_B(t)$ for the Core T7 fleet. The lightly shaded region represents the total forecasted mileage demand while the dark shaded region represents the portion of the mileage demand within California. This is an important distinction because some strategies such as fuel taxation and mileage taxation will only affect the mileage occurring within California, while others such as the SmartWay FST regulation will affect all of the truck mileage.

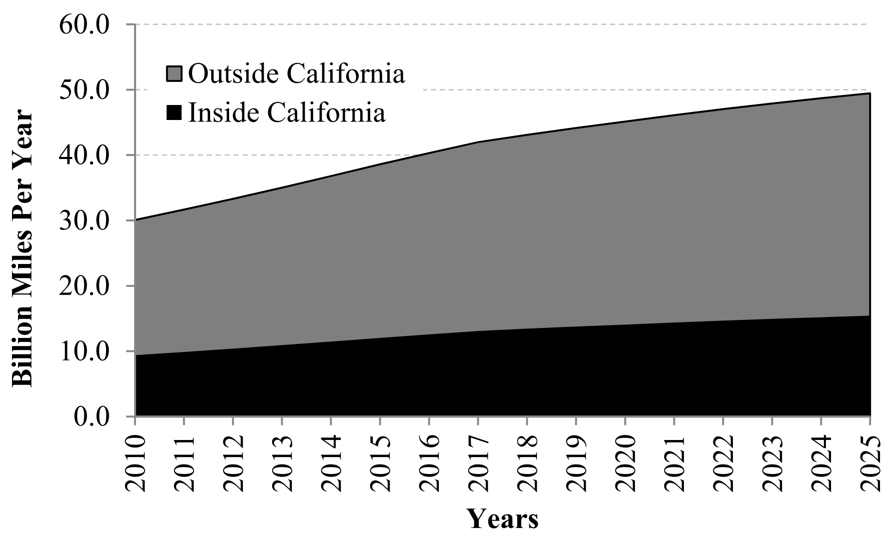

Figure 13: Forecasted Core T7 mileage demand (EMFAC 2011)

Trucking activity inside and outside California are tracked in this analysis because GHG emissions are a global pollutant that has the same climate change effect independent of where it is emitted. The implementation of mitigation strategies in California will affect trucks only partially in California, leading some GHG reductions outside the state. Whether or not these reductions should be accredited to California is a policy question beyond the present research.

3.1.9 Shipper Elasticity Parameters

LDS responses are modeled using elasticities that have been estimated in the literature. A review of the literature found that these estimated 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. Ideally the elasticities used for this study should have been estimated for California or another area with similar characteristics. Unfortunately it was unclear that any particular study met this criterion. Instead, several elasticity values were selected and averaged based on an extensive review of the literature. Three scenarios for this parameter where used to analyze the different mitigation strategies in order to deal with this uncertainty.

Various types of LDS elasticities have been estimated in the literature that provide different types of information. The most common elasticity shows the percent change in ton-miles shipped in response to a percent change in per-unit trucking costs. This elasticity type captures mode shifts, changes in the spatial distribution of demand, and sometimes final demand changes. However, it does not capture changes in shipment sizes. Other elasticity types show the percent change in tons shipped to changes in transportation costs, not capturing spatial responses. In this case study we are interested in the former.

Oum *et al.* (1992) also finds that throughout the literature elasticities have been estimated using different microeconomic assumptions on whether shippers' final output is assumed to be fixed or not. The ordinary elasticity captures changes in the quantity of goods shipped (in response to downward slopping consumer demand) in addition to changes in the LDS. On the other hand, conditional elasticities hold final output to be fixed.

Graham and Glaister (2004) conducted an extensive survey of research into freight demand elasticities (focusing on ton-miles as the unit of demand) and found that they ranged from −0.5 to −1.5. They concluded that this wide range of results can be attributed in large part to different modeling methodologies. This finding agrees with Oum (1989) which found that the type of model used makes a critical impact on the estimation of elasticities, obtaining results ranging from 0 to -1.34 when common models (translog, linear and random utility) were applied to the same circumstance. Friendlander and Spady (1980) estimated elasticities for different commodity groups and for different regions in the US using a consistent methodology and found that they did not vary significantly, with an expectation of -1.12 a standard deviation of 0.2. On the other hand, Graham and Glaister (2004) also point out that the variability of elasticities estimated for different commodity groups with different modeling techniques can be smaller than simply the variability between similar studies of the same commodity group. It is clearly important not to be overconfident in the predictive power of the elasticities found in the literature.

Given the difficulties outlined above, 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 case study 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 (1980) estimate of -1.12, and Chiang *et al.*'s (1981) estimate of -1.143, which are commonly cited studies.

The elasticities e_Q discussed above correspond to the change in ton-miles shipped with increases in transportation cost. On the other hand, the literature surveyed did not contain estimates for e_v, which relates changes in shipment sizes with changes in trucking costs. This relationship exists because shipment sizes result from the optimization of transportation costs and inventory costs. However, both e_Q and e_v are needed to obtain the elasticity of truck mileage with trucking costs e_D, which is the parameter used in the model. By making the simple assumption that e_v can be modeled with an EOQ model, the relationship between these elasticities can be derived to be approximated by $e_D = -\frac{1}{2} + \frac{1}{2} e_Q$ (see *Section 2.1.3*). Using this, the three elasticity scenarios for trucking mileage become $e_D = [-0.826, -1.035, -1.245]$.

Table 3: Summary of cost parameters for Core T7 trucks

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 2008a
Salvage Value Instantaneous Depreciation	k_d	0.75	proportion	Based on CARB 2008a
Salvage Value Mileage Depreciation	k_x	0.084	$/odometer	Based on CARB 2008a
Maintenance Costs Parameter	k_m	$1.85*10^{-7}$	$/odometer-mile	CARB 2008b
FSTs Cost Parameter 1	k_1	180,000	$	Based on CARB 2008a
FSTs Cost Parameter 2	k_2	0.6	unitless	Based on CARB 2008a
Truck Utilization Parameter 1	k_3	$1.4*10^{-11}$		
Truck Utilization Parameter 2	k_4	0.6		
Baseline Toll	θ_M	0	$/mile	
Baseline Additional Fuel Tax	θ_F	0	$/gallon	

3.2 Model Exploration

3.2.1 Reference Scenarios

GHG mitigation strategies were 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 forecasts as the EMFAC2011 inventory model. It does not however provide similar estimates of FMO (service life and truck purchases) as the EMFAC2011. This is because the EMFAC2011 inventory model does not utilize a cost optimization methodology to obtain its forecasts. Instead it relies on an exogenous truck retirement function that is applied to the truck fleet year-over-year, with new truck purchases determined exogenously from macroeconomic forecasts.

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.

Table 4 shows that optimizing the level of FSTs under the NAOB scenario makes a large impact on GHG emissions in 2020. The observed cost structure of the trucking industry suggests that it is optimal to invest significantly more in FSTs than is currently commonplace. In 2020 the optimal level of investment in FSTs without any mitigation strategy is $\gamma = 0.29$, which corresponds to investing in many of the FSTs listed in *Table 2.*

Table 4: 2020 GHG emissions under reference scenarios in CA (MMTCO2eq/year)

	CNT			**NAOB**		
Fuel Price and Elasticity Assumptions	*Low*	*Mid*	*High*	*Low*	*Mid*	*High*
Tailpipe	21.95	24.51	26.51	16.98	18.81	20.51
Pre-Combustion	1.14	1.27	1.38	0.88	0.98	1.07
Infrastructure	1.96	2.19	2.37	2.20	2.36	2.48
Vehicle Manu.	1.00	1.12	1.22	0.96	1.01	1.05
TOTALS	**26.06**	**29.09**	**31.48**	**21.03**	**23.16**	**25.12**

It is reasonable to expect that without mitigation strategies the trucking industry will operate in 2020 somewhere in between the results of the NAOB and CNT scenarios, probably closer to the CNT scenario.

3.2.2 Market Barriers to FST Investments

The large differences between the NAOB and CNT scenarios can be explained by market barriers that are currently disincentivizing trucking companies from investing more vigorously in seemingly cost-effective FSTs. Many studies have quantified the nature and magnitude of these types of energy-efficiency barriers in other industries; for a recent survey of the literature see Gillingham *et al.* 2009. However, to our knowledge, there have only been two studies into the market barriers that might be preventing greater adoption of FSTs in the trucking industry. One of them, Aarnink *et al.* (2012), conducted a survey of European carriers and shippers in order to understand their attitudes towards vehicle fuel economy, to find explanations for the weak implementation of FSTs also observed in Europe. A second study, conducted by Vernon and Meier (2012), identified the portions of trucking operations in the US that likely have principal-agent problems, where one party absorbs the costs of certain decisions while another one absorbs the benefits.

The following discussion draws from Aarnink *et al.* (2012), Vernon and Meier (2012), and from, the wider literature on “energy efficiency gaps” to provide explanations for why the ‘optimal’ level of investment in FSTs predicted by the NAOB scenario is currently not observed in the US (CNT scenario). These barriers are categorized as either **market**

failures or **non-market failures** following the framework presented by Jaffe and Stavins (1994). Future research should investigate these barriers more precisely by surveying carriers and shippers in the US to obtain disaggregated data of their costs and constraints. Without this empirical legwork, we are left to hypothesize about conditions in this industry. Note that in this discussion the word 'optimal' refers to the market outcome that maximizes private benefits in the industry, not the market outcome that maximizes total benefits to society. This distinction is important because the 'optimal' market outcome from the NAOB scenario does not consider the externality costs of GHG emissions or other pollutants.

Market failures occur when the allocation of resources is inefficient, that is, when there is conceivably another market outcome in which everyone is better-off. Strong arguments can be made that governments should intervene in these markets to achieve a more optimal allocation of resources that increases welfare. Principal-agent problems in the way that contracts are commonly structured represent significant sources of market failure in the trucking industry. These lead to split incentives where some agents in the industry do not see the full costs or benefits of their decisions. Vernon and Meier (2012) estimated that 91% of drivers do not pay for fuel costs, and therefore they have little direct incentive to drive the truck efficiently or take care of FSTs. Several of the FSTs, especially those that improve the aerodynamics of the vehicle, require drivers to change how they operate the vehicles to avoid damaging them. This might lead drivers to prefer trucks without certain cumbersome FSTs, and dissuade trucking companies from investing in them because of the higher probability of damaged. Vernon and Meier (2012) also found that 23% of the trailers are owned by entities that do not pay for fuel costs, and therefore do not have a direct incentive to invest in FSTs to improve the aerodynamics or rolling resistance of trailers. These companies could still be indirectly incentivized to improve the fuel economy of trailers if shippers and carriers paid a premium for them, but this has not been observed in Europe (Aarnink *et al.* 2012), and is likely not to be the case in the US as well.

In their surveys Aarnink *et al.* (2012) found other principal-agent problems in Europe's trucking industry. An interesting finding of this study is that even though fuel surcharges theoretically do not represent a principal-agent problem, because carriers with lower fuel costs are still more profitable, they do tend decrease the importance that carriers place on fuel economy improvements. A manager that is juggling various priorities will be less likely to invest in FSTs if their fuel costs are being reimbursed according to some formula pre-agreed with shippers. Carriers indeed indicated that they monitored the fuel economy of their trucks regularly, but with the objective of tracking the performance of truck drivers, and further training those that performed poorly. This fuel economy information was not used to consider making investments in FSTs. Generally, carriers appeared to be more concerned with finding fuel economy improvements from the operations of the trucks than from improving their technology, perhaps because the former has much lower up-front costs.

Another finding from Aarnink *et al.* (2012) that might apply to the US is that 73% of the European trucking companies surveyed (not a representative sample) indicated that they require financing to purchase new trucks. This in itself does not represent a market failure. However, lending institutions generally do not consider the technology of the truck when determining the size of the loan, which does represent a market failure. Lending institutions are effectively disincentivizing carriers from purchasing more expensive trucks with greater amounts of FSTs. This is even more problematic for the 40% of trucking companies that routinely had difficulties obtaining any kind of financing (Aarnink *et al.* 2012). Trucking companies in the US are also likely to face budgetary constraints as 90% of them have 6 or less trucks (ATA 2012).

The trucking industry also has market failures with regards to the availability of information. Aarnink *et al.* (2012) found that in Europe carriers were poorly informed on the off-the-shelf FSTs available. Even when companies were aware of particular FSTs, they did not have adequate or correct information about their effectiveness, maintenance costs and operational characteristics. This is predicted by theory as the existence of *search costs* will lead information about FSTs to be underprovided by the private sector (Jaffe and Stavins 1994). The government could benefit market participants by providing standardized and thorough information on the gamut of FSTs available. This is precisely the objective of the SmartWay program currently operated by the EPA, but there is significant opportunity for it to be expanded. Surveys should be conducted to assess the success of this program, and to find ways of strengthen it.

Non-market failures can also represent barriers to investments in FSTs. These occur when firms objectively consider a wider range of costs and constraints than the analyst used to determine the theoretical 'optimal' implementation of FSTs. In a sense, non-market failures represent deficiencies in the model used to determine the 'optimal' market outcome, and therefore there is no rational for governments to intervene to fix them (Metcalf 1994). One of the most significant non-market failures is that FSTs are likely to have various costs that are hidden to the analyst. Aarnink *et al.* (2012) found that in Europe trucking companies were concerned about how FSTs might affect their day-to-day operations, interact with weather (especially with snow), and/or increase the unreliability of trucks. These uncertainties make carriers hesitant to invest in new technologies because they operate in a low-profit industry where unreliability is costly.

In addition to responding to the hidden costs of FSTs, carriers also take into account uncertainties in the business environment when deciding whether to make these investments. The payback period of any FST depends on many factors, including: fuel prices, inflation rates, interest rates, truck mileage accrual, etc. Carriers also face uncertainty in how long they will own particular trucks, and whether potential buyers in secondary markets might value FSTs. In making optimal decisions, carriers will consider the underlying uncertainty in all of these variables, because it represents a cost to doing business. Increases in the uncertainty will increase the effective discount rate of firms and lead to lower levels of FST investments (Jaffe and Stavins 1994). Carriers even gain an 'option value' in postponing making irreversible investments until later in the future (Gillingham *et al.* 2009).

The implementation of FSTs might also be impeded by the considerable heterogeneity of the industry. While FSTs might seem highly cost-effective on average, their actual returns to individual firms might vary greatly. If there are many firms for which FSTs are barely cost-effective, then they will adopt them at a slower rate, it at all.

If the efficiency gap between the CNT and NAOB scenarios is caused primarily by market failures, then governments should correct them by introducing new market mechanisms that remove the market failures and/or by introducing regulations that shift market outcomes closer to 'optimality.' On the other hand, if the apparent efficiency gap is caused by non-market failures, then we need to reevaluate our optimality model (NAOB scenario in this case) to consider additional costs and constraints that are important. However, all indications are that both market failures and non-market failures could be responsible, at least to some extent, for this efficiency gap, and therefore it is difficult to delineate appropriate policy recommendations. As mentioned earlier, empirical research needs to be conducted that surveys carriers and shippers, and utilizes proprietary disaggregate cost data sets, in order to establish the frequency and magnitude of market failures and non-market failures in this industry. In the absence of this, *Section 3.3.8* argues that market failures are likely responsible for most of the efficiency gap. This reasonable assumption is backed by some evidence from current operations of the trucking industry.

3.2.3 Model Dynamics

A main contribution of the TSO model is the ability to study the dynamics of the trucking industry. This is important because often policies that are implemented in this industry need to be evaluated in the near term, not allowing enough time for the truck fleet to recycle and reach a steady-state. This is the case in California where *Assembly Bill 32* set GHG emission targets for 2020 and 2050.

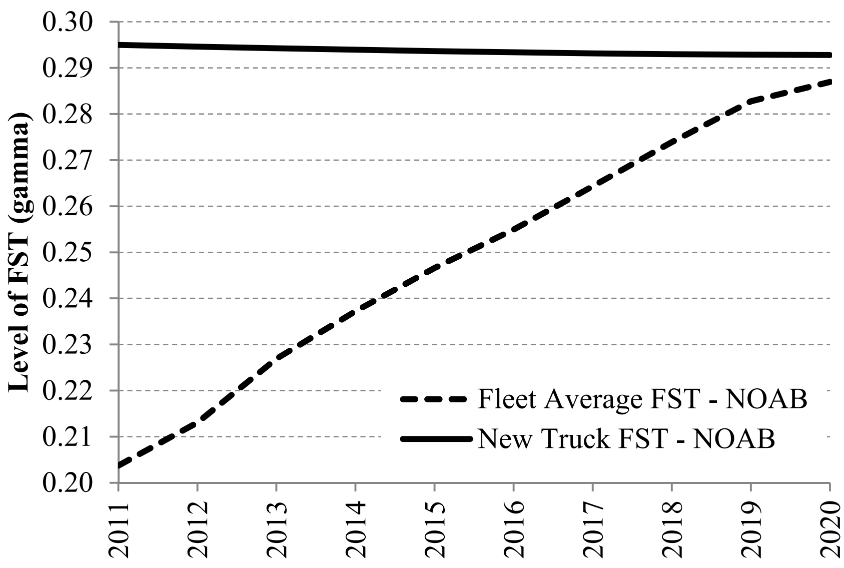

Figure 14: Level of FST investment under different scenarios

From *Figure 14* it can be observed how the average fuel economy of the truck fleet increases throughout time as more fuel efficient trucks are purchased. Even though in this model carriers invest in FSTs for existing trucks, they do so at a lower level than for new trucks because old trucks have fewer miles left in their lives on which to accrue fuel savings. Take for example the year 2020, the gradual penetration of FSTs in the truck fleet continues after this year, therefore an analysis that only considers the steady-state incentives of carriers will over-predict the fuel efficiency of the truck fleet at this time. If diesel taxation is evaluated earlier, assuming steady-state conditions would produce even more biased results. The cost minimization approach used in the TSO model to project the adoption of FSTs is more insightful and defensible than the ad-hoc approach adopted in the NEMS model developed by EIA (2012).

The TSO model is also able to capture the effect that the characteristics of the present truck fleet have on the decisions of carriers moving forward. *Figure 15* shows how the purchase rate of trucks jumps from year to year to accommodate the retirement of different segments of the existing truck fleet. This purchase rate is also increasing with time to supply the increasing demand for trucking. *Figure 15* also shows how the relatively erratic truck replacement behavior in the first five or so years is smoothened out as the system stabilizes to long-run optimal conditions. This is the result of the model transitioning from the current truck fleet, which is not optimal according to the cost parameters, to a truck fleet that is optimal. In the beginning of this transition in the CNT scenario the size of the truck fleet is reduced significantly. This occurs because in this scenario carriers are not allowed to invest in the FSTs of their fleet, therefore they prefer to retire existing trucks quicker. In the NAOB scenario carriers can invest in the FSTs of the existing truck fleet, making them more economical to operate for longer. The basic intuition can be found in equation (2.13) where $dX/d\gamma > 0$.

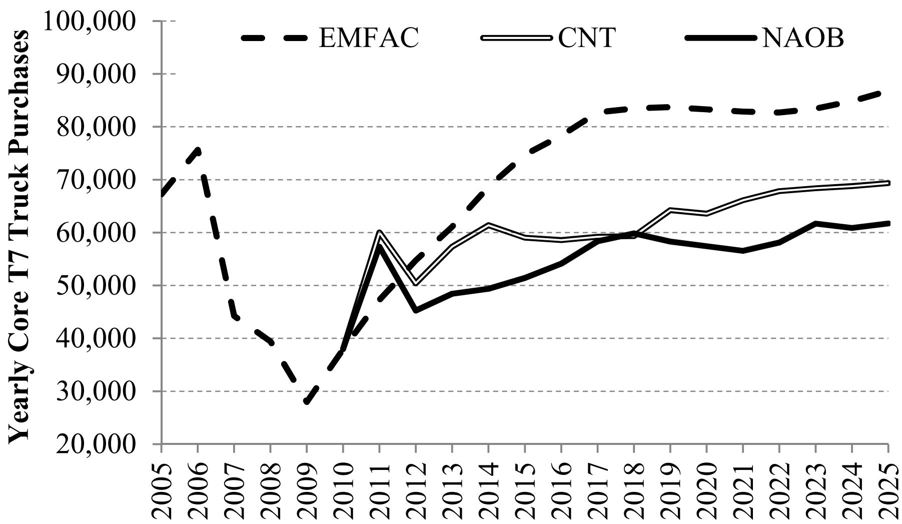

Figure 15: Truck purchases under different scenarios

Figure 16 shows some aspects of the vehicle stock dynamics captured by the TSO model. In this figure, each line represents the cumulative contribution of trucks purchases in each year to the stock of trucks. The slopes of these lines can be interpreted as the rate at which trucks cycle through the fleet, which is a function of both purchases and retirements. The summation of these contributions at a point in time provides an estimate of the size of the truck fleet.

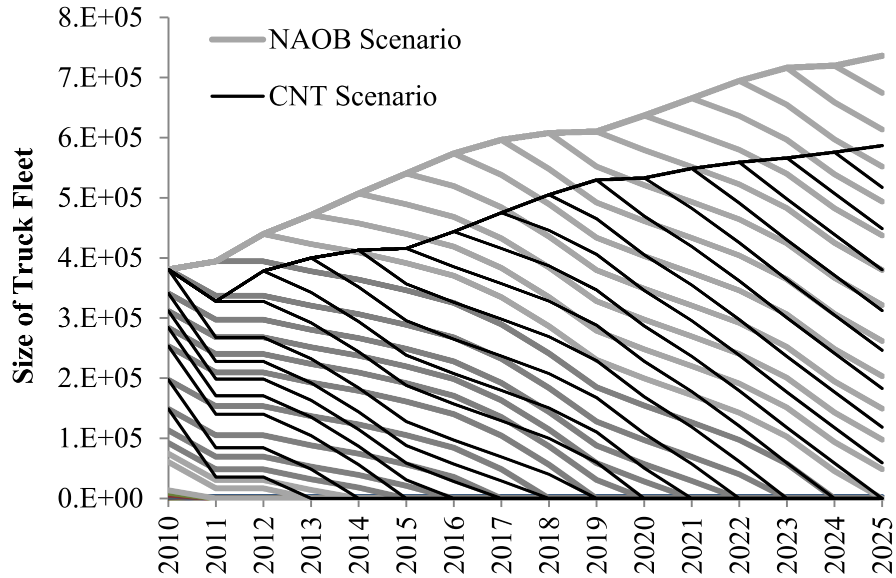

Figure 16: Evolution of Core T7 fleet composition

At first, it might seem inconsistent that in *Figure 15* the purchase rate is higher in the CNT scenario than in the NAOB scenario while in *Figure 16* the stock of trucks is larger in the NAOB scenario. However, this can be explained by the fact that the size of the truck fleet F is a function of both the rate of truck purchase and their service lives. Let's assume stationary conditions to illustrate this point succinctly. By substituting the inverse truck utilization function into (2.2) we can express the size of the fleet as $F = PU^{-1}(X)$. Using (2.1) we can rewrite this as $PU^{-1}\left(\frac{\psi}{P}\right)$. Taking derivatives we find that $\frac{dF}{dP} < 0$ when $\left(\frac{\psi}{P}\right)^2 > \frac{k_4}{k_3}$, which is overwhelmingly the case for any realistic values of k_4 and k_3. Therefore, from the stationary model we gain the intuition that reductions in truck purchasing P should be associated with increases in the size of the truck fleet F when demand ψ is held constant. This result also generally applies to dynamic truck fleets as the scenario with a higher truck purchase rate also has steeper stock contribution curves (corresponding to a quicker retirement of trucks) and a smaller fleet size.

The dynamics of the truck stock are also important in comparing regulation-based strategies to incentives-based strategies. Fuel taxation affects all of the trucks in the fleet to the same degree, incentivizing investments in FSTs in both new and old trucks. On the contrary, the heavy-duty truck fuel economy standards recently introduced in the US will only affect new trucks. Research has shown that the longstanding automobile fuel economy standards (CAFE) represent costly ways of achieving reductions in GHG emissions, in part because it only affects new cars purchases and the costs are not spread over time (Karplus *et al.* 2013). These problems will likely be more pronounced for the heavy-duty truck standard because of two reasons. Firstly, trucks have service lives that are much longer than those of automobiles, leading policies that only affect new vehicle purchases to take longer to have sector-wide effects. And secondly, unlike automobiles, the fuel economy of the existing truck fleet can be improved through investment in FSTs. Not taking advantage of this opportunity to reduce near-term emissions would be a significant shortcoming of applying fuel economy standards to the trucking industry. The importance of these transitional effects can be well studied with the TSO model.

Another reason for studying the dynamics of truck fleets is that fuel taxes, as well as other onerous strategies, are likely to be phased in to give carriers time to re-optimize their operations. The TSO model can be used to evaluate how the industry responds to different phase-in schedules, the effects of which can last many years after the strategy is phased in entirely.

Another issue that merits more research is the role that political and institutional boundaries have on the outcomes of policy in the trucking industry. For example, an unprecedented fuel tax in California of $1.3/gallon would only increases the average mileage costs of the Core T7 truck fleet by 2.1%. This is because only 23.4% of the mileage driven by these trucks occurs inside of California, where the tax would affect fuel purchases. However, considering only averages potentially hides a significant amount of heterogeneity in trucking operations that would impact how trucks respond to a diesel tax that is only imposed in California. The Core T7 truck fleet is composed both by drayage trucks that operate exclusively in the State and transcontinental trucks that only operate in California on route to its busy west coast ports. Each of these would respond different to tax increases. There also exists the potential for leakage to other states of fuel purchases and even trucking activity if high fuel price differentials are created by the tax. Future research should further disaggregate the trucking fleet to analyze each segment more precisely.

3.3 Mitigation Strategy Analysis

3.3.1 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 fuel tax increases are not passed onto shippers as a fuel surcharge.

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 17*. Here, 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.

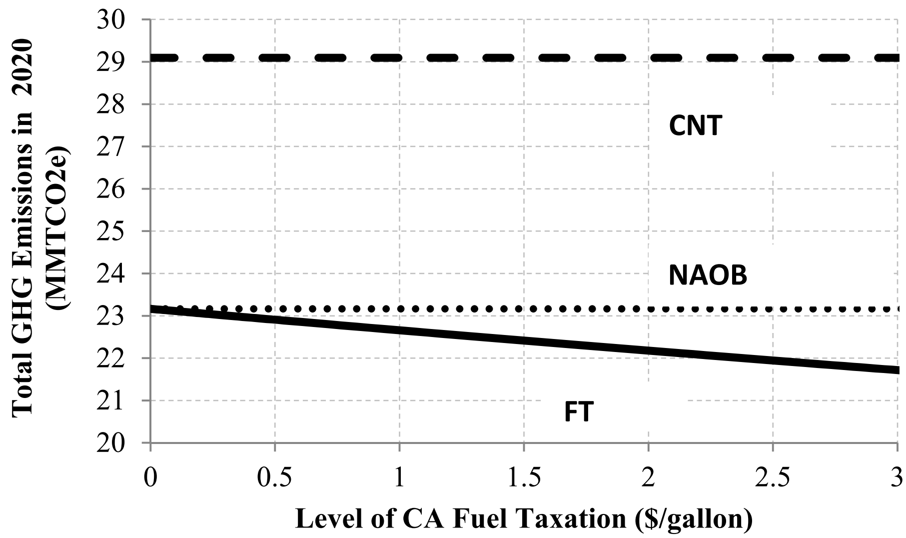

Figure 17: Effect of fuel taxation on GHG emissions

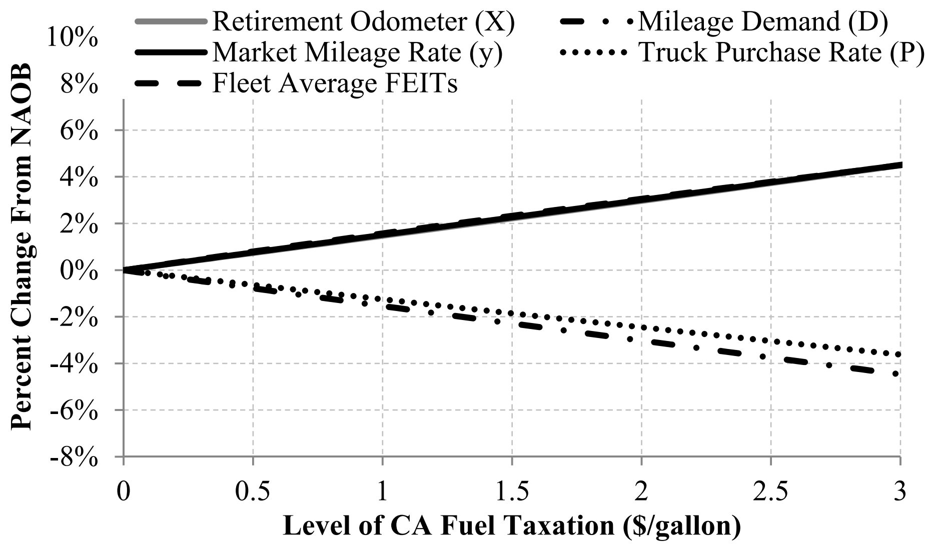

Figure 18: Effect of fuel taxation on truck fleet characteristics in 2020

Figure 18 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.

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 from *Figure 10* it can be seen that this value 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

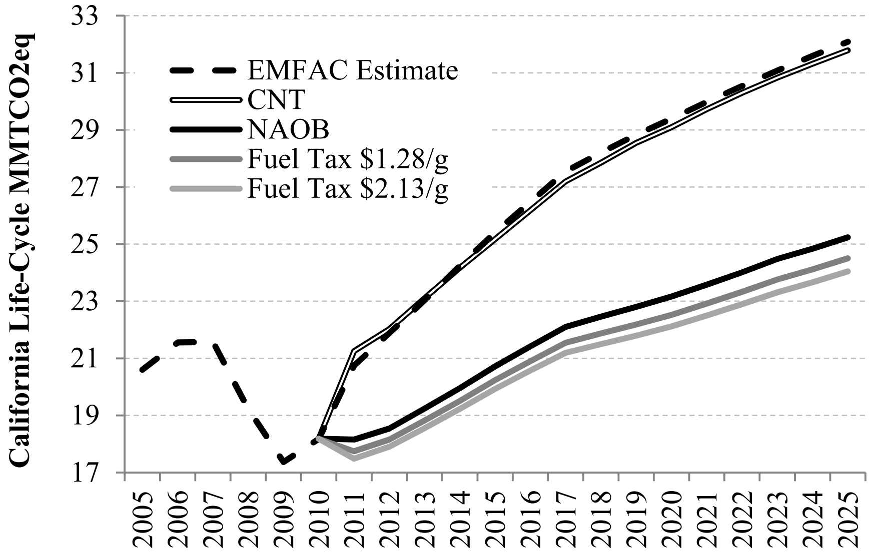

Figure 19: GHG emissions after fuel taxation

3.3.2 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. This has been found to incentivize trucking companies to retire old trucks and replace them with new trucks that are more fuel efficient (Aarnink *et al.* 2012). 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.

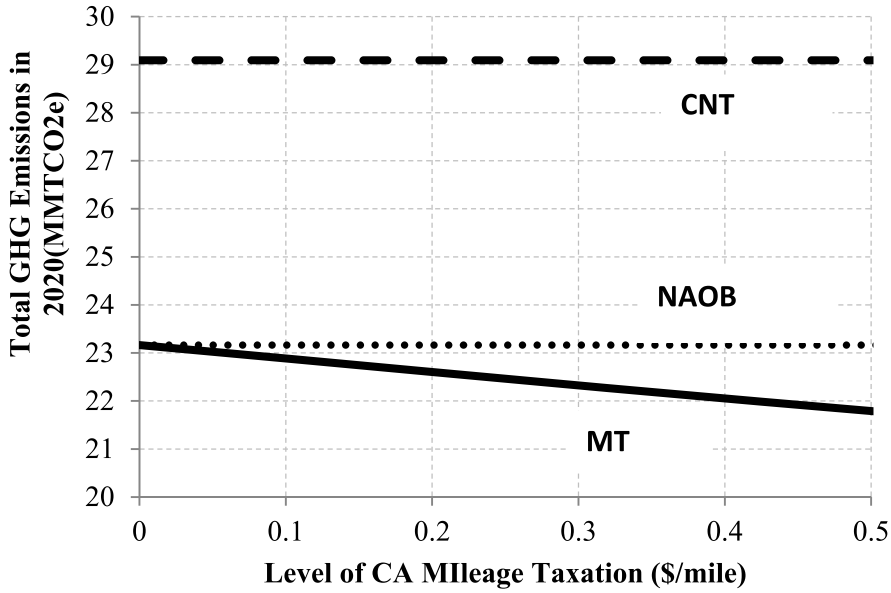

Figure 20: Effect of mileage taxation on GHG emissions

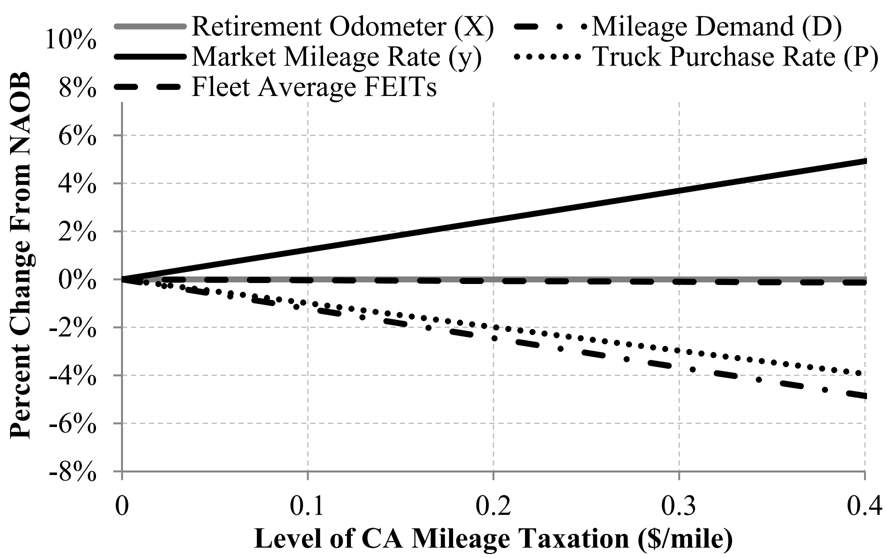

Figure 21: Effect of mileage taxation on truck fleet characteristics in 2020[3]

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[3] FEITs is another acronym for FSTs

The results of the analysis are shown in *Figure 20*. 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. 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. 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%.

Figure 21 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.

3.3.3 Truck Purchase Taxation

Taxation of truck purchases seeks to decrease GHG emissions by (1) reducing the amount of trucks being purchased, (2) increasing the truck retirement age which incentivizes greater use of FSTs, and (3) reducing shipper demand for trucking by increasing the market rate.

For simplicity we assume that California has the ability to tax all truck purchases in the Core T7 fleet, which is somewhat unrealistic given that the majority of truck purchases occur outside California. However, if California implemented a truck purchase tax within its borders only there will likely be a significant leakage of truck purchases to neighboring states that would not have this tax. This complication is avoided by assuming that California can implement a unit tax on all Core T7 truck. In practice the tax could be implemented on a yearly basis similarly to the nationwide Federal Heavy Highway Vehicle Use Tax, which is levied on all trucks and increases based on the maximum GVW.

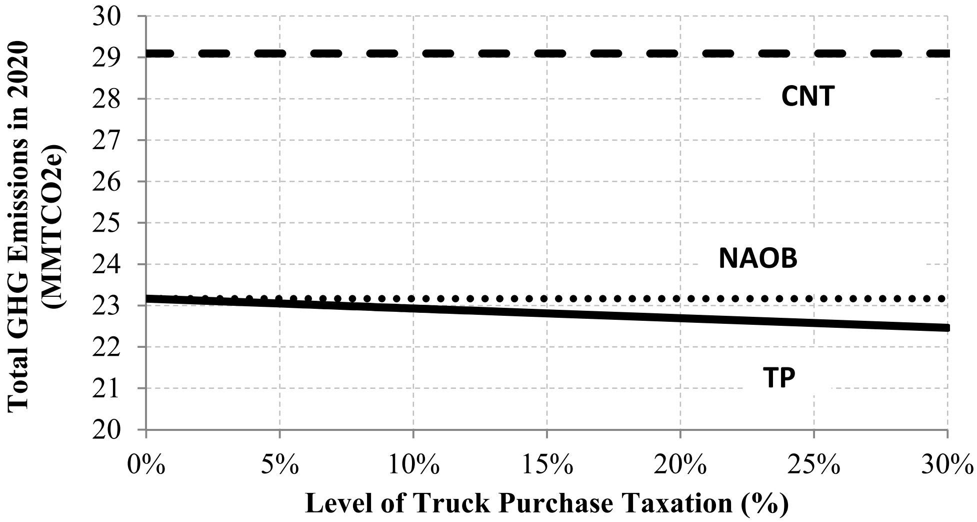

Figure 22: Effect of truck purchase taxation on GHG emissions

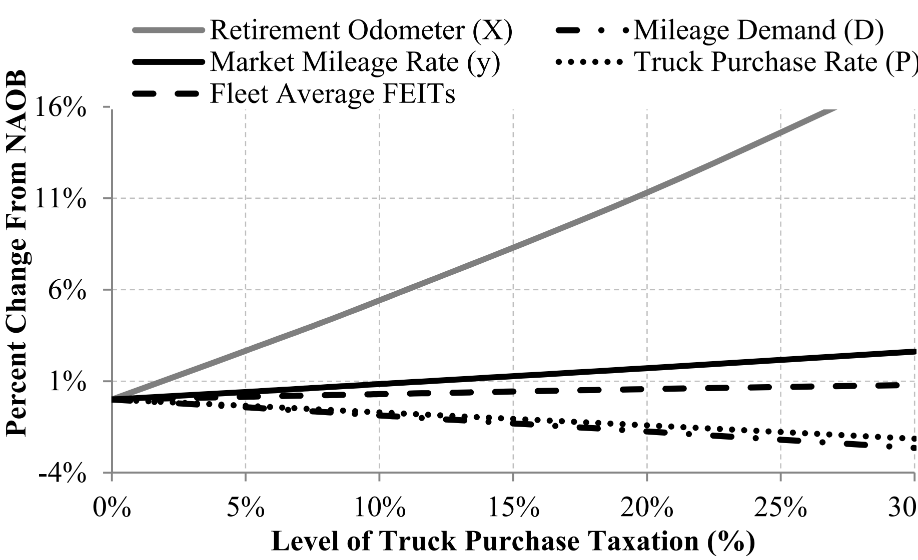

Figure 23: truck fleet characteristics in 2020

The analysis assumed that the tax is phased-in following the standard schedule. From *Figure 22* it appears that only a small amount of GHG reductions would result from a relatively large 30% tax on truck purchases, which amounts to more than $30,000 per truck. Nonetheless this tax is equivalent to an increase in mileage costs of less than 4.3%. Implementing this tax would reduce 0.62 MMTCO2eq in California and an additional 2.03 MMTCO2eq elsewhere in the US relative to the NAOB scenario. In the low scenario for fuel prices and LDS elasticity the total amount of GHG emissions under this strategy reduces by 9.4%, while under the high scenario it increases by 8.6%.

About 79% of the emission reductions from this strategy come from the tailpipe source, 4.1% from the precombustion source, 12.5% from the infrastructure source and 4.3% from the vehicle manufacturing source. In *Figure 23* we observe that as the truck purchase tax increases the retirement odometer increases significantly, which further incentivizes greater use of FSTs and results in reductions of tailpipe emissions.

3.3.4 FST Subsidy

Subsidies of FSTs seek to increase the fuel efficiency of the truck fleet to decrease GHG emissions. It was assumed that the subsidies are available to all Core T7 trucks independent of their proportion of California travel and that they are implemented fully starting in the year 2013 for new trucks only. A separate phase-in schedule could also be analyzed in future research where the strategy is phased out after a certain period of time, making the subsidy temporary.

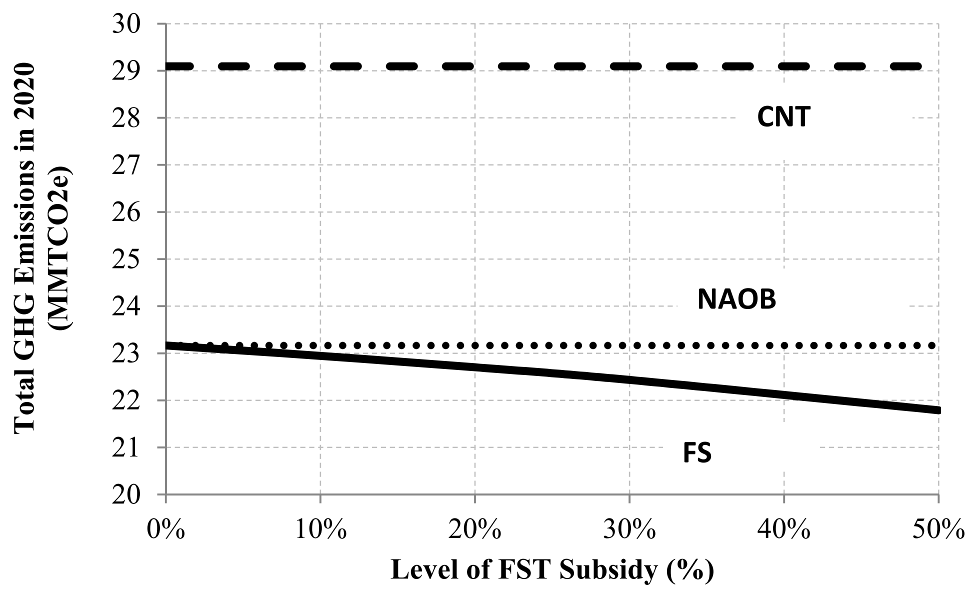

Figure 24: Effect of FST subsidies on GHG emissions

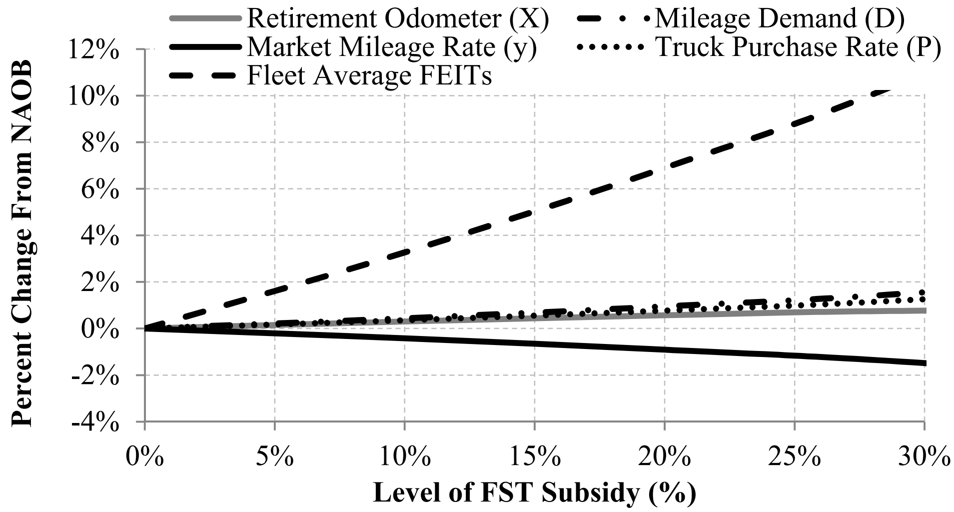

Figure 25: Effect of FST subsidies on truck fleet characteristics in 2020

Figure 25 shows that this strategy incentivizes significant investment in FSTs. This has the effect of lowering the market rate and therefore increasing the quantity demanded of trucking. As shown in *Figure 24*, the increase in fleet fuel efficiency more than offsets the latent demand response. Providing subsidies that reduce the costs of FSTs by 30% would result in GHG reductions of 0.72 MMTCO2eq in California and 2.34 MMTCO2eq elsewhere in the US relative to the NAOB scenario. These reductions occur despite a small increase in infrastructure and vehicle manufacturing emissions. In the low scenario for fuel prices and LDS elasticity the total amount of GHG emissions under this strategy reduces by 8.6%, while under the high scenario it increases by 7.8%.

The subsidy of FSTs should be much more effective starting from the CNT scenario (current operations) than from the theoretical NAOB scenario, because the benefit-to-cost ratio of the technology improvements will be higher.

3.3.5 Weight Limit Increases

California's truck size and weight limits are similar to those established by federal regulation, which limit trucks to a total Gross Vehicle Weight Rating (GWVR) of 80,000 lbs with a single axle-limit of 20,000 lbs and tandem axle limit of 34,000 lbs. Higher truck weight limits are present in other Western states and in the Midwest. Increasing the truck weight limit in California could allow carriers to ship larger loads (particularly those originating from ports in California) and reduce the trucking mileage of weight constrained loads.

Truck weight limits are significantly higher in Europe than in the US. The Netherlands and Finland have truck weight limits higher than 110,000 lbs and France, Italy, Denmark and Norway have limits above 88,000 lbs. In 2001 the weight limit in the UK was increased from 90,000 lbs to 97,000 lbs, leading to a decrease in GHG emissions of 0.65%

(McKinnon 2005). In this case much of the pavement deterioration was mitigated by increasing the number of axles of the trucks and greater use of air suspension.

The analysis of this mitigation strategy considers increasing the truck weight limit from 80,000lbs to 96,000lbs under two types of axle configurations: (1) carriers continue using 5-axle trucks to transport the increased loads, or (2) carries use 6-axle trucks to transport heavier loads (extra axle in the trailer). This difference is important because the number of loaded axles on a truck has a significant impact on infrastructure deterioration and the GHG emissions of rehabilitating it. Other truck weight limits and axle configurations are possible (and common in Europe), but they were not analyzed because they entail a large departure from existing operations.

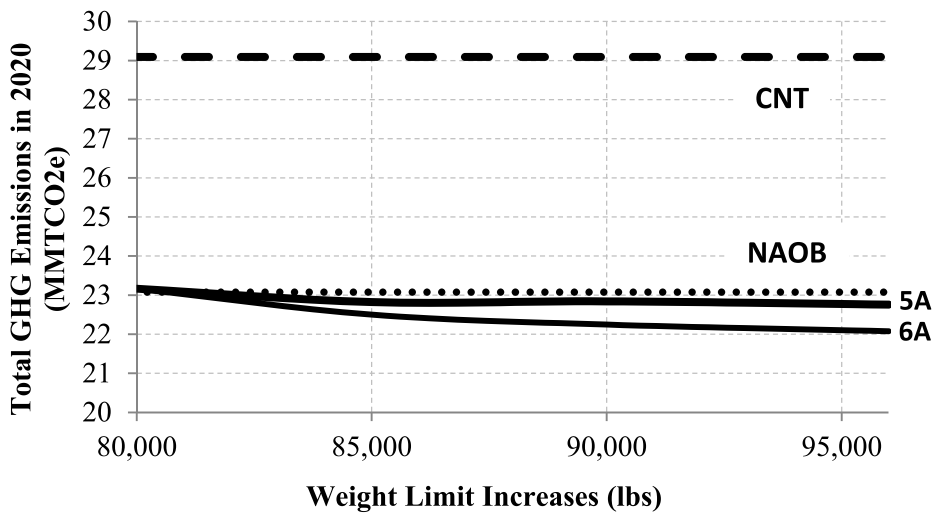

Figure 26: Effect of weight limit increases on GHG emissions

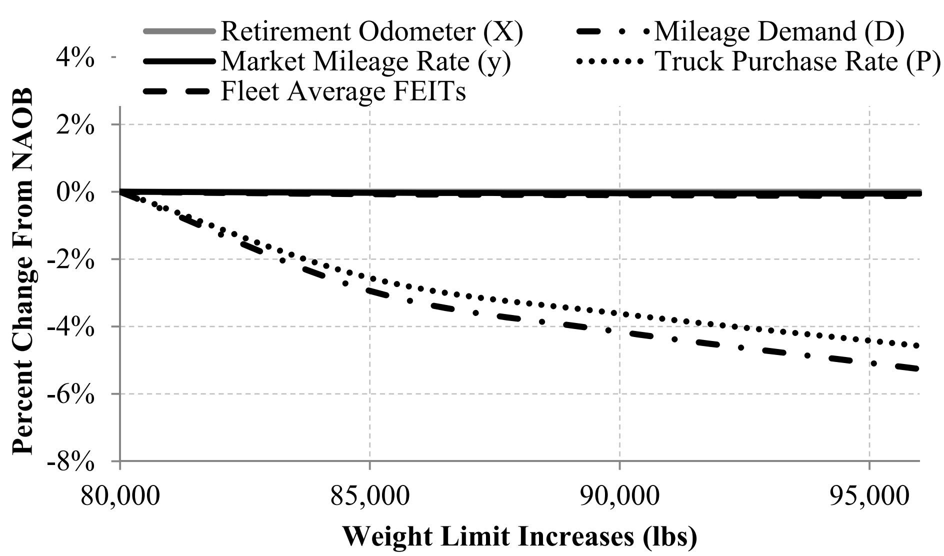

Figure 27: Effect of weight limit increases on truck fleet characteristics in 2020

Figure 26 shows the GHG emission reductions that occur if this strategy is implemented under the assumption of 5-axle trucks or 6-axle trucks. For the 5-axle case, the emission reductions from the decrease truck trips are almost offset by a 30% increase in emissions from infrastructure rehabilitation and maintenance. Additional rehabilitation and maintenance also carries a large cost that is not considered in this analysis. Increasing the axle limit to 6 for heavier loads can mitigate much of these additional costs and emissions. Changing the truck weight limit to 96,000 lbs for 6-axle trucks reduces GHG emissions by 1.07 MMTCO2eq in California and 3.48 MMTCO2eq elsewhere in the US relative to the NAOB scenario. In the low scenario for fuel prices and LDS elasticity the total amount of GHG emissions under this strategy is reduced by 9.1% while under the high scenario it increases by 8.3%. *Figure 27* shows that these reductions are driven primarily by the reduction of trucking mileage and truck purchasing rate.

3.3.6 Low Carbon Fuel Standard

The Low Carbon Fuel Standard (LCFS) implemented in California regulates the average carbon intensity of fuels. This has been estimated to impact the diesel fuel used for trucking as shown in *Table 5*. The third column in this table indicates the percent reduction in GHG emissions per gallon. The fourth and fifth columns contain estimates of the effect of the LCFS on diesel fuel prices estimated by CARB and by the California Trucking Association (CTA). These compliance cost estimates are very different from each other because they were calculated using different sets of assumptions. The effect of the LCFS strategy was analyzed under both of these estimates in order to avoid having to develop our own compliance costs estimate. By doing this we are not necessarily indicating that we consider both of these scenarios to be equally plausible.

Table 5: Effect of LCFS on diesel fuel (Andress *et al.* 2010; CARB 2011a, CTA 2012)

year	Diesel Carbon Intensity (gCO2e/Mj)	Reduction From 2010 (%)	Compliance Costs $/gallon	
			CARB Estimate	CTA Estimate
2010	94.23	0.00	0.00	0.00
2011	94.47	0.25	0.00	0.00
2012	94.24	0.50	0.04	0.06
2013	93.76	1.00	0.02	0.11
2014	93.26	1.50	0.08	0.19
2015	92.34	2.50	0.10	0.41
2016	91.40	3.50	0.17	0.46
2017	89.97	5.00	0.24	1.11
2018	88.55	6.50	0.23	1.20
2019	87.13	8.00	0.22	1.31
2020	85.24	10.00	0.20	1.47

The LCFS will only affect the portion of mileage driven within California. The more expensive low carbon fuel will only be purchased within California and will result in GHG reductions mostly within the state. The LCFS will also result in GHG reductions outside California as the additional fuel costs will affect the FST, FMO and LDS responses of the fleet. Just as in the analysis of fuel taxation, it is assumed that the proportion of fuel purchased within California does not change as a consequence of this strategy.

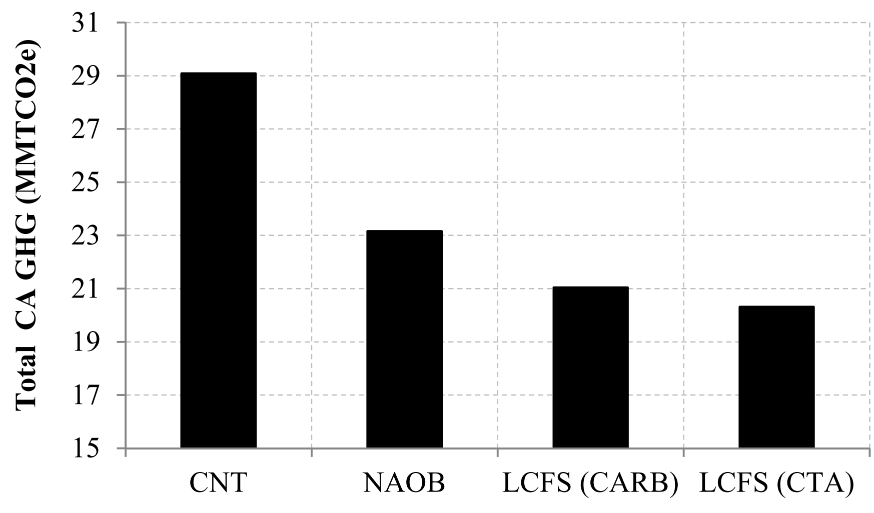

Figure 28: Effect of LCFS on GHG emissions

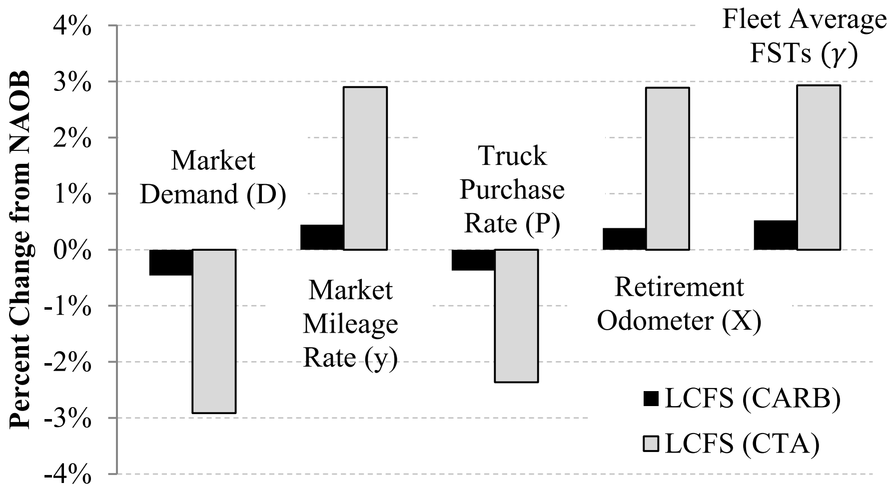

Figure 29: Effect of LCFS on truck fleet characteristics

The analysis results of the LCFS strategy using the CTA and CARB compliance cost scenarios are presented in *Figure 28.* The strategy was implemented on the theoretical NAOB scenario, therefore the results in this figure do not represent forecasts from current conditions. It can be observed in this figure that the CTA scenario achieves more GHG reductions than the CARB scenario because the higher fuel costs of the CTA scenario leads to GHG reductions from FST, FMO and LDS in addition to the lower carbon intensity of the fuel. In a way, the LCFS strategy is analogous to a fuel tax where the tax revenues are used to reduce the carbon intensity of the fuel. From the NAOB scenario, the LCFS (CARB) strategy would result in a relatively large reduction of GHG emissions of 2.1 MMTCO2eq within California and 0.5 MMTCO2eq from elsewhere in the US. In the low scenario for fuel prices and LDS elasticity the total amount of GHG emissions under this strategy is reduced by 9.2% while under the high scenario it increases by 8.3%.

From *Figure 29* it is clear that the higher fuel costs associated with the CTA scenario drive much of the changes. For the CTA scenario 93% of the reductions come from the tailpipe source, 5% from the precombustion source, 1.5% from the infrastructure source and 0.5% from the vehicle manufacturing source. For the CARB scenario 88.6% of the reductions come from the tailpipe source, 4.6% from the precombustion source, 5% from the infrastructure source and 1.8% from the vehicle manufacturing source.

3.3.7 SmartWay Regulation

CARB has recently implemented a regulation that forces tractor-trailers that travel within California (independent of registration location) to be SmartWay certified. SmartWay certification is part of a nationwide EPA program that incentivizes trucking companies to voluntarily invest in certain FSTs. Currently the certification requires about a 5% reduction in fuel consumption from aerodynamic improvements to the tractor, a 5% reduction in fuel consumption from aerodynamic improvements to the trailer and a 3% reduction in fuel consumption from the use of low rolling resistance tires. Using data from *Table 2* it was estimated that this regulation will results in a 11.1% reduction in the fuel consumption per mile of the Core T7 fleet at a capital cost of $14,560 per truck[4]. CARB (2008a) estimated the impact of the SmartWay regulation using a different set of assumptions and data, therefore their results are not directly comparable to ours.

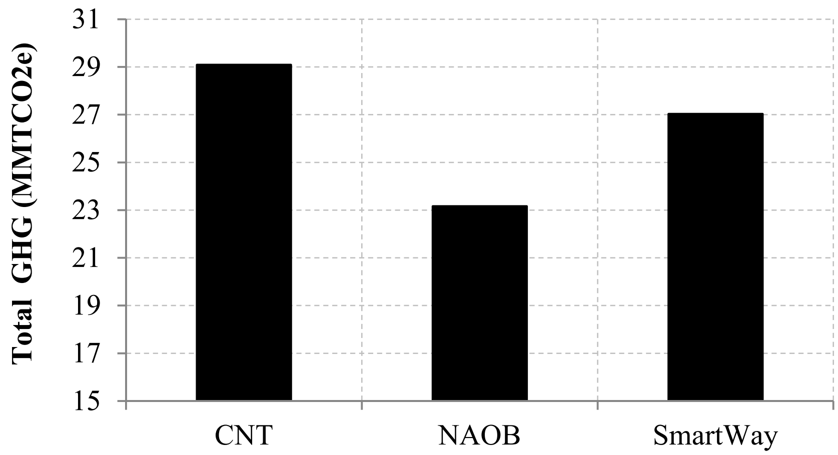

Figure 30: Effect of SmartWay regulation on GHG emissions

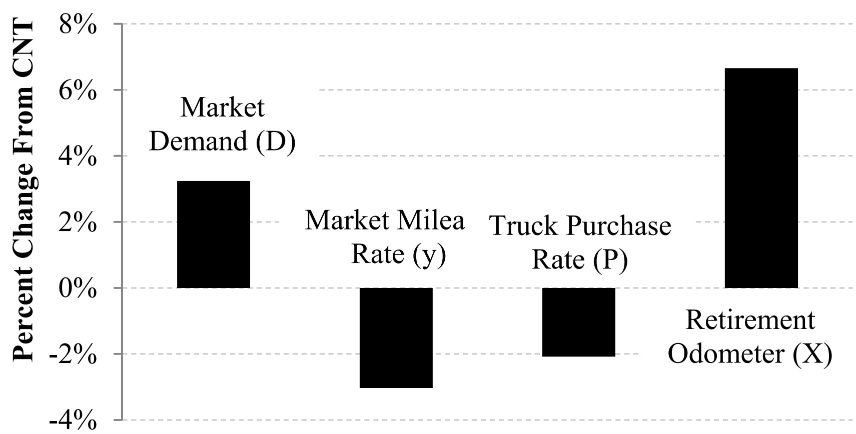

Figure 31: Effect of SmartWay regulation on truck fleet characteristics in 2020

Implementing only the FSTs mentioned above would result in the GHG emission reductions shown in *Figure 30*. The emissions under the SmartWay regulation strategy are higher than under the NAOB reference scenario because the level of FSTs that is optimal

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[4] This is a fairly conservative estimate of life time costs (high) assuming 2.5 trailers per tractor and financing costs.

under the NAOB scenario is higher than what is mandated by this strategy. Overall, the SmartWay strategy is estimated to reduce total GHG emissions from the CNT scenario by 2.04 MMTCO2eq in California and 6.63 MMTCO2eq elsewhere in the US. These values do represent forecasts as they are obtained in reference to the CNT scenario. In the low scenario for fuel prices and LDS elasticity the total amount of GHG emissions under this strategy is reduced by 9.2% while under the high scenario it increases by 7.0%. *Figure 31* shows that the decrease in the market rate should increase the demand for trucking.

3.3.8 Interpretation of Results

Section 3.2.1 provided various plausible explanations for why the 'optimal' level of FST investment predicted by NAOB scenario is not currently observed in the US trucking industry (CNT scenario). Barriers to the implementation of FSTs were categorized as either resulting from market failures (inefficiencies in the industry) or from non-market failures (deficiencies in the analyst's model of the industry). Conceptually, the main difference between these types of barriers is that governments should attempt to fix market failures but not non-market failures. As explained in this previous section, it is difficult to determine the frequency and magnitude of either of these types of barriers without conducting an in-depth survey of carriers and shippers to obtain disaggregated information about how the industry operates in reality. However, despite this lack of concrete evidence, there are still several interesting and important conclusions that can be drawn from the work presented in the previous sections to inform current policy debates.

First of all, this section argues that it is likely that the differences between the CNT scenario and the NAOB scenario are cause primarily by market failures. A key reason for this is that the decision to invest in FSTs is relatively simple in nature, and is definitely not any more complex than other decisions that carriers routinely make. Therefore, they are well equipped to judge the benefits and costs of FSTs, even in an uncertain business environment. In fact, Metcalf (1994) found that investing in energy-saving technologies helped firms hedge against uncertain energy costs, which in this case implies that carriers should invest in FSTs to counter uncertainty in diesel price. *Section 3.1.5* shows that in the TSO model the capital and maintenance costs of the FSTs were estimated very conservatively, for example it assumes that the technologies have to be replaced several times throughout the life of the truck. This leads the NAOB scenario to already consider many of the potential hidden costs. Other sources of hidden costs mentioned before, such as drivers disliking FSTs, would be partially mitigated if principal-agent problems are resolved.

Another reason why barriers to investments in FSTs are most likely driven by market failures is that non-market failures only disincentivize carriers at the margin, when in fact the differences between the CNT scenario and NAOB scenario are large. Carriers in the NAOB scenario invest $43,000 more in FSTs than in the CNT scenario. Considering non-market failures, such as hidden costs and business uncertainty, would reduce this 'optimal' level of investment somewhat, but it would not explain why carriers are not investing in FSTs at all in the present trucking industry (CNT scenario). On the other hand, market failures lead to fundamental dislocations in the industry that can easily explain this large efficiency gap. For example, carriers will not invest in any FSTs if they have no information about them (information asymmetry), are insulated from fuel costs (principal-agent problem) or cannot borrow capital to purchase them (budgetary constraint). Market failure can readily explain why the trucking industry is not investing more vigorously in FSTs.

Given that the differences between the CNT scenario and NAOB scenario are caused predominantly by market failures, we can now interpret the results of the strategy evaluations shown in the previous sections. These results were obtained by modeling the strategies in the idealized NAOB scenario; therefore they should not be interpreted as predictions of what would happen if the strategies were to be implemented in the present US trucking industry. Instead, the insights from these results are more subtle, but still interesting and useful in informing current policy debates.

Jaffe and Stavins (1994) pointed out that one of the most critical steps in understanding energy efficiency gaps commonly observed in many industries is to clearly identify optimality, which in this research is accomplished by the NAOB scenario. The responses of the industry in this idealized scenario serve as benchmarks. The understanding of economic incentives at optimality should guide efforts by governments to implement regulations or market mechanisms to fix the market failures. Also, once market failures are mitigated and the industry operates closer to the NAOB scenario, the results from modeling mitigation strategies in the NAOB scenario can be interpreted as predictions.

Analyzing governmental strategies in the NAOB scenario also provides an upper-bound for the responses of the industry because in this scenario carriers fully optimize their responses to strategies. Any market failure present would simply decrease the magnitude of these responses, because they prevent market participants from freely optimizing their operations. A lower bound could have been obtained by modeling the strategies in the CNT scenario, where truck technology remains unchanged.

The results of evaluating strategies in the NAOB scenario can be best interpreted when comparing between strategies. Generally, differences in the responses of the industry 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.

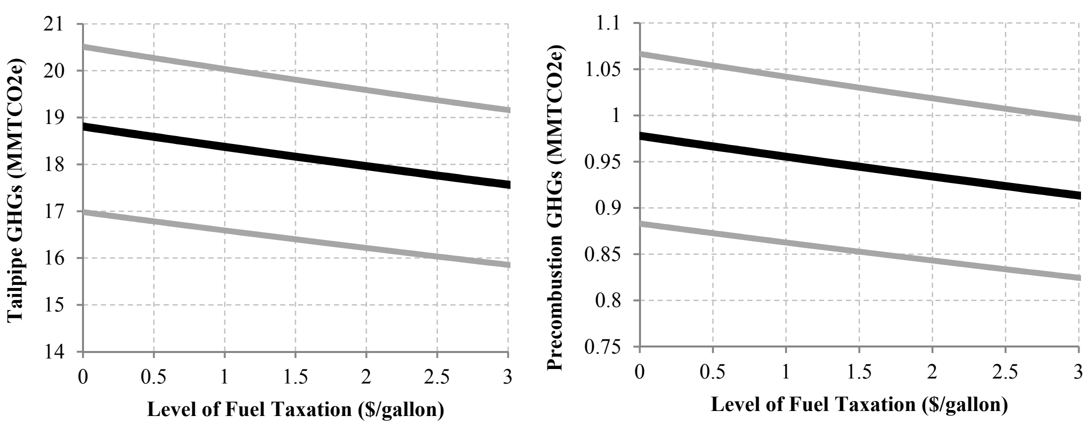
The results of the previous sections are partially summarized in *Table 6,* which compares the levels of strategy implementation required to achieve certain amounts of GHG emission reductions relative to the NAOB scenario in 2020. This table shows the levels of strategy implementation that are equivalent form an environmental point of view. For example, in comparing mileage taxation and fuel taxation we find that mileage taxation has to increase trucking costs by 11 - 9% more than fuel taxation to achieve the same reduction of emissions. This table also shows that increases in the weight limit of trucks should be accompanied with increases in the number of axles to reduce pavement deterioration. The LCFS and SmartWay FST regulation strategies were not shown in this table because they were only analyzed at a single level of implementation.

Table 6: Effectiveness of mitigation strategies in 2020 relative to NAOB scenario

Percent Reduction	Emission Reductions in CA (MMTCO2eq)	Fuel Taxation ($/gallon)	Mileage Taxation ($/mile)	Truck Purchasing Tax (%)	FST Subsidy (%)	WL 5-Axles (Lbs)	WL 6-Axles (Lbs)
0.9%	**0.2**	0.39	0.07	8.50%	9.09%	82,922	81,506
1.7%	**0.4**	0.79	0.14	16.95%	17.44%	95,474	83,013
2.6%	**0.6**	1.19	0.22	25.50%	25.15%	-- --	84,519
3.5%	**0.8**	1.61	0.29	-- --	32.16%	-- --	87,679
4.3%	**1.0**	2.03	0.36	-- --	38.38%	-- --	92,903
5.2%	**1.2**	2.46	0.43	-- --	44.59%	-- --	-- --

Even though it is not shown in *Table 6,* each of these strategies would reduce emissions outside of California by 3.2 – 3.3 times more than they would reduce emissions inside of California. The SmartWay regulation currently being implemented would have similar results. The main reason for this is that the Core T7 truck fleet operates only about ¼ of its mileage within California, therefore the industry responses to strategies implemented only in California will also have impacts outside of the state. It is unclear whether California can or should take credit for emission reductions occurring outside of its political boarders. However, because GHGs are global pollutants, strong arguments can be made that they should.

A sensitivity analysis was conducted to gauge how GHG emissions in the NAOB scenario in 2020 depended on the assumptions made about fuel prices and LDS response elasticity. The results of this sensitivity analysis for different levels of fuel taxation are shown in *Figure 32*. The *high* (*low*) emissions scenario was obtained by using the *lowest* (*highest*) estimate of fuel price and LDS elasticity. This represents the pessimistic (optimistic) scenario of emissions from the Core T7 truck fleet in CA in 2020. The fuel price values used can be found in *Table 3* and LDS elasticity values used can be found in Section 3.1.9.



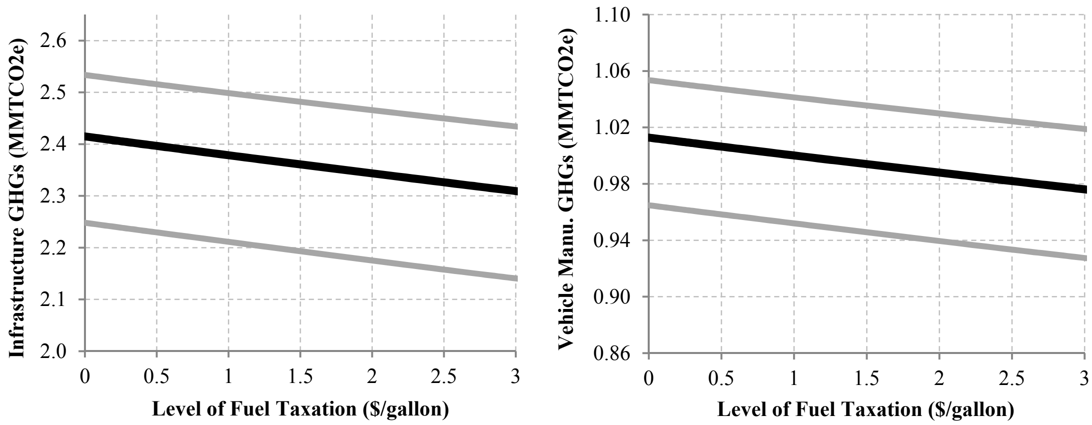


Figure 32: Reduction of 2020 GHG emissions from fuel taxation under different LDS elasticity and fuel price assumptions (LOW=high fuel price and high LDS elasticity, HIGH=low fuel price and low LDS elasticity)

Across the mitigation strategies, 81 - 84% of emission reductions come from tailpipe sources, 8 - 12% come from infrastructure sources, 4 - 5% come from precombustion sources, and 2 - 4% come from vehicle manufacturing sources. It is clear that GHG emissions from the trucking sector are dominated by the combustion of fuel. However, other criteria pollutants, such as NOx and PM, are emitted more heavily from vehicle manufacturing and infrastructure sources. Future research that studies the tradeoffs between emissions of different pollutants from the trucking industry would benefit greatly from the TSO model.

3.4 Policy Recommendations for California

As explained in the beginning of this chapter, the Climate Change Scoping Plan prepared by CARB (2008) found that the GHG emissions of the heavy-duty trucking sector should be reduced by 3 to 4 MMTCO2eq in the year 2020. This does not represent a mandate, but rather an estimate that forms part of a reasonable scenario for economy-wide emission reductions that achieve the objectives of AB 32. The results and discussions presented in the previous sections provide a clear policy roadmap of achieving these emission reductions.

3.4.1 Step 1: Regulation of FSTs

A sensible first step that CA's government should take is to use regulations to reduce the influence of market failures in this industry to make it operate closer to the NAOB scenario. This can be accomplished by regulating the level of FSTs that trucks need to have installed to operate in the state. CARB has recently adopted this approach by regulating that heavy-duty trucks need to have installed FSTs of $\gamma = 0.11$ (see *Section 3.3.7*) starting in 2014.

This would result in emission reductions of 2.04 MMTCO2eq of GHG emissions in CA in 2020 relative to the CNT scenario. Note that these estimated emission reductions are higher than those achieved by the incentives-based strategies in *Table 6,* which represent upper-bounds for these estimates because they were modeled in the NAOB scenario, where carriers respond fully to incentives.

Also, because in the NAOB scenario $\gamma^* = 0.29$, there is evidence that further tightening of FST regulations would be beneficial. Given that the difference of emissions between the CNT scenario and NAOB scenario is over 6 MMTCO2eq, this could contribute greatly towards the objective of the Climate Change Scoping Plan.

3.4.2 Step 2: Increase Truck Weight Limit

The results presented in *Section 3.3.5* provide a compelling argument for increasing the weight limit of heavy-duty trucks in California from 80,000 lbs to 90,000 lbs or even 97,000 lbs, while simultaneously requiring these heavier trucks to have 6-axles. This would result in a reduction of weight constrained trips to neighboring states that already allow trucks heavier than 80,000lbs (USDOT 2004), especially of cargo originating from ports in CA. In practice this strategy might require CA and neighboring states to homogenize their truck weight and size limits, but it would likely lead to many benefits.

A survey of shippers and carriers is required to have more certainty about how the industry would respond to this strategy, but the preliminary evidence is that the responses would be very positive. Increasing the truck weight to 97,000 lbs would reduce the VMT of the Core T7 truck fleet by around 5% and lead to reductions in emissions of 1.0MMTCO2eq in the state. Requiring 6-axle trucks to transport these heavier loads would reduce pavement maintenance and rehabilitation GHG emissions and costs. Even though this strategy does not target any market failure directly, its positive impacts on the environment and on the trucking industry makes it an important second step that government in California can take.

3.4.3 Step 3: Introduce Demand Management Strategies

Strategies that reduce the demand for trucking could be implemented at this point because their positive impact on emissions is not affected by the existence of market failures in this industry. These include reducing the packaging of goods, increasing the size of the shipments and shifting to more sustainable modes of transportation.

3.4.4 Step 4: Mitigate Market Failures

CA's government should then attempt to fix the root causes of market failure in this sector. This can be accomplished by sponsoring information campaigns on the FSTs available, providing cheap financing for purchases of FST, modifying the present fuel surcharge program, and promoting the importance of fuel economy throughout the sector. These will help mitigate information asymmetries, budgetary constraints and principal-agent problems, respectively. These interventions are considered as GHG mitigation strategies in the framework presented in *Figure 2.* The introduction of these mechanisms will allow for industry regulations of FSTs to be rolled back, as carriers will start to care more about fuel costs and reduce emissions. This step would reduce government's burden to use regulation to manage aspects of this industry.

3.4.5 Step 5: Replace FST Regulation with Incentives-based Strategies

The correction of market failures paves the way for incentive-based strategies to be effective. If incentives-based strategies—such as fuel taxation and subsidies for FSTs purchases—are implemented currently, they will likely have a small impact for the same reasons that carriers are currently not seeking out significant improvements in fuel economy (difference between CNT and NAOB scenarios). The regulation of FSTs proposed in *Step 1* (and currently being implemented in CA) will achieve substantial reductions of emissions, but it would not correct the market failures present in the industry, it simply overrides them. However, to implement the incentives-based strategies that are preferred by economists and by the industry these must be corrected first.

3.4.6 Step 6: Implement Strategies Regionally

One of the main reasons why they incentives-based strategies in *Table 6* do not lead to more significant reductions in GHG emissions, or at least reductions of emissions comparable with the regulations-based strategies, is that they are only being implemented on the portion of trucking operations that occur within CA. The Core T7 truck fleet predominantly services interstate trucking demand, and as such only drive about ¼ of its mileage within CA. Therefore, a fuel tax implemented in CA will on average have an impact equivalent to ¼ of the fuel tax increase on the whole truck fleet.

The openness of borders between states in the US necessitates that GHG mitigation strategies on the trucking industry be conceptualized regionally, if not federally. The first problem with implementing strategies at the state level is that there will be significant policy leakage, where economic activity and industry operations will be distorted by the fact that the business environment is different across state borders. For example, raising diesel taxes in CA further would greatly incentivize trucking companies to fuel outside of the state.

Another pitfall of mitigating climate change at the state level is that it is unclear how to treat emissions reductions that occur in other states. Theoretically, because GHGs are global pollutants, emissions have the same impact on climate irrespective of where they came from. If a strategy implemented in California lead to reductions in emissions in Texas, then it should be able to take credit for them. However, if every state has their own set of GHG mitigation strategies, and they cause reductions of emissions throughout the US, then it is unclear how responsibility should be divided. This is a significant problem faced presently in California as the mitigation strategies studied in previous sections reduce emissions outside of California by 3.2 – 3.3 times more than they reduce emissions inside California.

In summary, developing an institutional and regulatory framework to mitigate GHG emissions are the regional level or at the federal level would: (1) increase the effectiveness of mitigation strategies, (2) reduce policy leakage and (3) improve accounting of benefit.

3.4.7 Step 7: Implement Complementary Strategies

At this point CA's government should consider combining mitigation strategies in order to achieve emission reductions in a more balanced and effective way. As mentioned earlier, European countries have had many positive experiences combining complementary strategies. The combination of strategies that reward carriers (such as FST subsidies or increasing the truck weight limits) with those that are onerous to carriers (such as fuel taxation or technology regulation) represents a more balanced and politically palatable approach to achieving emission reductions. For example, the tax revenue from fuel taxation could be used to subsidize the purchase of FSTs or to cover the additional pavement rehabilitation costs of operating larger vehicles. Future work should use a welfare analysis to explore these types of complementarity between strategies can be exploited.

4 Trucking Sector Trip Segmentation Model (TSTS)

4.1 Introduction

Many view that governmental interventions in the US trucking sector to reduce GHG emissions are necessary, because by several accounts, carriers have been investing in FSTs at a much slower pace than would seem cost-optimal. In the analysis above it was found that it is optimal for trucking firms presently to invest more than $40,000 in off-the-shelf FSTs, to achieve more than a 40% increase in fuel economy. These large investments, which would represent anywhere from 30 – 35 % of the average purchase price of a new heavy-duty truck (CARB, 2008a), are rationalized by the fact that fuel consumption is responsible for around a third of the costs that trucking firms face (Fender & Pierce 2011). Investing in technologies that reduce these large costs should be highly desirable. This conclusion is fairly common in the literature (National Research Council 2010). However, the fact remains that most trucking firms have not been making these types of investments, which is why there is currently growing interest in the public sector for finding ways of improving the efficiency of this sector.

Many other industries have also been observed to have similar "efficiency gaps" (see Gillingham et al. 2009 for a review of this literature). Jaffe and Stavins (1994) explained that these gaps can be caused by various market failures and non-market failures that create barriers to investments in new technologies that improve energy efficiency. Some recent research has found that many of these failures have a strong influence on the European and US trucking sectors (Aarnink *et al.* 2012; Vernon and Meier 2012), causing them to operate less efficiently than is cost-optimal. While in the US there is no good publically available dataset to quantify these failures, they are manifested in the wide variety of trucks that currently operate on the highways, some of which have numerous FSTs, but most do not. How can all of these trucks, that have very different fuel economies, be competitive? Trucking is an industry that has low margins and a product that resembles a commodity (low opportunity for price discrimination). If this industry operates efficiently, simple economic analysis suggests that firms that do not make FST investments should be priced out of the market.

Even though it is important, this chapter does not study the nature of market failures in the trucking industry; this will be a topic of future research. The objective of this chapter is to describe a model of the trucking sector that incorporates some of this information about market failures, albeit in a simple way, in better characterizing how trucking firms make FST investments. Jaffe and Stavins (1994) suggested that some of the influence of market failures can be modeled through higher than *normal* discount rate, essentially capturing the higher uncertainty that firms face when making long-term investments. In this study, all of the results are presented as a function of this discount rate, as this value is difficult to ascertain and should be found empirically in future research for different market conditions.

Only using a higher discount rate to model how trucking firms make investments in FSTs misses half of the story. In reality, these decisions are made simultaneously with other decisions about how many trucks to purchase, how to operate them throughout their service-lives, and when to retire them. Research has often assumed, implicitly or explicitly, that FST investments are made in isolation, and that these other variables that trucking firms control are fixed (National Research Council 2010; Guerrero et al. 2013). The Trucking Sector Optimization Model (TSO) contributed towards bridging this gap by modeling FST investments simultaneously with truck purchasing/retirement decisions.

However, just like in most other models of the trucking industry, the TSO model assumed that the way trucks are utilized throughout their service-lives is exogenous. This refers to the types of services that trucks provide and the rate at which they accrue mileage. *Chapter 3* showed that this is a reasonable assumption if the discount rate is zero or *small*, because in this case firms are relatively indifferent about the timing of their operations, leading changes in truck utilization to have an indiscernible impact on their decisions.

On the other hand, is trucking firms have *large* discount rates, which is likely the case in the US, the utilization of trucks influences significantly the tradeoffs involved in making FST investments. For example, slowing down the rate at which trucks make deliveries will lead them to operate longer in time (until the retirement odometer is reached), discounting more heavily their variable costs, and therefore increasing the relative importance of capital costs. This would incentive trucking firms to invest less in FSTs, because fuel savings accrued in the future will be *worth* less to them. Another example, if a firm's rate of discounting increased because of new information or additional uncertainties, they will be incentivized to operate their trucks more intensely when newer, but retire them at a later odometer because maintenance costs are discounted more.

These interactions between FST investments and the management of truck fleets have not been studied previously in the literature, even though they are likely central to how this industry operates, and therefore have significant environmental impacts. One of the reasons for this, as explained in detail in the next section, is that existing models of truck utilization cannot be readily used to study these interaction. These models have their roots in the machine management literature, which has focused more on issues of stochastic demand and machine breakdowns. While these issues are also present in trucking, they are not likely to be the most important factors determining the utilization of trucks.

Instead, in this chapter truck utilization is modeled as resulting from carriers' need to service the geographically scattered demand of shippers with a physically constrained truck fleet. In tangible terms, there is a certain amount of time that a truck requires to supply a trip of certain characteristics (the performance of trucking), which is a function of the loading time, travel speeds, congestion, geography, etc. Hence, for a given spatial distribution of shipment demand, there exists a minimum amount of trucks that are needed. In the model, the shipment demand is segmented into “trip types” of common characteristics, and the truck fleet is segmented to service this demand, while operating differently, and optimally, in supplying each trip type. Accordingly, this model is called the Trucking Sector Trip Segmentation Model (TSTS). In contrast to the TSO model which specified the supply-demand equilibrium in terms of aggregate trucking mileage, the TSTS model specifies this equilibrium in terms of trips in particular segments. This increases the degrees of freedom of the problem, but it allows the responses of this industry to be captured more realistically.

In this chapter the TSTS model is used to evaluate some GHG mitigation strategies that could not have been studied with the TSO model. First, we investigate the interrelations between the discounting of costs and optimal truck utilization behavior. This allows us to determine how changes to the truck performance function (reducing wait times or speeding up trucks) can affect how capital and variable costs are weighed, impacting decisions made about FSTs. Then, we quantify the impact of the spatial distribution of demand on the FMO decisions that carriers make—indicating the changes in emissions and truck retirements with changes in mode-shifts. This can be studied because in this model demand is specified spatially, while in the TSO model it was aggregated for the whole truck fleet. And finally, several policy scenarios for FST regulations with cutoffs based on truck yearly mileage or truck odometer are analyzed. This analysis is possible with the TSTS model because truck retirements are modeled probabilistically.

4.2 Background

Truck utilization affects costs in non-obvious ways. Truck utilization is a key determinant of the time-costs associated with operating trucks, because it indicates the different points in time (age s) when particular costs are realized. This is important because many of the costs that carriers face increase with x, leading truck utilization to have a large impact on how carriers discount operating cash-flows to the present. This trade-off between present costs and future costs has a pivotal effect on carriers' investments in FSTs and on their truck retirement decisions. As mentioned before, the impact of truck utilization on these decisions will be very large if trucking firms discount the future heavily, which appears to be the case in the US currently. For example, decreasing truck utilization will spread the variable costs that increase with x over more years (taking longer to reach a retirement odometer X), leading them to be discounted more heavily and hence increase the relative importance of capital costs to carriers. This will directly incentivize them to invest less in FSTs, having significant environmental and economic impacts.

Despite of it importance, few attempts at modeling truck utilization behavior were found in the literature. It is common for truck fleet models to assume that utilization behavior is exogenous and unchanging throughout time. Which is the case in California's EMFAC2011 mobile emission sources model (CARB 2011) and the nationwide NEMES vehicle model (EIA 2012), two important models commonly used for policy analysis. In these trucking models and in others (Vemuganti *et al.* 2007; Kim *et al*., 2004; Redmer 2009), vehicle utilization behavior is determined empirically from surveys of how the industry currently operates. A common feature in all of the utilization functions adopted is that trucks are used less intensely as they age, more concretely that $0 < U''(s)$.

This observation is commonly explained in the literature (Redmer 2009) by pointing out that because older trucks are clearly costlier to operate (have higher maintenance costs for example) they should obviously be used less intensely than newer trucks. However, this argument not precisely correct. The economics of trucking indicate that a vehicle should be operated as long as it is profitable; that is, as long as the discounted sum of all of its revenues is greater (or equal) than the discounted sum of all of its costs. Carriers do not benefit from decreasing the utilization of trucks at any point in their lives because it would simply spread their costs and revenues into the future, gaining nothing in the process. In fact, any costs that increase directly with the size of the fleet should incentivize carriers to use trucks as intensively as possible.

Now, a simple model of the trucking industry is used to illustrate the basic insight that the fact that older trucks are more costly to operate as they age should not directly cause them to be utilized less intensively. This model is set up similarly as Jin and Kite-Powell (2000), who used an optimal control technique to study the replacement and utilization of maritime vessels.

Assume $y(t)$ is the market price [\$/mile] for trucking services, δ is the discount rate, $c[u.U]$ is the operations cost per time period [\$/year], which is a function of both the utilization rate $u(k,t)$ [mile/yr] and the cumulative utilization $U(k,t)$ [odom], of truck k at time t. Note that $u(t) = dU(t)/dt$. Also, assume the rate of truck purchases is $p(t)$ and the rate of truck retirements is $z(t)$. With these definitions, the objective of a trucking company can be specified as choosing $u(k,t)$, $z(t)$ and $p(t)$ in order to maximize profits over a time horizon T . To express this succinctly, the indices of trucks k that operate at t can be described by two cumulative count variables, such that $k \in (N_L(t), N_H(t))$. Therefore, the discounted lifetime profits of the firm can be summed as

$$\int_0^T \left\{ \int_{K_L(t)}^{K_H(t)} \{y(t)u(k,t) - c[u(k,t), U(k,t)]\} dk + z(t)V - A_p p(t) \right\} e^{-\delta t} dt$$

where the first term subtracts operating costs from revenues, the second term sums the salvage value of truck retirements, which for now is assumed to be constant at V [\$/truck], and the fourth term subtracts the capital costs of truck purchases, which for now is assumed to be constant at A_p [\$/truck]. Using the *maximum principle*, as described in Jin and Kite-Powell (2000), the above equation can be optimized over the variables of interest, finding that the optimal utilization of trucks can be described by

$$\dot{u}(t) = \left(\dot{y}(t) - \delta\left(y(t) - \frac{dc}{du}\right) - \frac{d^2c}{dudU}u + \frac{dc}{dU}\right) \Big/ \frac{d^2c}{du^2} \tag{4.1}$$

For a flexible cost function $c(u, U) = u\,[g(u) + f(U)]$, where $g(\cdot)$ and $f(\cdot)$ can be any functions that decompose the operational costs by its component that increases with utilization intensity u (fuel costs, labor costs, etc.) and its component that increases with cumulative utilization U (maintenance costs), expression (4.1) simplifies to

$$\dot{u}(t) = \left(\dot{y}(t) - \delta\left(y(t) - \frac{dc}{du}\right)\right) \Big/ \frac{d^2c}{du^2} \quad . \tag{4.2}$$

This expression indicates that costs that increase with vessel odometer $dc/dU > 0$ do not directly affect u, and only have an indirect effect through $dc(u, U)/du = [g(u) + f(U)] + g'(u)u$. However, if the discount rate is small, this indirect channel disappears, implying that truck owners do not gain any natural cost advantage from operating their vehicles less intensively as they age.

Lastly, note that the TSO model implicitly assumed that $d^2c/du^2 = 0$, which is reasonable for trucking. For $d^2c/du^2 > 0$, trucking costs would have to increase at an increasing rate with the yearly supply of mileage, which is hard to substantiate in the aggregate given that most of the costs that carriers face increase linearly with mileage. This mathematical exercise demonstrates that it is difficult to rationalize from a costs perspective the observation that currently in the trucking industry $\dot{u} < 0$.

A few papers have formulated models of optimal vehicle utilization (or utilization of machines in general) in situations where the demand fluctuates predictively or stochastically. Simms *et al*. (1982) found that the cost structure of bus operations did not warrant utilizing old buses at a lower intensity than new buses, except when the old buses can be used primarily to satisfy peaks in ridership throughout the day. Given that transit capacity shortfalls cause significant costs to society, operating older—more costly buses in this limited role is justified. An analogous story could be conjectured in the trucking industry, where old trucks are used predominantly to satisfy seasonal peaks in the demand of shippers, and therefore accumulate less mileage per year. Similarly, Hartman (2004) studied the optimal replacement and utilization of machines under stochastic demand, and concluded that it is optimal to keep some older more costly machines available to accommodate unexpected peaks in demand. This leads those machines to be utilized less intensely as they aged, because older more costly machines require more severe fluctuations in demand to justify postponing their retirement. Bethuyne (1998) also studied the optimal replacement and utilization of machines, although his conclusions are not readily applicable to the trucking industry because of the types of cost functions used.

Aggregate truck utilization behavior can also be influenced by other factors that have not been studied so far in the literature. Carriers probably give priority to newer trucks when assigning long-haul trips, leading them to accrue more miles. The heterogeneity of competency in the industry is also a factor; some carriers are more sophisticated and operate trucks at a high intensity while others are not as efficient in finding and satisfying shipments. Another factor could be that older trucks spend a greater proportion of their time getting serviced and maintained as opposed to fulfilling shipments.

All of these factors, and others that could be conjectured, are similar in that they do not result from a cost-optimization of operations—equation (4.1) could not have predicted them. Instead, they result from understanding that carriers operate in a highly constrained environment, where they do not have much room to optimize. It is almost always the case that trucking is just one of the many components of complex supply chains, leading their priorities to come behind those of shippers.

This research models truck utilization as resulting from the operational constraints that carriers face, which include the wait time between shipments, the loading time of trailers, the spatial and geographical characteristics of shipments, the time that trucks spend out-of-service, the level of roadway congestion, and the Hours-of-Service regulations, among others. All of these represent constraints that carriers face in the supply of trucking service, and therefore are the critical determinants of how trucks are utilized. These constraints also vary considerably for different types of service.

The TSO model provided a thorough representation of the costs that trucking companies face, but it expressed their constraints in the aggregate in a manner that did not provide much additional insights. The TSTS model seeks to build on the TSO model by specifying the constraints more realistically, considering the spatial distribution of shipment demand and the ability of physically constrained truck fleets to meet this demand. This methodological improvement allows truck utilization to be modeled endogenously, which in turn improves the modeling of inter-temporal investment decisions in this industry. Arguably the most important of which involves the purchase of FSTs, which significantly impacts the costs and emissions of trucking.

4.3 Model Outline

The schematic in *Figure 33* outlines the various components of the TSTS model. At its core lies the same optimization framework used in the TSO model, where carriers select an optimal truck purchase rate P^*, average truck retirement odometer $\bar{X}^*$, and level of investment in FSTs γ^*, in order to minimize discounted average costs y^*. Just as in the TSO model, the sector is assumed to operate competitively in the long-run such that trucking services are priced by the market at the point where discounted average costs are minimized. In addition to these variables, in the TSTS model carriers also select an optimal utilization function $x = U(s)$. These decisions in turn determine the fuel economy and LCA GHG emissions of the sector.

The responses of the sector are modeled based on a vector E that summarizes the costs and regulations that carriers face; a vector T_j that indicates the time it takes the trucking industry to supply a trip of type j; a vector n_j^B that indicates the baseline shipper demand for truck trips of length j, a vector L_j that indicates the length of trips of type j (which is assumed to be the most important characteristic differentiating truck trips); and a parameter ε that relates to the variance of truck retirements. This parameter is used in the TSTS model to capture some heterogeneity in truck retirements, which is an improvement over the TSO model which assumed that all trucks purchased in the same year retire at the same time. More details about all of these variables and parameters are presented in the following sections.

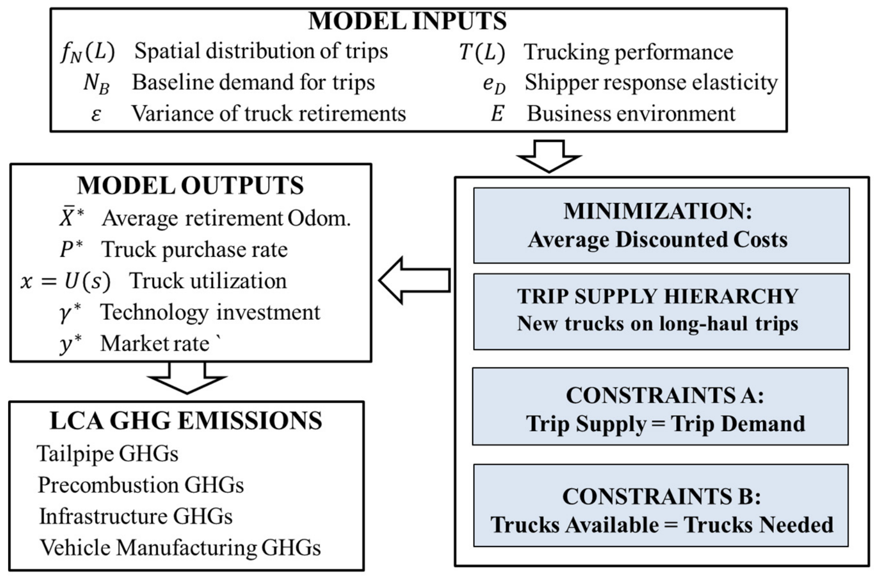


Figure 33: Schematic of the TSTS model

While the TSTS model (as described in the following sections) makes improvements of the TSO model by (i) modeling truck utilization endogenously, (ii) considering the spatial distribution of demand, (iii) considering trucking performance, and (iv) assuming trucks retire probabilistically, it has several limitations relative to the TSO model. The TSTS model (i) is a long-run model that does not track the dynamics of the vehicle stock, and (ii) assumes that mitigation strategies are applied to the whole truck fleet—disregarding issues of policy boundaries. It is theoretically possible to remove the first of these limitations, but because of the addition of new variables the state-space of the problem would have increased significantly beyond our computational capabilities. The problem would have to be reformulated differently, perhaps as a linear program, to be able to be solved. Also, it was not obvious how to model truck utilization in non-steady truck fleets that are changing throughout time to consider the dynamics of the stock of trucks. On the other hand, the second limitation can be eliminated trivially, but it was decided it would not add much to the results while complicating their presentation.

4.4 Carrier Model: Deterministic Truck Retirements

First, the TSTS model is introduced with the simplification that trucks retire deterministically, that is, that all truck purchased in a given year retire at the same time. This is relaxed in the next section.

Instead of specifying shipper's demand for trucking services in the aggregate as D [miles/year] as in the TSO model, the unit of demand is now defined to be the number of truck trips demanded in particular trip segment. Assume that the total demand for truck trips each year in a large area is denoted as N. These trips occur unevenly between a large number of origin-destination pairs. Suppose that trips can be categorized into segments indexed by $j = 1,2, \dots, m$ depending on common characteristics. In this analysis it is assumed that the single characteristic that distinguishes trips is their distance, which is defined as L_j [miles]. The number of truck trips demanded in each segment is n_j [trips/year]. The set of n_j and L_j captures the spatial distribution of trucking demand. By construction assume that $L_{j+1} > L_j$. The demand for trucking mileage in each segment is

$$D_j = n_j L_j \tag{4.3}$$

Carriers meet this demand with a certain performance (time per trip) that is a function of the travel speeds of trucks, the delay due to congestion, the rest schedule of drivers, the waiting time between trip assignments, the loading time of trucks, etc. The performance of carriers is described with a simple function $T(L)$, that indicates the time [in years] required to complete a trip of length L, including all waiting and overhead times. To simply the notation, $T(L_j)$ is replaced with T_j.

The number of trucks F needed in segment j to meet demand n_j is

$$F_j = n_j T_j \tag{4.4}$$

noting that $1/T_j$ is the number of trips of type j that a single truck can supply per year. All downtimes are already included in T_j. The total size of the truck fleet can be found as $\sum F_j$ and the total mileage demand can be found as $\sum D_j$.

A core assumption is that carriers operate trucks differently in each trip segment, essentially segmenting their truck fleet to match the segmentation of shippers demand. As shown in *Figure 34,* truck fleet segments are indexed by $i = 1, 2, \dots, m$ were in this case $m = 3$. Truck operations are stationary (invariant with time), with trucks being purchased at P [trucks /year] and retired at X [odometer]. Trucks are purchased into segment $i = 1$, where they operate exclusively until they reach odometer x_1, and transition to the next segment, $i = 2$. This continues until $X \equiv x_3$, where trucks operate in their last segment and are retired. The reasonableness of this characterization of truck fleets depends on the characteristics of the trucking industry being studied and the coarseness of the segmentation used by the modeler. These issues are discussed in the results section.

The intensity at which trucks are utilized in each segment is defined as u_1 [miles/year]. This figure shows the case where $u_i > u_{i+1}$, which conforms to the empirical evidence that older trucks are driven less intensely.

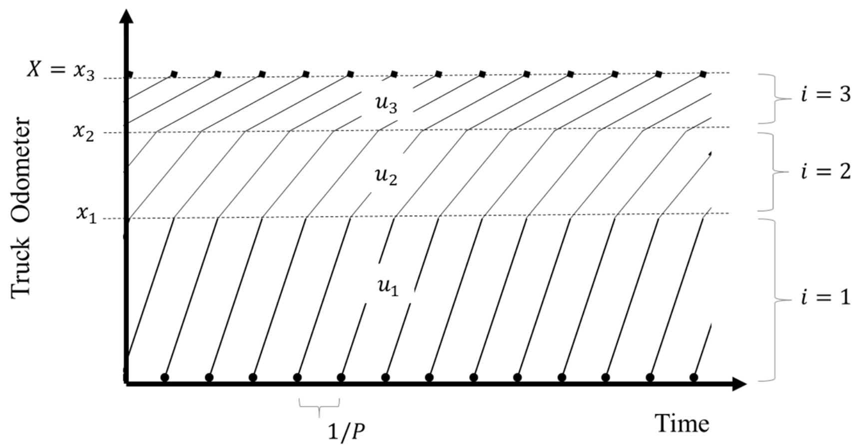


Figure 34: Stationary segmented truck fleet

For this segmented stationary truck fleet the truck utilization function $x = U(s)$ can be described by

$$x_i = \sum_{k=1}^{i} u_k(s_k - s_{k-1}) \tag{4.5}$$

where s_i is the age [years] at which trucks transition from segment i to $i + 1$. Note that x_0, $s_0 = 0$, and that following previous notation the salvage age $S \equiv s_3$.

Using the logic in (2.1), the mileage supplied by segment i of the truck fleet is

$$\psi_i = (x_i - x_{i-1})P \tag{4.6}$$

and using the logic (2.2) the size of truck fleet segment i is

$$F_i = (s_i - s_{i-1})P \tag{4.7}$$

Truck fleet segments i are assigned to demand segments j assuming that newer trucks (lower i) operate in the demand segments with longer trips (higher j). This agrees with empirical evidence (VIUS 2002) which indicates that trucks typically start off their lives providing long-haul interstate service and then are demoted to shorter-haul services as they age. This explains why drayage trucks are on average older. Note that by construction the number of fleet segments must equal the number of demand segments, therefore the correspondence identity can be expressed as

$$i = m - j \tag{4.8}$$

In their operations, carriers need to satisfy two constraints, (I) the demand for trucking mileage in each segment must be met and (II) this demand must be satisfied with a feasible number of trucks. Both of these are related but separate constraints.

Constraint (I) can be formulated by equating (4.3) to (4.6), obtaining

$$n_j L_j \leq P(x_i - x_{i-1}) \tag{4.9}$$

and constrain (II) can be formulated by equating (4.4) to (4.7), obtaining

$$n_j T_j \leq P(s_i - s_{i-1}) \tag{4.10}$$

where the index correspondence is provided by (4.8).

Constrain (4.10) states that enough trucks need to operate in each segment to supply the required mileage, given that each truck can only supply $1/T_j$ trips per year. Dividing (4.9) by (4.10) leads to

$$u_i \equiv \frac{x_i - x_{i-1}}{s_i - s_{i-1}} = \frac{L_j}{T_j} \tag{4.11}$$

which allows us to determine the rate at which trucks need to be driven in each segment as a function of the inputs L_j and T_j.

The truck utilization function $x_i = U(s_i)$ is represented by the parametric equations

$$x_i = \sum_{j=m}^{m-i} n_j L_j / P \qquad s_i = \sum_{j=m}^{m-i} n_j T_j / P \tag{4.12}$$

where P is determined endogenously with the set of x_i and s_i, and with the other variables that carriers control. To do this, the first order conditions for operating in this industry need to be derived.

The stream of profits from operating this truck fleet for one cycle can be expressed as

$$
\begin{aligned}
\pi = P \sum_{i=1}^{m} \int_{x_{i-1}}^{x_i} \beta^{(x/u_i+s_{i-1})} y ds \\
&- P \sum_{i=1}^{m} \int_{x_{i-1}}^{x_i} \beta^{(x/u_i+s_{i-1})} [M(x) \ + O(\gamma)] dx \\
&- PA(\gamma) + P\beta^{s_m} V(\gamma, x_m)
\end{aligned}
\tag{4.13}
$$

where the first term sums the discounted revenues from operating at a market price y [\$/mile] in all segments. The second term subtracts the discounted variable costs of maintaining trucks, which are represented by a function $M(x)$ such that $M'(x) > 0$ and $M''(x) \geq 0$, capturing the fact that trucks get more expensive to maintain as they age, and also subtracts the discounted variable costs of operating trucks, which are represented by a function $O(\gamma)$ such that $O'(\gamma) < 0$, where $\gamma \in [0,1)$ is a scalar representing the proportion of fuel consumption saved by investments in FSTs. The third term subtracts the capital costs of trucks, which are represented by a function $A(\gamma)$, where $A'(\gamma) > 0$ and $A''(\gamma) > 0$, such that there are diminishing returns to investing in additional FSTs. The purchasing price of a truck without FSTs is $A(0) = A_p$. The final term sums the discounted salvage value of retiring trucks of technology γ at odometer x_m, which are represented by a function $V(\gamma, X)$.

Similarly as in the derivation of (2.5), the trucking industry is assumed to operate competitively in the long-run, such that carriers will operate at the point where discounted average costs are minimized, which can be found by equating to zero the partial derivatives of

$$
y = \frac{\sum_{i=1}^{m} \int_{x_{i-1}}^{x_i} \beta^{(x/u_i+s_{i-1})} [M(x) \ + O(\gamma)] dx + A(\gamma) - \beta^{s_m} V(\gamma, x_m)}{\sum_{i=1}^{m} \int_{x_{i-1}}^{x_i} \beta^{(x/u_i+s_{i-1})} dx}
\tag{4.14}
$$

while making sure that constraints (4.9) and (4.10) are satisfied, and with s_i, x_i and u_i coming from (4.12) and (4.11) respectively.

Even though an analytical solution was not found for this problem using various specifications of $M(x)$, $O(\gamma)$, $A(\gamma)$ and $V(\gamma, X)$, it can be solved numerically easily.

Note that truck utilization enters into (4.14) through the discounting of the costs only. As explained before, truck utilization behavior does not affect costs if there is no discounting, however, there are good reasons to believe that trucking companies do discount the future heavily, especially for decisions that are made across decades, leading truck utilization to affect their operations significantly.

The optimized y^* represents the long-run market price for trucking services.

4.5 Carrier Model: Probabilistic Truck Retirements

The model presented in the previous section departs from reality in that it assumes that trucks retire deterministically. In reality, trucks purchased in the same year are observed to retire at different ages. This section describes a simple methodology for capturing some of this retirement heterogeneity using a survivability function in which trucks are assumed to retire following a log-logistic distribution. The survivability function

$$\omega(x; \alpha, \varepsilon) = 1 - \frac{1}{1 + \left(\frac{x}{\alpha}\right)^{-\varepsilon}}$$

indicates the proportion of trucks that have retired at odometer x, where α and ε are parameters that can be fitted to data. However, in this model, parameter α is determined endogenously from the carrier optimization of the average retirement odometer $\bar{X}$. Using the derivation for the expectation of log-logistic distributions, the survivability function is rewritten as

$$\omega(x; \bar{X}, \varepsilon) = \frac{1}{1 + \left(k_\omega \frac{x}{\bar{X}}\right)^{\varepsilon}} \qquad (4.15)$$

where $k_\omega = \pi / \left(\varepsilon \, sin\left(\frac{\pi}{\varepsilon}\right)\right)$.

Figure 35 shows three truck survivability functions with different values for the parameter ε. For the case where $\varepsilon \to \infty$ all the trucks purchased in a certain year retire at the same time, resulting in the same truck retirement behavior as in the TSO model. As ε decreases trucks will retire at a greater diversity of odometers. Note that survivability is specified to be a function of truck odometer and not age, because the underlying processes that determine when trucks are retired are assumed to correlate more strongly with their odometer.

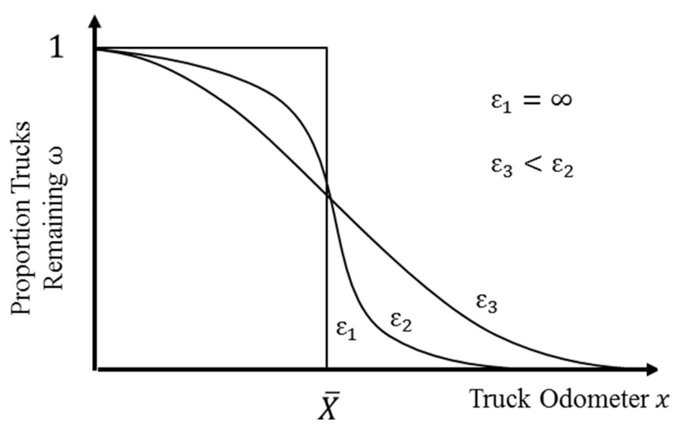


Figure 35: Truck survivability functions

Now, the truck survivability function can be incorporated into the model described in the previous section. Constraints (4.9) and (4.10) can be rewritten as

$$n_j L_j \leq P \int_{x_{i-1}}^{x_i} \omega(x; \bar{X}, \varepsilon) dx \tag{4.16}$$

and

$$n_j T_j \leq P(s_i - s_{i-1}) \left(\frac{\int_{x_{i-1}}^{x_i} \omega(x; \bar{X}, \varepsilon) dx}{x_i - x_{i-1}} \right) \tag{4.17}$$

respectively. The fraction within the parenthesis in (4.17)—which is always be lower than unity—captures the effect of truck retirements on the availability of trucks to satisfy demand. As $\varepsilon \to \infty$ these equations collapse to (4.9) and (4.10) as expected.

The discounted average costs in (4.14)(4.14)can be rewritten as

$$y = \frac{A(\gamma) + \sum_{i=1}^{m} \int_{x_{i-1}}^{x_i} \beta^{(x/\varphi_i + s_{i-1})} \left[\omega(x; \bar{X}, \varepsilon)[M(x) + O(\gamma)] - \frac{d\omega(x; \bar{X}, \varepsilon)}{dx} V(\gamma, x) \right] dx}{\sum_{i=1}^{m} \int_{x_{i-1}}^{x_i} \beta^{(x/\varphi_i + s_{i-1})} \omega(x; \bar{X}, \varepsilon) dx} \tag{4.18}$$

where $-d\omega(x; \bar{X}, \varepsilon)/dx$ represents the probability distribution of trucks retiring at odometer x. Invoking the same assumptions used in the previous section, this trucking industry will operate at the point where y is minimized, and constraints (4.16) and (4.17) are satisfied.

4.6 Carrier Performance

Earlier it was stated that T_j can be derived from a performance function $T(L_j)$ that returns the time required to complete a trip of length L_j, including all overhead times of assigning the truck to a shipment, loading it, etc. In this section we describe a simple model of trucking performance that can be used to describe this function.

Truck performance is specified as the piecewise function

$$T(L) = \begin{cases} \left(w^{SH} + \dfrac{L}{v^{SH}}\right)/\sigma^{SH} & L \leq L^e \\ \left(w^{LH} + \dfrac{L}{v^{LH}}\right)/\sigma^{LH} & L > L^e \end{cases} \tag{4.19}$$

where $L^e = (w^{SH}\sigma^{LH} - \sigma^{SH}w^{LH})/\left(\frac{\sigma^{SH}}{v^{LH}} - \frac{\sigma^{LH}}{v^{SH}}\right)$, so that $T(L)$ is continuous. L^e is a threshold distance that distinguishes shorter-haul operations from longer-haul operations, which captures the fact that the performance of short-haul trucking is likely to be fundamentally different to that of long-haul trucking. The waiting time w is the fixed time per trip spent assigning a trip to a truck, loading a truck, etc. The trip speed v is the on-road speed at which trucks are driven, including congestion, intermediary stops, etc. Variable σ represents the proportion of a day that trucks are in operations. For long-trucking this last parameter will be affected by the Hours-of-Service regulations that presently exist in the US. For short-haul trucking this variable would depend on whether trucks are utilized at night and on other constraints.

4.7 Shipper Model and Equilibrium

In this model shippers are represented similarly as in the TSO Model (described in *Section 2.1.3).*The main difference is that shipper response elasticities need to be specified for the unit of demand of this model, which is the number of truck trips demanded in different market segments.

The number of truck trips demanded in each segment n_j can be found through the identity

$$n_j = \frac{Q_j}{v_j} \tag{4.20}$$

where Q_j is the quantity of goods shipped by truck [tons/year] and v_j is the shipment size [tons/trip]. The elasticity e_n^j, which indicates how the number of truck trips demanded in each segment j changes *w.r.t.* the trucking market price y, can be derived from (4.20) as

$$e_n^j = e_Q^j - e_v^j$$

where e_Q^j is the elasticity of changes in the quantity of goods shipped *w.r.t.* trucking costs and where e_v^j is the elasticity of changes in the shipment size *w.r.t.* trucking costs. There exist many empirical studies that attempt to estimate e_Q^j through various econometric techniques. However, there are much fewer, if any, empirical studies into e_v^j. Therefore, a simple Economic Order Quantity (EOQ) model of inventories was used to provide a reasonable estimate of e_v^j. By minimizing per-ton transportation costs and inventory costs the optimal shipment size in each segment j can be derived as $v_j^* = \sqrt{yL_j 2Q_j/\phi_j}$, where ϕ_j [$/year-ton] is a measure of the time-costs of holding inventories. Substituting v_j^* into (4.20), n_j can be expressed as

$$n_j = \left(\frac{Q_j \phi_s}{2yL_j}\right)^{1/2} \tag{4.21}$$

Solving for $e_n^j = \frac{dn_j}{dy}\frac{y}{n_j}$ using e_Q and e_L results in

$$e_n^j = -\frac{1}{2} + \frac{1}{2}\left(e_Q^j - e_L^j\right) \tag{4.22}$$

where e_L^j captures the effect of decreasing shipment sizes as the length of trips decreases with trucking costs. Using the fact that the elasticity of ton-miles is defined as $e_K = e_Q + e_L$, (4.22) can be rewritten as

$$e_n^j = e_Q^j - \frac{1}{2} - \frac{1}{2}e_K = e_Q^j - e_D^j - 1 \tag{4.23}$$

Therefore, the elasticity of trip demand (n) can be approximated from estimates for the elasticity of tons shipped (Q) and elasticity of ton-miles shipped (K), which are two parameters commonly estimated in the literature.

Using this approximation, for reasonably small changes in trucking costs y, the demand function for truck trips in each segment can be specified as

$$n_j = n_j^B \left(\frac{y}{y_B}\right)^{e_n^j} \tag{4.24}$$

The equilibrium between shippers and carriers is obtained by solving the carrier and shipper models iteratively as described in *Section 2.1.4.*

5 California Case Study: TSTS Model

Three case studies are presented that demonstrate the ability of the TSTS model to analyze: (i) the interrelationships between FST investments and the management of truck fleets (FMO and LDS responses), (ii) the impact of mode-shifts on the optimal management of truck fleets (FMO and LDS responses), and (iii) the effectiveness of FST regulations with odometer cutoffs.

The analysis in (i) is possible because the model represents how carriers make decisions about the utilization of their vehicles, which affects time related costs and intertemporal tradeoffs (FST investments); the analysis (ii) is possible because the model represents trucking operations and shipper demand spatially, which are affected differentially by mode-shifts; and the analysis (iii) is possible because the model represents some of the heterogeneity in truck retirements, and thus is able to capture better the proportion of trucks that fall under particular regulations. The TSTS model allows us to study aspects of the trucking sector that could not be studied with the TSO model.

5.1 Data Sources

There are several types of data needed to furnish this model, including data on the costs that carrier's face, data on the performance of truck fleets to supply trucking services of different types, and data on the spatial distribution of demand. Each of these types of data are discussed in detail in the following sections.

5.1.1 Spatial Distribution of Demand

As described in the previous section, the demand for trucking is now specified for each trip type j as the number of trips demanded n_j and the average driving distance of these trips L_j. Data on particular truck trips is not available in the US, but it can be reasonably approximated using data on the flow of commodities and the average truck payloads of shipping these commodities. The most complete commodity flow data publicly available in the US is the Freight Analysis Framework v2.2 (FAF2.2) prepared by Federal Highway Administration. This dataset, which builds on the Commodity Flow Survey dataset, contains an estimate of the tons and value of commodities shipped by truck (and other modes) between over one hundred zones in the US. However, all shipments to and from

California are aggregated in just 4 zones within the State. This makes it very difficult to use this dataset to study the characteristic of the demand for trucking in California. Fortunately, Cambridge Systems (2009) disaggregated these commodity flows to the county level using socioeconomic data. This enhanced dataset is used to develop a reasonable estimate of n_j with refined spatial attributes.

More precisely, the disaggregated FAF2.2 dataset provides an estimate of the tonnage T of commodities c that is shipped from origins o to destinations d using various transportation modes. Just considering shipments made by truck to and from zones in California, the FAF2.2 dataset can be represented with parameters T_{odc}. An external dataset was then used to obtain the distances between all of the origins and destinations in this survey; this information was represented with L_{od}. Data from Alam and Rajamanickam (2007), shown in *Table 7,* was used to determine the average shipment size for different commodities, which is represented with V_c.

Table 7: US average payloads for 5-axle combination trucks (Alam and Rajamanickam 2007)

SCTG2	*Commodities*	*Average Payload (Tons)*	*SCTG2*	*Commodities*	*Average Payload (Tons)*	*SCTG2*	*Commodities*	*Average Payload (Tons)*
1	Live animals/fish	20.8	15	Coal	24.4	29	Printed prods.	17.8
2	Cereal grains	24.8	16	Crude petroleum	21.5	30	Textiles/leather	22.0
3	Other agricultural prod	20.9	17	Gasoline	27.0	31	Nonmetal min. prods.	23.9
4	Animal feed	22.3	18	Fuel oils	26.0	32	Base metals	20.3
5	Meat/seafood	21.8	19	Coal-n.e.c.	24.4	33	Articles-base metal	20.0
6	Milled grain prods.	20.4	20	Basic chemicals	22.0	34	Machinery	18.8
7	Other foodstuffs	21.8	21	Pharmaceuticals	15.6	35	Electronics	19.8
8	Alcoholic beverages	21.9	22	Fertilizers	22.7	36	Motorized vehicles	18.2
9	Tobacco prods.	21.2	23	Chemical prods.	22.8	37	Transport equip.	22.5
10	Building stone	20.9	24	Plastics/rubber	19.1	38	Precision instruments	17.5
11	Natural sands	23.6	25	Logs	24.8	39	Furniture	18.7
12	Gravel	22.8	26	Wood prods.	21.7	40	Misc. mfg. prods.	23.6
13	Nonmetallic minerals	23.9	27	Newsprint/paper	21.1	41	Waste/scrap	21.5
14	Metallic ores	26.2	28	Paper articles	20.4	43	Mixed freight	19.5

Many different types of trucks can be used to transport the commodity flows in FAF2.2, but we are only interested in those trucks that are part of the Core T7 fleet. Therefore the data shown in *Figure 36* was used to determine the proportion of truck trips that are performed by this specific truck type. A variable $p_h(L)$ was defined that indicates the proportion of truck trips at a certain trip length L that are performed by trucks of type h. Finally, data from Alam and Rajamanickam (2007) shows that the proportion of trips performed by class-8 heavy duty trucks that are empty is $r_e = .19$.

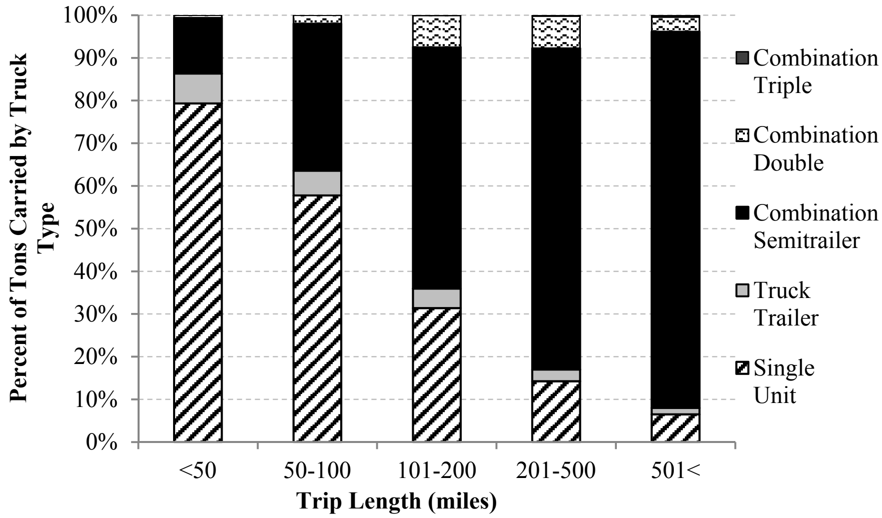


Figure 36: Nationwide composition of truck type by trip length (Battelle 2011)

The process to estimate n_j can be summarized by

$$n_j = \sum_{\forall od|L_{od} \in l_j} \sum_{\forall c} \frac{1}{1 - r_e} T_{odc} p_k(L_{od})/V_c \tag{5.1}$$

where $\forall od|L_{od} \in l_j$ identifies set of origin-destination pairs od that have a length L_{od} that lies within the trip length segment l_j. By assuming trip length segments that are relatively fine (almost continuous) we can use the approach summarized in (5.1) to estimate the distribution of truck trips by trip length and distribution of trucking mileage by trip length. The cumulative distributions of both of these types of data are shown in *Figure 37.* From these two figures it is clear that while intercity trips within California are responsible for the bulk of numbers of trips made, that interstate trips account for most of the mileage from this truck fleet. In fact, the mileage demand for intracity trips in California (short-haul drayage) is almost insignificant.

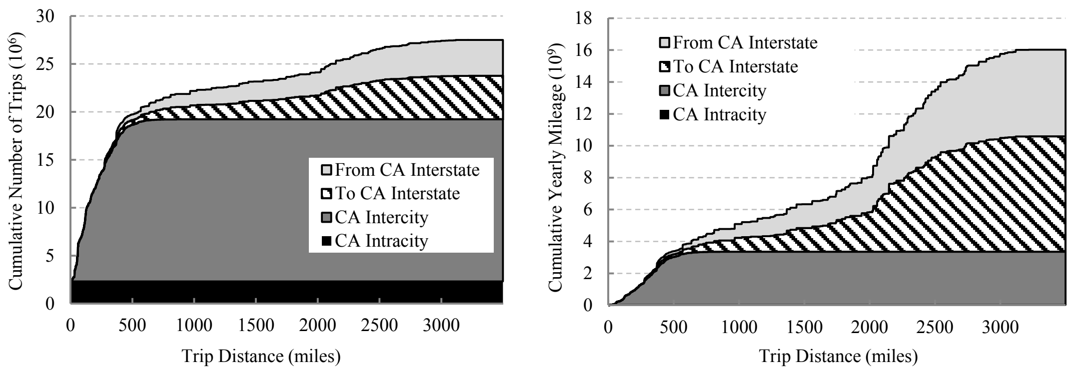


Figure 37: Distributions of a) trip demand and b) mileage demand by trip distance

To reduce the size of the optimization problem (to be able to run various policy scenarios with reasonable runtimes), the demand information shown above was discretized into three segments: trips shorter than 100 miles, trips longer than 100 miles but lower than 500 miles, and trips longer than 500 miles. These trips distances were selected because they represent soft thresholds across which trucking operations are different. Truck trips less than 100 miles are most often drayage trips between ports, intermodal facilities, retail outlets, and regional distribution centers. These trips some shared characteristics. The second threshold was selected at 500 miles because this is the distance that trucks typically cover in 1 day, and because *Figure 37* shows a kink at this distance. This discretization was also used to specify the shipper response elasticities. This three-level discretization produced similar result to finer ones for the circumstances of this study.

5.1.2 Cost Data

The TSTS model uses the same cost data described in *Section 3.1* and summarized in *Table 3.* The only difference is that now truck fuel economy was assumed to improve at 1% per year.

5.1.3 Truck Performance

The parameters used to characterize the truck fleet performance function (4.19) were determined by starting off with averages calculated from the VIUS (2002) and then calibrating them to match the truck utilization behavior observed in the EMFAC 2011 inventory model. The parameters selected are shown in *Table 8.*

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Table 8: Parameter values of trucking performance

Parameters	*Short-Haul*	*Long-Haul*
Waiting time per trip w [hrs/trip]	5.0	18.4
Commercial speed v [mi/hr]	20.1	40.0
Proportion of use σ [unitless]	0.5	0.4

The commercial speed of short-haul trucking is smaller than that of long-haul trucking because those trucks spend a greater proportion of their operations in urban centers, being slowed down by congestion and driving slower on arterial roads. Long-haul trucks still face some congestion, but trucks are able to average higher speeds on rural highways. Their commercial speed should consider the truck stops and weight checks that are not already captured explicitly by σ. Lastly, the waiting time per trip for short-haul trucking is smaller than for long-haul trucking because they are more often providing a recurring service (drayage operations), reducing the time for assigning trips and loading merchandise. Long-haul trucking have longer wait times per trip, because trips are less frequent and usually not recurring. Also, shipments are likely to be larger, taking more time to load the truck.

As described above, parameter σ represents the proportion of time that trucks are used throughout the day. Therefore, the values in *Table 8***Figure 8** imply that short-haul and long-haul trucks only make deliveries throughout the day time. Unless there exists a specific night delivery program—like the one that has been very successful in New York City—it is reasonable to assume that short-haul trucks do not operate at night. On the other hand, in the US, long-haul truckers have Hours-of-Service regulations that limit the number of hours that truckers can operate their vehicles. These regulations are somewhat complex, with various exemptions and rules, but the end result is that long-haul trucks can only be operated for about 40-35% of the time (with some exceptions). Therefore its value of σ was assumed to be 0.4.

The truck fleet performance function described above represents a reasonable approximation of the ability of California's heavy-duty truck fleet to service shipments. Future research could develop more complex truck fleet performance functions that incorporate information about local geography, local speed limits, local congestion and local trip assignment procedures, etc. These functions can also capture heterogeneity in trucking operations by specifying a distribution for the relevant parameters. Some information about the performance of truck fleets is available in the discontinued VIUS (2002) dataset. However, a new survey is required to better specify this part of the model, without it, these values suffice to demonstrate the methodologies.

5.1.4 Dispersion of truck Retirements

As described in *Section 4.4,* one of the key advantages of the TSTS model is the ability to capture some heterogeneity in truck retirements by assuming that truck survival follows a log-logistic distribution. This distribution of truck retirements has an expectation of $\bar{X}$, by construction, and a variance that is a function of both $\bar{X}$ and a parameter ε. So, for any given variable $\bar{X}$ (which is being optimized in the TSTS model), the variance of truck retirements is determined by ε. The analyst should calibrate and tweak ε, in conjunction with the truck performance parameters in *Table 8,* so that the model best predicts responses in the trucking industry.

Figure 38 compares the operations of the operations of the trucking industry in the TSTS model under various assumptions of ε to the operations of the trucking industry in reality as seen in the EMFAC 2011 model. The figure on the left shows the proportion of trucks remaining after a certain odometer and the figure on the right shows the utilization rate φ of trucks as they age. The TSTS model results were obtained using the cost parameters shown in *Section 5.1.2* and performance parameters in *Table 8*. In this figure it can be seen how i) the TSTS model captures some of the heterogeneity in truck retirements currently observed (albeit not all of it)[5], and ii) is able to reproduce very accurately the truck utilization behavior currently observed. Further tweaking of ε, w, v and σ should achieve even better results.

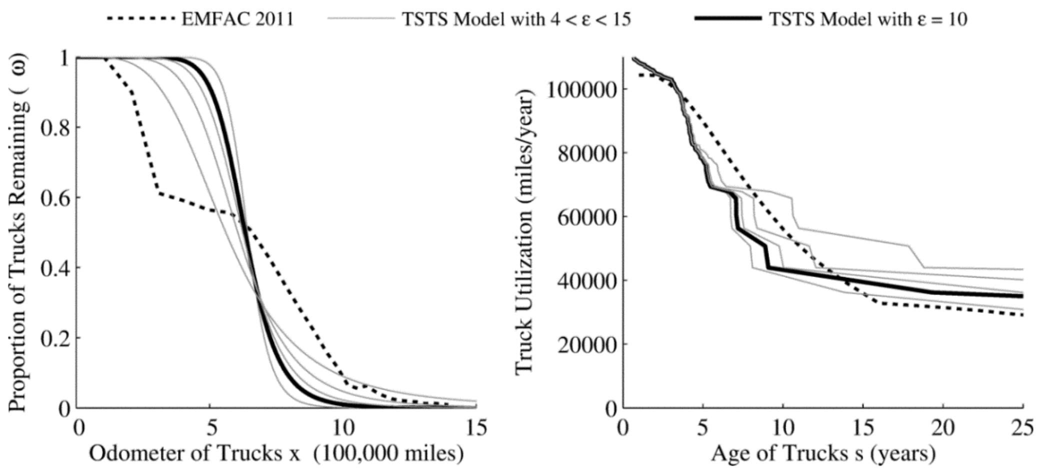

Figure 38: Comparison between EMFAC 2011 model and TSTS model for different values of ε

5.1.5 Shipper Elasticity

An understanding of how e_n^j varies with trip length can be developed by using the relationship $e_n^j = e_Q^j - e_v^j$ shown in *Section 4.6.* Realistic values of e_Q^j should be negative while realistic values of e_v^j should be positive, because $v^* \propto \sqrt{y}$. A reasonable assumption that can be made is that e_Q^j is more negative for longer-haul trips than for short-haul trips, because: (1) in these trips there exist more opportunities for mode-shifts, especially to railroads, and (2) the trucking costs incurred in these trips are probably a larger component of total supply chain costs. On the other hand, it is likely that e_v^j is less positive for longer-haul trips because a greater proportion of them will be weight constrained, as $v_s^* \propto \sqrt{L_j}$.

The shipper response elasticity parameters used in this analysis can be found in *Table 9.* These values were detemrined based on the qualitative understanding of shippers responses outlined above and engineering judgement. Future studies should invest more effort on attempting to estimate these paramters using behavioral data or on surveying the literature

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[5] The very sharp retirement of trucks in the EMFAC 2011 model seems implausible in reality.

to get more acurage values. However, the values in this table represent reasonable approximations that allow us to demostrate the usefulness of some of the more innovative components of the TSTS model.

Table 9: Shipper Responsiveness in TSTS Model

j	L_j Range (mi)	e_Q^j	e_v^j	e_n^j
Short-Haul	0 - 100	0	0.3	-0.3
Medium-Haul	100 - 500	-0.5	0	-0.5
Long-Haul	500 +	-1.0	0	-1.0

These elasticities can now be used in equation (4.24) to characterize responses in the demand for truck trips with changes in the market price y. Note that in this model all truck trips face the same market price y [$/mile]. This represents an approximation because in reality it is observed that the per-mile price of long-haul transportation is different than that of short-haul transportation. This market price could also vary geographically and with the characteristics of the trucks. However, in this version of the model it is assumed that trucks are owned by only one carrier throughout their lives, and that carriers determine the market price for trucking services based on their anticipated operations of that truck throughout its life. Under these assumptions, carriers would not gain from varying the market price strategically by trip-type because they face all of the costs that the truck will incur.

5.2 Analysis of Mitigation Strategies

5.2.1 Improvements in Trucking Performance

This case study explores the effect that changes in the performance of trucking can have on their investments in FSTs, and ultimately on their GHG emissions. Most truck mileage (and fuel combustion) occurs on long-haul trips. Therefore, this case study focuses on the impacts of changing the long-haul portion of the performance function, which can occur by improving highways, reducing congestion, better coordinating shipments and reducing loading times. Operations are observed in the year 2020 because this represents a long-term model of the sector. *Figure 39* summarizes the impact of these changes on GHG emissions. As trucking performance improves, with either v_{LH} increasing or w_{LH} decreasing, the life-cycle GHG emissions of the sector decrease. Note that changes in v_{LH} are plotted on the left vertical axis and changes in w_{LH} are plotted on the right vertical axis. The results are shown for different discount factors, because as mentioned earlier, there are many indications that trucking companies discount the future heavily, impart because of existing market failures. Future research should attempt to quantify this discount factor empirically.

Before delving into the reasons behind these responses, it is interesting to note that their magnitude as shown in *Figure 39* is quite significant. The total GHG emissions in 2020 of

California's HD truck fleet have been estimated to be 123.4 MMTCO2 (EMFAC 2011). Even modest changes in trucking performance reduce emissions by several percentage points.

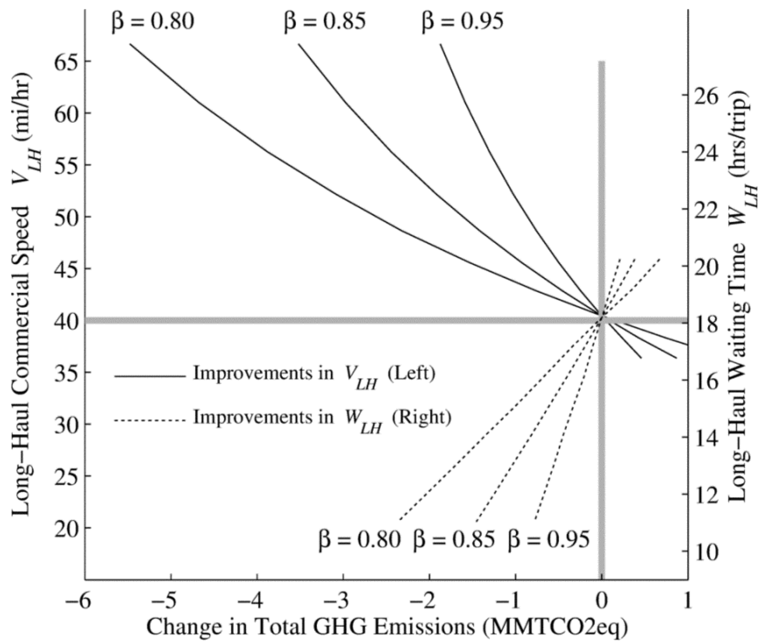

Figure 39: Reductions of GHG emissions from improvements in long-haul trucking performance in 2020

As expected, *Figure 39* clearly shows that if carriers discount the future more heavily (lower discount factor) the changes in trucking performance have a greater effect on emissions. This occurs because the time savings that result from improving trucking performance will affect trucking operations more as time becomes more costly. This figure also shows how the effect of improving v_{LH} is proportionally higher than improving w_{LH}; because of this, the remainder of this paper focuses only on improvements in v_{LH}.

Changing v_{LH} will have the most direct impact on truck utilization. *Figure 40* shows that indeed, increasing v_{LH} will allow trucks to supply more mileage per year, as they complete trips quicker. The utilization function in this figure has three discrete steps corresponding to the shipment demand discretization introduced earlier. Note that only the utilization intensity of trucks in the first segment increases, because these are the trucks involved in long-haul transportation that benefit from improvements in v_{LH}. For the other segments, the rate at which trucks can supply miles does not change. However, the ages at which trucks transition from one segment to another s_i do change, because at higher initial utilization rates trucks can meet the demand for trips sooner.

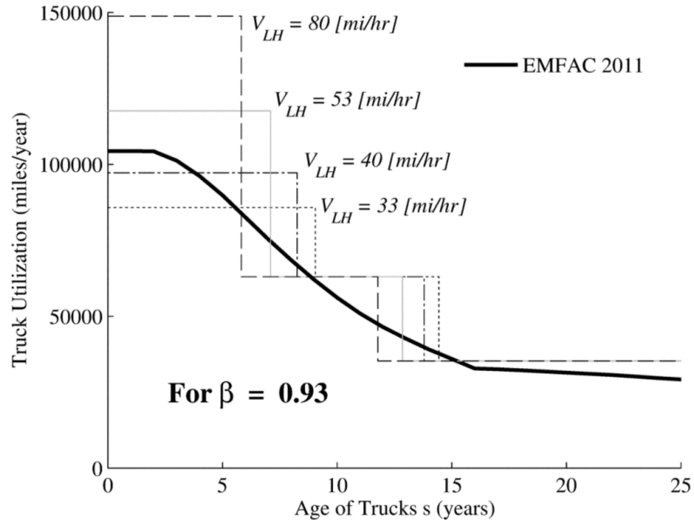

Figure 40: Effect of long-haul commercial speed on truck utilization

Changes in truck utilization will affect the decisions that carriers make because future costs will be weighed differently. *Figure 41* contains four contour plots that describe, for different discount factors, the effect that changes in v_{LH} will have on (a) GHG emissions, (b) truck purchases, (c) average fleet fuel economy and (d) mileage demand. Through these plots three channels can be identified for how increases in v_{LH} impact GHG emissions.

First, it reduces the time-costs from discounting, because trucks can reach their optimal retirement odometer sooner in time. This results in a lower market price y, which leads shippers to demand more trucking services as seen in *Figure 41d*. This 'rebound' effect will offset some of the reductions in emissions achieved through the other channels discussed below. The simple shipper model used assumes that shippers only care about y, when in reality they also care about shipping times. In this respect, increasing v_{LH} will lead to even larger demand responses because shipping times are also being reduced at the same time that y is being reduced. This additional channel should be explored in future research, because it could end up being very significant.

The second and third channels have the effect of reducing emissions. The strongest of these relates to the increase in average fuel economy seen in *Figure 41c*. This occurs because speeding up the utilization of trucks leads carriers to value more the future fuel savings that can be achieved with investments in FSTs, because they occur sooner and are therefore discounted less heavily. On the other hand, the weaker channel that affects emissions, relates to changes in the truck purchase rate P precipitated by changes in both the optimal average truck retirement $\bar{X}$ and the demand for trucking D, through the relationship $P = \psi/\bar{X}$, were at equilibrium $D = \psi$. Both $\bar{X}$ and D are changing endogenously with v_{LH}, but have an indeterminate impact on P because the fraction $\psi/\bar{X}$ can increase or decrease. For the cost parameters used in this model, this crossover of responses occurs at around $\beta \approx 0.85$.

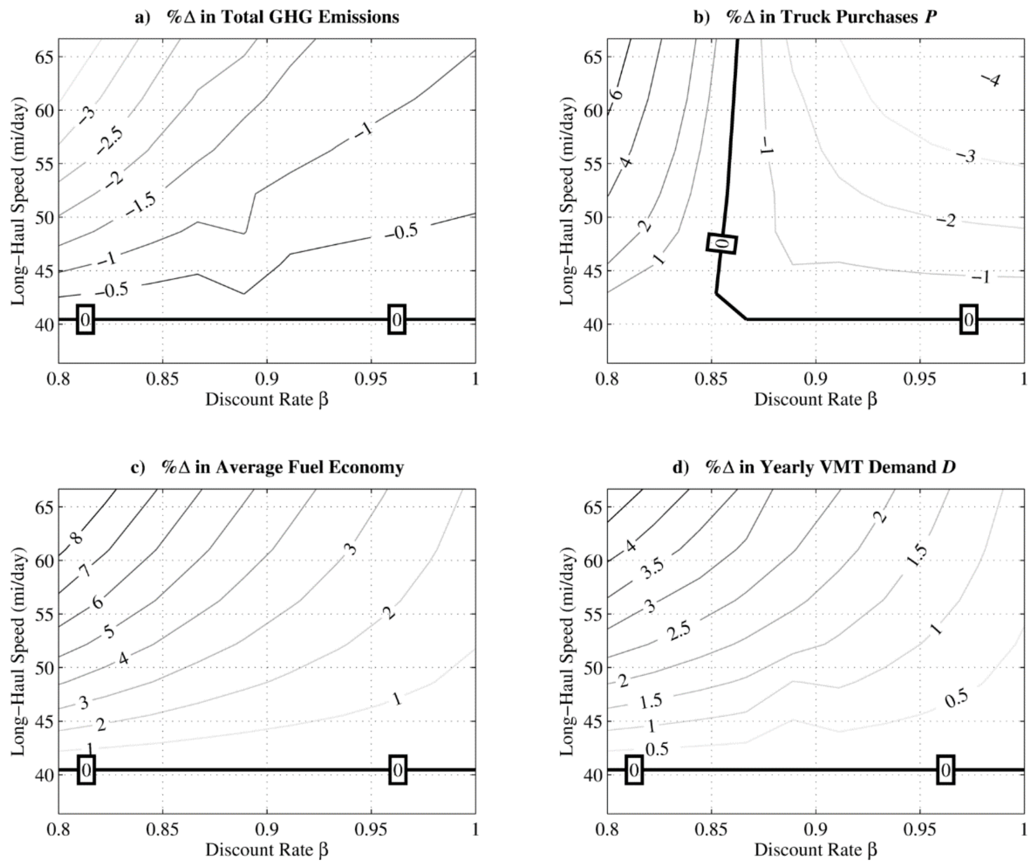

Figure 41: Industry responses with improvement in long-haul speed

The reduction of emissions shown in *Figure 41a* are of the order of magnitude of other strategies that have been considered in the literature. And in fact, based on data from *Figure 41c* and *Figure 41d* it can be calculated that the latent demand responses offset from 40 - 50% of the emission reductions that result from improvements in fuel economy. However, the value of these results goes beyond suggesting opportunities for reducing emissions. They also demonstrate the ability of the TSTS model to (i) predict responses in truck utilization, (ii) capture the effect of some market failures on the operations of the trucking sector, (iii) capture some heterogeneity in truck retirements, and (iii) link truck performance to long-term investment decisions. These represent significant improvements over the TSO model and over the broader research literature in general.

5.2.2 Mode shifts

Shifting shipments from the truck mode to other modes (primarily rail) will also affect how carriers manage their truck fleets in two important ways, one obvious and one not so obvious. The obvious impact will be that the total demand for trucking will be reduced, decreasing truck VMT and GHG emissions from all sources. Mode-shifts will also cause secondary impacts on the truck fleet by changing the spatial distribution of demand. The values in *Table 9* summarize the understanding that mode-shifts are more likely to happen in longer trips. This is because trucking companies compete more directly with railroads for these types of shipments. Therefore, disproportionate reductions in long-haul trips vs. short-haul trips will change the distribution of trip types that trucks have to supply throughout their lives, which will change how carriers should use trucks optimally.

First, we need to determine how the spatial distribution of demand will change with mode-shifts. For this, we utilize the FAF2.2 dataset described in *Section 5.1.1.* This data allows us to compare the competitiveness of railroad transportation and trucking transportation for different OD pairs for each commodity. The simple approach taken here is to identify all of the commodity flows for which the mode-split of trucking is less than a certain value r_e,

$$\frac{T_{odc}}{R_{odc} + T_{odc}} < r_e \qquad \forall\, odc \tag{5.2}$$

and shift these flows to rail. As r_e is increased from 0 to 1 and competitive flows are identified, an estimate for how mode-shifts affect the distribution of trucking demand can be obtained. The main assumption of this estimate is that the first commodity flows to shift from truck to rail will be those that are most competitive. More elaborate methodologies could be used to generate mode-shift scenarios that are more realistic, but the approach described above suffices for the purpose of this dissertation. The resulting distributions of trip demand for four different mode-shift scenarios are shown in *Figure 42.* Here we can observe that, indeed, mode-shifts occur primarily in long-haul transportation.

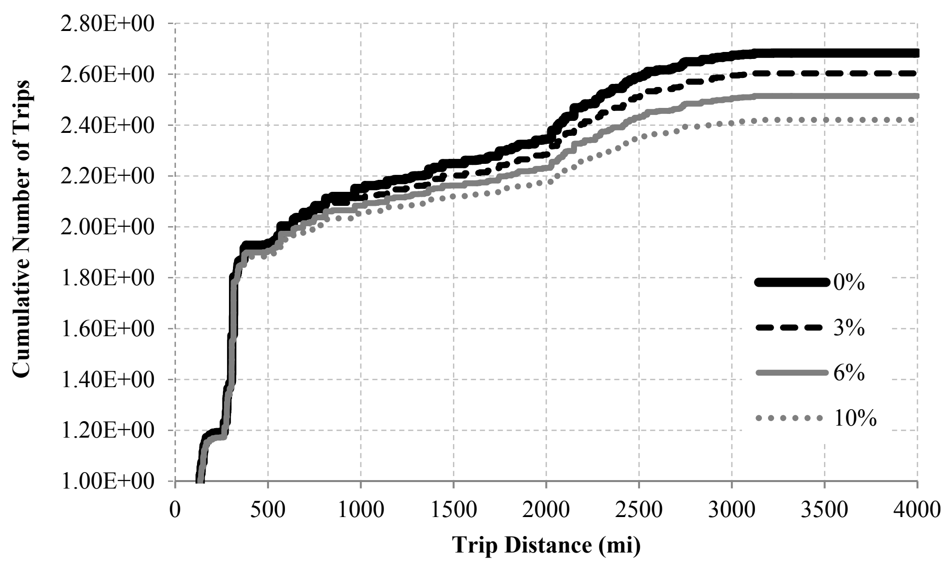

Figure 42: Trip distribution after different mode-shifts

The TSTS model is then used to evaluate how carriers might react to these different demand scenarios. The results are shown in *Figure 43.* The biggest responses that we observe is that the total mileage demanded *D* of carriers will decrease substantially. At the point where 10% of shipments made by truck are diverted to rail you see that aggregate trucking mileage has decreased by around 25%. This is because long-haul shipments are diverting more readily.

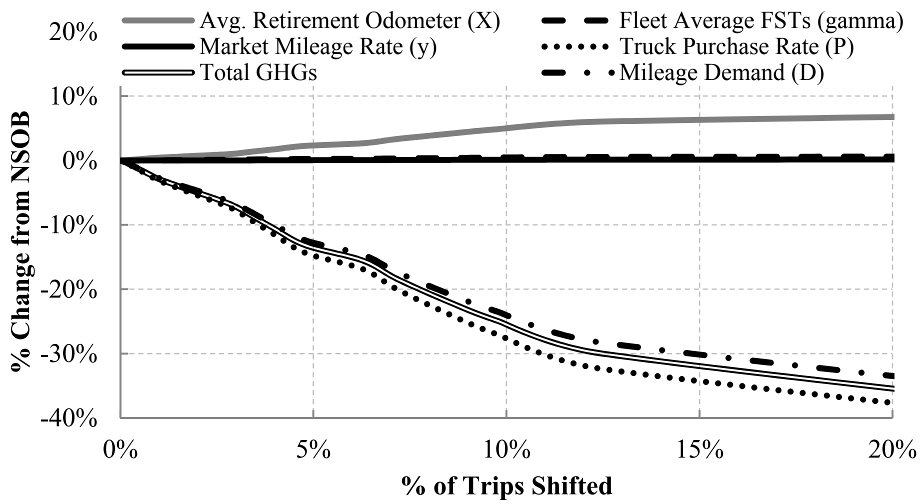

Figure 43: Effect of mode-shifts on trucking operations

From *Figure 43* we also see that truck purchases decrease slightly more than the demand for trucking mileage. This can be explained by the fact that the changing distribution of trucking demand leads carriers to retire trucks at a higher average odometer $\bar{X}$ than before. In *Figure 44* we observe that trucks are spending more of their mileage providing medium-haul trips which occur later in life.

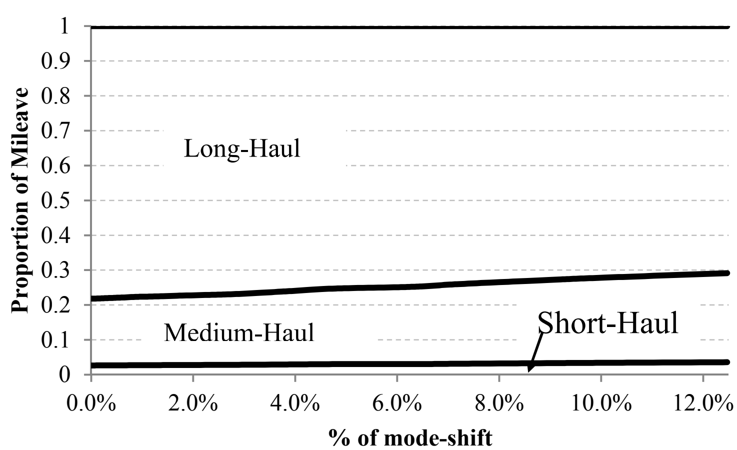

Figure 44: Proportion of mileage by trip type

5.2.3 *Regulation of FSTs with Yearly Mileage Cutoff*

In California a regulation was passed recently that requires all Class-8 trucks that operate within the state to be equipped with a certain degree of FSTs starting 2014 (this was modeled after a nationwide voluntary program that is currently run by the EPA). For now, the required level of FST investments is roughly equivalent to $\gamma = 0.11$. However, an exemption was added to the legislation such that trucks that are utilized less than 50,000 mile per year are exempt from this requirement (this cutoff utilization was increased from a lower level after industry backlash).

The TSTS model can be used to analyze the effectiveness of this policy because it considers explicitly the decisions that carriers make about truck utilization and models truck retirements with a survivability curve. *Figure 45* shows how this model would predict the industry would operate under policy scenarios where the FST regulation takes values of 0.11 and 0.25 and the yearly mileage cutoff takes values of 40,000 mi/yr and 72,000 mi/yr. This figure has four subplots that show how trucks are used at different points in their service lives $U'(s)$. Subplot a) is shows how the utilization intensity of the trucks (mi/yr) changes as the truck age and are used to supply shorter haul trips, accruing mileage less intensely. Subplot b) shows the proportion of trucks that have survived up to a given odometer; these curves follow the log-logistic function described previously. Subplot c) indicates the proportion of yearly mileage supplied by trucks of different odometer. Subplot d) shows the cumulative distribution of fuel consumption, which indicates the relative sources of tailpipe emissions and their totals.

At first glance, this subplot might appear to conflict with subplots a) and b). At the beginning of a truck's life before they start to retire (say <500,000 mi), the fraction of VMT supplied by trucks of the same odometer remains constant (horizontal lines in subplot c) despite the fact that individually each of them is driven less intensely as they age (decreasing slopes in subplot a). A casual observer might conclude that the contribution of trucks of a certain age to the supply of aggregate mileage will decrease with how intensely they are utilized. However, this is incorrect, as illustrated in *Figure 45*—the contribution of trucks towards aggregate mileage (subplot c) only depends on proportion of truck retirements (subplot b). A simple way of seeing this is to take the derivative of (2.1), resulting in $d\psi/dx = P$, which clearly states that the rate at which mileage supply ψ changes with truck age X only depends on the number of trucks available P. The role of the $U(s)$ curves shown in subplot a) is simply to determine the size of the truck fleet operating in each segment dx.

The four vertical that intersect the four subplots indicate the odometer at which trucks stop having to abide by the FST regulation.

The plots in *Figure 45* shows that different FST regulations can have large impacts on how the industry operates. First, focus on jumping from an FST regulation of 0.11 to 0.25 keeping the cutoff constant at 40,000 mi/year. The most immediate response would be that carriers will retire trucks later in life so that they can accrue more fuel savings to offset the increased capital costs. This can be seen in the horizontal shift to the right in subplot b). As trucks are used later in life, now less trucks need to be purchased to satisfy the demand of shippers, per equation (2.1). In this particular case truck purchases P decrease by 13.9% (not shown in figure). From equation (4.12), a reduction of P will increase the x_i at which trucks transition from one demand segment to another, essentially stretching the curve in subplot a) to the right. The intuition for this is that as less trucks are being purchased, trucks need to remain in the same demand segment longer to supply the demanded mileage, therefore slowing the rate at which truck utilization decreases (less negative slope in subplot a).

Continuing with this example, the increase of FST regulation will increase the proportion of VMT supplied by older trucks as shown in subplot c). This can have policy implications if this policy is combined with a truck retirement program. And finally, in subplot d) we observe how the increased FST regulation does indeed reduce total fuel combustion and therefore tailpipe GHG emissions.

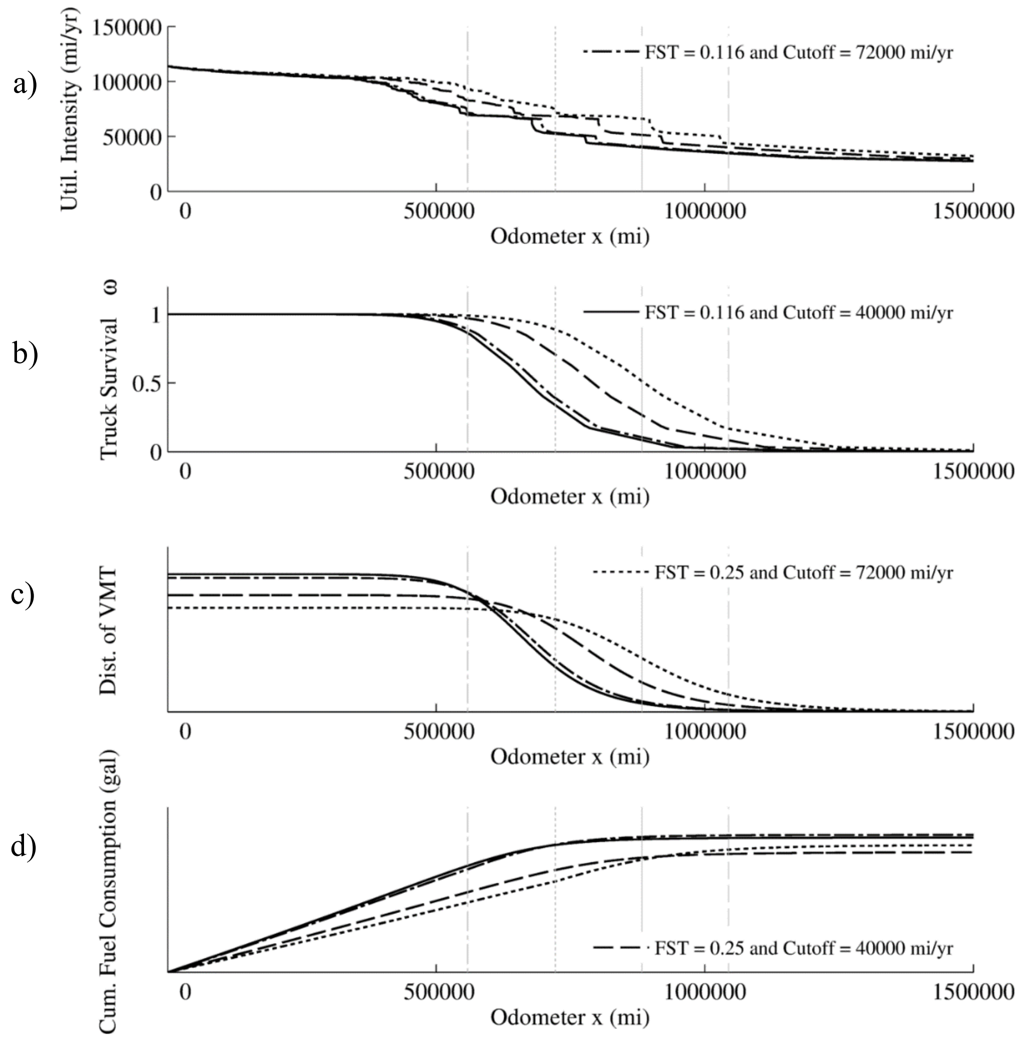

Figure 45: Effect of different FST regulations on (a) truck utilization (b) truck survival (c) distribution of VMT and (d) cumulative fuel consumption.

Figure 46 shows four contour plots that describe how the optimal operations of the industry will change in response to different combinations of FST regulation and yearly mileage cutoff. The circles in these plots represent the current regulation which mandates $\gamma = 0.11$ for trucks that operate more than 50,000 mile per year. The dark contours that pass through these circles represent the combinations of FST regulation and mileage cutoff that leave the industry unchanged relative to this existing regulation.

In subplot a) we see that indeed as the FST regulation increases the total GHG emissions decrease, and that cutoff mileage decrease (more trucks have to abide by FST regulation) emissions also decrease. Both of these responses are expected, as they depend significantly on the average fuel economy of the truck fleet shown in subplot c). From this plot we see that if the mileage cutoff is set lower than 70,000 mi/year it does not affect emissions much. This is primarily because relatively few trucks are operating below that threshold, but also because truck purchase emissions increase, which offsets some of the tailpipe emission reductions. This is consistent with the results of *Figure 45* which indicate that as the mileage cutoff increases trucks retire later in life in subplot b) and therefore have lower truck purchase rate.

The reduction of emissions resulting from decreases in the mileage cutoff are also offset by increases the demand for trucking (subplot d). As the FST regulation is applied to more vehicles (the mileage cutoff is decreased), the costs of trucking will decrease because any FST investment in this range of γ will decrease total costs for carriers, therefore decreasing the equilibrium market price and eliciting shippers to demand more transportation services. As explained before, the existence of various market failures in this industry is preventing FST investments from being made, but there is strong indication that if they are forced through regulation that the trucking industry will operate at lower costs. If for political reasons the FST regulations cannot be extended to all vehicles, and exemptions to this rule need to be made, then the TSTS model can used to analyze the consequences of these exemptions.

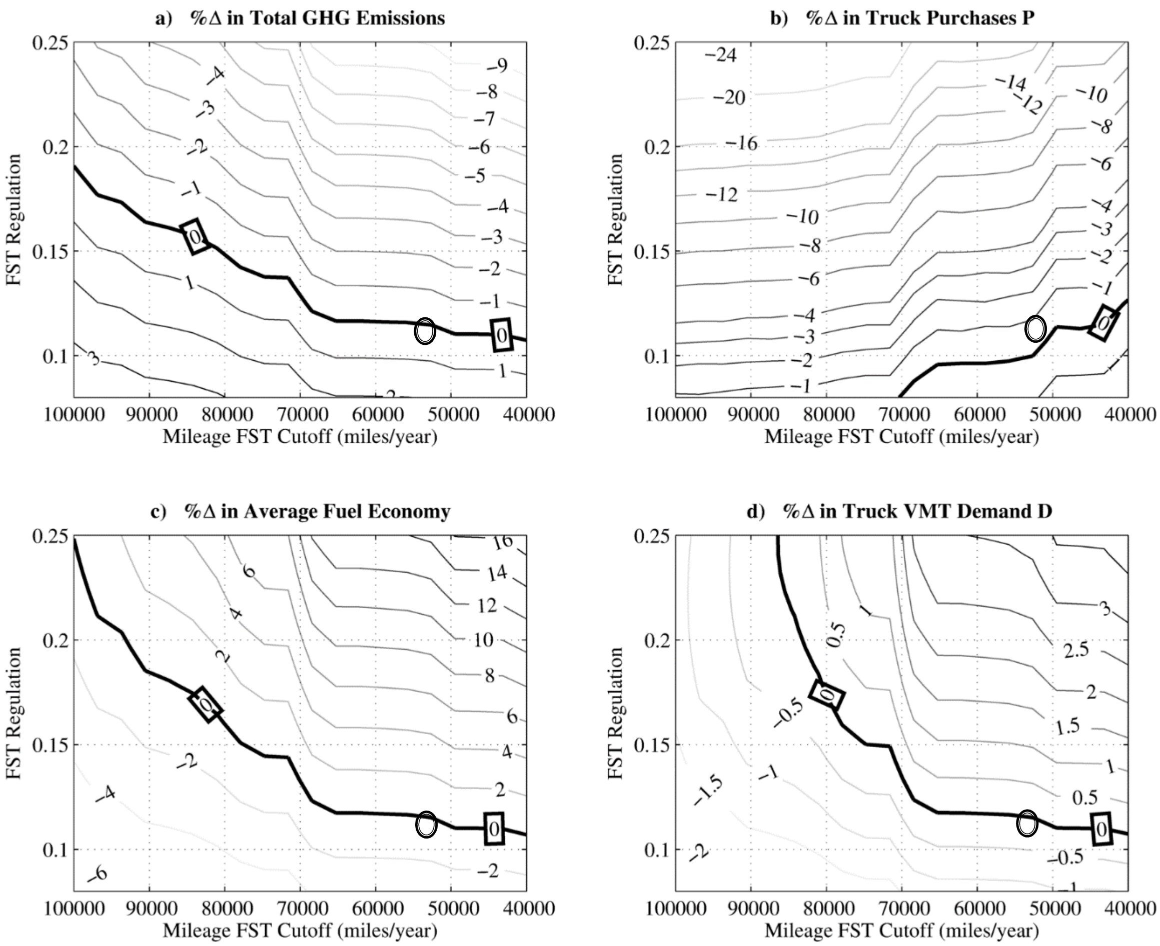

Figure 46: Long-run percent changes in trucking industry from FST regulation with yearly-mileage cutoff

These contour plots do not indicate the optimal amount of FST regulation or mileage cutoff that governments should pursue in California. The purpose of the results of these contour plots is to demonstrate the various unintended impacts (increase in truck purchase rate and latent demand) that apparently simple policy instruments—such as the yearly mileage exemption—can have in the trucking industry. These unintended impacts can reduce the effectiveness of policy.

Figure 47 shows the proportion of fuel combustion that is affected by the FST regulation given different values of yearly mileage cutoff.

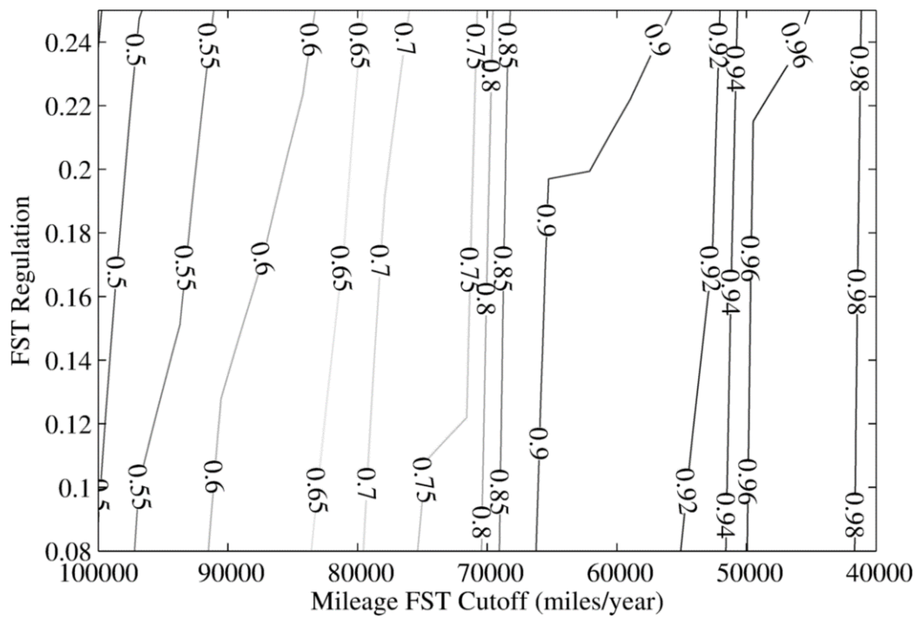

Figure 47: Proportion of GHG emissions under FST regulation

6 Conclusions

Governmental interventions that seek to reduce the GHG emissions of the trucking sector and improve its sustainability need to be designed very carefully—considering potential unintended responses and impacts—because the quality and efficiency of this sector fundamentally affects our economy. Interventions should also be designed in consideration of the potential market failures that might be causing this industry to operate less energy efficiently than is cost-optimal. To accomplish all of this, policy makers require models that capture the key incentives, constraints and dynamics of this industry—while making the most out of the scarce data available. This way both environmental and economic objectives can be achieved simultaneously.

6.1 The TSO Model

The TSO model introduced in this dissertation considers the optimal decisions that carriers and shippers make throughout time, essentially modeling the transitional dynamics of today's trucking sector in responses to time-dependent governmental interventions and changes in their business environment. As its name suggests, carrier's decisions are modeled through the optimization of a mathematical program that is specified on the average costs observed for this industry. The costs considered includes: labor costs, fuel costs, capital costs, FST costs, salvage value, etc. Shipper's decisions are represented with response elasticities obtained from the literature. The model is solved using a two-stage heuristic that provides satisfactory approximate results. The GHG emissions of the sector are then calculated using methodologies from the life-cycle assessment literature.

The main methodological contributions of the TSO model to the research literature are: (i) the simultaneous consideration of FST, FMO and LDS responses, (ii) the modeling of the transitional dynamics of aggregate truck fleets, and (iii) the consideration of life-cycle GHG emissions in modeling this industry. These represent substantial improvements over the EMFAC, NEMS and other trucking sector models that are currently being used to inform policy. More specifically, with the TSO model policy makers can: (i) evaluate the responses of the sector to meet policy targets in the near-term, (ii) compare regulation-based strategies to incentives-based strategies, (iii) evaluate the impact of the phase-in schedule of strategies on the trajectory of emissions, (iv) evaluate the impact of the existing truck fleet on the optimal decisions that marries make moving forward, (v) evaluate the penetration rates of FSTs, (vi) evaluate the tradeoffs between different emission sources, and (vii) find ways to mitigate market failures in this industry that are leading to inefficient outcomes.

The TSO model was then used to study the cost structure of the Core T7 truck fleet in California (Class-8 combination trucks) and how this sector responds to the implementation of different GHG mitigation strategies. These strategies were evaluated in their ability to help meet the GHG emission reduction target set by AB 32 in California. Current policy scenarios indicate that the trucking sector should contribute around 3 – 4 MMTCO2eq/yr in emission reductions in 2020.

The analysis of the current cost-structure of trucking suggests that carriers should invest significantly more in FSTs beyond what is currently observed in the industry. Investing optimally in FSTs leading up to 2020 would save around 6 MMTCO2eq/year relative to continuing current levels of FST investment. This large efficiency gap suggests that there exist significant market barriers to these types of investments. Correcting these barriers would reduce emissions significantly and allow for incentives-based governmental interventions to have their full effect.

The TSO model was then used to analyze the effect of various incentives-based strategies in an ideal world where market barriers have been corrected. Several discrete regulation-based strategies were also analyzed, finding that the Low Carbon Fuel Standard would achieve reductions of 2.1 MMTCO2eq and the current SmartWay regulation would achieve reductions of 2.0 MMTCO2eq. Overall, incentives-based strategies achieve less emission reductions in an ideal world than regulation-based strategies can achieve currently. This has important implications on the prioritization of mitigation strategies.

The above findings were combined with other analyses to formulate the following common sense steps that California's government—or any other government in the US—could take to sensibly reduce emissions from the trucking sector.

1) Regulation of FSTs achieves significant reductions in emissions while bypassing existing market barriers (current approach taken in California).
2) Increasing truck weight limits up to 97,000 lbs. and increasing the number of axles of weight constrained trucks to 6 reduces emissions significantly while having a negligible impact on pavement rehabilitation.
3) Introduce strategies that reduce the total demand for trucking, bypassing existing market barriers.
4) Mitigation of market barriers achieves significant emission reductions.
5) Correcting market barriers allows for FST regulations in (1) to be replaced with incentives-based strategies, improving the economic efficiency of achieving emission reductions.
6) Implement strategies regionally to avoid policy leakage and other unintended substitution effects (truckers increasingly purchasing cheaper fuel outside the State, for example).
7) Implement complementary strategies that provide *carrots and stick*, such as using fuel tax revenues to subsidize FST investments.

Overall it was found that across different mitigation strategies roughly 80-84% 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. By assuming the low (high) scenario for shipper elasticity and fuel prices, emissions from tailpipes and precombustion change by -10% (+11%), emissions from infrastructure change by -7% (+5.5%), and emissions from vehicle manufacturing change by -5% (+5). These values where consistent across different mitigation strategies with some exceptions.

6.2 The TSTS Model

Carriers have to make many long-term decisions about how to manage their truck fleets, which includes determining how much to invest in FSTs. To do so, carriers have to weigh costs and benefits over planning horizons that can be quite long, and affected by many factors. The TSTS model is formulated to capture these long-term decisions made in this sector better than the TSO model by: (i) modeling endogenously how trucks are utilized throughout their service-lives, and (ii) capturing some heterogeneity in truck retirements. The first of these improvements is made possible by incorporating information on the performance of trucking (the ability of carriers to complete shipments) and on the spatial distribution of shipment demand. The second of these improvements is made possible by assuming that truck retirements follow a log-logistic function. Combining both of these methodological improvements with a parameterized discount rate provides analysts a more flexible model for studying the long-term decisions made in the trucking sector, especially regarding FST investments, which impact greatly emissions and costs.

The TSTS model was then used to identify the cost-optimal decisions of carriers and shippers under different policy scenarios to predict their impact on GHG emissions. The first analysis indicates that improving the performance of trucking—the ability of carriers to complete shipments—can significantly incentivize investments in FSTs, and reduce GHG emissions. However, 40 – 50% of these reductions are offset in the aggregate by increases in shipper demand for trucking services precipitated by its lower market price. A second analysis found that mode-shifts also incentivize investments in FSTs because they distort the spatial distribution of shipments in ways that favor making greater capital investments because trucks are used more intensely and retired quicker. And finally, a third analysis found that implementing FST regulations that only apply to a subset of the truck fleet (as in California currently) also reduces emissions, but incentivizes other changes in how the industry operates.

The TSO model is best suited for studying the dynamics and transitions of truck fleets in response to governmental interventions, while the TSTS model is best suited for studying long-run responses. Together, they allow policy makers and researchers to study a wide range of issues in the trucking sector, considering many interactions and responses that had not been adequately explored previously.

The understanding of the trucking sector provided by the TSO and TSTS models has the potential to immediately improve future research in this field in four key dimensions. (1)

As mentioned in *Section 1.3.4,* welfare studies into the optimal level of implementation of FSTs have represented the responses of the trucking industry using elasticity parameters that are largely assumed, which detracts considerably from the weight of their conclusions. The models presented in this dissertation would allow future work on the economic efficiency of trucking sector interventions to be based on more realistic representations of industry responses. (2) The modeling of various sources of emissions is even more important for studying ways to mitigate Particulate Matter (PM) and NOx emissions, because these other pollutants are emitted more intensely in the manufacturing of vehicles and rehabilitation of pavements than for GHGs. The models presented in this dissertation are especially salient for understanding these types of tradeoffs. (3) With little modifications, these models could be also applied to study the responses of other sectors, such as railroad, air or waterborne transportation. The economic tradeoffs faced in managing fleets of trains, airplanes and ships are not fundamentally different than those of managing fleets of trucks. And perhaps more importantly, (4) they provide a rich theoretical framework on which to build future models of the trucking industry, which define explicitly their key assumptions and relationships.

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Appendix A: Glossary

x Truck odometer, cumulative mileage.
s Truck age (years)
$x = U(s)$ Truck utilization function. Time s for truck to reach x odometer
$P(t)$ Truck purchase rate at time t (trucks/year)
$X(t)$ Truck retirement odometer at time t (miles)
$S(t)$ Retirement age of truck purchased at t (years)
$\gamma(t)$ Level of Fuel Saving Technologies (FSTs) on trucks purchased at t
$\psi(t)$ Aggregate rate of trucking mileage supply by carriers (miles/year)
$F(t)$ Aggregate size of truck fleet (units)
$D(t)$ Aggregate rate of trucking mileage demanded by shippers (miles/year)
$y(t)$ Equilibrium market rate between carriers and shippers ($/trucking mile)
$E(t)$ Economic environment at t, captures effect of GHG mitigation strategies
$A(\gamma)$ Purchase cost of truck with technology γ ($/truck)
$V(\gamma, X)$ Salvage Value of trucks of technology γ sold at odometer X
$M(x)$ Maintenance costs ($/mile)
$O(\gamma)$ Operational costs as a function of γ ($/mile)
β Effective discount factor
θ_M Mileage tax ($/mile)
θ_F Fuel tax ($/gallon)
p_F Fuel price ($/gallon)
f Pre-FST fuel efficiency (gallons/mile)
k_o Fixed mileage trucking cost ($/miles)
k_d Instantaneous depreciation rate constant
k_x Mileage depreciation constant
k_m Maintenance costs constant
Q Quantity of goods shipped (tons/year)
L Trip length (miles)
v Shipment size (tons/trip)
e_D Elasticity of trucking mileage D with respect to trucking rate y
e_Q Elasticity of commodity shipment demand Q with respect to trucking rate y
R_x GHG emissions rate from diesel combustion
R_P GHG emissions rate from truck manufacturing
R_I GHG emissions rate from infrastructure rehabilitation and maintenance
E Equivalent Single Axle Loading
a_k Number of truck axles
GVW_k Gross vehicle weight of truck weight range k
TW Tractor weight
f_k Fraction of highway mileage supplied by trucks in weight range k

W Proportion of trucking miles reduced by allowing higher truck weight limits