The Cost-Effectiveness of Alternative Policies for Reducing GHG emissions in the Freight Sector

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A Research Report from the Pacific Southwest Region University Transportation Center

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16. Abstract

We integrated a route-choice model with a multi-market simulation model to evaluate the effectiveness of alternative public policies that stimulate a faster adoption of cleaner technologies to reduce GHG emissions in the freight sector. Specifically, we illustrate the capabilities of the model by simulating fuel economy values for EPA's Phase 1 regulations and ZEV's. Traditionally, the evaluation of the potential of alternative technologies for climate mitigation starts with simple lifecycle analysis (LCA) of the GHG emissions resulting from various technologies, including all phases of its production and use. However, if public policies that support the same technology result in different multi-market and route-level adjustments, and therefore GHG emissions impacts, per unit of the technology added to the economy, technology-based LCA metrics may result in estimates of emissions savings that are misleading. The model developed here allows for capturing economy-wide GHG emissions that are generated whenever any of the agents in the model, directly or indirectly, adjusts their behavior in response to policies introduced in the freight sector that aimed to reduce GHG emissions in that sector. Here simulations should be interpreted as illustrative of the capabilities of the model developed. In future work, we will continue to improve on the calibration, which will allow for more precise quantification of the impacts of alternative policies.

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About the Pacific Southwest Region University Transportation Center

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The Pacific Southwest Region UTC conducts an integrated, multidisciplinary program of research, education and technology transfer aimed at *improving the mobility of people and goods throughout the region.* Our program is organized around four themes: 1) technology to address transportation problems and improve mobility; 2) improving mobility for vulnerable populations; 3) Improving resilience and protecting the environment; and 4) managing mobility in high growth areas.

U.S. Department of Transportation (USDOT) Disclaimer

Disclosure

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Abstract

We integrated a route-choice model with a multi-market simulation model to evaluate the effectiveness of alternative public policies that stimulate a faster adoption of cleaner technologies to reduce GHG emissions in the freight sector. Specifically, we illustrate the capabilities of the model by simulating fuel economy values for EPA's Phase 1 regulations and ZEV's. Traditionally, the evaluation of the potential of alternative technologies for climate mitigation starts with simple lifecycle analysis (LCA) of the GHG emissions resulting from various technologies, including all phases of its production and use. However, if public policies that support the same technology result in different multi-market and route-level adjustments, and therefore GHG emissions impacts, per unit of the technology added to the economy, technology-based LCA metrics may result in estimates of emissions savings that are misleading. The model developed here allows for capturing economy-wide GHG emissions that are generated whenever any of the agents in the model, directly or indirectly, adjusts their behavior in response to policies introduced in the freight sector that aimed to reduce GHG emissions in that sector. Here simulations should be interpreted as illustrative of the capabilities of the model developed. In future work, we will continue to improve on the calibration, which will allow for more precise quantification of the impacts of alternative policies.

Research Report - The Cost-Effectiveness of Alternative Policies for Reducing GHG emissions in the Freight Sector

Executive Summary

We develop a novel simulation that integrates aspects of route-level and multi-market models to evaluate the cost-effectiveness of alternative public policies that stimulate a faster adoption of cleaner technologies to reduce GHG emissions in the freight sector. The route-level model adds important spatial features that influence fuel consumption and fleet composition, such as nodes of pickup and delivery; while the multi-market model allows for adjustments in final prices, which in turn affect the sizes of fleet sectors and output markets. Most of the effort was in conceptualizing this integration and highlight its benefits. Preliminary simulations are conducted to illustrate the emissions that result from Phase 1 EPA regulations and ZEV's.

Traditionally, the evaluation of the potential of alternative technologies for climate mitigation starts with simple lifecycle analysis (LCA) of the GHG emissions resulting from various technologies, including all phases of its production and use. However, if public policies that support the same technology result in different multi-market adjustments, and therefore GHG emissions impacts, per unit of the technology added to the economy, technology-based LCA metrics may result in estimates of emissions savings that are misleading (Bento and Klotz, 2014). Our proposed multi-market model overcomes these limitations by simultaneously considering the behavior of consumers, producers of final goods (including goods that require delivery and trucking costs), the freight sector, and the regulator/government that affects freight decisions through a variety of public policies. In turn these decisions are affected and constrained by routing choices, which are determined by pre-existing locations of drop and pick up of goods. In our case, we consider that trucks depart and return to the port of Los Angeles at the end of the day. These pre-existing nodes are critical constraints, often ignored in the economics literature that models the freight sector. Finally, the nature of the model allows for capturing economy-wide GHG emissions that are generated whenever any of the agents in the model, directly or indirectly, adjusts their behavior in response to policies introduced in the freight sector that aimed to reduce GHG emissions in that sector.

Our model has unique four features relevant for the estimation of the impact of these AFV policies and resulting emissions: 1) impacts on trucking firms, which are constrained by their pre-determined routing decisions, since nodes of pick-up and delivery remain fixed (at least in the short and medium run), 2) impacts on product demands, and 3) impacts on net GHGs. Trucking firms will incur costs of purchase and operation of AFVs, including any added costs due to differences in vehicle performance and fuel consumption. For the case of ZEV trucks, we also consider refueling time and battery range. We assume that any additional costs from purchase and operation of AFVs incurred by the trucking firm will be passed forward into prices to the

final consumer. An increase in price will affect demand, and hence we expect an overall decline in demand, which means a decline in freight shipments. In order to determine the net impacts on GHG emissions, we must consider not only the GHG reductions associated with the replacement of conventional diesel vehicles, but also any change in traffic conditions that would affect the level of congestion. The change could be positive or negative, depending on whether the added truck VMT due to AFV performance is offset by reduced VMT due to reduced demand. It is also possible that the use of AFVs will be subsidized by government. To the extent that trucking firms do not incur additional costs, prices should not change, and demand should be affected only by the reduced income represented by the subsidy.

At the present time, simulations should be interpreted as illustrative of the modeling features. Therefore, results should be seen more as qualitative rather than precise estimates of the effects of policies. We use the model to illustrate the emissions that result from Phase 1 regulations and ZEV's. In the future, we will use the model to evaluate the cost-effectiveness of mandates and subsidies for the adoption of cleaner technologies under the following extreme scenarios: Mandates and subsidies that either stimulate the adoption of all battery electric heavy-duty trucks, or alternatively, the adoption of all CNG heavy duty trucks. Given current performance and ranges of these technologies, these scenarios represent extreme cases, and thus should bound the potential effects of regulatory policies.

Introduction

Motivation

In order to further reduce fuel consumption and GHG emissions in the transportation sector, greater attention must be paid to the freight sector[1]. In this paper, we integrate a route-level with a multi-market analytical and simulation model to evaluate the cost-effectiveness of alternative policies that promote the adoption of cleaner technologies and fuels in the freight sector with the goal of reducing GHG emissions. By considering pre-existing spatial features, such as the nodes of pickup and drop of goods, incorporating routing models into general-equilibrium multi-market models not only adds realism but can alter key aspects of the decisions of freight operators, in particular their choices of the fuel economy and whether to incorporate ZEV trucks into their fleet.

Interestingly enough, cleaner technologies are becoming available in the market place. However, due to their capital and operating costs, relatively lesser range and, in some cases, lower load capacity relative to conventional vehicles, and limited availability of fueling stations, these technologies have only been modestly adopted by trucking companies. Further, if trucking companies only consider private costs (capital and operating) when making decisions and these options are not cost-competitive, it is unlikely that these cleaner technologies will be adopted anytime soon. Therefore, there is a need to consider the costs and benefits of public policies that can correct for the external costs imposed by the freight sector and hasten the transition towards these technologies.

In California, the focus is to move towards zero emission vehicles (ZEVs). However, a priori, it is not clear whether policies that support such a strategy are the most cost-effective ones in reducing GHG emissions. For trucking companies to operate ZEVs, they will likely need more vehicles and more vehicle miles to service a given demand partly determined by existing nodes of origin-destination captured by the routing model, relative to conventional fuels (Shao and Dessouky, 2017). In turn, in metro areas with congestion, the likely added miles needed when operating cleaner technologies impose more congestion, leading to even more emissions from all other vehicles. In contrast, while on a per unit bases CNG technologies may not appear as effective as electric batteries, due to their current range, they may still be preferred. Thus, a priori, it is not immediately obvious which technologies should be promoted by public policy.

Existing literature can be divided into three broad categories: First, engineering studies that rely on lifecycle analysis methods to evaluate alternative fuel and technology options, analyze GHG emissions, and the economic attractiveness of various technologies (UCS, 2012; Zhau et al., 2013; Burke and Zhu, 2014; ARB, 2015a; ARB 2015b). By calculating the differential vehicle cost of each powertrain option and corresponding breakeven alternative fuel price needed to

[1] Heavy-duty trucks are the second largest segment and collectively make up the biggest increase in the U.S. transportation sector in terms of emissions and energy use. These vehicles currently account for about 20% of GHG emissions and oil use in the transportation sector. Further, and critical from a GHG emissions perspective, globally heavy-duty vehicles are growing rapidly and are expected to surpass emissions from passenger vehicles by 2030.

recover the additional cost, given a payback period, such studies provide an important input in the calculations of the level of public policy support needed to sustain these technologies. However, as argued in Bento and Klotz (2014), climate policy decisions, including the choice of cleaner technologies in the freight sector, require *policy-based lifecycle analysis*, not just simpler lifecycle analysis methods. This is because the adoption of such cleaner technologies will likely alter the overall operating costs of the freight sector and, as a consequence, generate multi-market adjustments that standard lifecycle analysis methods are unable to capture. For example, to the extent that the prices of final goods that rely on trucking increase, consumers are likely to substitute away from those goods. In turn, this *'output effect'* will further contribute to the overall reduction of GHG emissions. Similarly, policies that alter the operating costs of the freight sector are likely to lead to adjustments in the total number of trucks used by each operator, miles driven, route choices, and potentially even total load and weight carried per vehicle. Not only will these behavioral adjustments translate into different levels of GHG emissions, but there can also be interactions with passenger vehicles mileage, especially in more congested environments, which will have additional GHG emissions impacts. In addition, these effects may vary depending on the policy instrument that triggers these adjustments, as alternative policies might have different effects on the operating costs per mile of vehicles. That is, the GHG emissions associated with the adoption of a technology are critically affected by the policy instrument that stimulates its adoption. Finally, the measurement of the costs and benefits of alternative options doesn't necessarily scale up linearly (as implicitly assumed in standard lifecycle analysis), requiring a careful understanding of the driving cycles, range, and performance of different technologies, given miles driven, load and weight decisions of trucking operators.

Second, sophisticated transportation models that explicitly consider the routing decisions of trucks in multimodal transportation environments have been developed (e.g. Zhao, Ioannou, and Dessouky, 2016). These models, including COSMO (CO-Simulation Optimization) developed by Dessouky - one of the CO-PIs of this project-, can lead to more efficient decisions in freight routing by exploiting the availability of powerful computation software tools in the state estimations of complex and dynamic multimodal transportation networks. However, these models don't typically consider the choice of fuel economy technologies by trucking companies. Yet, depending on multimodal transportation environments, levels of diesel prices, congestion, and alternative public policy options, routing and fuel economy decisions are done jointly by trucking operators. An important feature of these models, however, is the spatial treatment of nodes of origin/destination (e.g. drop and pick up locations), which typically will remain fixed and are exogenous constraints to the freight operations. Such features clearly affect resulting fleet composition and fuel consumption. A limitation of routing models is that they treat output prices, and therefore, sizes of the sectors as given.

Finally, there is a literature in economics that uses multi-market models to examine the optimal level of diesel taxes for heavy-duty trucks (Calthrop, 2003; Parry, 2008). An advantage of these models is that they allow for multi-market interactions amongst the agents affected, directly or indirectly, by changes in the price of fuel. And adjustments of all agents in the system are critical for the evaluation of the cost-effectiveness of policies in reducing GHG emissions.

However, these models rely on overly simplifying assumptions that limit their ability to inform and guide public policy. First, they ignore a broader set of more commonly implemented policies to foster the adoption of cleaner technologies, including fuel economy standards, mandates for specific technologies, and other subsidy-style incentives, and their treatment of alternative technologies is rather rudimentary. Second, unlike the transportation models cited above, they ignore important behavioral adjustments of trucking companies, including route choices, miles driven, load capacity, and the number of vehicles depending on alternative technologies, that critically affect performance and, as a consequence, GHG emissions. Finally, these models ignore key spatial features such as nodes of pickup and drop of goods, which reflect features of cities that are exogenous to the freight operator, but certainly affect and constraint their decisions of fuel economy and fleet composition.

Why is it important?

To overcome some of the limitations of prior work, we propose to integrate a routing model with a multi-market simulation. The routing model starts with a fleet of vehicles that picks up and drops goods at pre-determined locations. In our case, we consider the port of Los Angeles as the starting point and assume that trucks return to the port at the end of the day. Daily distances are therefore pre-determined. The multi-market model considers the behavior of consumers, producers of final goods (including goods that require delivery and trucking costs), the freight sector, and the regulator/government that affects freight decisions through a variety of public policies.

In relation to the integration of multi-market and routing models, a few novelties are worth mentioning: First, when modeling the behavior of the freight sector, we integrate a routing decision model, such as COSMO, in the multi-market model, allowing for decisions by the freight sector to have multimodal impacts and be determined by overall levels of congestion and route availability. We note however, that we haven't yet explicitly modeled congestion. Second, when measuring the cost-effectiveness of alternative instruments, we consider a broad range of technologies, which performance is affected by driving cycles, route decisions and congestion levels captured in COSMO. And finally, the integration in itself represents a contribution to the literature. This integration exercise crucially combines the strengths of two different types of modelling approaches to address the weaknesses in the other. In this instance, we use the strength of multi-market models in explaining the economic effect of fuel efficiency policies and that of using battery-run ZEV's. These multi-market models, however, are incomplete with respect to the spatial component involved in the operations of the freight sector. This weakness is overcome by incorporating a routing choice model that explicitly considers space and routing decisions of the freight operators. An integration exercise like this is particularly relevant to cost-benefit analyses of policies trying to address externalities associated with mobile sources.

The rest of the report is structured as follows: First, we present an intuitive and brief overview of the modeling effort, which is most useful for readers less familiar with the mathematical details of these classes of models; Second, we discuss in greater detail some of the challenges associated with the integration of the routing and multi-market models and our proposed solutions; we present the functional forms used in the model; and discuss in detail the algorithm solution for two alternative policy cases: (a) vehicles are run on diesel but their fuel economy improves, via mandates; (b) existing diesel vehicles are replaced by ZEVs. Third, we briefly outline the calibration strategy. Forth, we present preliminary results that should be interpreted qualitatively and are exclusively meant to highlight the features of the model at this point. Finally, we provide some concluding thoughts.

Methods

We integrated a route-level choice with a multi-market simulation model to evaluate the cost effectiveness of alternative public policy instruments to reduce externalities in the heavy-duty freight sector. Below, we outline the structure of the model. Instead of presenting a formal mathematical version of the model, we describe the various components of the model in a simpler and more intuitive fashion.

Brief Overview of the Modeling Effort

Multi-market model

The multi-market model considers the behavior of all relevant economic agents needed to evaluate the effects of policies that promote the adoption of cleaner fuel-efficient trucks and reduce GHG emissions in the Freight Sector. These include: Consumers, Producers of Final and Intermediate Goods, the Freight Sector, and the Regulator/Government. Each of these agents has their own mathematical optimization problem (which we describe below in more detail), and the combined solution of these agents' optimization problems leads to an equilibrium vector of (private) prices in the economy[2]. There is rationale for regulatory/government intervention in the model because, when making decisions, agents only consider their private costs. Therefore, by ignoring the external costs they impose on society, their actions generate externalities. As a consequence, the vector of (private) prices that characterizes the equilibrium is not optimal, and overall welfare can be increased through policies that correct for these market failures. The model has the capability of accounting for two major externalities: greenhouse gas emissions (GHG), and congestion, although at this point we have only modeled the GHG emissions externality[3].

Consistent to previous literature, the general equilibrium nature of this multi-market model ignores any spatial consideration. For example, in the multi-market model there are no nodes of origin/destination that determine where goods are picked up and delivered. Below we

[2] Multi-market equilibrium models are the most commonly used tool for the evaluation of cost-effectiveness of alternative instruments by public policy analysts, because they allow for adjustments in the behavior of all agents that are, directly or indirectly, affected by policy. See, for example, Goulder et. al. (1999), Bento et al. (2005), Bento et al. (2009). Simple mathematical assumptions assure uniqueness of the equilibrium.

[3] While important other externalities, such as road damage, local air pollution, and noise, are beyond the scope of the proposed study. But the proposed framework could be extended in the future to include these externalities.

explain how this issue is handled when the multi-market model is integrated with the route choice model.

Behavior of Agents in the Model and Key Assumptions

Consumers – We consider the behavior of a representative consumer (meant to reflect the average over all households in a region). This individual makes choices over levels of consumption of final goods, which are divided into two categories: goods that involve significant trucking costs[4], and goods for which transportation costs are minimal (e.g. services)[5]. Changes in operating costs in the freight sector affect consumer choices, as these result in adjustments in the price of the final good that involves trucking costs. Following Parry (2008), we assume that higher product prices for freight-intense consumption goods only cause a substitution into the non-freight intensive final goods (such as services). That is, they do not directly affect other consumer choices.

Consumers are also adversely affected by the negative externalities from all auto and heavy-duty freight vehicles: congestion, and greenhouse gas emissions[6]. At the present time we only consider GHG emissions. By reducing externalities related to fuel consumption from heavy-duty vehicles, policies can generate an external benefit to consumers.

Production Sector of Final Goods – We model the behavior of competitive firms that produce intermediate and final goods. These firms are profit maximizing firms. The model considers two intermediate goods - Gasoline used by consumers and diesel fuels used by heavy-duty freight vehicles – and two final goods – a good that represents a composite of all final goods that requires trucking and a good that doesn't. We define a unit of consumption good that requires trucking by the quantity delivered per mile of freight; therefore, in equilibrium, consumer demand for this good is equivalent to truck mileage incurred in transporting that product. Increases in the price of the final good that requires trucking costs, lead to a reduction in the demand for this good, and an overall shrink of the size of this sector (relative to the other final good).

Freight Sector – We model the behavior of homogenous and competitive heavy-duty trucking companies. The companies ship goods to consumers at given cost per mile. These firms maximize profits by minimizing the costs of transportation of goods, given the demand they face from consumers. They face exogenous diesel prices, and therefore, choose the level of fuel economy (or specific mix of alternative technologies in the simulation model) and total mileage (and route in the simulation model) of each truck, as part of their overall cost minimization

[4] There is obviously a lot of variation in the amount of trucking costs associated with a physical product. The model is meant to capture an average value.

[5] Some services can be provided with or without transportation. For example, to fix a minor problem with internet connection, consumers might be able to call customer services for instructions to isolate and remedy the problem, or they might also opt for a personnel send by the service provider to fix it at the location of the consumer household.

[6] The mathematical assumptions needed to solve each agent's optimization problem are standard and follow Calthrop (2003), Bento et al. (2005), Parry (2008).

strategy. If there were no regulations, trucking companies would choose diesel trucks sized to the demand of their business. Finally, we consider the vehicle capital/maintenance/operating costs and express this on a per mile basis. Trucking companies (in aggregate) supply the mileage that is required to meet consumer demand for final goods that require freight transportation.

Although the freight sector in reality in the state of California is not necessarily perfectly competitive it's a simplifying assumption in the model. In the absence of this assumption, the final prices of goods delivered by trucks will not be equal to the marginal cost of trucking firms. Even though this may potentially affect the exact magnitude of the estimated GHG emissions, it does not directly impact the quality of results, in terms of the observed reduction or increase in GHG emissions for different distributional values of fuel economy in the case of diesel vehicles, or charging times considered for ZEV's. Accounting for firm level heterogeneity and imperfection in markets will provide more precise estimates but to estimate the parameters of such a model, we need more and better quality data, and it can be the subject of another future study.

Regulatory Agency/Government and Policy Instruments to be considered – Very much like in other transportation equilibrium models for passenger vehicles (Bento et al. 2005; Bento et al. 2009), the government faces a budget constraint, and equates spending on household transfers and road maintenance with revenues from gasoline and diesel taxes. The government will also regulate the freight sector through a variety of public policy instruments, which we discuss below.

The structure of the multi-market model described here, while simple, will allow us in the future to develop analytically-tractable formulas for the cost effectiveness of a variety of policies aimed at reducing the externalities from freight transportation. We will use the model to evaluate the cost-effectiveness of two policy instruments under the following extreme scenarios: Mandates and subsidies that either stimulate the adoption of all battery electric heavy duty trucks, or alternatively, the adoption of all battery-run heavy duty trucks. These scenarios represent extreme cases, and thus should bound the potential effects of regulatory policies. Currently, what we are able to do are simple simulations that measure the emissions impacts of these two extreme cases. Below we present that.

The model is particularly powerful to measure the effects and disentangle the sources of adjustment of these instruments. For example, economists have often argued that the most cost-effective way of reducing GHG emissions from transportation, whether passenger vehicles or freight, is by increasing the level of the fuel tax. This is, in part, because the fuel tax effectively exploits all sources of adjustments in the model, and therefore, can reduce GHG emissions at minimum cost. First, an increase in the diesel fuel tax will increase the operating costs of the freight sector. This will lead to the following adjustments: increases in the price of the final good (that relies on transportation), contracting demand for this good (*output effect*). An increase in operating costs will likely also translate in a reduction of vehicle miles travel by trucks (*VMT effect*). Finally, an increase in operating costs of freight will create incentives for the sector to explore ways to get around the increase in fuel cost, including the adoption of cleaner technologies. When the regulator increases the diesel tax, the regulator doesn't 'pick and choose' winning technologies. It is the market, through the freight sectors' optimization problem, that moves towards the optimal mix of technologies (*technology mix effect*).

An important output of our model is that, at current technology performances, ranges, and prices, driving cycles and miles, and fuel prices, we will infer the optimal mix of technologies for the freight sector. Other policy instruments, while popular amongst policy makers, are likely to be less cost-effective, depending on the empirical importance of each of the three effects: *Output, VMT, and Technology Mix*. For example, an increase in the fuel economy standard for new trucks is likely to generate a similar 'output effect' (since the capital costs of the vehicle may increase), some 'technology mix effect', but to the extent that a fuel economy standard actually reduces (rather than increasing) the cost per-mile of operating the truck, the 'VMT effect' is likely to be of the opposite side of that generated by the diesel tax. However, to the extent that the range of vehicles decreases with certain technologies that can be used to meet the fuel economy standard, the rebound effect can also be manifested by an increase in the number of vehicles used by the operator. Therefore, there could be a case where more vehicles and more miles are occurring in response to the policy and technology adoption. In turn, these behavioral adjustments should affect congestion, which will further impact the fuel economy and GHG emissions of all other vehicles in the road. In other words, it may be costlier to get the same level of GHG emissions with the standard than with a diesel tax. Similarly, mandates for specific technologies or subsidies for the purchase of cleaner technologies or retirement of older vehicles are likely to be less cost-effective, because of the way these instruments exploit the different channels of adjustment in the multi-market model.

Ultimately, the magnitude of these various effects – *output, VMT, technology mix* - under different policy instruments is an empirical question. Therefore, a major contribution of the simulation model is to empirically quantify the importance of each of these adjustment channels, when calculating the cost-effectiveness of alternative instruments and considering different technologies. Of course, while we are already describing these channels, we note that our current simulations do not decompose these effects, since most of the effort this year was to integrate the economics model with the route level model, which we describe below.

Route Level Model

A fundamental difference between the economics model described above and the route-level model is its unit of analysis or spatial coverage. The model above was initially developed for a more aggregate scale, typically representing a country. In contrast, the route-level model is a rather disaggregated model. In our case, the routing model represents the city of Los Angeles, in particular origin and destinations around the Port of Los Angeles. We highlight three features of the routing model: (a) fleet of vehicles start at the port of Los Angeles and drop/pick goods at various demand points and return to the port at the end of the day; (b) we assume a constant vehicle speed (neglecting traffic and congestion effects) and incorporate a fixed refueling time; (c) the routing model minimizes the time taken to complete all delivery, given speed, refueling time, and estimate the miles in a constraint optimization framework.

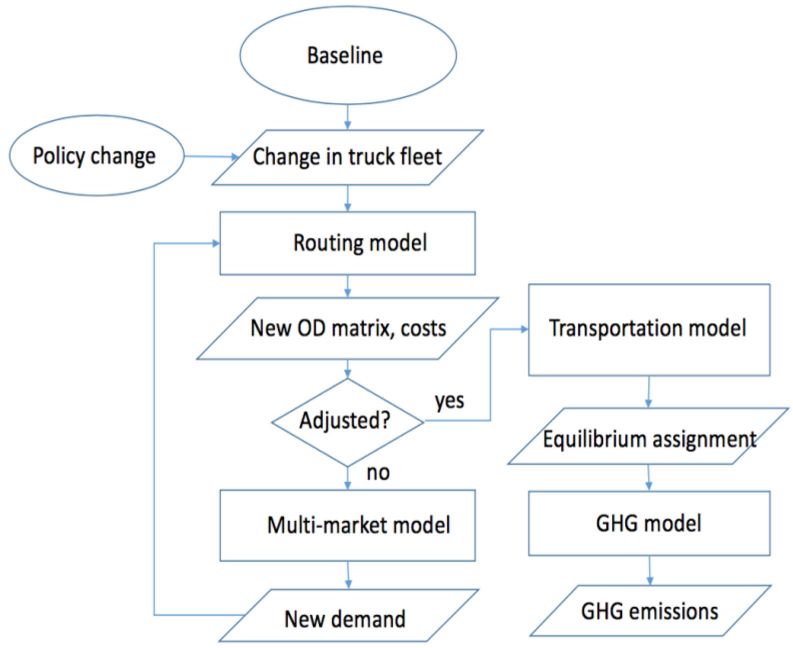
Integration of the Multi-market and Route-level Model

To integrate the route-level model with the multi-market model a fundamental challenge needs to be overcome and a series of additional assumptions have to be made. First, an important challenge relates to the definition of the spatial coverage. The multi-market model is typically developed to represent an entire economy, while the route-level model is a spatially disaggregated model that represents in great detail the port of Los Angeles. To address this mismatch in spatial coverage, we have done the following: (a) we use GDP data to estimate scale factor between LA MSA and CA; and we use freight miles to estimate scale factors between the Port of Los Angeles and CA. Second, to allow for solutions in reasonable amounts of time, we avoided loops between the two models.

Further Details on the Integration of Models and Calibration

We calibrate the economics model to represent Southern California's economy. The implementation of the simulation model proceeds in four steps: *First*, choice of functional forms that capture the behavior of the various agents in the model. In choosing functional forms, we will follow closely the strategy adopted by the PIs research team in related work that examined the cost-effectiveness for reducing fuel consumption by passenger vehicles (Bento et al, 2005; Bento et al. 2009), and will rely on a series of constant elasticity of substitution (CES) and Cobb-Douglas functional forms that allow for flexibility in representing the sizes of the sectors and implied elasticities that capture the degree of response to prices (for more details on functional forms refer to the Appendix). *Second*, collection of a comprehensive dataset to calibrate the various sectors in the model, including calibration of the sizes and economic value of the sectors, key elasticities that capture the response of different agents to changes in the vector of equilibrium prices, and valuation of externalities. A starting point for such calibration will come from Parry (2008) and Calthrop (2003) who provide a range of values for these key parameter and elasticities based on consensus estimates from the literature. For example, in Parry (2008) much of the data on mileage and fuel come from FHWA and BTS, while most of the external costs are from a detailed and widely cited assessment for the year 2000 by FHWA. Through a careful literature review, we will update the values for these parameters whenever necessary, and when more recent estimates are available. In addition, because the model will be calibrated to represent California, we will complement data and elasticity estimates from the literature, which typically are meant to be representative of the nation, with California specific data. Further, recent econometric work provides some of the first empirical magnitude of the 'rebound effect' from fuel economy standards for heavy-duty vehicles. *Third*, we define the baseline of current conditions: a set of demand and prices based on diesel heavy duty trucks. The baseline is from the most recent SCAG transportation model calibrated for 2014. The SCAG model has separate O-D matrices for light-medium and for heavy duty trucks. We use the truck O-D matrices as the baseline demand. We run the O-D data in a routing model that optimizes routes for the given demand, accounting for the refueling process. That is, different from most of the routing literature, the model takes into consideration the fuel level of each vehicle and enforces trips to the fueling station when needed. Although this is not an important issue for diesel trucks due to the abundance of gas stations that sell diesel fuel as well as the large tank capacity for this type of truck, it is an important consideration for AFVs since there is limited infrastructure for fueling and the driving range for these vehicles before refueling could be limited for these types of vehicles. The routes are based on minimizing the travel distance and fleet size. Based on the optimized routes, we will be able to generate the list of trips for each vehicle to create a new O-D matrix for the trucks. We then use the new O-D matrix and generate a revised equilibrium on the transportation network; the revised equilibrium is the basis for estimating baseline GHGs. *Finally*, we simulate scenario impacts. We use three models to estimate the impacts of our scenarios. See Figure 1.

Figure 1. Model Structure



Each scenario requires a change in the truck fleet to vehicles with different performance and refueling characteristics. These are fed into the routing model to generate a new set of truck trips and operating costs (capital costs are estimated outside the model). In the first round, the changes in costs are translated to price effects, and the multi-market model estimates the change in demand for goods. The new demand matrix is fed into the routing model, and a second set of trips and costs are estimated. The revised O-D matrix is then fed into a transportation model that generates a new network equilibrium assignment. The equilibrium assignment gives VMT and speed by vehicle class (passenger vehicles, light and medium duty trucks, heavy duty trucks). We use this data, together with passenger vehicle fleet characteristics, in a GHG model to estimate GHG emissions for the scenario.

With the economics model calibrated, we then solve the full model for two extreme cases: a diesel vehicle simulation, where we consider an increase in the fuel economy and a simulation where the existing fleet is converted into ZEVs. Figures 2 and 3 outline the algorithm used for each of the simulations. Both runs start with a calibration of the share parameters from the consumer module.

Figure 2. Algorithm for Diesel Vehicles

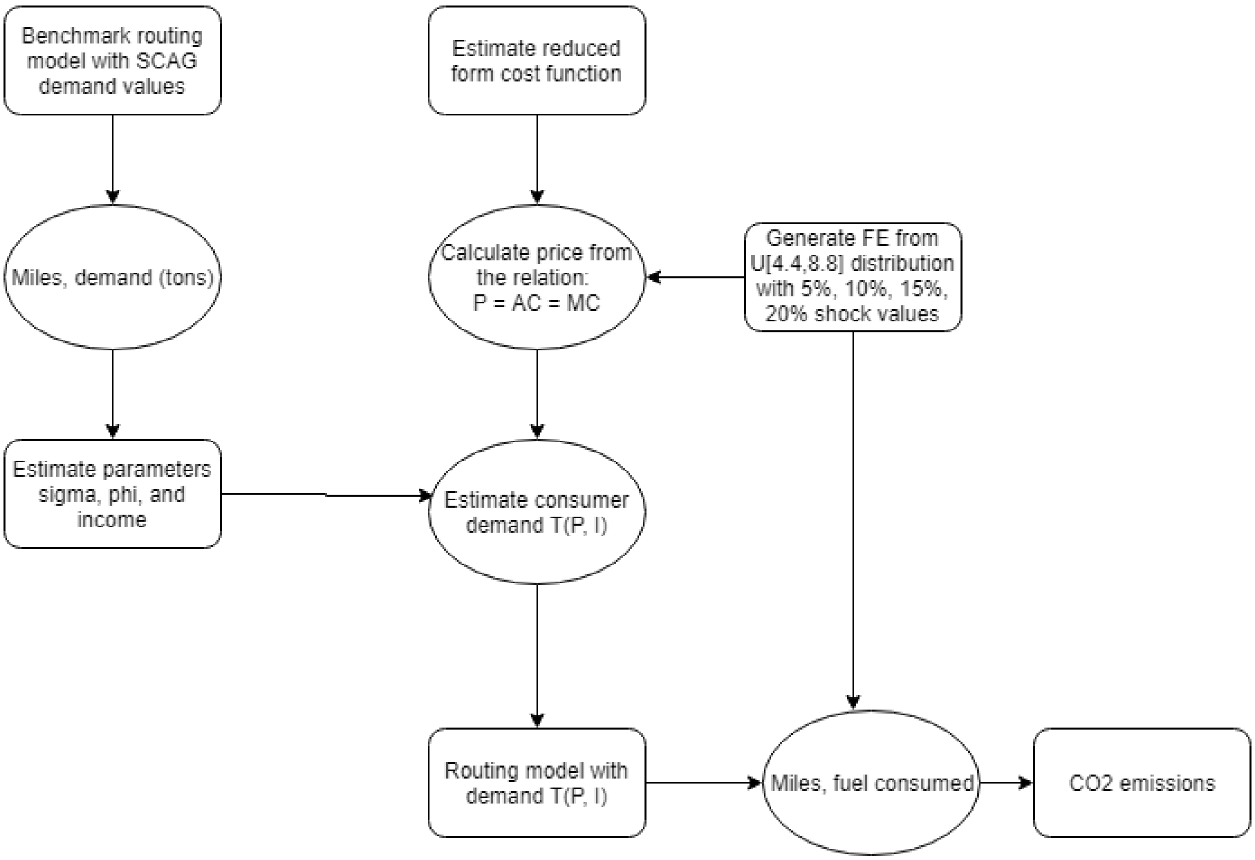
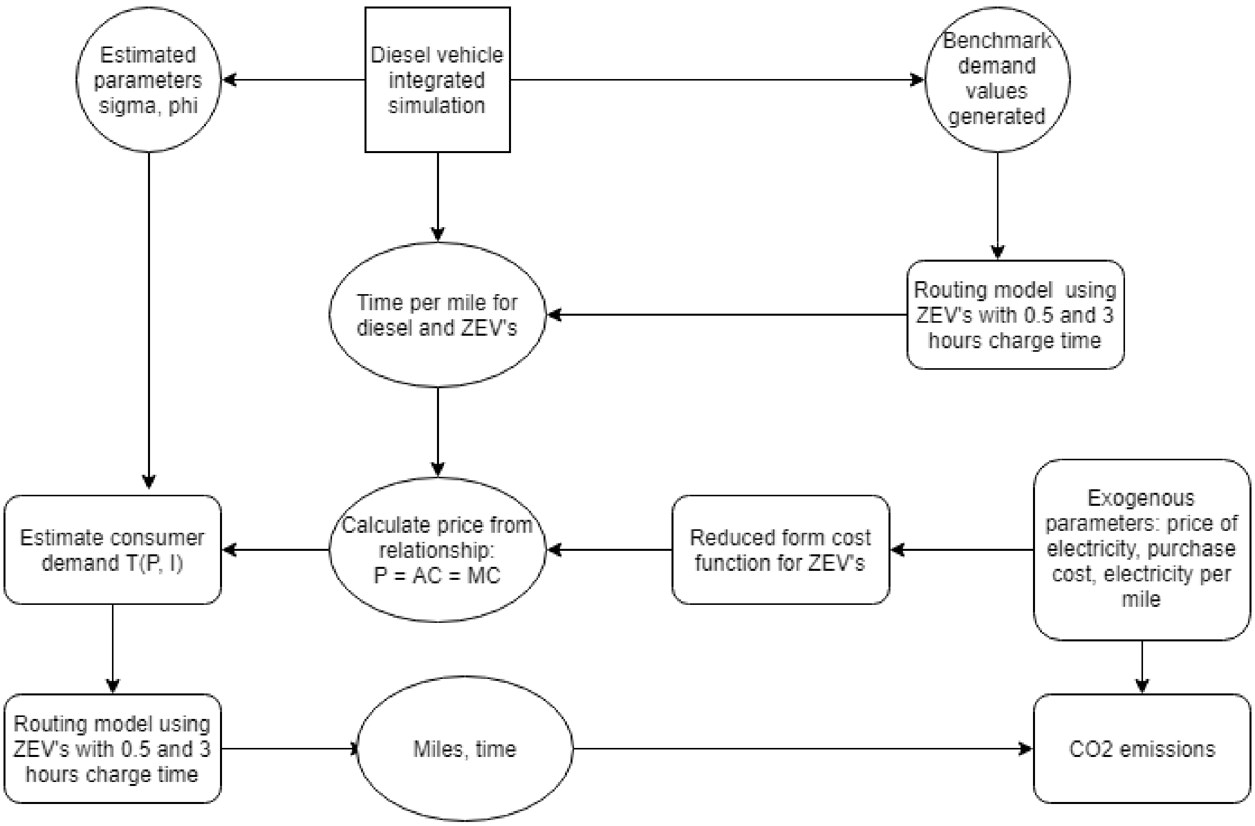


Figure 3. Algorithm for ZEV's



Specifically, we calibrate income and the share of trucking and non-trucking goods. Table 1 summarizes the parameters used in the calibration.

Solving the model for two extreme cases: diesel runs with increased fuel economy and ZEVs run.

Solving for each of these runs requires a series of steps. Specifically, for the algorithm runs on diesel vehicles, we proceed with the following 17 steps. Specifically,

1. We start with the SCAG demand data of 1260 tons for a given day, which is distributed in the LA region. Trucks start at the port of LA (POLA) and delivers at individual demand nodes before returning to a destination at the end of day.
2. Routing simulations on the demand value of 1260 tons generates a total of 9550 miles. Using these values, we generate a mile-ton ratio to be used for converting miles and tons. The consumer model takes miles as a commodity throughout the consumer simulation, so the resulting miles from a consumer demand function is converted to tons equivalent goods using the mile-ton ratio.

3. Using the tons and miles values from above, the price of driving trucks every mile (from ATRI reports) and scale factors (calculated from CA GDP and trucking sector data) we generate a replica of an economy compatible with the POLA demand of 1260 tons.

Table 1. Type and Values of Parameters Used in Integrated Simulation

Parameter	Type	Values	Unit	Source
Elasticity of substitution	Consumer demand	1.6396	NA	Estimated
Share parameter	Consumer demand	0.4139	NA	Estimated
Maintenance cost parameter 1	Truck operator cost	0.0959	NA	Estimated
Maintenance cost parameter 2	Truck operator cost	0.0267	NA	Estimated
Maintenance cost parameter 3	Truck operator cost	-0.0001	NA	Estimated
Purchase cost parameter 1	Truck operator cost	0.0172	NA	Estimated
Purchase cost parameter 2	Truck operator cost	0.0312	NA	Estimated
Purchase cost parameter 3	Truck operator cost	-0.0003	NA	Estimated
Driver wage rate (per mile)	Truck operator cost	0.678	Dollars	Hooper & Murray (2017)
Diesel price (per gallon)	Exogenous	3.015	Dollars	EIA (2015)
Electricity price (per kwh)	Exogenous	0.1523	Dollars	EIA (2016)
ZEV maintenance cost (per mile)	Exogenous	0.2	Dollars	Davis & Figliozzi (2013)
ZEV purchase cost (per mile)	Exogenous	0.5	Dollars	Feng & Figliozzi (2013)
Daily total distance	Routing	350	Miles	Assumed
Tank range diesel truck	Routing	Infinity	NA	Assumed
Range ZEV	Routing	100	Miles	Assumed
Refuel penalty diesel truck	Truck operator	None	NA	Assumed
Refuel penalty ZEV 1	Truck operator	0.5	Hours	Assumed
Refuel penalty ZEV 2	Truck operator	3	Hours	Assumed

Note: ZEV purchase cost based on a price of $150,000 reported by Feng & Figliozzi (2013) and a life of 15 years with 20,000 miles driven every year.

4. In this replicate economy we estimate the elasticity of substitution sigma and calibrate the share parameter phi. This share parameters, estimated to be 0.41, reflects the size of the goods sector that require transportation services. This is substantially lower than the upper bound for these goods, given the proportional average housing costs incurred by households at approximately 0.3-0.35. The elasticity of substitution reflects the substitutability between the trucking and non-trucking goods. This is based on an optimization exercise with a starting value of elasticity of demand for trucking goods taken from Friedlaender & Spady (1980). Rudimentary calculations based on parameter values that are lower or higher than these values imply that the quality of the results are not significantly affected, hence, the results for this sensitivity analyses is not presented here.

5. In a separate estimation exercise, we estimate the parameters of the cost function for freight operators running diesel trucks – vectors alpha and beta.
6. These parameter estimates along with other exogenous parameters are listed in table 1.
7. The cost function for diesel truck operators is written fully as a function of fuel economy.
8. Fuel economy values are generated from a uniform distribution between 4.4 and 8.8 mpg. These generated fuel economy values reflect the pre-Phase I period with no policy intervention. We call this the benchmark fuel economy values.
9. On the benchmark fuel economy values Phase I regulations impose fuel economy improvements between 5% to 20%. The median fuel economy benchmark value is 6.55 mpg for heavy duty diesel trucks as can be seen in table 2.
10. Assuming the same effect of Phase I regulations at every percentile of the fuel economy distribution, we observe the policy shocks through a 5, 10, 15, and 20% increase in fuel economy for heavy duty trucks. All the values can be seen in table 2. Let us denote this fuel economy matrix F.
11. We plug these fuel economy values (or the matrix F) in the freight operator's cost function to generate the per mile cost of operating the diesel trucks.
12. With competitive assumptions, this estimated per mile cost becomes the price in the market facing consumers.
13. Using the previously estimated consumer parameters sigma and phi and the price in the CES demand functions, we get the total number of miles demanded by consumers in a given day. Let us call this matrix of demanded miles M.
14. These demanded miles (or the matrix M) are converted into tons of goods using the mile-ton ratio. This demand in terms of tons of goods reflect the new higher price due to the higher fuel economy imposed by Phase I regulations. The higher price is due to the resulting higher per mile costs to freight operators after cost adjustments due to decreased fuel expenditure but increased maintenance and purchase costs. Let us call this matrix of demanded goods X.
15. These demand values (or the matrix X) are fed into the routing model to generate the number of miles. Using the previously generated fuel economy values (or matrix F), we also calculate the total amount of fuel consumed by trucks in delivering the given amount of goods.
16. With EIA estimates of 10.16 kgs of CO_2 emissions per gallon of diesel consumed, we estimate the overall CO_2 emissions in delivering the demanded goods at 5, 10, 15, and 20% increased fuel economy of trucks.
17. These emissions values in million metric tons, for the entire LA metropolitan region in a given day, can be seen in columns 2 through 6 in table 3. Table 4 shows the same but for the state of CA.

For the algorithm used for the ZEV's runs, we proceed with the following steps:

1. We rerun the routing model with the same SCAG demand of 1260 tons to generate 9700 miles and 242 and about 350 hours for ZEV's with charging time of 30 minutes and 3 hours respectively. We generate the mile-ton ratio for ZEV's.
2. These values are used to generate a replicate economy (just like the one in case of diesel trucks) compatible with the SCAG demand values for POLA, but with ZEV's instead of diesel vehicles (since the total number of miles changes the replicate economy has different sizes of trucking and non-trucking sector in the ZEV and diesel vehicle case respectively).
3. We already have consumer parameters sigma and phi and the demanded goods (or matrix X) reflecting the phase I regulations impact, from the diesel vehicle simulation.
4. Using the demand value matrix X, we run routing simulations for diesel vehicles and ZEV's with charging time of 30 minutes and 3 hours.
5. We get the time per mile for ZEV's with charging time of 30 minutes and 3 hours, and the time per mile for diesel vehicles, for delivering the same amount of goods.
6. These time per mile estimates are used to calculate the opportunity cost of driving ZEV's. The opportunity cost arises due to the higher time taken by ZEV's to deliver goods because of the additional charging time. Let us call the opportunity cost O.
7. Plugging the opportunity cost, the electricity expenditure per mile, maintenance and purchase costs (all of which barring the opportunity cost are parameters and can be seen in table 1) into the freight operator's cost function for driving ZEV's, we get the per mile cost of driving ZEV's.
8. Under competitive assumptions, this per mile cost is the price per mile.
9. Plugging the price, the previously estimated sigma and phi (consumer parameters) into the CES demand function, we get the demand for the total number of miles.
10. Using the mile-ton ratio for ZEV's we convert these miles to tons equivalent goods.
11. This new demand of goods in terms of tons is fed into the routing model to generate the total number of miles. This new value of miles reflect the cost adjustments due to driving ZEV's.
12. Using EIA's estimate of 427 g of CO_2 emissions per kwh of electricity consumed, we estimate the total amount of CO_2 emissions from the total number of miles estimated by the routing model.
13. Columns 7 and 8 of tables 3 and 4 provide the amount of CO_2 emissions from driving ZEV's as opposed to driving diesel trucks with the benchmark fuel economy values.
14. Columns 3 through 8 in Table 5 provide the percentage reduction of CO_2 emissions due to phase I regulations and ZEV's with charging time of 30 minutes and 3 hours respectively from the benchmark situation of no-policy.
15. Table 6 provides the demand in tons for diesel trucks and ZEV's with charging time of 30 minutes and 3 hours. These demand values are the ones for which we calculate the total CO_2 emissions for delivering them.

Results

Here we brief highlight some preliminary results. We note that the major contribution of the project was really the integration of the two models. Additional work is needed to improve the calibration of the model. Therefore, we report preliminary results here, but interpret them with caution. Further, the results should be considered for their qualitative properties, as opposed to precision in quantitative magnitudes.

Fuel-economy Distribution due to Phase I Standards

Table 2 reports the fuel economy distribution and percentage changes due to the implementation of the EPA Phase 1. Here we focus on percentiles values of fuel economy, and we increase fuel economy standards by 5%, 10%, 15%, and 20% as projected by the EPA phase 1 standards.

Table 2. Fuel Economy Distribution at the Benchmark with Positive Shocks Due to Phase I Regulations

Percentile FE	Benchmark FE	FE increases 5%	FE increases 10%	FE increases 15%	FE increases 20%
10	4.86	5.11	5.35	5.59	5.84
25	5.44	5.71	5.98	6.25	6.52
50	6.55	6.88	7.21	7.54	7.86
75	7.62	8	8.38	8.76	9.14
90	8.3	8.71	9.13	9.54	9.96

Note: Benchmark column indicates baseline FE values unperturbed by EPA regulations.

Simulated CO2 Emissions

Tables 3 and 4 summarize simulated CO2 emissions per day in Los Angeles and California respectively.

Table 3. Simulated CO2 Emissions per day in LA (in MMT)

Percentile FE	Benchmark FE	FE inc. 5%	FE inc. 10%	FE inc. 15%	FE inc. 20%	ZEV ½ hr.	ZEV 3 hr.
10	12.713	12.212	11.771	11.328	11.057	2.765	1.2511
25	11.716	11.327	10.856	10.405	9.9803	2.9484	1.4133
50	9.994	9.5117	9.1934	8.8785	8.4359	2.9184	1.1763
75	8.7393	8.313	7.9342	7.4511	7.1152	2.8643	1.1978
90	8.0002	7.5182	7.1574	6.8338	6.5015	2.7421	1.3448

Note: Benchmark column indicates baseline CO2 emissions unperturbed by EPA regulations.

Table 4. Simulated CO2 Emissions per day in CA (in MMT)

Percentile FE	Benchmark FE	FE inc. 5%	FE inc. 10%	FE inc. 15%	FE inc. 20%	ZEV ½ hr.	ZEV 3 hr.
10	32.99	31.69	30.55	29.4	28.7	7.18	3.25
25	30.41	29.4	28.18	27	25.9	7.65	3.67
50	25.94	24.69	23.86	23.04	21.89	7.57	3.05
75	22.68	21.58	20.59	19.34	18.47	7.43	3.11
90	20.76	19.51	18.58	17.74	16.87	7.12	3.49

Note: Benchmark column indicates baseline CO2 emissions unperturbed by EPA regulations.

Each of the columns in these tables represents increases in fuel economy through an increase in the standard. The last two columns reflect two different assumptions related to the charging time. In the first one, we assume that ZEV's have a charging tome of ½ hour, while in the second we assume 3 hours. We compare the resulting emissions of tightening the fuel economy standard of existing diesel trucks with an electrification strategy. To interpret the results, consider two examples. First, consider the 4th column in the 3rd row in table 3, which has a value of 9.1934. This indicates that at the 50th percentile value of fuel economy (which is 7.21 mpg based on table 2), CO2 emissions reduce to 9.91934 mmt from 9.994 mmt at the benchmark in Los Angeles. This is a result of improving fuel economy by 10%.

Similarly, looking at the 8th column and 5th row in table 4, the value is 3.49 mmt. For demand values corresponding to the 90th percentile fuel economy benchmark value (8.3 mpg in Table 2), CO2 emissions reduce from 20.76 mmt (seen in column 1 row 2) to 3.49 mmt in California, from using ZEV with 3 hours charging time.

Percentage Emissions Reduction

Table 5. Percentage CO2 Emissions Reduction

Percentile FE	Benchmark FE	FE inc. 5%	FE inc. 10%	FE inc. 15%	FE inc. 20%	ZEV ½ hr.	ZEV 3 hr.
10	0.00	-3.94	-7.40	-10.89	-13.02	-78.25	-90.16
25	0.00	-3.31	-7.34	-11.19	-14.81	-74.83	-87.94
50	0.00	-4.82	-8.01	-11.16	-15.59	-70.80	-88.23
75	0.00	-4.88	-9.22	-14.74	-18.58	-67.23	-86.29
90	0.00	-6.03	-10.53	-14.58	-18.73	-65.73	-83.19

Note: Benchmark column indicates baseline CO2 emissions unperturbed by EPA regulations.

Table 5 shows the percent reduction in CO2 emissions. Consider the following example – in the 7th column and 4th row in table 5, the value is -67.23. For demand values corresponding to 75th percentile fuel economy benchmark value (8.7393 in Table 2), CO2 emissions reduce by 67.23% from using ZEV with ½ charging time.

We further highlight the following key points:

First, the entire diesel truck fleet has a range of FE from 4.4 mpg to 8.8 mpg. The median level of truck FE is 6.55 mpg. In other words, the average truck has a fuel economy of 6.5 mpg. Second, at median levels of fleet fuel economy, CO2 emissions in the LA metropolitan region and in the state of California, due to diesel vehicles, in a simulated economy without any policy intervention are approximately 10 million metric tons and 26 million metric tons. Third, the effect of Phase I regulations in enhancing the fuel economy standards results in a 5% and 16% reduction in CO2 emissions at the median level of fleet fuel economy. If instead of driving a diesel truck with fuel economy of 6.5 mpg an operator runs a ZEV with 30 minutes charging time, the amount of CO2 emissions reduction is approximately 711%. Running a ZEV with 3 hours of charging time leads to CO2 emissions reductions of about 88% compared to a diesel truck with 6.5 mpg FE. The later effect happens through a massive contraction of demand, since with 3 hours charging prices of goods to be delivered increases substantially. In other words, with EPA Phase I regulations, the increased FE of 5-19% leads to a reduction of about 5-16% of CO2 emissions on average. Driving ZEV's reduce the corresponding CO2 emissions from 70-88%, but these drops are likely very costly, since they are achieved through large reductions in the size of the trucking sector and the demand for goods that require transport.

Conclusions

We integrated a route-level model into a multi-market economics model to evaluate the emissions impacts of Phase I EPA fuel economy standards for trucks and ZEV mandates. Specifically, we illustrate the capabilities of the model by simulating fuel economy values for EPA's Phase 1 regulations and ZEV's. Traditionally, the evaluation of the potential of alternative technologies for climate mitigation starts with simple lifecycle analysis (LCA) of the GHG emissions resulting from various technologies, including all phases of its production and use. However, if public policies that support the same technology result in different multi-market and route-level adjustments, and therefore GHG emissions impacts, per unit of the technology added to the economy, technology-based LCA metrics may result in estimates of emissions savings that are misleading. The model developed here allows for capturing economy-wide GHG emissions that are generated whenever any of the agents in the model, directly or indirectly, adjusts their behavior in response to policies introduced in the freight sector that aimed to reduce GHG emissions in that sector. Here simulations should be interpreted as illustrative of the capabilities of the model developed. In future work, we will continue to improve on the calibration, which will allow for more precise quantification of the impacts of alternative policies.

One key point that needs mentioning in the context of the presented results and potential future work is the effect of congestion. In a general equilibrium multi-market model, congestion should ideally enter through an additional variable in the utility function of representative households. More specifically, as done by Parry (2008), a variable representing the time spent by households in driving can be incorporated into the model, along with a driving time in the cost function of freight operators. This driving time reflects the congestion-induced externality, in the sense that, an increase in the driving time due to the *rebound effect* would reflect higher levels of congestion in the model. However, modelling such driving times explicitly would require a consumer's elasticity of substitution between consumable trucking goods and the time spent in driving, for which we do not have estimates as of now. In addition, this congestion effect is also likely to affect local pollution around port areas or the greater LA metropolitan region. These local pollution effects are, however, out of scope of this study since the major focus here is on GHG emissions.

Moving forward we will continue to improve the calibration of the model and will expand the model to include congestion but also the evaluation of alternative policies.

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Data Management Plan

Products of Research
No primary data was collected for this project. Instead we relied on estimates from a variety of studies to calibrate our model.

Data Format and Content
Not applicable.

Data Access and Sharing
The source of data, which are publicly available, are given in the list of references.

Reuse and Redistribution
No restrictions.

Appendix

To simulate the demand for goods as a function of prices of those goods, we model a representative household, who maximizes a utility function subject to a budget constraint. We use the following constant elasticity of substitution (CES) utility function characterizing the preferences of this representative household:

$$U(T,Y) = \left(\varphi_u T^{\frac{\sigma_u - 1}{\sigma_u}} + (1-\varphi_u) Y^{\frac{\sigma_u - 1}{\sigma_u}}\right)^{\frac{\sigma_u}{\sigma_u - 1}}$$

where, T, Y are respectively the goods that require transportation by freight and that do not. In the model, we assume that the unit of goods that require transportation is equal to miles. Hence, T is also equal to the total number of miles traveled in the process of delivering the goods. φ_u is the share parameter reflecting the share of the sector of goods that require freight transportation, and σ_u is the elasticity of substitution between the goods that require transportation and the ones that do not require transportation. The price of good T is given as P and the price of Y is normalized to unity (following Parry, 2008). Households earn an exogenously given income I. Hence, the budget constraint of the household is given as:

$$PT + Y = I$$

Solving the maximization problem with the utility as the objective function and the budget as the given constraint, we obtain the following uncompensated demand functions for T and Y, as follows:

$$T = \left(\frac{\varphi_u}{P}\right)^{\sigma_u} \left(\frac{I}{{\varphi_u}^{\sigma_u} P^{1-\sigma_u} + (1-\varphi_u)^{\sigma_u}}\right)$$

$$Y = \left(\frac{1-\varphi_u}{1}\right)^{\sigma_u} \left(\frac{I}{{\varphi_u}^{\sigma_u} P^{1-\sigma_u} + (1-\varphi_u)^{\sigma_u}}\right)$$

These demand functions are used to calculate the amount of goods T and Y consumed for given prices P and the parameters φ_u and σ_u.

We posit that the effect of the policy is realized through the cost function of the freight operator. Under competitive assumptions, the price of the trucking good P is equal to the average or marginal cost of the freight operator. This is a key step in the simulation process seen in the algorithm.

The cost for diesel vehicles is modeled as a function of the fuel economy of the vehicles since we are essentially comparing the Phase I fuel economy regulations to that of ZEV's. Following standard economic theory of firms, we assume the cost function to be quasiconvex, with both linear and convex components. This cost (per mile) function is given as:

$$C_D = P_D\left(\frac{1}{F}\right) + w + g(F) + h(F)$$

where, P_D is the price of diesel, F is the average fuel economy of the fleet of vehicles owned by the operator, w represents the wage costs incurred by the operator (in paying drivers and personnel) per mile, and $g(.)$ and $h(.)$ represent the maintenance and lease/purchase cost components incurred by the freight operator. $g(.)$ is a convex function in F following Parry (2008). $h(.)$ is a convex function in fuel economy F because new vehicles with higher fuel economy costs significantly higher, thereby, leading to higher lease/purchase costs. For the purposes of simulation, we assume both $g(.)$ and $h(.)$ to be second order polynomial functions in F, given as:

$$g(F) = \alpha_0 + \alpha_1 F + \alpha_2 F^2$$

$$h(F) = \beta_0 + \beta_1 F + \beta_2 F^2$$

The parameters $\alpha \equiv (\alpha_0, \alpha_1, \alpha_2)$ and $\beta \equiv (\beta_0, \beta_1, \beta_2)$ are estimated using ordinary least squares regression after generating the values of F randomly, from the distributional moments given by Hooper & Murray (2017) and Schoettle et. al. (2016).

For operators driving only ZEV's, the cost function is slightly different from those running conventional diesel vehicles. This is because with ZEV's there is an additional vehicle charging time, during operation, which is substantially higher than the refueling time of conventional diesel vehicles. This additional time of operation to deliver the same amount of goods, is reflected in the cost function, as an opportunity cost of time. This opportunity cost of time represents the lost revenue due to operation of ZEV's instead of diesel vehicles because of the added recharging time. The opportunity cost of time π is defined as follows:

$$\pi = \frac{\delta_E - \delta_D}{\delta_D}$$

where, δ_E and δ_D are respectively the average amount of time taken to drive one mile with ZEV's and diesel vehicles. Using this opportunity cost of time, we write the cost (per mile) function for ZEV operators, as follows:

$$C_E = \left(\frac{1}{1-\pi}\right)(EP_E + w + g_E + L)$$

where, E is the amount of electricity consumed, P_E is the price per unit of electricity, w is the amount of wage costs incurred by operators per mile, and g_E and L are fixed maintenance and lease/purchase cost components respectively, per mile.

The values of the estimated parameters φ_u, σ_u, α, and β, and the other parameters taken from the literature are given in table 1 in the methods section.