Undervaluation of Future Fuel Savings and Efficiency Standards for Heavy-Duty Trucks

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Abstract

Fuel economy standards are a widely used tool to reduce vehicle emissions, though their welfare implications depend on how much consumers value future fuel savings when they make initial vehicle purchases. This paper is the first to measure the effect of the 2014 U.S. fuel economy standards for heavy-duty trucks on consumer welfare, manufacturer profits, and environmental damages. To do so, I estimate a model of demand and supply in the heavy-duty vehicle market. First, I find empirical evidence that buyers substantially undervalue future fuel savings, likely due to both split incentive problems and incomplete information about vehicle performance. Then, I simulate the manufacturer and buyer responses to the policy and find that internalized welfare costs exceed the environmental benefits. However, because of the considerable undervaluation in the commercial vehicle market and the magnitude of fuel savings associated with the policy, the fuel savings and environmental benefits of the 2014 standard exceed the direct costs to consumers and manufacturers.

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1 Introduction

Heavy-duty trucks, the subset of trucks with the highest weight capacities, are only 1% of vehicles on the road, but they contribute nearly 30% of on-road greenhouse gas emissions (Tong et al. 2021). While policies have been in place to reduce passenger vehicle fuel usage since the 1970s, policies targeting truck emissions have lagged behind: the first engine standards for trucks were only introduced in the late 2000s and fuel economy standards were introduced a few years later. However, as in the passenger vehicle setting, there is a debate about the effectiveness and efficiency of imposing fuel economy standards for new vehicle purchases rather than directly imposing a cost on diesel. This debate hinges on how well consumers trade off future fuel savings from more efficient vehicles with up-front costs.

Consumer failures to purchase energy efficient products with positive net present values, dubbed the "energy efficiency gap" (Jaffe & Stavins 1994, Gillingham & Palmer 2014), have been documented in a range of settings, from air conditioners (Hausman 1979) to lightbulbs (Allcott & Taubinsky 2015) to passenger cars (Allcott & Wozny 2014, Gillingham et al. 2021), although some evidence suggests there may not be failures in the context of vehicles (Busse et al. 2013, Sallee et al. 2016). This undervaluation of future energy cost savings is used to rationalize federal standards or mandates, because even in the presence of a Pigouvian tax, consumers may choose inefficiently energy-intensive products.

This paper asks whether there is indeed evidence of undervaluation and if so, what are the welfare consequences of this undervaluation for recent fuel economy standards. In the heavy-duty truck sector, unlike the market for passenger vehicles, buyers are firms and may be less susceptible to behavioral biases than individual consumers. Even so, EPA and NHTSA motivate recent fuel economy standards for heavy-duty trucks in part by citing future fuel savings that, they argue, buyers undervalue.

To measure the valuation of future fuel savings and estimate the costs and benefits of the fuel efficiency policy, I estimate a model of demand and supply in the heavy-duty truck market. On the demand side, buyers choose trucks based on their industry and their expected vehicle usage patterns. In making their decision, consumers trade off price and other vehicle attributes including fuel efficiency (and corresponding future fuel savings), which allows an estimate of willingness to pay for future fuel savings. On the supply side, profit maximizing manufacturers choose vehicle prices and technology in light of consumer preferences. When the policy is imposed, manufacturers can comply in two ways: they can adjust prices so that consumers buy more fuel efficient models, a practice called "mix shifting," or they can adopt technology that improves vehicle fuel efficiency. A major challenge in analyzing the truck market is data availability and particularly, data on model-specific fuel efficiency. I compile data on empirical fuel usage that has not previously been used in academic research and combine this with other data on additional truck characteristics in order to estimate demand and supply parameters and policy effects.

Using variation in fuel efficiencies induced by the policy, I find that truck buyers undervalue future fuel savings. I estimate that buyers of non-vocational trucks (also known as combination tractors) are willing to spend \$1200 for fuel efficiency improvements worth almost \$5800 over a vehicle's 30-year lifetime, or, put differently, they only value approximately 21% of future fuel savings, a number slightly smaller than previous estimates of approximately 30% (Adenbaum et al. 2019). I investigate several mechanisms that may explain this high degree of undervaluation and find suggestive evidence that this reflects split incentives and the ability of truck owners to pass fuel costs on to the firms whose goods they transport. It may also be due to incomplete information about vehicle fuel efficiency, because comprehensive efficiency data by vehicle model is surprisingly difficult to find.

Using the demand results and EPA's estimates of technology costs, I simulate manufacturer decision making in response to the policy. To do so, I first estimate the optimal pre-policy technology adoption level. Then, I can derive manufacturer decisions relating to optimal technology adoption and price changes under the policy. Ultimately, the (internalized) policy costs to consumers are larger than direct costs to firms, but there is considerable variation in the burden imposed on different kinds of buyers: buyers more inclined to buy vocational vehicles, which are less affected by the policy, see smaller price changes, while buyers with higher truck usage also benefit more from cost savings. However, these welfare costs to buyers, and the financial costs to manufacturers, are dwarfed by the fuel savings and, to a lesser extent, the environmental benefits of those fuel savings. Because of the high degree of undervaluation, a diesel tax commensurate with the social cost of carbon would induce only limited fuel savings from shifting purchase behavior, though the overall fuel savings from reducing vehicle usage on the intensive margin are quite large.

This paper exists at the intersection of several literatures. First, it contributes to a long literature on the energy efficiency gap (reviewed in Jaffe & Stavins (1994), Allcott & Greenstone (2012), Gillingham et al. (2009), Gillingham & Palmer (2014), Gerarden et al. (2017)), documenting undervaluation of future fuel savings in the truck setting. The most related paper to this one, Adenbaum et al. (2019), examines undervaluation of future fuel savings among truck buyers using older data covering a subset of used vehicles and a hedonic approach. The present paper estimates fuel savings undervaluation in the market for new trucks via a discrete choice demand framework and also finds substantial undervaluation, but incorporates these results into a full model of supply and demand to estimate the welfare implications of fuel efficiency policy.

Second, this paper adds to a surprisingly small economics literature on the trucking industry. Wollmann (2018) develops a model of truck manufacturer decisions with endogenous product attributes in order to assess the implications of recent bailouts on the sector. This project builds upon features of Wollmann's model, but incorporates fuel efficiency standards, which were not in place during the period he examines, as well as additional vehicle characteristics relevant to the policy and to prospective truck buyers, such as the presence of a sleeper compartment. Rather than endogenizing product entry, I endogenize the relevant vehicle attribute for my setting: fuel intensity. Other papers in this literature examine decisions made by truck owners, including the relationship between market structure and adoption of technology affecting truck performance and efficiency (Hubbard 2000, 2001, Baker & Hubbard 2003, 2004, Vernon & Meier 2012) and responses to changes in fuel costs. Leard et al. (2016) estimate the rebound effect among trucks in order to calculate the expected savings from truck fuel efficiency standards. Cohen & Roth (2016) consider the effect of fuel costs on another margin, dispatch decisions, finding that increases in fuel cost lead freight truck owners to reallocate load to fewer but heavier shipments. These papers address margins of response to fuel efficiency standards outside of the main purview of this paper, which focuses on production and demand.

Finally, this paper builds upon research studying closely related regulations for light-duty vehicles, called Corporate Average Fuel Economy (CAFE) Standards in the US. Goldberg (1998) considered how manufacturers responded to the standards by shifting production between foreign and domestic manufacturing locations. Others instead focused on longer-term adjustments in vehicle technology (Kleit 2004, Austin & Dinan 2005, Shiau et al. 2009), some with an eye toward distributional consequences and used vehicle markets (Bento et al. 2009, Jacobsen 2013). In light of a shift toward attribute-based regulation in the light-duty vehicle standards, Ito & Sallee (2018) consider how the design of the policy affects outcomes. In the context of European standards, Reynaert (2021) considers the role of gaming as a potential manufacturer response, though there is no evidence of gaming in the heavy-duty truck markets. Another strand of the literature focuses on the extent to which fuel economy improvements were attained via technological progress versus tradeoffs along the technological frontier (Knittel 2011, Klier & Linn 2012, 2014).[1] This paper contributes to the CAFE literature by being the first paper to systematically analyze the heavy-duty truck fuel economy standards[2], which are a complement to CAFE.

[1] This approach may be less relevant here, because evidence from the trucking sector suggests that the ability to substitute vehicle attributes like horsepower for fuel efficiency is weaker in heavy-duty vehicles compared to those under the purview of CAFE (He 2017).

[2] Excluding the EPA's Regulatory Impact Analysis (EPA & NHTSA 2011*a*), which does not allow flexibility in truck manufacturer or buyer decisions, and also does not map fuel savings and costs results to

This paper is organized as follows. Section 2 provides background on truck attributes, the heavy-duty truck fuel efficiency standards, available data, and market structure. Section 3 outlines the model, and section 4 provides detail on the estimation approach. Model results are presented in section 5, and section 6 contains the counterfactual simulations, including a welfare analysis of the policy. Section 7 concludes.

2 Background

2.1 Product Characteristics

Before examining the truck efficiency standards, this section briefly discusses truck characteristics, which are necessary to understand both how the fuel efficiency policy is set up and modeling decisions. Heavy-duty trucks are characterized by a limited set of features: gross vehicle weight rating (GVWR), vehicle type (i.e., whether it is a combination tractor, in which the vehicle pulls a detachable trailer, or a straight truck, in which the cargo-carrying component is permanently attached to the vehicle), cab type, axles, and fuel efficiency. GVWR, the amount of weight the vehicle can carry (including the weight of the vehicle itself), takes a range of values; the Department of Transportation categorizes vehicles into classes 1 through 8 based on their GVWR (see table A.1.1 and figure A.2.1 in the appendix for more detail), and the light- vs. medium- vs. heavy-duty designation is determined by these classes. Heavy-duty vehicles fall into classes 7 (between 26,0001 and 33,000 lbs) and 8 (>33,000 lbs). The weight rating affects the uses of a vehicle (i.e., a truck intended to tow heavy machinery needs to be rated for loads greater than the weight of the machinery) and, in general, price is increasing in GVWR.

The cab, the portion of the vehicle that encloses the driver, any passengers, and potentially a sleeping area, is also important to potential buyers. Cab length affects comfort, safety, and ease of navigation. Shorter cabs, particular cab-over-engine designs, place the seating area directly over the engine and front axle and allow improved visibility but reduced safety. Longer cabs provide greater comfort and safety for the driver. Cabs also differ in roof height, which affects the height of trailer that can most efficiently be attached as well as the ability of the driver to stand up comfortably in the cab. Finally, some class 8 cabs feature a sleeper compartment, in which drivers can spend the night. Sleeper cabs are important for long-haul trucks that will be used for multi-day transport, but as they involve additional amenities, sleepers tend to be more expensive than non-sleeper alternatives.

As in cars, axles determine the configuration of wheels and, in the case of drive axles

welfare.

connected to the engine, transmit torque to the wheels. All axles also carry the weight of the attached trailer. As the number of drive axles increase, trucks are able to maintain better traction on poorly maintained or slippery roads, but efficiency tends to decrease. The same make and model can be sold with a number of different axle configurations. Historically, configurations with more drive axles have been more popular due to presumed higher retail value (Cummins 2016).

Finally, fuel economy is an important characteristic for trucks, as it governs one of the main variable costs (i.e., fuel costs) for truck owners. Fuel economy is, for the purpose of this paper and the policy it examines, measured in gallons per thousand ton-mile, as the fuel usage of a given truck differs considerably depending on whether it is empty or towing as much as 26,000 or more pounds. Limited information about truck efficiency is available to prospective buyers; manufacturers produce designated energy efficient models, but do not publicize the expected fuel usage in a standardized way.

2.2 Policy

Though CAFE standards were first enacted for light-duty vehicles in 1975, the federal government only recently undertook the regulation of heavy-duty vehicle fuel economy. Diesel fuel and engine emission standards were implemented in the 2000s, and in August 2011, the Environmental Protection Agency (EPA) and the National Highway Traffic Safety Administration (NHTSA) issued joint greenhouse gas emissions and fuel economy standards for medium- and heavy-duty trucks (EPA & NHTSA 2011*c*). Phase I of the rule covers model years 2014 through 2018, while Phase II, introduced in 2016, covers model years through 2027. The Heavy-Duty (HD) National Program features separate standards for three categories: combination tractors (see definition above), heavy-duty pickup trucks and vans, and vocational vehicles. This paper focuses on the first category, but includes a subset of heavy-duty vocational vehicles to accurately represent tradeoffs between potential substitutes. Heavy-duty pickups and vans are omitted.

The EPA standards for combination tractors are delineated across cab type and three roof heights for a total of nine categories (class 7 vehicles are only offered as day cabs) and, as is discussed below, compliance with the standards allows averaging across several weight categories (see table 2 for the 2014 and 2017 combination tractor standards). By contrast, heavy-duty pickup trucks and vans (classes 2b and 3) are regulated in a similar manner to light-duty vehicles, subject to adjustments based on vehicle capacity and 4-wheel drive. Finally, vocational vehicles is the catch-all category covering vehicles as varied as cement mixers, school buses, tow trucks, etc., and this wide range of forms and purposes dictates the manner of regulation. Vocational vehicles, which fall into classes 2b-8, are divided into subcategories based on engine size, and though the standards consist of emissions/fuel economy targets, adherence is primarily based on tire choices.

Though fuel economy standards are intended to drive research and development in efficiency measures, the standards target levels of efficiency that are achievable with existing technology. The standards rely upon a subset of technologies included in a 2010 National Research Council (NRC) report on approaches to reduce medium- and heavy-duty truck fuel consumption (EPA & NHTSA 2011*b*). Some of the largest efficiency improvements are available via improvements to engines, aerodynamics, rolling resistance, and drivetrain (NRC 2010).

Compliance with the standards is determined using a simulation model, the "Greenhouse gas Emissions Model" (GEM). The model pre-defines a number of inputs including tractor frontal area, tire radius, etc. (EPA 2011*b*). When examining combination tractors, users are able to input the coefficient of aerodynamic drag, steer and drive tire rolling resistance, whether the vehicle has a speed limiter, weight reductions from lighter components, and the use of extended idle reduction technology. Vocational vehicle standards only consider engine fuel intensity and improvement in tire rolling resistance.

2.3 Data

Analyzing the effect of heavy-duty truck fuel efficiency policy requires data on the quantity and characteristics of trucks sold, buyer attributes, and fuel efficiency technologies and their costs. I combine data from a number of sources. First, class 7 and 8 vehicle sales data for 2010-2018 come from IHS Markit (formerly R.L. Polk).[3] The sales are disaggregated by brand, model name or number, GVWR class (7 or 8), cab length, axle configuration, engine size, engine manufacturer and model (where available), and buyer information. The buyers are delineated into 13 broad categories including for-hire, local/state/federal government, private, individual, utilities, multiple lease categories, and dealer or manufacturer. Buyer types are further broken down by industry where possible (e.g., general freight, specialized/heavy hauling, forestry/lumber products, etc.). There are 32 categories in this latter field, though for this paper I often combine vocations.

To the sales data, I join a panel of vehicle models and their characteristics from Price Digests. The characteristics from Price Digests include brand, model name or number, gross vehicle weight, axle configuration, BBC (a measure of the distance from bumper to back of cab), an indicator variable reflecting whether a vehicle is a tractor, a sleeper type field that

[3]The IHS Markit data includes all class 7 and 8 trucks. I omit vehicles that are neither tractors nor straight trucks, which are primarily buses, fire trucks, step vans, and motor homes.

includes roof height where available, wheelbase (the distance between front and rear wheels), and manufacturer suggested retail price (MSRP). The attribute data was merged with the sales data based on brand, model name, GVWR category, axle configuration, and the tractor flag. Where no matches were available, I first checked for alternate names (sometimes model numbers were used in one source while model names were used in the other; in other instances, one source combined models under a broader model name while the other distinguished between e.g., "model name 500" and "model name 600") and then relaxed the attributes on which the merge was performed. A feature of the heavy-duty vehicle sector (that also applies to cars and light trucks to a lesser extent) is that multiple configurations may be categorized as falling under the same brand-model within a year. Where multiple models in the Price Digest data mapped to a category in the sales data, I calculated the average price and gross vehicle weight to use in the demand estimation. Of the more than 1.8 million class 7 and 8 vehicle sales in the data, almost 98% can be mapped to price and other attribute data. Price Digests also includes information on retail price, which I use to adjust MSRP.

Table 1 contains the summary statistics for vehicles available in model years 2011-2019. There are more class 8 vehicles than class 7, and the largest number of unique vocational vehicle offerings (though this table counts all sleeper roof heights as a single product offering). At the level of disaggregation I consider, there are several hundred product offerings per year, and both within and across time, there is considerable variation in price and other attributes. It is also worth noting that the total market size for the included class 7 and 8 trucks is considerably smaller than the market for cars and light trucks. Market size is responsive to a number of economic conditions, and the minimum annual sales are for the 2011 model year, when the Great Recession was ongoing. The maximum sales occurred for model year 2016.

Importantly, neither the IHS Markit data nor the Price Digests data include empirical measures of fuel efficiency. While fuel efficiency data for cars and light trucks is made available by the EPA[4], no such source exists for heavy-duty vehicles.[5] The lack of reliable, agency-vetted data on performance has been noted by other stakeholders, who have advocated for more public data including a labeling program comparable to that which exists for light-duty vehicles.[6] As a result, I use empirical data on fuel efficiency performance from a

[4] `www.fueleconomy.gov`

[5] EPA and NHTSA of course collect the GEM outputs to determine firm compliance with the standards. An anonymized version of the data was made available following a FOIA request, but without further information, it is not possible to map observations to models. The full data with make-model-configuration information was not made available following the FOIA request because it is classified as "Confidential Business Information," though there is an ongoing legal process to challenge this designation. The proposed 2027 standards also include efforts to increase data availability going forward (`https://www.epa.gov/regulations-emissions-vehicles-and-engines/proposed-rule-and-related-materials-control-air-1#rule-history`).

[6] As ACEEE noted in their public comments on the Phase II standards, "The absence of a label or any

website used by truck drivers to track their fuel usage.[7] Drivers are able to register their trucks on the website and for each fuel up, record the gallons of fuel used and the distance travelled. Their trucks are identified by year, make, and model, and drivers are able to record additional details, including average speed, average GVW, modifications they have made to the vehicle, etc. See appendix figure A.2.2 for what the data looks like at the aggregate and individual-truck level. I combined this data to calculate average miles per gallon for each truck model-year, and using known GVWR and assumptions about how full the trucks typically operate, rescaled this into a fuel intensity measure in gallons per thousand ton-mile. While it is possible that this measure of fuel efficiency may be biased due to the selection of drivers who participate in the fuel tracking website, I am able to confirm that models designed to be relatively more fuel efficient were determined to have lower fuel intensities than other models. Figure 1 shows the sales-weighted average fuel intensity among sleeper cabs over time. There is an observable decline in fuel intensity in the first year of the standards (2014).

Several additional data sources merit discussion. The costs of different fuel efficiency technologies were derived from EPA's Regulatory Impact Analysis. Patterns in annual VMT and payload are based on the Vehicle Inventory Use Survey (VIUS) with adjustments that bring the data in line with the Regulatory Impact Analysis. Historically, the VIUS was conducted by the Census Bureau in concert with the Bureau of Transportation Statistics and the Federal Highway Administration at five-year intervals, and it collected vehicle-level fuel usage, mileage, and average payload in addition to owner demographics and other data. The survey was discontinued after 2002, which is why fuel efficiency measures from the survey are not available for my analysis, but many papers examining truck-buying behavior (Wollmann 2018) or fuel price responsiveness among truck owners (Adenbaum et al. 2019), relied on this dataset. The Census has begun a new iteration of the survey, and results will be available in late 2023. In addition to industry-specific usage patterns, I use the VIUS self-reported fuel efficiency measures for historical vehicles in some descriptive analysis. State-level manufacturing wages by year, used to construct an instrument for price, come from the Bureau of Labor Statistics, while Canadian province-level manufacturing wages were ascertained via Statistics Canada.[8] Wages were then matched to the assembly plants at which each model is assembled, which in turn was derived from model VINs. The US

other publicly available information stating the fuel efficiency of the vehicle at the time of sale means the consumer is in effect cut out of the market for efficiency."

[7] www.letstruck.com

[8] Virtually all trucks in the data are manufactured in the US, Mexico, or Canada due to an import tariff of 25% applied to all trucks, known as the "Chicken Tax" (Canada and Mexico are exempt due to NAFTA and its replacement, the USMCA).

Census County Business Patterns data provided the numbers of firms and employees in each industry. The variation in this data is the basis for the distribution of truck buyer industry types each year.

2.4 Market Structure

The structure of the truck market–in which a small number of manufacturers produce most of the models purchased by commercial buyers–informs the modeling decisions made in the following section.

2.4.1 Manufacturers

The heavy-duty truck market is more concentrated than the light-duty vehicle market. There are 19 brands, or makes, of class 7 and 8 vehicles in the sales data, and 14 of these produce models available as conventional tractors (i.e., are affected by the tractor-specific policy). 10 of the brands can be found in the Price Digests data (the remaining four sell less than 1% of vehicles in the sales data). Several of these brands are owned by the same parent company: while Autocar, Caterpillar, Ford, and International brands are all separately owned, Daimler's brands include Freightliner and Western Star; PACCAR owns Kenworth and Peterbilt; and Volvo produces both the brand of the same name and Mack. These ownership structures are accounted for in the supply model. Figure 2 shows the market share of each brand over time. Through the entire period, Freightliner's market share is at or above 30%.[9] The only other brand that comes close is International, which gradually loses market share for much of the time period.

In addition to market concentration, the supply side of heavy-duty trucks differs from that of light-duty vehicles in a few key ways. For example, not all components are produced by the manufacturer. Rather, axles, transmissions, and engines are often produced by outside companies. When a customer purchases a new vehicle from a particular brand, the buyer is given a choice of many attributes, and the brand serves as the central contact point to acquire and assemble parts within the main vehicle body. Because of this role, the efficiency standards are enforced at the manufacturer level, though separate engine standards also apply.

[9]Freightliner is, as noted above, one of two brands owned by Daimler, but Freightliner's sales are considerably larger than the other Daimler brand, Western Star. Interestingly, the vast majority of Freightliner's sales come from the Cascadia model, which is available in a range of configurations. Between 2010 and 2019, the Freightliner Cascadia's sales were between 13 and 28% of all class 7 and 8 sales included in the data.

2.4.2 Buyers

The majority of trucks are purchased for commercial purposes. In the data, approximately 4% of class 7 and 8 trucks are purchased by local, state, and federal government, while the remainder go to individuals and firms. Among vehicles sold to firms for which data is available, the freight industry purchases nearly half of vehicles (48%), while service industry buyers purchase 13%, the wholesale and retail sector buys 7.2%, and construction firms purchase another 7.1% of vehicles.[10] However, there is also meaningful variation in industry shares over time.

Buyer industry is important because it determines the distance traveled and weight carried, which in turn shapes preferences for cab characteristics and fuel efficiency. The relationship between buyer industry and vehicle attributes is evident in table 3, which shows that sanitation and construction are much more likely to purchase vocational vehicles than general or specialized freight or other industries, and that while all industry groups are more likely to purchase class 8 vehicles than class 7, sanitation and general freight in particular purchase a large share of class 8 vehicles.

Beyond industry, firm size is an important attribute that affects the appropriate choice of demand model. The size of truck-purchasing firms varies tremendously. At the time of the most recent VIUS, 70% of respondents operated 1-6 tractors, but more than 8% operated more than 50 tractors. The decisions made by large fleet operators may be different from those made by smaller purchasers, but following Wollmann (2018), this paper abstracts from these issues. Future research may consider how decisions made by the managers of smaller or larger fleets differ.

A number of surveys study the decision-making and behavior of truck owners. Large fleets sell or replace tractors more frequently than small fleets do–generally, after three to five years (Schoettle et al. 2016). While both types of fleet operators seem to require payback periods for efficiency-improving technologies considerably shorter than the expected lifespan of a given tractor, Klemick et al. (2015) and Schoettle et al. (2016) found that larger fleets had longer payback periods. Fuel economy was rated a major consideration in tractor purchase decisions but was a relatively lower priority for operators of short-haul or regional fleets.

[10]This excludes leased vehicles, for which only the nature of the lease (rental, finance, manufacturer sponsored) is available. Unfortunately, the industry of the lessee is unavailable in the data. This might be an issue for my estimation if particular industries are disproportionately likely to lease vehicles rather than purchase outright.

3 Model

To analyze the effects of the fuel economy policy, I estimate a model of consumer and manufacturer decision-making. The demand model features heterogeneous buyers choosing vehicles to maximize utility based on vehicle attributes and their own industry-specific preferences for truck characteristics. On the supply side, manufacturers choose vehicle prices and technology to improve fuel efficiency. Pre-policy, they face an unconstrained profit maximization problem, but once the policy is in place, they must make their choices while complying with average fuel economy standards for each vehicle subgroup. This is one advantage of studying fuel economy standards in the heavy truck setting compared to light-duty vehicles: because the policy was adopted more recently, we are able to observe the results from the unconstrained problem and estimate marginal costs without assumptions about relative dealer and manufacturer markups that are common in the CAFE literature.

3.1 Demand

Each buyer i considers the set of trucks J and the outside good and makes a purchase decision in order to maximize utility.[11] For each truck j in J, the buyer derives utility from the attributes of the truck, though the utility may vary according to buyer characteristics, and derives disutility from the price. The expression for buyer i's indirect utility from inside good j is

$$U_{ij} = x_j(\beta_x + \beta_x^o z_i^o) + p_j\beta_p + \xi_j + \varepsilon_{ij} \tag{1}$$

and from outside good is $u_{i0} = \varepsilon_{i0}$. x_j is a vector of vehicle j's characteristics, including gross vehicle weight rating, indicators for each cab type (sleeper vs. day vs. vocational) and roof height, indicators for common axle configurations, estimated fuel intensity, and make dummies. Price p_j enters separately. Buyers have heterogeneous preferences for some characteristics that differ at the industry or individual level: the preferences are determined by individual characteristics z_i^o. The two shocks are ξ_j, representing unobserved attributes of truck j, and $\varepsilon_{i,j}$, representing idiosyncratic preferences for product j. From this specification, the purchase probabilities can be derived. That is, the probability that buyer i chooses

[11] The outside good in this setting includes the decision not to purchase a truck, to purchase a used truck, or to purchase a vehicle outside the categories considered in this paper (i.e., medium-duty trucks or certain vocational vehicles).

product j is given by

$$\Pr(j|x) = \frac{\exp(x_j(\beta_x + \beta_x^o z_i^o) + p_j\beta_p + \xi_j)}{1 + \sum_{j' \in J} \exp(x_{j'}(\beta_x + \beta_x^o z_i^o) + p_{j'}\beta_p + \xi_{j'})} \tag{2}$$

The aggregate demand s_j can be found by integrating this probability over the distribution of demographics.

This demand specification assumes that each buyer only buys one vehicle at a time, is a price taker, and makes a static decision without regard to other vehicles he or she may own (i.e., buyers do not purchase trucks as a "bundle" or consider complementarity or substitutability across their fleet). In practice, there are some large freight companies that purchase many trucks for their fleet at the same time, but the majority of buyers are small firms that may own multiple vehicles but purchase a limited number of new vehicles each year.

3.2 Supply

In this section, I outline a supply model in which firms respond to a fuel economy standard imposed at the class-sleeper-roof height (henceforth, regulatory-group) level. This is the model used to simulate welfare outcomes below. The initial estimation uses pre-policy data to estimate a standard, unconstrained supply model.

In this model, firms have chosen the set of vehicles and their non-fuel intensity characteristics well in advance, i.e., the product set is exogenous. In order to comply with the policy, firms have two levers: vehicle price and additional technology that improves their fuel efficiency by a given percentage.

Each firm f, offering a set of vehicles J_f, maximizes profits subject to the constraint imposed at the regulatory-group level:

$$\max_{\mathbf{p},\mathbf{t}} \sum_{j \in J_f} \pi_f(p, t) \tag{3}$$

subject to

$$\frac{\sum_{j \in J_f^r} q_j e_j}{\sum_{j \in J_f^r} q_j} \leq \bar{e}_r \ \forall\ r \tag{4}$$

where J_f^r is the set of firm f's vehicles that are in regulatory group r, e_j is the fuel intensity of vehicle j, and $\bar{e}_r$ is the fuel intensity standard for regulatory group r. Technology adoption t is modeled as a percentage reduction in fuel consumption, where $0 \leq t \leq 1$. I ignore the possibility of permit-trading across firms and do not consider dynamics.[12]

We can write the firm's Lagrangian as follows:

$$\mathcal{L} = \sum_{j \in J_f} (p_j - c_j(t_j)) s_j(p,t) N + \sum_r \mathbb{1}\{j \in J_f^r\} \lambda_f^r s_j(p,t) N L_{j,r} \tag{5}$$

where c_j is the marginal cost of producing vehicle j, s_j is vehicle j's share of the total market, N is the market size, λ_f^r is the shadow cost of the regulation per unit of sales specific to firm f and regulatory group r, and L_j is a measure of how far vehicle j is from complying with the standard: $L_{j,r} = (1 - t_j)e_j - \bar{e}_r$. If the standard is not binding, λ_f^r will be 0. For firm-groups for which the standard is binding, at the optimum, λ_f^r should be equal for all vehicles in J_f^r, but because averaging is not allowed across groups, we would not expect λ_fs to be equal for vehicles in different regulatory groups.

The solution to firms' profit maximization problem in the presence of the regulation is pinned down by two first-order conditions and the assumption that firms comply with the standards exactly. The $2J$ first-order conditions with respect to price and technology are:

$$\frac{\partial \mathcal{L}}{\partial p} = \mathbf{s} + \Phi \circ \Delta_p (\mathbf{p} - \mathbf{c} - \lambda \circ \mathbf{L}) \tag{6}$$

$$\frac{\partial \mathcal{L}}{\partial t} = (-\mathbf{c_t}' + \lambda \circ \mathbf{e}) \circ \mathbf{s} + \Phi \circ \Delta_t (\mathbf{p} - \mathbf{c} - \lambda \circ \mathbf{L}) \tag{7}$$

Bold letters refer to $J \times 1$ vectors of characteristics, Φ is a $J \times J$ ownership matrix where $\Phi_{j,k} = 1$ if product j and product k are produced by the same firm, and λ is a $J \times 1$ vector where the jth element contains the shadow price for product j's firm-regulatory group. Δ_p is a matrix of the derivatives of market shares with respect to price where $\Delta_{j,k} = \frac{\partial s_k}{\partial p_j}$, and Δ_t is the similarly defined matrix of the derivatives of market shares with respect to technology. $\mathbf{c_t}'$ is a vector of the derivative of marginal costs with respect to technology. $\circ$ denotes the Hadamard product. For tractability, in the counterfactual simulation, I impose that t decisions are made at the firm-regulatory group level, which reduces the number of first-order conditions with respect to technology to the number of firm-regulatory group combinations.

[12] These assumptions are standard in the CAFE literature.

4 Estimation

4.1 Demand Estimation

The set of parameters I estimate are β_x (the common tastes for characteristics), β_x^o (the individual- and industry-specific tastes for characteristics), and β_p (the sensitivity to vehicle prices). Demand estimation follows the Berry et al. (1995) approach. That is, the procedure starts with a guess of the linear $\beta_1 = (\beta_x, \beta_p)$ parameters. From this, $\delta(\beta_1)$, the implied mean utility, can be derived using the standard contraction mapping approach. In turn, the non-linear parameters, β_x^o, are estimated via GMM. The GMM problem is:

$$\min_{\beta_2} g(\beta_2)' Z W Z' g(\beta_2) \tag{8}$$

where $g(\beta_2)$ is a vector of moments, and in all specifications, it includes the unobserved characteristics, ξ_j. Because product characteristics are chosen before the realization of the consumer demand shocks, $\mathbb{E}[\xi | x, w] = 0$, where x is product characteristics and w is manufacturing wages. W is a weighting matrix and Z is a matrix of instruments.

Instruments are required to address the endogeneity of price and fuel intensity. The excluded instruments for price must shift the price of product j without directly affecting utility from purchasing product j. These include the typical BLP instruments–own-firm and other firms' products, which affect price via competitive effects–and wages corresponding to the region in which each tractor is produced, which affect price via marginal cost. While there may, over the long term, be strategic decisions about where to open factories and which vehicles to produce in different locations, these decisions are made well before the product-specific preference shocks are revealed.

Finding excluded instruments for fuel intensity poses a challenge. In other settings, people have used measures of the endogenous characteristics in other markets or the endogenous characteristics on other vehicles that share the same platform (Reynaert 2021, Klier & Linn 2012). Unfortunately, here we lack data on truck efficiency in other markets and there is no clear analogue to platforms. One source of variation is the policy itself: there is a meaningful drop in fuel intensity following the first stage of the policy and a smaller reduction following the second stage. I use indicators for being in the post-standard period interacted with cab type (sleeper vs. day) as instruments for fuel intensity. In this case, identification of the fuel intensity preferences comes from differences in fuel intensity among otherwise similar vehicles across time, rather than the cross sectional variation.

With the IHS buyer industry data, I also include micro-moments in $g()$ as in Wollmann (2018) or Petrin (2002) in order to estimate individual- and industry-specific heterogeneity in preferences. Specifically, I match the probability the buyer of a vocational vehicle belongs to a specific industry (sanitation, construction, general freight, specialized/heavy hauling, and other). Identification of industry-specific preferences comes from differences in vocational share across industries and the variation in this share across years as other attributes of vocational and non-vocational vehicles change. Additionally, the demand specification allows individual truck usage patterns to affect utility from vehicle fuel efficiency. Individual new vehicle thousand ton-miles (ktm_i, referring to the product of miles and payload in the vehicle's first year of use) interact with vehicle costs per thousand ton miles (the product of fuel intensity per thousand ton miles and fuel costs, in the year prior to the vehicle's model year[13]). Measures of individual ktm_i come from the VIUS survey (scaled up to match more recent mileage, as done elsewhere). Values of observed ktm_i for a subset of observations are chosen based on the industry of the truck owner; that is, simulated freight buyers will have a randomly selected (scaled) ktm from the historical data. This reflects the observed differences in vehicle usage across buyer industries (Appendix figure (A.2.3) shows the distribution of miles and payloads by industry for new vehicles in the VIUS survey). While I cannot include moments that directly capture the relationship between ton-miles and vehicle fuel intensity (as the VIUS fuel intensities are several decades old), identification for the parameter on $ktm_i \times$cost per mile$_j$ comes in part from additional moments that match expected fuel intensity by industry. Because the cost per mile term also includes the diesel cost, estimation of this parameter also depends on variation across time in fuel prices, and how market shares for relatively more efficient vehicles differ in years with higher or lower diesel prices. Identification of other preferences for exogenous vehicle characteristics comes from the variation in vehicle market shares as the bundle of other attributes vary both within each market and across time.

4.2 Supply Estimation

I obtain marginal costs of vehicles produced in the year before the policy comes into effect from the firm's pre-policy first-order condition with respect to price, equation 6. s and p come directly from the data, Δ_p is derived from the demand results, and $\lambda = 0$ when the policy is not in place.

In the post-policy period, I need estimates of the cost of technology adoption. For this, I rely on estimates from EPA's regulatory impact analysis, fit to a quadratic function for each regulatory group. However, given the low costs of compliance (less than \$9000 in 2018 \$ to improve high-roof sleeper cabs by 15-16%), consumers may be willing to pay for these

[13] A significant share of trucks are purchased in the calendar year before a vehicle's model year.

improvements even with incomplete valuation of future fuel savings.

If we observe that these fuel economy-improving technologies are not fully adopted, an explanation for why profit maximizing manufacturers would not have done so is needed. There are several potential explanations, with different implications for the costs and benefits of the policy. First, EPA's marginal cost estimates may be overly optimistic. To address this concern, I use the first-order condition with respect to technology, equation 7, to calculate the pre-policy slope of the marginal costs of improving fuel efficiency (this approach is based on Reynaert (2021)). I can then use the pre-policy value as the intercept of the post-policy cost functions in the counterfactuals. Second, there may be fixed costs of adopting the technology that are not observed, such that adopting the technology is only worthwhile once the costs of non-compliance are added to firms' profit maximization.

5 Results

Table 4 contains the estimates of the demand parameters. The discrete cab categories are class 7 day cabs, class 8 day cabs, low-roof sleeper cabs, mid-roof sleeper cabs, and high-roof sleeper cabs; the omitted category is vocational vehicles. The results are shown for a random coefficients model in which utility is affected by vehicle characteristics as well as buyer expected first-year fuel costs (the interaction between cost per ton-mile and individual ton miles) and industry-wide tastes for vocational vehicles. As expected, consumers dislike higher prices and prefer vehicles with higher GVW, all else equal. The average price elasticity of demand for vehicles is between -2.5 and -2.8, slightly lower than elasticities estimated for passenger vehicles. Consumers also prefer most non-vocational (tractor) vehicles to vocational alternatives, with sleepers generally preferred to day cabs. Only class 7 day cabs have a negative coefficient. The industry-specific preferences for vocational vehicles are also consistent with expectations–construction and sanitation, two industries that tend to use special-purpose vehicles, have positive coefficients, as does specialized/heavy hauling, which relies in part on severe duty vehicles that can be classified as vocational. Only freight prefers tractors to vocational vehicles.

5.1 Fuel Cost Undervaluation

The coefficients on first-year fuel costs merit further discussion. The coefficients are separately estimated for vocational and non-vocational vehicles. Both terms are negative, suggesting that buyers dislike additional fuel costs, though the coefficient on fuel costs for non-vocational vehicles is larger. I calculate the willingness to pay for fuel savings in trucks, providing some of the only estimates of this parameter and the first that do not rely primarily on decades-old VIUS results. Buyer i's lifetime fuel expenditures from vehicle j depend on both i's truck usage (in terms of miles and payload) and vehicle j's efficiency: specifically, the net present value of lifetime fuel expenditures are equal to

$$\sum_{t=0}^{T} \frac{\gamma_t \times ktm_i^0 \times dpktm_j}{(1+\delta)^t}$$

where T is the maximum vehicle lifetime, assumed to be 30 years (following the EPA calculations)[14]; γ_t represents the ratio of ton-miles in year t relative to the first year of vehicle ownership, and is calculated using VIUS data[15]; ktm_i^0 is buyer i's ton-mileage in the first year of ownership (measured in thousands of ton miles); $dpktm_j$ is vehicle j's cost per thousand ton-mile; and δ is the discount rate, assumed to be 5%. Under these assumptions, \$1000 of first-year fuel savings is worth \$5,785 over the vehicle's lifetime. The willingness to pay for these fuel savings is only \$1220, as determined by the ratio of the price and fuel cost coefficients. Thus, I calculate that consumers only value 21.1% of future fuel savings.

This high degree of undervaluation is potentially surprising, but not unprecedented. In a study of fuel efficiency valuation among class 8 truck owners, Adenbaum et al. (2019) found truck owners were willing to pay for 29.5% of expected future fuel savings using a higher discount rate. Truck buyers have also stated in a number of surveys that they require a 3-4 year payback period for fuel efficiency improvements (Schoettle et al. 2016), despite the long lifetime of heavy-duty trucks. When the estimated willingness to pay is compared to fuel expenditures in the first 3 years, there is still considerable undervaluation (49%).

5.2 Potential Undervaluation Mechanisms

There are several possible explanations for why truck buyers, who use their vehicles for business purposes and should be optimizing for cost, may not be doing so. The first explanation is a split incentive problem. Specifically, some of the trucks in my data are purchased by private companies to transport their own products; these firms must fully bear the costs of fuel expenditures. However, many trucks transport goods for other companies. The owner of the truck contracts with the firm that produces goods, and these contracts usually involve a fuel surcharge, covering some or all of the fuel expenses. Thus, it is the set of goods-producing firms who must bear the cost of less efficient vehicles, but they cannot make the

[14]Because of the decline in fuel usage over the vehicle lifetime, as well as the discounting of future fuel costs, results are not very sensitive to cutting off the vehicle lifetime as early as 10 years.

[15]Specifically, I estimate a linear relationship between age and log miles. The decline is large enough that in the 10th year, the miles traveled are less than 30% of miles traveled when the vehicle is new.

initial vehicle purchase decision themselves and may not always have information about the fuel efficiency of the exact truck being used to ship their goods. A second explanation is incomplete information. As discussed in the data section, information on vehicle fuel efficiency is not available systematically. Buyers can peruse message boards or assess the historical performance of other vehicles they own, but may not be able to definitively determine the savings associated with each vehicle model available. Finally, it might be the case that fuel efficiency improvements are bundled with other, less desirable attributes that are not observable in the available data.

I am able to test whether the first two explanations might be relevant using the VIUS data. If split incentives are at play, we would predict that trucks owned by private companies would be more fuel efficient (conditional on vehicle attributes and other usage variables) than those owned by companies who ship on behalf of other firms and can pass on some or all costs. I compare the reported fuel efficiency for respondents who report that a majority of their mileage is driven privately ("carry own goods, or use truck for internal company business only") to those who report that a majority of the mileage is driven by owner operators ("independent truckers hired to carry other people's goods") or by motor carriers ("company-owned trucks hired to carry other people's goods") and who are categorized as either freight or other in industry (i.e., omitting the primarily vocational truck-buying industries). The results, shown in table 5, reveal that private shippers in fact do have significantly higher reported fuel efficiencies. This evidence supports the contention that the ability to pass on fuel costs affects the valuation of fuel economy improvements.

Similarly, I test whether information about fuel efficiency is limited, such that firms must learn about it from their own fleet. If this is the case, firms with more trucks would be expected to have better information about fuel efficiency and therefore have higher efficiency (again, conditional on attributes and usage). I compare the reported fuel efficiency for truck owners with less than or equal to 10 trucks in their fleet to those with larger fleets, and find that those with smaller fleets report lower efficiencies, but the difference is not statistically significant. Thus, this may be weak evidence for the role of incomplete information. However, there are other reasons we might expect fleet size to be related to fuel efficiency (including the ability to optimize shipping routes more effectively with more trucks to choose from, or the endogeneity of fleet size, which is itself an outcome of business profitability). There is not an obvious way to test for the possibility that efficiency is correlated with undesirable truck attributes with currently available data in the VIUS or in the other vehicle attribute data, though this may be a question for future work. Ultimately, there are plausible explanations for a high degree of undervaluation of future fuel savings, which in turn provides motivation for government intervention in fuel efficiency policy.

5.3 Marginal Cost Estimates

Using the demand parameters and observed prices and quantities, I derive marginal costs for each vehicle in each pre-policy year based on the unconstrained first-order condition, equation 6. Appendix figure A.2.4 contains the sales-weighted average marginal costs by vehicle category, before and after the policy. Vocational vehicles have the lowest marginal costs (at an average of \$51,000), and high-roof sleepers have the highest marginal costs (at an average of \$89,000). Because I rely on engineering estimates for the cost of fuel intensity improvements needed to comply with the policy, structural supply parameters are not needed for counterfactual simulations. However, for completeness, they are shown in table 6 for the different demand specifications, with and without make fixed effects in the cost function. The costs of increasing gross vehicle weight and reducing fuel intensity (i.e., making vehicles more efficient) are both positive, as well.

6 Counterfactuals

I use the estimated demand and supply results to simulate outcomes under the fuel efficiency policy and under a Pigouvian tax on diesel.

6.1 Simulation Setup

When the policy is in place, firms choose prices and technologies to maximize profits while complying with the policy, as in equation 3. I simplify the problem somewhat by only allowing firms to choose technology improvements at the regulatory group level–thus, rather than J first-order conditions with respect to technology, there is one technology first-order equation per firm-regulatory group.

Firms start with the set of vehicles they had in the year prior to the policy, 2013. I estimate the marginal costs of the vehicles in the baseline from equation 6. I solve for the equilibrium so that each firm complies with the policy exactly. While it is possible that firms may have chosen to not comply and instead pay fines, the regulation was extremely vague about the magnitude of fines, and firms may have chosen compliance rather than risk both the bad publicity and the uncertain costs of non-compliance.

The solution approach is to find the set of technology choices, t and shadow costs, λ, such that equations 6 and 7 hold. That is, for a given guess of λ and t, I determine the updated marginal cost for each vehicle (baseline marginal cost + the additional cost of improving fuel efficiency by t percent) and the λL cost of adjusting prices. I use these to solve for equilibrium prices and shares in equation 6. With these, I define my objective function to be the set of constraints and first-order conditions with respect to technology, and use a root finding approach[16] to solve for the t and λ such that these equations hold exactly. In the case of firm-regulatory groups that are already in compliance prior to the policy implementation, and might choose a negative t or λ, I constrain their technology choice and shadow costs to 0.

I compare equilibrium outcomes with and without the policy, including firm profits, consumer welfare, and changes in environmental damages. To estimate the change in CO_2 emissions, I first calculate how ton-miles decline over vehicle lifetime using VIUS data. Then, I calculate the annual fuel usage over the vehicle lifetime for each buyer-vehicle pairing based on first-year ton-miles and the annual adjustment factors. With these results, I calculate total diesel consumption and CO_2 generation per gallon. Vehicles have a maximum lifetime of 30 years, but vehicle miles traveled in year 30 fall to less than 5% of their total miles traveled when new. I use the 2014 Social Cost of Carbon from the Obama Administration's estimates, which is around $42 in 2018 dollars, and assume a 5% annual discount rate for both environmental damages and fuel savings (IWG 2016).

A second set of counterfactuals considers the effect on the vehicle fleet of a direct diesel tax at the social cost of carbon, which generates an approximately 43 cent per gallon surcharge on diesel. In the baseline specification, truck buyers do not directly adjust their mileage (a rebound effect), but they make new purchases with an expectation that future fuel costs will change. To reflect that the value of the outside good, which may include holding onto existing trucks for longer or purchasing used vehicles, will also be affected by the diesel tax, I shift all inside good utility based on an assumed outside good efficiency. This allows the focus of the counterfactual to be on how buyers reallocate purchases within the vehicle fleet rather than on the extensive margin decision of whether to purchase a new truck at all. A second counterfactual allows truck buyers to respond to the tax by also adjusting their ton-miles driven based on elasticities from the literature (Leard et al. 2016).

6.2 Welfare Results

In order to comply with the policy, optimizing manufacturers will choose price changes and technological improvements so that the marginal loss in profits from each are equal. The largest price changes occur for sleepers, which see a greater than $5000 (or 3%) increase, on average, while the smallest price changes occur for vocational vehicles, whose prices increase by only a few hundred dollars (see table 8). In aggregate, truck buyers pay 2.5% more following the imposition of the policy. Because of the relatively low elasticities of demand,

[16] MINPACK's hybrid routine

this does not meaningfully reduce the total number of trucks sold. From the standpoint of environmental policy, this is potentially good news, as some of the buyers who choose the outside good may do so by keeping old vehicles on the road longer. There is some degree of shifting across classes: approximately 3% fewer sleepers are purchased, and 1% fewer day cabs are purchased, and the majority of these are replaced by vocational vehicles which see smaller price increases but tend to be less efficient. This class shifting reduces consumer welfare, as buyers are choosing vehicles with features they do not prefer; it also reduces the magnitude of environmental benefits.

Table 7 contains the welfare results (in millions of 2018 $) from introducing the fuel efficiency policy in the first year, including changes in consumer surplus, changes in manufacturer profits, changes in environmental benefits (from reduced CO_2 production), and because buyers do not fully consider the future fuel savings when they make their initial purchase, it includes the additional fuel savings that they accrue. Notably, the magnitude of the environmental benefits is smaller than the direct costs to consumers and manufacturers. However, the magnitude of undervalued future fuel savings dwarfs the costs: if even 25% of the total future fuel savings are incorporated into the welfare calculation, the policy's benefits exceed the costs.

Because of the different tastes for truck characteristics and the different usage patterns, we can also examine how the costs and benefits for buyers vary across industry and usage. Appendix table A.1.2 shows the industry-specific change in consumer surplus induced by the policy. The magnitude of the welfare effects are determined by two factors: the propensity to purchase vocational vehicles, which are assumed to have a lower cost of fuel-intensity improvement, and the usage intensity of the truck. Buyers who were predisposed toward vocational vehicles face limited changes in the vehicles they are most likely to buy, explaining the small costs to sanitation and the slightly larger costs to construction. A second factor, however, is that all buyers face the same prices for purchasing the same truck, even if they are using the truck in very different ways. Thus, while the policy raises the price of every vehicle, the purchasers of a given vehicle who drive the most will recoup the largest share of costs. This explains the benefits to the specialized/heavy hauling industry, who have both a taste for vocational vehicles and drive long distances and/or carry heavy payloads, such that the savings from the policy are quite large. The tradeoff between the two factors is highlighted in appendix figure A.2.5.

The second set of counterfactuals address this unequal distribution of internalized costs. A first-best policy, in which truck owners are taxed according to the damage associated with their driving patterns, would target the costs more precisely than a policy that raises the cost of most vehicles. However, the tax increases future fuel costs, which earlier results suggest are not fully accounted for in purchase decisions, so the capacity of the tax to reduce fuel usage via truck purchases is limited. Figure 3 shows the relative magnitudes of the first-year fuel savings associated with the policy, the tax when it only affects vehicle purchases and not total driving behavior, and the tax when it can affect vehicle purchases and total driving behavior. The effect of the tax on fuel usage via purchase changes (and technology improvements, shown in appendix figure A.2.6) is limited–only 3 million gallons of diesel compared to more than 60 million gallons saved due to the policy in the first year. However, the Leard et al. (2016) ton-mileage elasticities in response to fuel costs reveal that truck owners are much more able to respond to fuel costs via other channels, and the magnitude of the fuel savings is more than twice that of fuel savings under the policy. Ultimately, there are multiple market failures at play in the truck market: the environmental externality from combusting diesel, as well as the several interrelated market failures, including split incentives and incomplete information, that prevent truck buyers from fully internalizing future (private) fuel costs when they purchase new trucks. Optimal policy would use distinct policy instruments to tackle each market failure.

7 Conclusion

This paper estimates the degree of undervaluation of future fuel savings among heavy-duty truck buyers and the corresponding effects of the 2014 heavy-duty vehicle fuel economy standards using a structural model of demand and supply of trucks. I find that buyers meaningfully undervalue future fuel savings, which may reflect the industrial organization of the major truck buying firms as well as incomplete information. When manufacturers are required to improve average vehicle fuel economy, the internalized costs to consumers are large relative to the costs to manufacturers and the environmental benefits. However, the un-internalized fuel savings benefits more than offset the costs, as drivers of heavy-duty tractors only internalize less than one quarter of future fuel savings. This undervaluation of future fuel savings supports not only the imposition of fuel efficiency standards, but potentially also the collection and public provision of more information about expected fuel usage for heavy-duty trucks. Such information is available in the light-duty vehicle segment and potentially to owners of large fleets who can observe their own historical performance, but other buyers may struggle to make optimal choices with incomplete information.

These results have some caveats. First, the estimates rely on the best data available on truck fuel efficiency, but it remains imperfect data. The estimates also rely on EPA's engineering estimates of technology costs. Future work with improved data may directly estimate the cost of adopting different fuel economy technologies and measure preferences for different characteristics that vary along with fuel economy (e.g., more aerodynamic designs vs. low rolling resistance tires). In doing so, it may be possible to disentangle other potential reasons that technologies EPA believes are cost effective were not adopted prior to the policy. Second, the joint decision of vehicle and how it will be used is more important in the truck context than in the light-duty vehicle setting because of the high variance in truck miles driven and weight of cargo; this paper treated truck usage as exogenous, but it may be useful to more rigorously consider how changes in fuel costs per ton mile affect truck deployment decisions.

Other caveats may best be addressed in other papers. I did not account for dynamics or the used vehicle market in this analysis. Buyers may have made strategic timing decisions about when to purchase new vehicles or hold onto existing vehicles; such an effect has proven important in the light-duty vehicle context and merits further investigation. Finally, both truck manufacturers and owners have other modes of response to changes in fuel economy standards and corresponding vehicle fuel costs. In the former case, other attributes may be adjusted, and the supply model could be revised to account for the endogeneity of other product features. In the latter cases, truck owners can make changes in individual or fleet-wide driving behavior, vehicle weight, routes, or the adoption of technology like trailer skirts. Understanding how fuel efficiency standards interact with these other behaviors is an important question for future research.

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Tables

Table 1: Summary statistics.

	Min.	Max.	Mean
Panel A. Count of product offerings by type			
Class 7	46	61	55.11
Class 8	104	124	115.78
Vocational vehicles	77	96	88.67
Conventional tractors with sleeper cab	17	25	22.00
Conventional tractors with day cab	50	66	60.22
Panel B. Prices and quantities			
Prices ($1000s)	48.85	213.63	120.91
Quantity	122068	301455	218900.56

Notes: Data include sales of model years 2011-2019. Counts contain the number of unique make-model-sleeper-class combinations that are available in each category (e.g., a make-model available as both a class 7 day cab and a class 8 day cab will count as two distinct products), but a make-model-sleeper-class available in multiple configurations that fall under the same category (e.g., a sleeper with multiple roof heights or two class 7 vocational vehicles with different axle configurations) will only count as a single offering.

Table 2: EPA and NHTSA standards for combination tractors.

	EPA Emissions Standards ($g\ CO_2$/ton-mile)			NHTSA Fuel Consumption Standards (gal/1000 ton-mile)		
	Low Roof	Mid Roof	High Roof	Low Roof	Mid Roof	High Roof
Panel A. 2014 Standards						
Day Cab Class 7	107	119	124	10.5	11.7	12.2
Day Cab Class 8	81	88	92	8.0	8.7	9.0
Sleeper Cab Class 8	68	76	75	6.7	7.4	7.3
Panel B. 2017 Standards						
Day Cab Class 7	104	115	120	10.2	11.3	11.8
Day Cab Class 8	80	86	89	7.8	8.4	8.7
Sleeper Cab Class 8	66	73	72	6.5	7.2	7.1

Notes: CO_2 and fuel standards are set separately by EPA and NHTSA but designed to be compatible with one another. The first set of standards applied to model years 2014-2016, and a higher set of standards applied to model years 2017 and 2018. Standards data are from Table 2-34 in the Regulatory Impact Analysis.

Table 3: Industry Vehicle Attributes.

	Total Sales	Shr Vocational	Shr Sleeper	Shr Day	Shr Class 7	Shr Class 8	Average GVW
Sanitation	47258	0.93	0.03	0.04	0.08	0.92	5143.37
General Freight	602911	0.08	0.54	0.38	0.12	0.88	5004.91
Construction	85527	0.79	0.10	0.11	0.18	0.82	4717.86
Other	1267693	0.36	0.37	0.27	0.21	0.79	4691.57
Specialized/Heavy Hauling	16497	0.50	0.11	0.39	0.22	0.78	4520.66

Notes: This table contains sales by industry for the full dataset (including some model year 2019 vehicles sold in 2018). The share columns indicate the share of vehicles sold to buyers in each industry that are predicted to fall into one of three cab categories: vocational vehicles, sleepers, or day cabs and one of two weight class categories. The final column contains the average gross vehicle weight of vehicles purchased by each industry buyer type.

Table 4: Demand parameter estimates.

prices (1000s)	-0.022^{***}
	(0.008)
GVW (10000 lbs)	1.705
	(1.076)
day 7	-0.934^{***}
	(0.226)
day 8	0.050
	(0.271)
low-roof sleeper	0.050
	(0.211)
mid-roof sleeper	0.741^{***}
	(0.230)
high-roof sleeper	0.541^{***}
	(0.197)
4×2 axles	0.668^{***}
	(0.113)
6×6 axles	2.245^{***}
	(0.112)
$8 \times$ x axles	-0.453^{***}
	(0.160)
Dollars per thousand ton mile (dpktm) $\times$ thousand ton miles (ktm_i) (thousands)	-0.010^{***}
	(0.0003)
dpktm $\times$ non_voc $\times$ ktm_i	-0.017^{**}
	(0.007)
vocational $\times$ construction_i	1.850^{***}
	(0.078)
vocational $\times$ general freight_i	-1.841^{***}
	(0.238)
vocational $\times$ sanitation_i	2.971^{***}
	(0.131)
vocational $\times$ specialized/heavy hauling_i	1.011^{***}
	(0.252)

*p<0.1; **p<0.05; ***p<0.01

Notes: The main demand model, with individual mileage that determines fuel costs, and industry-specific preferences for vocational trucks. Brand fixed effects are included. Class 7 Day, Class 8 Day, Low-Roof Sleeper, and High-Roof Sleeper are all indicator variables indicating that a truck falls into one of these regulatory groups (the omitted category is vocational vehicles). The three axle categories are also indicators for a vehicle having a 4×2 axle configuration, a 6×4 axle configuration, or one of the configurations with 8 wheels (8×4, 8×6, or 8×8). The omitted category is all 6-wheel configurations. Dollars per thousand ton miles is the product of fuel intensity (measured in gallons per thousand ton miles) and diesel price. Thousand ton miles (ktm) vary at the individual level, and represent the usage for the first year of vehicle ownership.

Table 5: Descriptive VIUS regressions.

	MPG	
	(1)	(2)
Private Shipping	0.116***	0.143***
	(0.032)	(0.033)
≤10 trucks		-0.041
		(0.029)
Age controls	×	×
Weight/payload controls	×	×
Miles controls	×	×
Observations	14,880	13,382

*p<0.1; **p<0.05; ***p<0.01

Notes: This table contains descriptive regressions of self-reported fuel efficiency (measured in miles per gallon) vs. truck and truck owner characteristics using data from the 2002 VIUS survey. The first column tests for the role of split incentives by comparing fuel efficiency for private shippers to fuel efficiency of shippers who transport goods on behalf of other firms. The second column tests whether truck buyers learn about fuel efficiency from other vehicles in their fleet. Both regressions control vehicle age, vehicle weight and weight including payload, miles traveled, and vehicle class. Tractors belonging to individuals/companies in the freight industry or who are categorized as "other" (i.e., not construction or sanitation) are included in the observations.

Table 6: Supply parameter estimates.

	log(mc)	
	(1)	(2)
GVW (10000 lbs)	3.042***	2.679***
	(0.224)	(0.233)
4 × 2 axles	-0.062	-0.154***
	(0.044)	(0.046)
6 × 4 axles	0.093***	0.013
	(0.037)	(0.039)
8 × x axles	0.091*	0.036
	(0.048)	(0.048)
Class 7 Day	-0.031	-0.113
	(0.084)	(0.082)
Class 8 Day	-0.609***	-0.621***
	(0.054)	(0.058)
Canadian production	-0.394***	-0.24***
	(0.067)	(0.075)
Fuel Intensity	-0.042***	-0.047***
	(0.004)	(0.004)
log(wages)	0.066***	-0.126***
	(0.018)	(0.028)
High-Roof Sleeper	-0.241***	-0.281***
	(0.052)	(0.058)
Low-Roof Sleeper	-0.382***	-0.437***
	(0.059)	(0.068)
Mid-Roof Sleeper	-0.302***	-0.482***
	(0.059)	(0.066)
Brand FEs		×

Notes: The supply parameters associated with alternative demand specifications. The first two columns are a logit model, the second two columns allow for industry-specific preferences on vocational vehicles, and the final two columns are a logit model that adds the use of instrumental variables for the fuel intensity measure. Class 7 Day, Class 8 Day, Low-Roof Sleeper, and High-Roof Sleeper are all indicator variables indicating that a truck falls into one of these regulatory groups (the omitted category is vocational vehicles). The three axle categories are also indicators for a vehicle having a 4 × 2 axle configuration, a 6 × 4 axle configuration, or one of the configurations with 8 wheels (8 × 4, 8 × 6, or 8 × 8). The omitted category is all 6-wheel configurations. Fuel intensity is measured in gallons per thousand ton-mile. log(wages) are the log of manufacturing wages in the region in which a vehicle is produced, and Canadian production is an indicator variable for vehicles produced in Canada.

Table 7: Welfare costs (millions).

Δ Consumer Surplus	-356.89
Δ Manufacturer Profits	-37.67
Environmental Benefits	148.63
(Undervalued) Fuel Savings	1,008.70
Total (excl. fuel savings)	-245.93
Total (incl. fuel savings)	762.77

Notes: Components of overall welfare changes under the policy. The consumer surplus is calculated based on compensating variation. The CO_2 benefits are based on fuel usage reduction over the lifetime of the truck, at a 5% discount rate. The "(undervalued) fuel savings" presents the value of fuel savings over the lifetime of the vehicle less the fuel savings that were already incorporated into buyers' utility. The "total (excl. fuel savings)" is the sum of changes in consumer surplus, producer surplus, and environmental damages excluding benefits from undervalued fuel savings. The "total (incl. fuel savings)" adds the additional value of fuel savings that were not valued by buyers upfront. All values in millions of 2018 $.

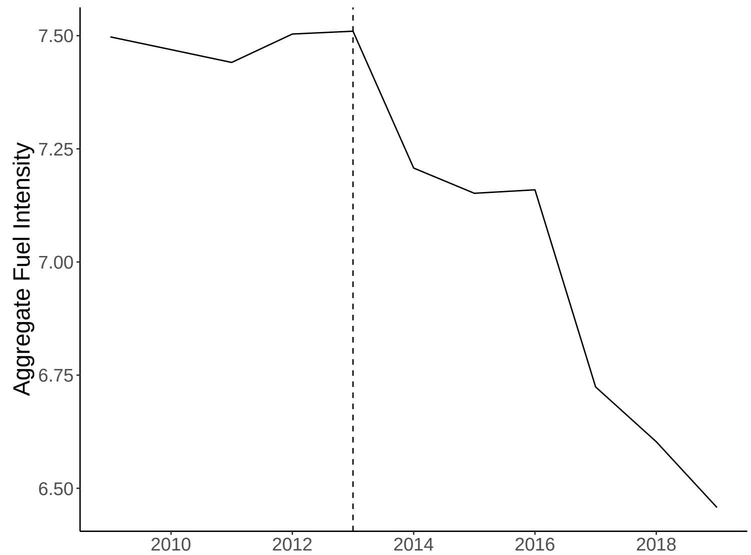
Table 8: Changes in prices, quantities

	Δ Price	Unweighted Δ Price	Δ Sales
Vocational	$119	$49	3188
Sleeper	$5304	$6862	-2691
Day	$3103	$6876	-774
Combined	$2420	$3484	-277

Notes: Change in prices and quantities of vehicles sold by category. "Δ Price" is the change in price weighted by vehicle sales, while "Unweighted Δ Price" is the average change in price across vehicle offerings, not weighted by sales. "Δ Sales" is the change in total number of vehicles sold. The changes are grouped by vehicle type (vocational vehicles, day cabs, and sleeper cabs, and also aggregated in the "combined" category).

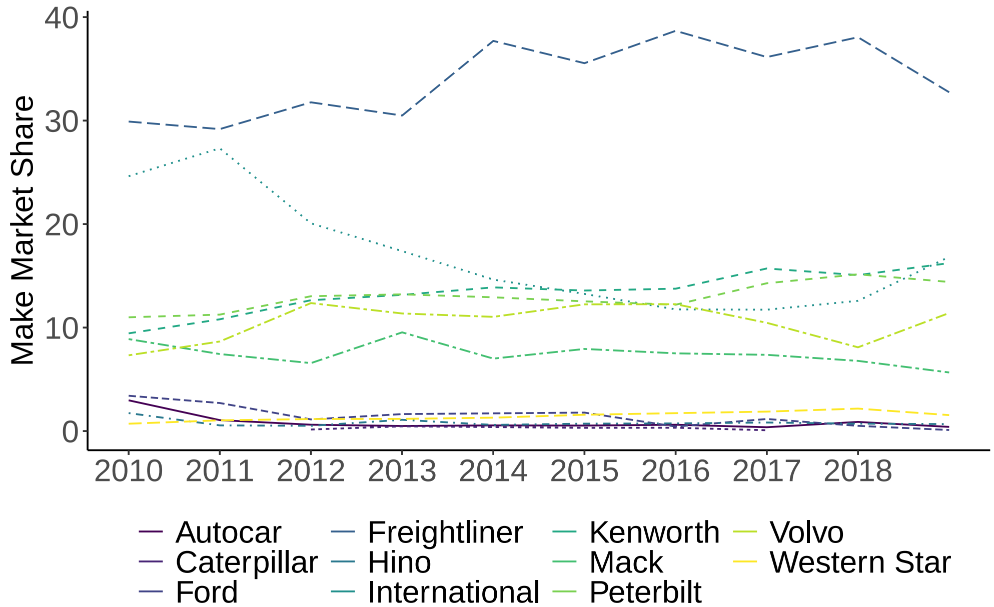
Figures

Figure 1: Aggregate Fuel Intensity of Sleeper Cabs



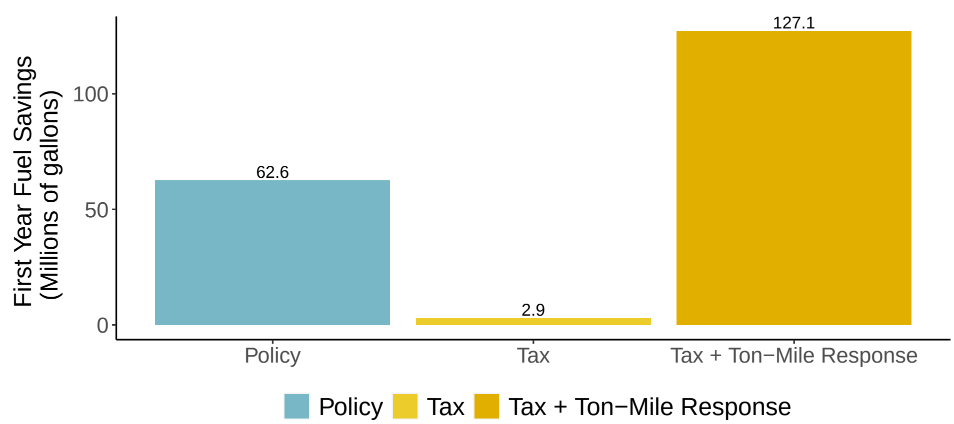
Notes: Sales-weighted average fuel intensity of all sleeper cabs in the data. The dashed line indicates the year before the standards were put in place.

Figure 2: Market Share by Brand



Notes: Market share is calculated as the share of vehicles sold among included brands (or makes, used here interchangeably). Line color corresponds to the different brand, and brands owned by the same parent company share the same linetype (e.g., Freightliner and Western Star, both owned by Daimler).

Figure 3: Counterfactual First-Year Fuel Savings



Notes: First-year fuel savings by scenario relative to baseline. Policy refers to the 2014 levels of the main fuel efficiency standards. Both tax scenarios involve the imposition of a 43 cents/gallon diesel tax. In the scenario identified as "Tax," buyers' expected vehicle usage is fixed, i.e., the tax can only affect the technology improvements adopted by the manufacturers and the buyers' decision of which truck to buy. In the "Tax + Ton-Mile Response," buyers also adjust their usage of the truck, based on elasticity estimates from Leard et al. (2016).

Appendices

A Appendix Tables

Table A.1.1: DOT vehicle weight classes

Class	Description/examples	Empty weight range	Gross weight range	Typical fuel intensities	
		Tons	Tons	Gallons per thousand miles	Gallons per thousand ton-miles
1c	Passenger cars	1.2-2.5	<3	30-40	67
1t	Small light-duty trucks (including SUVs and minivans)	1.6-2.2	<3	40-50	58
2a	Standard pickups, large SUVs	2.2-3	3-4.25	50	39
2b	Large pickups, utility vans	2.5-3.2	4.25-5	67-100	39
3	Utility vans, minibuses	3.8-4.4	5-7	77-125	33
4	Delivery vans	3.8-4.4	7-8	83-140	24
5	Large delivery vans, bucket trucks	9.2-10.4	8-9.75	83-166	26
6	School buses, large delivery vans	5.8-7.2	9.75-13	83-200	20
7	City bus, refrigerated truck, fire engine	5.8-7.2	13-16.5	125-250	18
8a	Dump/refuse trucks, city buses, fire engines	10-17	16.5-40	160-400	9
8b	Large tractor trailers, bulk tankers	11.6-17	16.5-40	133-250	7

Source: Harrington & Krupnick (2012)

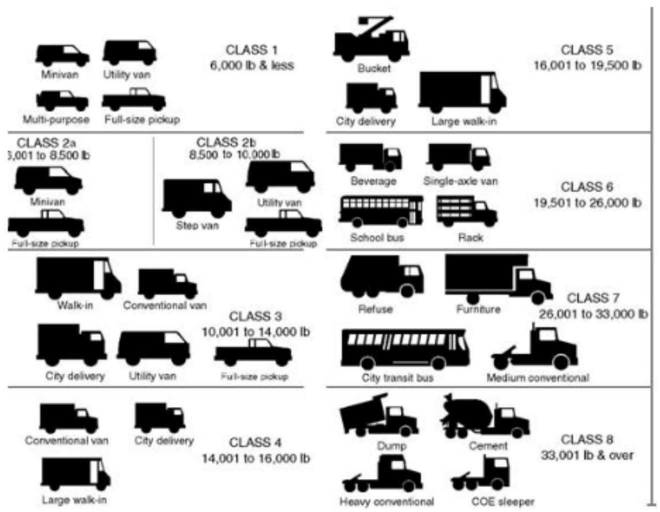
Table A.1.2: Industry Change in Consumer Surplus

	Other	Construction	General Freight	Sanitation	Specialized/Heavy Hauling
ΔCS	-1.818	-0.569	-1.141	-0.064	0.272

Notes: Average per-consumer change in consumer surplus by industry. Prices in 1000s of 2018 $.

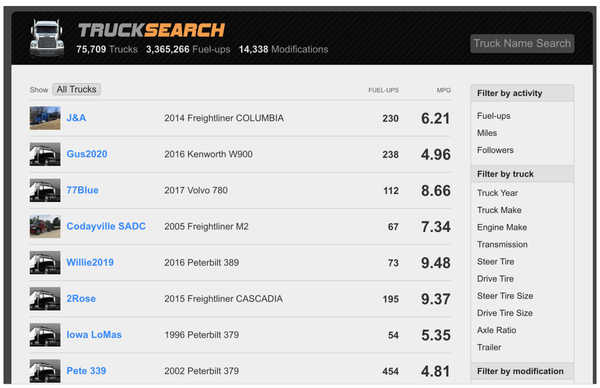
B Appendix Figures

Figure A.2.1: Vehicle weight classes, illustrated



Source: Commercial Carrier Journal http://www.ccjmagazine.com

Figure A.2.2: Screenshots from `letstruck.com` fuel tracking website.



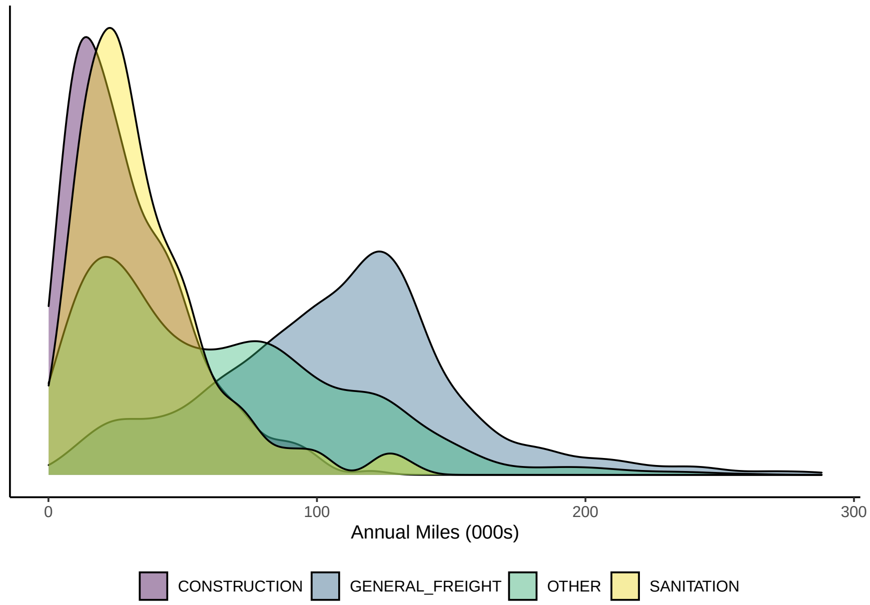
(a) The main page, organized by vehicle.

(b) Individual truck data.

Notes: For each vehicle on the main page, the year-make-model, number of recorded fuel ups, and average miles per gallon is displayed. More information is available about each individual truck, including more recent fuel usage, miles tracked, modifications made to the vehicle, etc.

Figure A.2.3: Distribution of miles and payload by industry from the Vehicle Inventory Use Survey (VIUS).

(a) Annual miles (1000s) reported by vehicles with ages of zero or one in the survey.



(b) Average payload (tons) reported by vehicles with ages of zero or one in the survey.

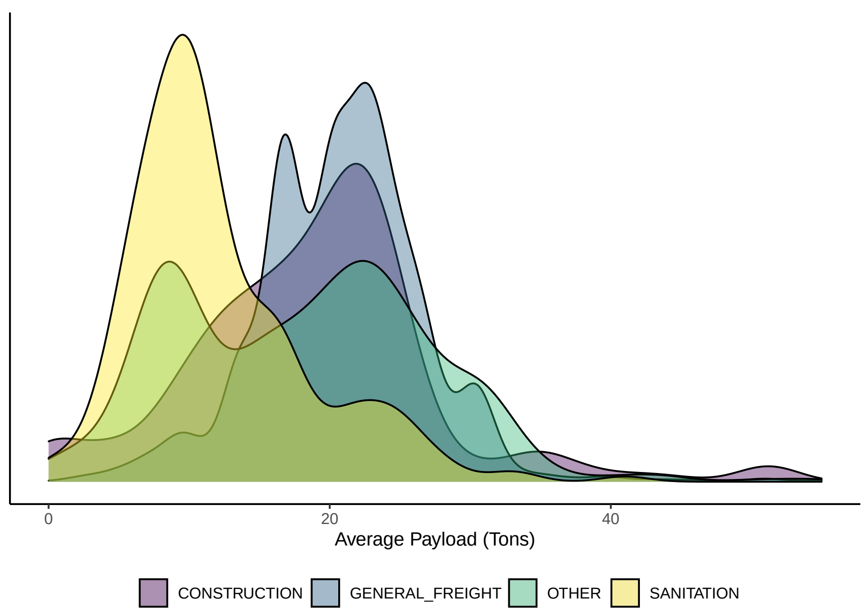


Figure A.2.4: Estimated sales-weighted average marginal costs by vehicle category, before vs. after the policy.

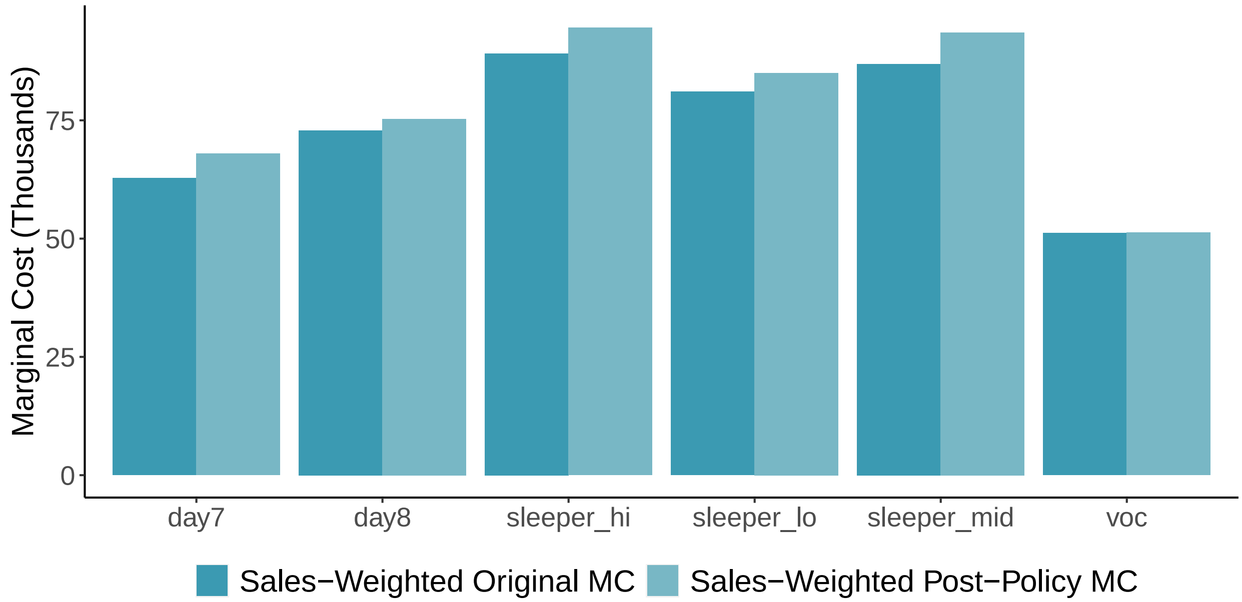


Figure A.2.5: Change in consumer surplus by industry and ton-miles driven.

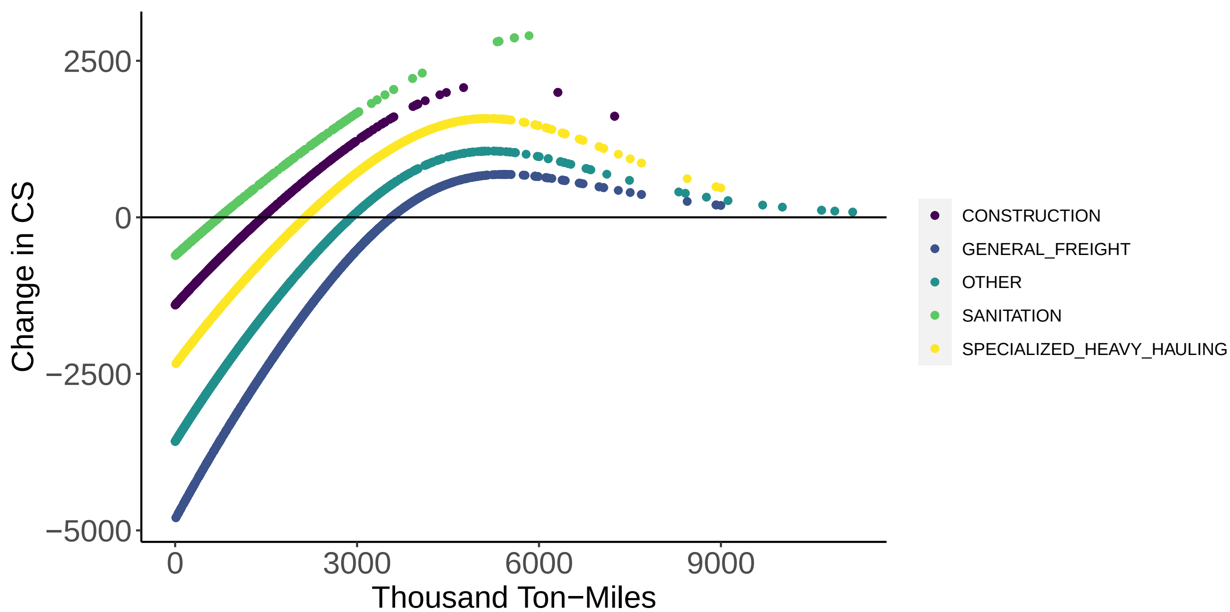
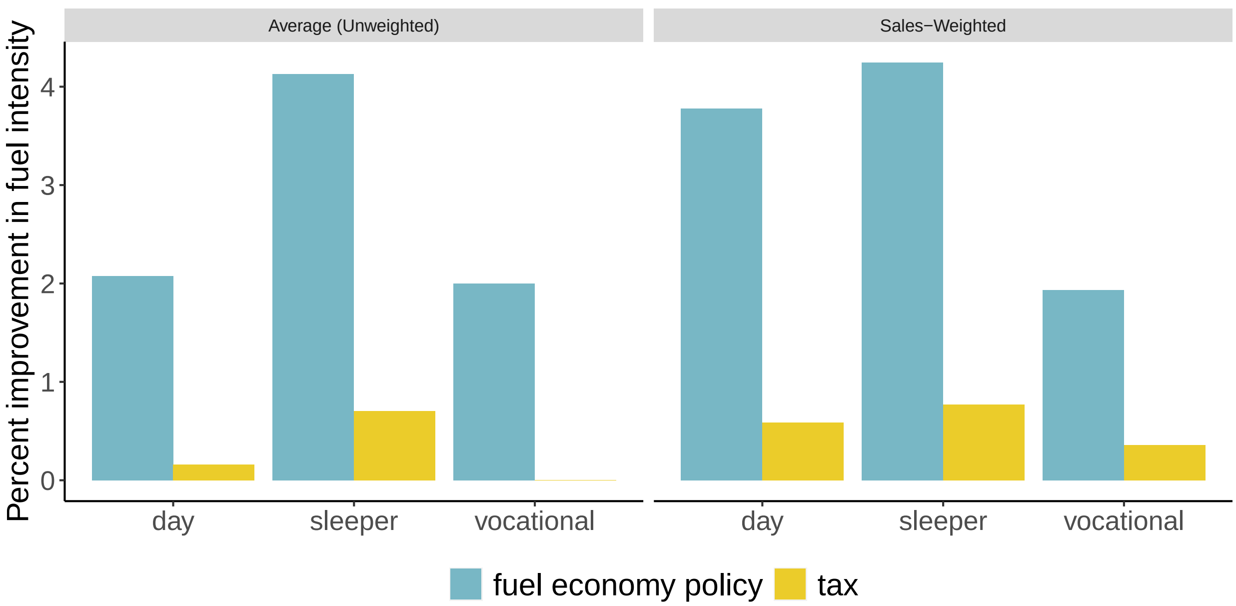


Figure A.2.6: Percent improvement in vehicle fuel efficiency in response to counterfactuals.



Notes: This figure shows the average technology improvement (percentage) compared to the baseline in response to either the fuel economy policy or the tax (before considering mileage changes). The left figure shows the unweighted average for all product offerings, while the right figure shows the sales-weighted average and reflects the combined effects of profit-maximizing decisions made by manufacturers and the utility-maximizing vehicle purchases by consumers. The counterfactual tax scenario does not allow vocational vehicles to change their fuel efficiency via technology, but in the presence of the tax, some aggregate improvements are observed in the sales-weighted average as buyers shift their purchase behaviors.