ABSTRACT

Title of dissertation:	REGULATION, MARKET AND TECHNOLOGY: EVIDENCE FROM THE U.S. TRUCKING INDUSTRY
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Dissertation directed by:	Professor Sébastien Houde Agricultural and Resource Economics

My dissertation focuses on the environmental regulations in the trucking industry and their impacts in the United States. I explore the causal effects of environmental policies on trucking decisions, the technological challenges of reducing fuel consumption and the optimal fuel taxes to account for the externalities of trucking operation. As the fuel economy standards for medium- and heavy-duty trucks are finalized in August 2016, my dissertation addresses a timely and important issue – how to effectively reduce greenhouse gases emissions from trucking operation. Three essential policy tools are examined – taxes, fuel economy standards, and engine replacement schedule.

In the first essay, I exploit a rich vehicle-level micro dataset of the U.S. heavy-duty trucking fleets to examine how truckers respond to changes in per-mile fuel cost. Per-mile fuel cost depends on the fuel economy of the vehicle and on the price of diesel, which is taxed at a different rate than other motor fuels. The U.S. Environmental Protection Agency (EPA) categorizes medium- and heavy-duty trucks

into two groups - combination trucks and vocational vehicles. They are regulated separately due to their distinctive driving patterns and trip distances. *Combination trucks* are tractor-trailers weighing more than 26,000 pounds, typically with a body type of either an enclosed box or a platform. They are mostly used for long-haul shipping. *Vocational vehicles* are straight trucks (with a loading area as part of the vehicle) with gross vehicle weight greater than 10,000 pounds. They travel locally for various professional purposes and include step vans, dump trucks, concrete mixers, etc. My empirical results show that the average medium-run elasticities of vehicle-miles-traveled are -0.23 for combination trucks and -0.27 for vocational vehicles; the average elasticities of payload distance are -0.43 for combination trucks and -0.36 for vocational vehicles. Within each of the two groups, the estimated elasticities vary significantly among different truck weight classes and business sectors. The heterogeneity in truckers' responsiveness calls for differentiated policies, particularly in fuel taxes. I derive the optimal fuel taxes in a general equilibrium model that includes the externalities of truck operation (such as air pollution, road damage, accidents, and noise pollution), measures shipping demand in terms of payload distance and allows truckers to choose their routes based on shipping demand. In the second-best setting, most of the optimally differentiated diesel taxes are about twice or three times the actual rate. Compared to the optimal uniform tax, implementing differentiated taxes based on vehicle weight classes reduces the existing distortion and generates an overall welfare gain of about 17.5 billion US dollars per annum.

In the second essay, I look at the evidence about fuel economy and other truck attributes from the U.S. Vehicle Inventory and Use Survey (VIUS). I estimate the trade-off effects between fuel economy and truck attributes, providing implications for a dynamic baseline of improvements in fuel economy. My estimation results show that the annual rates of fuel economy improvement from 1973 to 2002 are about 0.93% for combination trucks and 0.83% for vocational vehicles. In other words, in the absence of regulations, we can expect reductions in fuel consumption by 8.01% for combination trucks and 7.15% for vocational vehicles in ten years, just under half of the targets. The difference in technological progress among fleets with various sizes suggests that incentivizing trucking fleets to update their vehicles more frequently can be an effective channel to improve overall on-road in-use trucks' fuel economy.

In the third essay, I examine the industry responses to the California Statewide Truck and Bus Regulation – a schedule for truckers to retrofit or replace their vehicles – using two empirical approaches. First, the arbitrary choice of the cutoff year allows me to conduct a regression discontinuity design. I find a 71.4% reduction in the population of targeted truck group as the deadline approaches. Second, I compare the targeted group with trucks having similar body types but different model years and investigate the effect in a difference-in-difference framework. Once the natural business-as-usual rate of replacement is accounted for, the estimated reduction in truck population due to the regulation drops to 57.8%. Using this estimate and necessary assumptions, I also back out the proportion of trucks registered in NO_x-exempt counties that are solely operated within these counties.

REGULATION, MARKET AND TECHNOLOGY:
EVIDENCE FROM THE U.S. TRUCKING INDUSTRY

by

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List of Abbreviations

ARB	Air Resources Board
BAU	Business-as-usual
CAFE	Corporate Average Fuel Economy
CID	Engine displacement (cubic inch displacement)
DD	Difference-in-difference
EGR	Exhaust gas recirculation
EIA	U.S. Energy Information Administration
EMFAC	Emission FACtors Web Database
EPA	Environmental Protection Agency
GVWR	Gross vehicle weight rating
HD	Heavy-duty
IV	Instrumental variables
LSFC	Load specific fuel consumption
MEC	Marginal external cost
MPG	Fuel economy (miles per gallon)
MY	Model year
NHTSA	National Highway Traffic Safety Administration
NO_x	Oxides of nitrogen
OLS	Ordinary least squares
PD	Payload distance
PM	Particulate matter
RD	Regression discontinuity
RIA	Regulatory impact analysis
TBR	Truck and Bus Regulation
VIUS	U.S. Vehicle Inventory and Use Survey
VMT	Vehicle-miles-traveled

Chapter 1: Heterogeneous Responses and Differentiated Taxes: Evidence from the Heavy-duty Trucking Industry in the U.S.

1.1 Introduction

The trucking industry hauls about 70% of all freight in the United States. Although medium- and heavy-duty trucks account for only about 5% of all the on-road vehicles, they contributed about 20% of the greenhouse gas emissions and oil use in 2015 (EPA, 2015). Existing policies intending to reduce fuel consumption and greenhouse gas emissions, such as engine emission standards and fuel economy standards, have been mostly technology-based and targeted at manufacturers. Fuel pricing policies have rarely been considered as policy instruments to reduce greenhouse gas emissions (Decker and Wohar, 2007; Knittel, 2011). Fuel taxes provide a combination of incentives with flexibility - a merit lacking in other alternatives (Williams, 2016). The flexibility allows manufacturers and drivers to choose the most cost effective ways to reduce fuel consumption, while taking into consideration of negative externalities caused by the operation, which include greenhouse gas emissions, local air pollutants, noise pollution, traffic congestion, road deterioration and vehicle accidents. Ideally, one would design a tax for each category of externalities, but such policy would be impractical (Williams, 2016). Instead, fuel taxes can be used to address the sum of all externalities on a per-gallon basis. The challenge lies in possible inequality due to the difference in truckers' responses to changes in fuel costs. Imposing a uniform tax is potentially detrimental for truckers who reduce driving more than the average level. Such heterogeneity in behavior calls for optimally differentiated fuel taxes.

Among the few existing studies that have discussed the relationship between trucking decisions and fuel costs, most of the empirical analyses are based on aggregated data (Barla et al., 2014; Dahl, 2012; Ramli and Graham, 2014). At the regional level, Greene (1984) finds that diesel fuel consumption is inelastic to fuel costs. At the national level, Dahl (2012) summarizes the fuel price elasticities from existing studies and looks for their relationship with national income. Barla et al. (2014) apply a Partial Adjustment Model to national diesel fuel data in Canada and find the elasticities at -0.43 for the short run and -0.80 for the long run. Adenbaum et al. (2015) take advantage of disaggregated data and find that truck owners undervalue the expected lifetime fuel savings from better fuel economy, which therefore supports a policy introducing fuel economy standards in the heavy-duty trucking industry. Leard et al. (2015) use truck-level survey data to estimate the effect of higher fuel economy on driving distance, and suggest cautious evaluation of the benefit of such policy.

I exploit a rich vehicle-level micro dataset of the U.S. heavy-duty trucking fleet to examine truckers' heterogeneous responses to changes in fuel costs. I start with Leard et al. (2015)'s empirical framework, in which they estimate the rebound effect (the increase in energy use caused by lower fuel cost of driving each mile) for heavy-duty trucks. In contrast, I look at a broader set of truck characteristics and estimate how fuel cost affects vehicle-miles-traveled (VMT) heterogeneously among weight classes and business sectors. I find that a 10% increase in per-mile fuel cost reduces VMT by 2.3% for combination trucks and 2.7% for vocational vehicles. Heavier trucks are less responsive to changes in fuel cost, since they are more likely to be limited by road use restrictions. The estimated elasticities vary significantly among different business sectors. Sectors with more flexible schedules and driving routes, such as manufacturing, business and personal service, tend to have higher elasticities. In addition to VMT, I also examine truckers' decisions regarding payload distance (PD). The value of PD is derived from multiplying VMT by the average cargo weight. The indicator, PD, is particularly relevant to the heavy-duty trucking industry as both driving distance and payload weight contribute to total fuel consumption.

An important goal of this paper is to derive the optimally differentiated fuel taxes and to conduct welfare analysis in the second best setting, i.e., in the presence of tax distortion in other markets. My model builds upon and contributes to several strands of the recent literature. First, the analytical model fits in the literature of optimal environmental taxation in a general equilibrium setting. Bovenberg and Goulder (1996) first extend this framework to consider taxes imposed on intermediate inputs while taking into account the presence of other distortionary taxes. The interaction between the taxed commodity and the labor market is important, as ignoring it can cause bias in estimated excess burden by a factor of 10 or more (Goulder and Williams, 2003). Calthrop et al. (2007) apply the general equilibrium model to explore the effect of a partial tax reform on freight transport in the U.K. Special attention is paid to the congestion effect of freight taxes on passenger vehicles' VMT - the ambiguous effect is offset by passenger vehicles as they fill up the space vacated by trucks. Such an offset effect by automobiles is explored by Parry (2008), who estimates the optimal uniform diesel tax for heavy-duty trucks in the U.S with elasticity parameters drawn from existing studies. My general equilibrium model allows differentiation in fuel taxes among truck weight classes and business sectors, using the elasticities from my empirical analysis. The derived optimally differentiated taxes are adjusted to take into account the interaction with the labor market, using the method developed in Goulder and Williams (2003). Second, my work connects to the literature on the distributional effects of fuel taxes. For example, West (2004) estimates the effects of gasoline taxes on different income groups using a discrete-continuous choice model; Bento et al. (2009) investigate the distributional effects of gasoline taxes by income, race and employment. While most of the related literature focuses on the effect of gasoline taxes on households, less is known about diesel taxes on the heavy-duty trucking industry. I examine the distributional effects of diesel fuel taxes among heavy-duty trucks of different weight classes and business sectors.

The remainder of the paper is organized as follows. In Section 2, I explain the data and provide descriptive analysis. I discuss the empirical model in which vehicle-miles-traveled is estimated as a function of per-mile fuel cost, truck characteristics and business features. I also explain the identification strategy in detail. In Section 4, I present the estimated elasticities and the heterogeneity in truckers' responsiveness to changes in per-mile fuel cost. Section 5 provides robustness and falsification checks. In Section 6, I construct a general equilibrium model and derive the expression of an optimal tax. Drawing elasticity parameters from the empirical analysis in Section 4, I calculate the optimally differentiated fuel taxes, as well as potential welfare gain. Section 7 concludes.

1.2 Data

1.2.1 Data Sources

The primary source of data is the Vehicle Inventory and Use Survey (VIUS), which was conducted by the Census Bureau every five years from 1982 to 2002.[1] The surveying process remained almost the same across all survey years. The sampling frame was drawn from state registration records of active trucks as of July 1 in the survey year. Five strata were created based on truck weights and body types. In

[1]VIUS was originally referred as Truck Inventory and Use Survey. In 1997, the survey was renamed as Vehicle Use and Inventory Survey to reflect its expanded scope. The first round of survey was conducted in 1967, while only the data from 1977 to 2002 are in public domain. In this study, I use five years of data from 1982 to 2002. Survey year 1977 is omitted due to its lack of compatibility with the following survey years.

each stratum, a random sample of truck registrations was taken without replacement. Questionnaires were mailed out during the second season in the following year. Follow-up mailings and/or phone calls were conducted on truck owners if they failed to respond in the first round. Both the sample size and response rate stayed relatively stable across all survey years.[2]

VIUS provides detailed information on both physical characteristics and operational features of the U.S. trucking fleet. Weight class, defined as gross vehicle weight rating (GVWR), is commonly used to distinguish light-duty and heavy-duty vehicles. Vehicles with a GVWR from class 2b to 8, or a gross vehicle weight greater than 8,500 pounds, are classified as heavy-duty vehicles. I restrict my sample to heavy-duty vehicles, which account for about 70% of the original dataset.

Following the classification published in the regulatory impact analysis (RIA) by the EPA, I examine the heavy-duty fleet in two distinct categories – combination trucks and vocational vehicles. *Combination trucks* refer to tractor trailers[3] with a GVWR of class 7 or 8 (gross vehicle weight greater than 26,000 pounds). Most combination trucks are meant for long-distance cargo hauling on highways. The body type of a trailer is typically either an enclosed box or a basic platform. These two

[2]From 1977 to 2002, the sample size ranges from 116,400 to 153,914, and the response rate varies between 72.52% and 90.20%.

[3]A truck tractor is a motor vehicle designed primarily for drawing truck trailers. Truck tractors often lack a load area and instead have a “fifth wheel” on the back chassis area, which accepts a locking mechanism under the trailer to attach it.

body types account for more than 50% of the combination truck fleet in my sample. Examples of other commonly seen trailer body types include insulated refrigerated vans, tank trucks for liquid or gas, and dump trucks. *Vocational vehicles* refer to straight trucks with a gross vehicle weight greater than 10,000 pounds.[4] A straight truck typically has a load area as part of the vehicle. Compared to combination trucks, vocational vehicles generally undertake shorter trips. For instance, dump trucks, which account for 24% of all vocational vehicles in my sample, primarily drive locally. Ninety-four percent of the dump trucks operate within their home base states for more than 80% of the time. Vocational vehicles are used for various purposes besides hauling cargo. For example, a turnable ladder can be installed behind the cabin to provide a platform for tasks such as ventilation or overhaul. A box truck with a rear door can be converted into a mobile workshop. A multi-stop or step van is usually used for local package delivery. Winch, crane trucks, and concrete mixers are particularly important for the construction industry.

I eliminate trucks from the sample if 1) the truck was acquired before or in 1972, 2) the engine model year is 1972 or earlier, 3) the truck used fuel other than diesel, 4) the truck spent most of the year not in use,[5] 5) the truck was used for personal transportation, government operations or transporting passengers, 6) there

[4]Class 2b (gross vehicle weight from 8,501 pounds to 10,000 pounds) straight trucks are also classified as heavy-duty vocational vehicles in RIA. Unfortunately, I cannot separate Class 2b from Class 2 in the data set.

[5]There is no clear quantified criterium based on the questionnaire. The answer is up to truck owners.

are missing critical variables after imputation[6] or 7) the data are miscoded.[7]

The fuel cost per mile, measured in dollars/mile, is derived from taking the ratio of diesel price and the fuel economy.[8] Annual diesel prices at the state level are approximated by the inflation adjusted distillate fuel prices published by the United States Energy Information Administration (EIA), as well as federal and state fuel tax rates published in Highway Statistics by the United States Department of Transportation. All prices are in 2002 U.S. dollars.

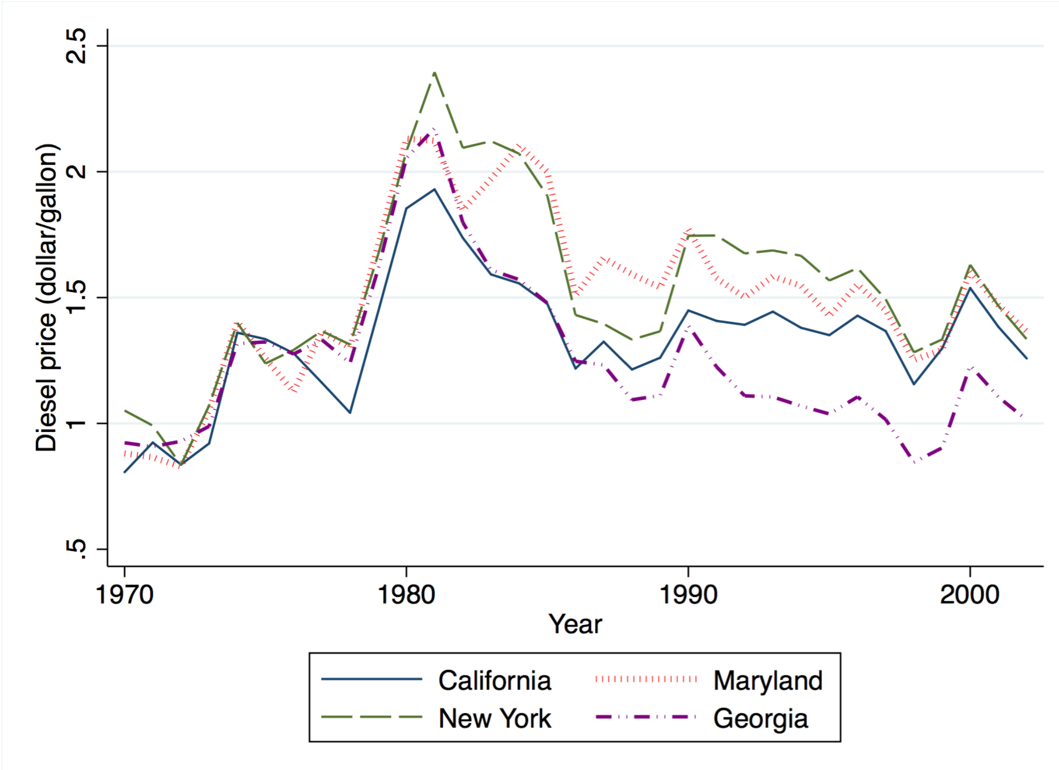
The variation in fuel prices comes from two sources. One is driven by the variation in fuel prices across states and the other is mostly determined by the difference in travel distance among truckers. Figure 1.1 shows, for a selection of states, the trend of diesel price from 1973 to 2002. Truckers in interstate business are more likely to face different fuel prices than those who primarily drive within their home base states. VIUS provides information regarding the percentage of in-state trips and out-of-state trips for each truck surveyed. It is useful to construct

[6]Missing data are imputed by replacing with the mode in the population of similar trucks. Such population includes trucks that share the same GVWR, model year, make, body/trailer type, home base state, operator class, main cargo product and business sector.

[7]I consider the data miscoded in the following situation where cargo weight is negative, or VMT is greater than 275,000 miles per year, or fuel efficiency is greater than 20 miles per gallon for combination trucks or zero for any truck, or average vehicle weight (with or without cargo) is less than 5,000 pounds for combination trucks or 1,000 pounds for vocational vehicles.

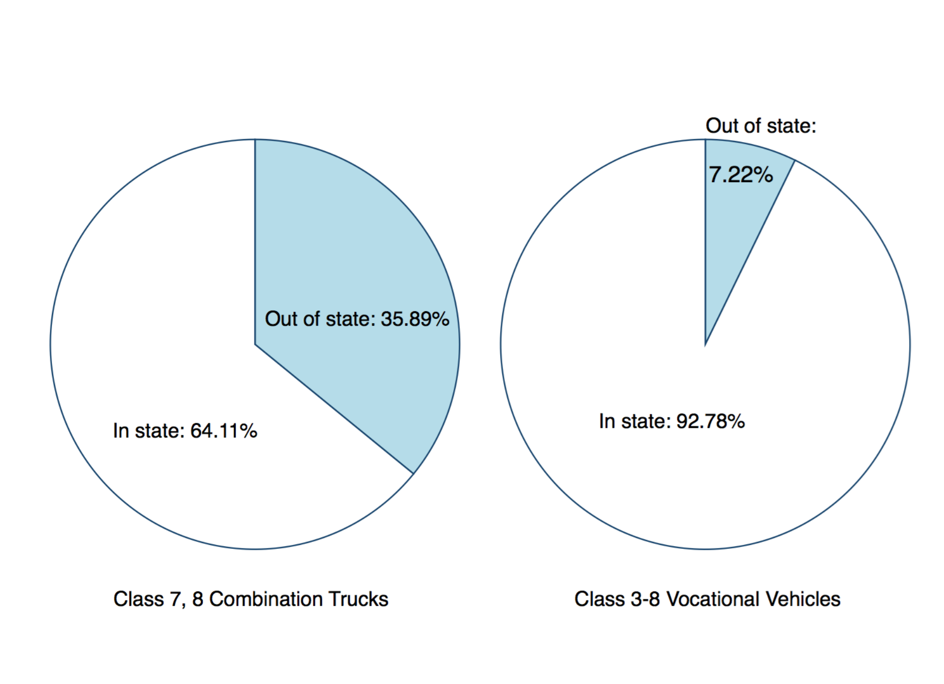
[8]Fuel economy is measured in miles/gallon. It is usually used interchangeably with "fuel efficiency" in the literature.

Figure 1.1: Diesel fuel price (in 2002$) for selected states



trip-based fuel prices to approximate the actual diesel fuel prices which truckers encountered at the pump. I assume that truckers face the diesel prices in their home base states while driving within the home base states, and the national average diesel price while driving outside of the home base states. The trip-based diesel fuel price is the average of these two situations weighted by the percentage of trips. Figure 1.2 shows the average percentage of these two situations for both types of trucks. While vocational vehicles mostly stay in their home base states (92.78% of the time), combination trucks spend a little over one-third of their time out of home base states. This allocation implies that the second source of variation in fuel prices - how far trucks travel - is more relevant to combination trucks than to vocational

Figure 1.2: Allocation of trips between in-state and out-of-state



vehicles.

1.2.2 Summary Statistics

Table 1.1 provides the summary statistics of the decision variables, VMT and PD, along with selected control variables. On average, combination trucks are driven about 64 thousand miles per year, which is more than triple the distance traveled by vocational vehicles. The difference is more dramatic for payload distance. The average PD for combination trucks is almost eight times that of vocational vehicles. When comparing truck characteristics between these two groups, combination trucks, on average, have lower fuel efficiency, greater lifetime mileage and heavier total vehicle weight.

Table 1.1: Summary Statistics

	Combination Trucks		Vocational Vehicles	
	Mean	St.d.	Mean	St.d.
	(1)	(2)	(3)	(4)
VMT (1,000 miles/year)	63.74	45.25	20.16	20.64
Payload distance (10,000 ton-miles/year)	79.25	85.39	9.44	20.85
Fuel economy (miles per gallon)	5.58	1.27	7.19	3.14
Odometer reading (10,000 miles)	43.22	31.37	20.44	22.20
Average vehicle weight (10,000 lbs)	5.70	1.51	3.19	1.56
Axle Configuration:				
2 axles	0.00	0.00	0.41	0.49
2 axles; 2 axle trailer	0.11	0.31	0.04	0.21
3 axles	0.00	0.00	0.36	0.48
3 axles; 2 axle trailer	0.71	0.45	0.05	0.21
Vehicle Make:				
Ford	0.07	0.26	0.23	0.42
Freightliner	0.30	0.46	0.20	0.40
International/Harvester	0.21	0.41	0.22	0.41
Kenworth	0.16	0.36	0.05	0.22
Mack	0.14	0.34	0.15	0.36
Peterbilt	0.12	0.32	0.04	0.19
Body/Trailer Type:				
Basic enclosed van	0.32	0.47	0.13	0.34
Basic platform	0.16	0.36	0.12	0.33
Dump truck	0.08	0.27	0.24	0.43
Insulated, refrigerated van	0.11	0.31	0.03	0.18
Cab Type:				
Cab over engine	0.26	0.44	0.20	0.40
Conventional	0.73	0.44	0.77	0.42
Radial tires installed	0.69	0.46	0.62	0.49
Primary Cargo:				
Building materials	0.09	0.29	0.28	0.45
Farm products	0.11	0.32	0.08	0.28
Petroleum products	0.04	0.20	0.05	0.21
Processed foods	0.15	0.35	0.07	0.26
Tools, machinery and equipment	0.10	0.30	0.10	0.31

Note: The category dummy variables with mean less than 0.1 are omitted from this table, but they are included in the regressions. A list of these variables can be found in A.1. Other characteristics not presented in the table include number of cylinders and engine displacement.

Truck body/trailer type and axle configuration determine the business use as well as its carrying capacity. A good design of the cabin (or cab) can reduce the aerodynamic drag substantially, and therefore improve the fuel efficiency. The conventional cab is most common in North America. In such a cabin, the driver is seated behind the engine, as in most passenger vehicles. The next most common cabin type is "cab over engine" – with the cabin located on top of the engine. This type of design, also called "flat nose", often results in more wind resistance and higher drag. In the sample from VIUS, 73% of combination trucks and 77% of vocational vehicles have conventional cabs.

Radial tires also contribute to better fuel efficiency. The cored plies are arranged perpendicularly to the direction of travel, so that the tires experience longer tread life, better steering characteristics and less rolling resistance. Although bias tires have the merit of weight carrying ability, radial technology has become the standard design. In my sample, about 69% of combination trucks and 62% of vocational vehicles are equipped with radial tires.

1.3 Estimation Strategy

1.3.1 Model

The decision of VMT can be considered as an optimal outcome of a profit-maximization problem. Suppose a driver with truck i in state s in year t receives an exogenous P_b for each mile (or ton-mile as discussed below) of delivery services in business b. The cost of operation includes fuel costs and maintenance costs. The per-mile fuel cost, c_i, can be derived from dividing fuel price, p_i, by the average MPG. (Note that MPG is the average fuel efficiency of all trucks with the same type as i.) Maintenance cost is a function of truck characteristics, $\boldsymbol{X_i}$, and fleet operational characteristics, $\boldsymbol{Z_i}$. Equating the marginal revenue with the marginal cost gives the optimal solution of VMT,

$$\mathrm{VMT}_i = F(c_i, \boldsymbol{X_i}, \boldsymbol{Z_i}, \theta_s, \tau_t, \phi_b) \ . \tag{1.1}$$

The state-level fixed effects, θ_s, capture the time-invariant factors. For example, if an intrastate driver in California drives more on average than a driver with the same truck in Rhode Island due to the geographical difference between these two states, the state-level fixed effects would prevent such factor from biasing the estimation results. The survey year fixed effects, τ_t, are included to systematically identify time-specific influences on VMT, such as macroeconomic factors, nationwide demand shocks, and measurement errors for a specific survey year. ϕ_b represents the business sector of the cargo delivery, such as agriculture or forestry, construction and for-hire transportation. The business fixed effects capture any industry-specific shocks that may affect trucking decisions. In addition, ϕ_b also absorbs the effect of shipping price, assuming that the shipping price in a particular business is relatively time-invariant.

Suppose function F takes the following parametric form:

$$\text{VMT}_i = c_i^{\gamma} \exp(\beta_0 + \boldsymbol{X_i}'\boldsymbol{\beta_X} + \boldsymbol{Z_i}'\boldsymbol{\beta_Z} + \theta_s + \tau_t + \phi_b + \epsilon_i) \ , \tag{1.2}$$

in which c_i is the fuel cost per mile driven, derived from the following calculation:

$$c_i = \frac{p_i}{\text{MPG}} \ . \tag{1.3}$$

ϵ_i is assumed to be a mean-zero stochastic error term. Taking the natural logarithm on both sides of equation (1.2), I derive the specification for empirical estimation.

$$\ln \text{VMT}_i = \beta_0 + \gamma \ln c_i + \boldsymbol{X_i}'\boldsymbol{\beta_X} + \boldsymbol{Z_i}'\boldsymbol{\beta_Z} + \theta_s + \tau_t + \phi_b + \epsilon_i \tag{1.4}$$

where γ can be interpreted as the elasticity of VMT with respect to fuel costs.

If shipment price is calculated based on payload distance, P_b is the price for delivering each payload-ton per mile. It is particularly relevant when the primary business use of a truck is hauling cargo. The payload distance is constructed as follows:

$$\text{PD}_i = \text{VMT}_i \cdot w_i \cdot \xi_i \tag{1.5}$$

where w_i denotes the payload weight (in tons), and ξ_i is the percentage of loaded trips. To estimate how payload distance responds to changes in per-mile fuel cost, I follow the same specification as in equation (1.4):

$$\ln \text{PD}_i = \alpha_0 + \delta \ln c_i + \boldsymbol{X_i}'\boldsymbol{\alpha_X} + \boldsymbol{Z_i}'\boldsymbol{\alpha_Z} + \theta_s + \tau_t + \phi_b + \varepsilon_i \tag{1.6}$$

where δ is interpreted as the elasticity of payload distance with respect to per-mile fuel cost.

1.3.2 Identification

To derive consistent estimates of elasticities of VMT and payload distance, I need to ensure that the variations in both fuel efficiency, MPG, and fuel price, p_i, are exogenous. Given the possibility of reverse causality between truck i's VMT and its own fuel efficiency (MPG_i), using individual MPG_i in equation (1.3) would be problematic. Instead, I use the mean MPG of all trucks that share the same characteristics as truck i. Since fuel efficiency of a vehicle is largely determined by its engineering characteristics and payload weight, the mean MPG represents the fuel efficiency at the truck-model level, which is exogenous to an individual trucker's decision. Thus, this adjustment eliminates the influence of individual fuel efficiency on the decision of VMT, which is commonly known as the "rebound effect". Admittedly, if owners of similar trucks share similar expectations of VMT and factor such anticipations of usage into their purchase decisions, the estimated responsiveness using the stated methods would be biased upwards (Gillingham, 2012).[9] In an alternative specification, I include the interaction terms of survey year, business sector and region fixed effects to capture the common effect on trucking due to regional industry shocks during the year in question. If, for example, the construction industry is booming in California in 2002, it should increase the demand for trucking

[9] Gillingham (2012) estimates the fuel price elasticities for passenger vehicles and compares the estimates with and without considering people's anticipation of driving. He finds that the elasticity (in absolute value) is higher by 0.06 if failing to consider the anticipation of driving, compared to the alternative case.

on the west coast. Such shocks will be absorbed by the interaction terms. In fact, as shown in Tables 1.2 and 1.3, the estimation results remain almost the same with or without the interaction terms, showing that the potential bias from ignoring the anticipation effect is relatively trivial. That being said, I conservatively claim that my estimates are the upper bounds of elasticities.

The assumption that individual drivers are price-takers with respect to fuel prices, though common in the literature, can be questionable in some cases. For example, a local demand shock to VMT may cause a short-term drawback of fuel supply and therefore temporarily drive up local fuel prices. Another scenario which may bias the estimates stems from truckers' forecasts of future fuel prices. To control for the plausible endogeneity of fuel prices, I instrument fuel prices with the inflation-adjusted average prices in states that are not bordering with the home base states.[10] As fuel prices across states are correlated, the relevance condition of a valid instrument is satisfied.[11] The exclusion condition that a valid instrument must satisfy relies on a rather strong assumption: a driver in home base state s is not affected by fuel price changes in states further than his neighboring states. Neighboring states are excluded due to the possibility that drivers may cross states to purchase fuel if lower price is observed. Another plausible instrument is global crude oil price. Global oil price is clearly correlated with local diesel fuel prices,

[10] In regressions, the instrumental variable is constructed by taking the ratio of diesel price in non-neighboring states over average MPG of the same type of trucks.

[11] First stage estimation results shown in Table A.1 in A.2.

and it is unlikely that an individual trucker's operational decision would affect the global oil price. I provide the estimation results with the alternative instrumental variable in section 1.5.2.

The exclusion restriction holds once I control for some important unobservables with fixed effects. Home base state fixed effects and survey year fixed effects account for time-invariant and nationwide influences respectively. The growth in state GDP is included to capture the potential impact of local economic development on the demand for VMT. I control as much as possible for truck characteristics that affect driving and capture the variation solely due to difference in fuel costs. The truck characteristics include model year, make, body/trailer type, cab type, axle configuration, average vehicle weight (in natural log), odometer reading (in natural log), engine displacement, radial tire installation and number of cylinders. In addition, I account for business characteristics in the estimation, such as operator class, business sector of the shipment, fleet size and primary cargo product. Depending on the operational area, the unobserved factors should affect trucks in the same region (broader than states)[12] in a similar way. Robust standard errors are obtained in all regressions.[13]

[12]I adopt the regional division provided by the U.S. Energy Information Administration. See the map shown in Figure A.1 in A.3.

[13]I cluster the standard errors at the level of home base states in baseline OLS regressions. State and year two-way clustering are used in IV regressions.

1.4 Empirical Results

1.4.1 Elasticities

The results from estimating equation (1.4) are shown in Table (1.2). The estimations are conducted separately for combination trucks and vocational vehicles. All fixed effects and controls discussed above are included. Columns (1) and (4) present the medium-run elasticities of VMT with respect to fuel costs, estimated using ordinary least squares (OLS). To address the plausible endogeneity of fuel cost per mile, I show the elasticities using two-stage least squares in columns (2) and (5), with the instrumental variables (IV) being the average cost per-mile of driving in states that are not bordering the home base states. The estimated elasticities of VMT are highly statistically significant. In general, vocational vehicles are more responsive to changes in cost per-mile of driving. Specifically, a 10% increase in fuel cost per mile results in a 2.34% reduction in driving distance for combination trucks and 2.70% for vocational vehicles. The estimated coefficients of other control variables show the expected signs and remain relatively stable across specifications – highlighting the robustness of the main results. Interaction terms among business sectors, survey years and regions are included in columns (3) and (6). These specifications address concerns regarding VMT anticipation – drivers with similar trucks may have similar expectations of future driving demand which may affect today's choices of fuel economy. Comparing columns (2) and (3) for combination trucks, as well as columns (5) and (6) for vocational vehicles, I find that the elasticities remain

Table 1.2: Estimated Elasticities of VMT

	Combination Trucks			Vocational Vehicles		
	OLS	IV	IV	OLS	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)
ln(per-mile fuel cost)	-0.182***	-0.234***	-0.238***	-0.260***	-0.270***	-0.272***
	(0.0400)	(0.0311)	(0.0304)	(0.0208)	(0.0211)	(0.0203)
Control variables						
ln(average vehicle weight)	0.400***	0.402***	0.393***	0.212***	0.213***	0.210***
	(0.0229)	(0.0225)	(0.0217)	(0.0169)	(0.0168)	(0.0162)
ln(odometer reading)	0.488***	0.489***	0.487***	0.489***	0.489***	0.490***
	(0.00761)	(0.00765)	(0.00754)	(0.0109)	(0.0108)	(0.0108)
ln(state GDP)	0.0784	0.0786*	0.0401	0.0146	0.0148	-0.0135
	(0.0380)	(0.0376)	(0.0300)	(0.0464)	(0.0459)	(0.0320)
Survey year FE	Yes	Yes	Yes	Yes	Yes	Yes
Home base state FE	Yes	Yes	Yes	Yes	Yes	Yes
Other truck characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Operational characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Business × year × region	No	No	Yes	No	No	Yes
No. of observation	112,364	112,364	112,364	83,242	83,242	83,242
Adjusted R^2	0.550	0.550	0.556	0.426	0.426	0.430

Note: $^{*}: p < 0.1$; $^{**}: p < 0.05$; $^{***}: p < 0.01$
The robust standard errors (in parentheses) in (1) and (4) are clustered at the level of home base states.
The robust standard errors in (2), (3), (5) and (6) are clustered at the level of states and survey years.
Other truck characteristics include model year, average vehicle weight (including cargo), odometer reading, axle configuration, make, body/trailer type, cab type, engine displacement, number of cylinders and radial tire installation.
Operational characteristics include operator class, business sector, fleet size and main cargo product.

nearly the same. The robustness of the results suggests that the anticipation effect resulting from local industry demand shock is small.

Table (1.3) presents the estimated elasticities of payload distance with respect to per-mile fuel cost. A 10% increase in per-mile fuel cost induces a reduction in payload distance by about 4.28% for combination trucks and 3.62% for vocational vehicles once I control for the endogeneity of fuel prices, as shown in columns (2) and (5). The estimates are highly statistically significant. The fact that they are even higher than elasticities of VMT in absolute terms implies that the average

Table 1.3: Estimated Elasticities of Payload Distance

	Combination Trucks			Vocational Vehicles		
	OLS	IV	IV	OLS	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)
ln(per-mile fuel cost)	-0.366***	-0.428***	-0.425***	-0.355***	-0.362***	-0.361***
	(0.0442)	(0.0317)	(0.0306)	(0.0250)	(0.0259)	(0.0252)
Control variables						
ln(average vehicle weight)	2.540***	2.543***	2.534***	1.935***	1.935***	1.929***
	(0.0353)	(0.0345)	(0.0346)	(0.0268)	(0.0264)	(0.0266)
ln(odometer reading)	0.484***	0.485***	0.483***	0.512***	0.512***	0.509***
	(0.00838)	(0.00841)	(0.00828)	(0.0120)	(0.0118)	(0.0114)
ln(state GDP)	0.0616	0.0618*	0.0500	0.0497	0.0498	0.0254
	(0.0379)	(0.0375)	(0.0343)	(0.0691)	(0.0683)	(0.0503)
Survey year FE	Yes	Yes	Yes	Yes	Yes	Yes
Home base state FE	Yes	Yes	Yes	Yes	Yes	Yes
Other truck characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Operational characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Business × year × region	No	No	Yes	No	No	Yes
No. of observation	107,963	107,963	107,963	75,142	75,142	75,142
Adjusted R^2	0.681	0.681	0.685	0.561	0.561	0.565

Note: $^{*}: p < 0.1$; $^{**}: p < 0.05$; $^{***}: p < 0.01$
The robust standard errors (in parentheses) in (1) and (4) are clustered at the level of home base states.
The robust standard errors in (2), (3), (5) and (6) are clustered at the level of states and survey years.
Other truck characteristics include model year, average vehicle weight (including cargo), odometer reading, axle configuration, make, body/trailer type, cab type, engine displacement, number of cylinders and radial tire installation.
Operational characteristics include operator class, business sector, fleet size and main cargo product.

payload weight decreases as per-mile fuel cost increases. While the reason cannot be tested with the available data, it is possible that truckers undertake shorter but more frequent trips (therefore lighter cargo on average) and/or they pick up more profitable cargo to compensate for the increase in fuel costs.

1.4.2 Heterogeneity in Responsiveness

It is important to understand the heterogeneity in responsiveness to changes in fuel costs for two main reasons. First, unlike passenger vehicles, heavy-duty trucks serve a wide range of purposes besides transporting goods from point A to point B.

Heterogeneity in truckers' responsiveness to fuel cost reflects differences in flexibility of schedule and shipping demand. For this reason, trucks for business or personal services are likely to be more responsive than those in mining or forestry. Second, truck characteristics, such as vehicle weight and loading capacity, affect truckers' sensitivity to changes in fuel costs and their ability to comply with environmental policies. Heavier trucks may encounter more difficulties in changing routes and/or schedules, due to business restrictions and road limitations. Operational factors, such as operator class and fleet size, can also result in different responsiveness to changes in fuel costs. Long distance shipment may be assigned to trucks with relatively low per-mile fuel cost, for example. Such substitution is more likely to appear in a large fleet. For owner operators, however, opportunities for such substitution may be more limited. Ignoring these differences and imposing uniform policies may result in inequality and overall welfare loss. It is thus essential to recognize the heterogeneity of elasticities among various truck groups, and design policies and compliance strategies accordingly. In the rest of this section, I explore the heterogeneity in responsiveness of VMT and payload distance to fuel costs by vehicle weight class and business sector. The elasticities are necessary to calculate the optimal differentiated fuel taxes. The heterogeneous responsiveness by operator class and fleet size is discussed in A.4.

1.4.2.1 Weight Class

Gross vehicle weight rating (GVWR) is the most common vehicle classification used by government agencies to set differentiated standards. GVWR defines the weight range of the maximum loading capacity in addition to the weight of the vehicle itself. By definition, GVWRs of combination trucks are either class 7 or 8, while the weight ratings for vocational vehicles range from class 3 to 8. The estimation is consistent with the main specification, discussed in section 2.2, with additional interaction terms of GVWR dummies and per-mile fuel cost. I use *t-test* on the coefficients of the interaction terms to decide if the heterogeneity in responsiveness is valid. If the coefficient is statistically significant, it indicates that the responsiveness of truckers in this groups is significantly different from that in the baseline group. As shown in Table 1.4, lighter combination trucks are generally more responsive to changes in fuel costs. Facing a 10% increase in per-mile fuel cost, combination trucks that are lighter than 26,000 pounds (or GVWR 7) tend to reduce their annual mileage by 3.81%, while heavier trucks' VMT only drops by 2.16%. Heavy-duty 18-wheeler trucks face not only more road use limits than lighter trucks, but also more schedule constraints especially for long-haul trucks. The trend holds true for vocational vehicles in most cases, except for class 3. It is plausible that most class 3 vocational vehicles are step vans, primarily used for local delivery businesses. Their choice of routes or schedules tend to be less flexible.

Table 1.4: Elasticities by Weight Class

Dependent variable:	ln(VMT)		ln(PD)	
	Combination	Vocational	Combination	Vocational
	(1)	(2)	(3)	(4)
Elasticities by weight class:				
GVWR = 3		-0.225***		-0.499***
		(0.0833)		(0.134)
GVWR = 4		-0.373**		-0.363
		(0.190)		(0.251)
GVWR = 5		-0.461***		-0.627***
		(0.161)		(0.197)
GVWR = 6		-0.295***		-0.311***
		(0.0354)		(0.0507)
GVWR = 7	-0.381***	-0.296***	-0.465***	-0.352***
	(0.0485)	(0.0335)	(0.0618)	(0.0434)
GVWR = 8	-0.216***	-0.206***	-0.418***	-0.293***
	(0.0326)	(0.0238)	(0.0327)	(0.0265)
Control variables				
ln(average vehicle weight)	0.403***	0.247***	2.546***	2.000***
	(0.0229)	(0.0180)	(0.0345)	(0.0285)
ln(odometer reading)	0.486***	0.488***	0.483***	0.510***
	(0.00736)	(0.0108)	(0.00807)	(0.0118)
ln(state GDP)	0.0827**	0.00746	0.0675*	0.0359
	(0.0374)	(0.0459)	(0.0375)	(0.0660)
Survey year FE	Yes	Yes	Yes	Yes
Home base state FE	Yes	Yes	Yes	Yes
Other truck characteristics	Yes	Yes	Yes	Yes
Business characteristics	Yes	Yes	Yes	Yes
No. of observation	113,464	83,970	109,047	75,829
Adjusted R^2	0.548	0.426	0.679	0.562

Note: $^{*}: p < 0.1$; $^{**}: p < 0.05$; $^{***}: p < 0.01$

All robust standard errors (in parentheses) are clustered at the level of home base states and survey years. In each regression, GVWR dummy variables are interacted with ln(fuel cost per mile). The elasticity for a particular weight class is the sum of coefficient of the interaction term and that of ln(fuel cost per mile). The robust standard errors are calculated based on the linear combinations.

Table 1.5: Distribution of Business Sectors in 2002

Business sector	Combination trucks (1)	Vocational vehicles (2)
Agriculture or forestry	12%	10%
Business and personal service	1%	8%
Construction	8%	26%
For-hire transportation	56%	12%
Manufacturing	5%	6%
Mining or quarrying	2%	2%
Rental or contractor	1%	4%
Retail and wholesale trade	10%	18%
Other	5%	14%
Total	100%	100%

Data source: VIUS 2002

1.4.2.2 Business Sector

Business sector refers to the industry of either the shipment cargo or the primary task. The distribution of truck counts across the nine business sectors in my sample are given separately in Table 1.5 for combination trucks and vocational vehicles. The majority of combination trucks are used for for-hire transportation. Other major business sectors include retail/wholesale trade, farming, manufacturing and construction. Trucks in different business sectors are subject to various purposes and constraints; therefore, their VMT and payload distance decisions may respond to fuel costs differently from one another. To examine such heterogeneity among business sectors, I estimate equation (1.4) and equation (1.6) with interaction terms of the nine business sector dummy variables and the natural log of per-mile fuel cost. The elasticities of interest are obtained by adding the coefficient of ln(cost of driving) to the coefficients of the interaction terms.

The heterogeneity in elasticities of VMT by business sector is presented in

Table 1.6: Elasticities by Business Sector

Dependent variable:	ln(VMT)		ln(PD)	
	Combination	Vocational	Combination	Vocational
	(1)	(2)	(3)	(4)
Elasticities by business sector:				
Agriculture or forestry	0.174**	-0.310***	-0.0677	-0.308***
	(0.0721)	(0.0458)	(0.0672)	(0.0500)
Business and personal service	-0.490***	-0.318***	-0.668***	-0.384***
	(0.13)	(0.0298)	(0.153)	(0.0448)
Construction	-0.262***	-0.257***	-0.377***	-0.351***
	(0.065)	(0.0314)	(0.084)	(0.0362)
For-hire transportation	-0.271***	-0.223***	-0.513***	-0.453***
	(0.0362)	(0.0343)	(0.0431)	(0.0435)
Manufacturing	-0.481***	-0.258***	-0.616***	-0.325***
	(0.0583)	(0.0486)	(0.0671)	(0.0648)
Mining or quarrying	-0.19	-0.0984	-0.293**	-0.0866
	(0.125)	(0.0731)	(0.129)	(0.107)
Rental or contractor	-0.294***	-0.347***	-0.416***	-0.478***
	(0.077)	(0.0484)	(0.117)	(0.0652)
Retail and wholesale trade	-0.317***	-0.245***	-0.533***	-0.300***
	(0.0482)	(0.0264)	(0.0525)	(0.0378)
Other	-0.244	-0.272***	-0.172	-0.549***
	(0.185)	(0.0376)	(0.161)	(0.0581)
Control variables				
ln(average vehicle weight)	0.408***	0.215***	2.547***	1.938***
	(0.0226)	(0.0169)	(0.0347)	(0.0266)
ln(odometer reading)	0.489***	0.490***	0.486***	0.511***
	(0.00768)	(0.0108)	(0.00847)	(0.0119)
ln(state GDP)	0.0799**	0.0134	0.0631***	0.0463
	(0.0371)	(0.0457)	(0.0372)	(0.0688)
Survey year FE	Yes	Yes	Yes	Yes
Home base state FE	Yes	Yes	Yes	Yes
Other truck characteristics	Yes	Yes	Yes	Yes
Business characteristics	Yes	Yes	Yes	Yes
No. of observation	112,364	83,242	107,963	75,142
Adjusted R^2	0.550	0.427	0.681	0.562

Note: $^{*}: p < 0.1$; $^{**}: p < 0.05$; $^{***}: p < 0.01$
All robust standard errors (in parentheses) are clustered at the level of home base states and survey years. In each regression, business sector dummy variables are interacted with ln(fuel cost per mile). The elasticity for a particular business sector is the sum of coefficient of the interaction term and that of ln(fuel cost per mile). The robust standard errors are calculated based on the linear combinations.

Table 1.6. All of these regressions use IV to control for the plausibly endogenous fuel costs. Most of the estimates are highly statistically significant. The estimated elasticities for combination trucks range from -0.49 to 0.17, and for vocational vehicles from -0.35 to -0.10. Combination trucks in business and personal services are the most responsive to changes in per-mile fuel cost. A 10% increase in per-mile fuel cost induces reduction in VMT by 4.9%. For both types of trucks in mining or quarrying, the estimated elasticities are not statistically significant, possibly because of the relatively rigid demand for truck transportation at mines. Surprisingly, combination trucks in agriculture or forestry are driven more as per-mile fuel cost rises.

Columns (3) and (4) in Table 1.6 provide the heterogeneous estimates of elasticities of payload distance in different business sectors. In particular, trucks in business and personal service, as well as for-hire transportation, have higher elasticities (in absolute value) for both VMT and PD than the averages shown in Table 1.3. The reduction in payload distance ranges from 0.7% to 6.2% across the nine business sectors when per-mile fuel cost increases by 10%.

1.5 Robustness and Falsification Checks

I conduct two robustness checks. First, I aggregate the data at the truck model level to address any potential measurement error.[14] Second, I construct an

[14]Some variables in the survey rely on truckers' recall of driving distance and travel location. Thus, the self-reported data may contain measurement error.

Table 1.7: Robustness checks and falsification test

	Primary results (1)	Aggregate data (2)	Alternative IV (3)	Falsification test (4)
Combination Trucks:				
Elasticity of VMT	-0.234***	-0.229***	-0.225***	-0.00679
	(0.0311)	(0.0332)	(0.0313)	(0.00637)
Elasticity of PD	-0.428***	-0.418***	-0.419***	-0.00538
	(0.0317)	(0.0276)	(0.0317)	(0.00917)
Vocational Vehicles:				
Elasticity of VMT	-0.270***	-0.276***	-0.269***	0.00991
	(0.0211)	(0.0131)	(0.0210)	(0.00965)
Elasticity of PD	-0.362***	-0.355***	-0.359***	0.0176
	(0.0259)	(0.0178)	(0.0256)	(0.0131)

Note: * : $p < 0.1$; ** : $p < 0.05$; *** : $p < 0.01$
All robust standard errors (in parentheses) are clustered at the level of home base states and survey years.

alternative set of instrumental variables by taking the ratio of truck-level MPG and inflation adjusted crude oil prices. I show that the primary results, as well as the heterogeneity in elasticities, remain robust in these specifications. Following the robustness checks, I conduct a falsification test by randomizing the observations of fuel costs to eliminate the possibility that my estimation results might be driven by factors outside of the model.

1.5.1 Aggregate Data

To minimize the potential effect of measurement errors or outliers, I aggregate the data at the level of survey year, home base state, body/trailer type, make axle configuration, business sector and operator class.[15] I apply the same methods as discussed in section 2.2. Column (2) in Table 1.7 presents the estimated overall elasticities using the IV approach.[16] The estimates look similar to the primary

[15]The data aggregation method in general does not affect the robustness of my results.

[16]Detailed estimation results using aggregate data can be found in Table A.5.

estimation results, shown in section 1.4 and repeated in column (1) in Table 1.7. The similarity in results indicates that the primary estimation outcomes are not driven by individual outliers or measurement errors.

1.5.2 Alternative Instrumental Variables

Global crude oil is the source of all distillate products. Its price is often used as an instrumental variable for the plausibly endogeneous fuel price (Gillingham, 2014). The second instrumental variable I use is constructed as the ratio of crude oil price over truck model-level fuel efficiency. Diesel prices in each state are clearly correlated with the price of their upstream product, crude oil. I show further evidence of this correlation in the first-stage estimation results in A.2. The second instrument also satisfies the exclusion requirement, as the global crude oil price is exogenous to individual truckers' driving decisions. The estimation results of overall elasticities using the IV approach are presented in column (3) in Table 1.7.[17] The estimates are within or identical to the 95% confidence interval of the primary results shown in column (1), confirming the robustness of my main results.

1.5.3 Falsification Test

I conduct a falsification test by randomizing the variable, fuel cost per mile, among all observations. If the model is reasonable and the data are adequate, the coefficients on randomized fuel costs should be insignificant. As shown in column

[17]The heterogeneity in elasticities in different subgroups of trucks are presented in Table A.6.

(4) in Table 1.7, none of the estimated elasticities is significantly different from zero. This suggests that the negative effects of fuel costs on VMT and payload distance are valid.

1.6 Differentiated Fuel Taxes

The estimated heterogeneous elasticities for trucks in different weight classes and business sectors provide important inputs for calculating optimally differentiated fuel taxes. It is evident in both theory and empirics that implementing differentiated fuel taxes achieves higher welfare gains than traditional average taxes. Based on the framework built by Parry and Small (2005) and Parry (2008), I develop a general equilibrium model including households, production sectors, the trucking fleet and the government. The main difference from Parry (2008) is three-fold. First, shipping-intensive goods[18] are priced at the per-ton-mile level, in lieu of per-mile level as in Parry (2008). This setup is more realistic for the heavy-duty trucking industry and consistent with how trucking operation is measured in the newly announced regulatory standards in 2016. Second, I allow truckers to choose routes based on shipping demand, while VMT is assumed constant in Parry (2008). Third, the model incorporates the implementation of differentiated diesel taxes, while Parry (2008) presents the structure for a uniform fuel tax. From the analytical model, I derive the expression for the marginal welfare effect. The optimal tax is set to maximize welfare. The numerical calculation of the optimal tax relies upon the estimates

[18] A shipping-intensive good is defined as a market good whose production/distribution involves significant trucking costs (Parry, 2008).

in this study, parameters from the existing literature, and a number of assumptions.

1.6.1 The analytical framework

(i) Household

Suppose a representative household's utility function can be written as follows:

$$u = u\{R_i, Y, A, M, Z\} \tag{1.7}$$

R_i, measured in ton-miles, denotes consumption of a market good whose production and/or distribution involves nontrivial shipping cost. All terms are expressed per capita per year.[19] Index i indicates a GVWR class.[20] R_i is defined by the product of vehicle-miles-traveled, T_i and cargo weight, W_i:

$$R_i \equiv T_i \cdot W_i \ . \tag{1.8}$$

All other consumption is denoted by Y. A is the household's VMT of passenger vehicles. M denotes total travel time. Z represents all negative externalities incurred due to auto and trucking activities, including air pollution, energy security, noise, and accidents. The utility function $u\{\cdot\}$ is increasing and quasi-concave in R_i, Y and A. It is decreasing in M and Z with $u_{MM}, u_{ZZ} < 0$.

[19] The time frame is not important for the model setup *per se*, but I specify it to be annual average in consistence with the empirical analysis.

[20] Technically, index i can refer to any type of categorization, such as truck body types, operation classes, fleet sizes or shipping business sectors. In the numerical calculation, I extend it to distinguish operations in rural or urban areas.

The household is subject to two constraints - a time constraint and a budget constraint, shown in equations (1.9) and (1.10) respectively. In equation (1.9),

$$M = \pi A \ , \tag{1.9}$$

π is the inverse of the average on-road driving speed.

$$I + LST = \sum_i p_i R_i + Y + (t_G + P_G) f_G A \tag{1.10}$$

In equation (1.10), I denotes household income; LST denotes a lump-sum transfer from the government. p_i is the market price for good R_i, measured in dollars/ton-mile. The price of general consumption Y is normalized to one. The final gasoline price for consumers consists of the gasoline tax, t_G, and the pre-tax gasoline price, P_G. f_G is the inverse of fuel economy of the household's automobile.

(ii) Production

Shipping costs during production and distribution of good R_i are assumed to be borne by the final consumers through the equilibrium market price, p_i, which can be written as the following expression.

$$p_i = p_i^0 + p_i^R \ . \tag{1.11}$$

Per-unit production cost is denoted by p_i^0, while p_i^R is the per-ton-mile shipping cost paid to the trucking companies. The unit of production (and consumption) of R_i is normalized by the quantity transported by per-ton-mile of freight.

(iii) Freight

The fleet manager in a trucking company takes the demand for freight R_i as exogenous, and chooses fuel efficiency and travel routes to minimize the total operation costs. Note that the rebound effect is incorporated since I allow the travel distance to vary with the fuel efficiency. If the industry is perfectly competitive, the shipping price in equilibrium is equal to the operation cost on a per-ton-mile basis:

$$p_i^R = (t_i + P_D)q_i + \frac{1}{W_i}\big(\omega\pi + k_i\{a_i\}\big) \ , \tag{1.12}$$

in which t_i refers to the diesel fuel tax; P_D is the pre-tax diesel price. q_i denotes the shipping efficiency, measured in gallons/ton-mile. Truck drivers are paid by the distance traveled at the rate of ω, which can be translated to per-mile wage by multiplying the time spent driving one mile, π. $k_i\{a_i\}$ indicates the maintenance cost, which is a convex function of truck vintage, a_i. Solving the fleet manager's cost minimization problem yields the following equation:

$$(t_i + P_D - \frac{k_i'}{f_i^2})T_i = -[\omega\pi + k_i + (t_i + P_D)f_i]\frac{dT_i}{df_i} \ . \tag{1.13}$$

(iv) External costs

The traffic congestion can be reflected in the average time of per-mile travel, π. Following Parry (2008), I write π as a function of truck miles, T_i, and auto miles, A_i:

$$\pi = \pi(T_i, A) \ . \tag{1.14}$$

The negative externality on pavement, L, is proportional to the shipping intensity,

R_i, and can be written as follows:

$$L = \sum_i z_i^L R_i \tag{1.15}$$

where z_i^L is the per ton-mile damage to the pavement caused by truck operation. Other externalities, Z, induced by both truck and auto driving, include local and global air pollution, energy security, noise, and accidents:

$$Z = z^A A + \sum_i (z_i^F F_i + z_i^T T_i) \ , \tag{1.16}$$

in which z^A is the per-mile external cost induced by auto driving. This term provides a combined effect of local and global pollution, oil dependency, accidents and noise pollution. The total external cost of auto driving is proportional to the miles driven, A, since per-mile fuel use is assumed content. In contrast, a truck's fuel efficiency may vary with payload weight; therefore, I define them separately. z_i^T indicates the milage-related external costs per mile from noise and accidents. z_i^F denotes the fuel-related external costs per gallon, which include local and global air pollution, as well as oil dependency.

(v) Government

Suppose the government spends fuel tax revenue on road maintenance and a lump-sum transfer to households. The government's budget constraint can be expressed as follows:

$$LST + L = \sum_i t_i F_i + t_G f_G A \ . \tag{1.17}$$

1.6.2 Formulation of the Optimal Taxes

The optimally differentiated taxes that capture each group of trucks' marginal external damage can be calculated as follows. I derive the expression of marginal welfare effect by totally differentiating household's indirect utility function, $\tilde{u}$, with respect to diesel fuel tax, t_i:[21]

$$\frac{1}{\lambda}\frac{d\tilde{u}}{dt_i} = (MEC_i^F - t_i)(-\frac{dF_i}{dt_i}) + MEC_i^T\big(-\frac{dT_i}{dt_i}\big) - (MEC_i^A - t_G f_G)\frac{dA}{dt_i}\ , \quad (1.18)$$

in which

$$MEC_i^F = z_i^F(-\frac{u_Z}{\lambda})\ , \quad (1.19)$$

$$MEC_i^T = z_i^T(-\frac{u_Z}{\lambda}) + z_i^L W_i + (\omega T_i - \frac{A}{\lambda}u_\pi)\pi_{T_i}\ , \quad (1.20)$$

and

$$MEC_i^A = z^A(-\frac{u_Z}{\lambda}) + \Big[(\omega T_i - \frac{A}{\lambda}u_\pi)\pi_A\Big]\ . \quad (1.21)$$

As shown in equation (1.19), the marginal external cost related to fuel use by trucks, MEC_i^F, combines the monetized externalities of local and global air pollution, as well as oil dependency. The marginal external cost, MEC_i^T, *i.e.* the marginal damage of an additional mile driven, is derived by summing the three terms in equation (1.20). The first term is the monetized per-mile costs of noise pollution and accidents. The second term - the product of per-ton-mile pavement damage cost and payload weight - is the per-mile cost of road deterioration by truck operation. The last term computes the effect of per-mile truck driving on road congestion. π_{T_i} is the incremental time of per-mile travel for all road users as a result of truck i's

[21] Derivation detail can be found in A.6.1.

additional mile of operation. The total miles driven by both trucks and passenger vehicles are weighted by their value of time – ω for trucks and $-\frac{u_\pi}{\lambda}$ for autos. The marginal external cost of auto driving, detailed in equation (1.21), summarizes the monetized per-mile external cost of air pollution, oil dependency, noise, accidents and road congestions.

The (second-best) optimal diesel fuel tax for each type of truck can be derived by setting the marginal welfare effect to zero. After collecting and rearranging terms, the optimal diesel tax is expressed as follows:[22]

$$t_i^* = MEC_i^F + MEC_i^T\Big(\frac{1}{f_i}\Big)\Big(\frac{\varepsilon_i^T}{\varepsilon_i^F}\Big) - (MEC_i^A - t_G f_G)e_i\beta_i\Big(\frac{1}{f_i}\Big)\Big(\frac{\varepsilon_i^T}{\varepsilon_i^F}\Big)\ , \tag{1.22}$$

in which ε_i^T denotes the elasticity of VMT with respect to fuel price; ε_i^F refers to the elasticity of fuel use with respect to fuel price; congestion offset β_i and passenger vehicle equivalent e_i are expressed as

$$\beta_i = -\Big(\frac{\partial\pi}{\partial A}\frac{dA}{dt_i}\Big)/\Big(\frac{\partial\pi}{\partial T_i}\frac{dT_i}{dt_i}\Big) \tag{1.23}$$

and

$$e_i = \frac{\partial\pi/\partial T_i}{\partial\pi/\partial A}\quad . \tag{1.24}$$

1.6.3 Parameters

Table 1.8 provides the estimates of elasticities and mean values of fuel efficiency in each category of weight class and business sector. Column (1) shows the

[22]Detailed derivation can be found in A.6.2.

Table 1.8: Elasticities and Fuel Economy

Truck category	η_i^T (1)	ε_i^f (2)	ε_i^T (3)	ε_i^F (4)	MPG (5)
Combination trucks					
GVWR = 7	-0.37	-0.01	-0.36	-0.38	6.35
GVWR = 8	-0.21	0.03	-0.21	-0.18	5.53
Vocational vehicles					
GVWR = 3	-0.23	0.20	-0.28	-0.08	11.60
GVWR = 4	-0.29	0.09	-0.32	-0.23	10.58
GVWR = 5	-0.47	0.19	-0.56	-0.36	9.99
GVWR = 6	-0.30	0.01	-0.30	-0.29	7.83
GVWR = 7	-0.30	-0.01	-0.29	-0.31	7.73
GVWR = 8	-0.20	0.06	-0.22	-0.15	6.50
Combination trucks					
Agriculture or forestry	-0.23	0.02	-0.23	-0.21	5.36
Business and personal service	-0.49	-0.06	-0.46	-0.52	5.79
Construction	-0.26	-0.01	-0.26	-0.27	5.54
For-hire transportation	-0.27	0.06	-0.29	-0.23	5.53
Manufacturing	-0.48	-0.01	-0.48	-0.49	5.71
Mining or quarrying	-0.19	-0.10	-0.17	-0.27	5.10
Other	-0.24	-0.02	-0.24	-0.26	5.94
Rental or contractor	-0.29	0.06	-0.31	-0.25	6.04
Retail and wholesale trade	-0.32	0.04	-0.33	-0.29	5.86
Vocational vehicles					
Agriculture or forestry	-0.31	0.08	-0.34	-0.25	6.85
Business and personal service	-0.32	0.14	-0.36	-0.22	7.02
Construction	-0.26	0.06	-0.27	-0.21	6.49
For-hire transportation	-0.22	0.05	-0.24	-0.18	6.86
Manufacturing	-0.26	-0.01	-0.26	-0.26	6.93
Mining or quarrying	-0.10	-0.06	-0.09	-0.15	5.91
Rental or contractor	-0.35	0.01	-0.35	-0.34	8.52
Retail and wholesale trade	-0.25	0.01	-0.25	-0.23	8.41
Other	-0.27	0.11	-0.30	-0.19	7.95

Note: η_i^T: elasticity of VMT with respect to per-mile fuel cost; ε_i^f: elasticity of inverse of MPG with respect to fuel price; ε_i^T: elasticity of VMT with respect to fuel price; ε_i^F: elasticity of fuel use with respect to fuel price.

elasticities of VMT with respect to per-mile fuel cost. The estimated elasticities of f_i (inverse of MPG) with respect to diesel fuel price, listed in column (2), are derived by taking the opposite sign as elasticities of MPG. The full estimation results are shown in Table 1.10. The elasticity of VMT with respect to diesel fuel price, ε_i^T, can be derived as follows:

$$\varepsilon_i^T = \eta_i^T(\varepsilon_i^f + 1) \ , \tag{1.25}$$

in which η_i^T is the elasticity of VMT with respect to per-mile fuel cost (in column 1), and ε_i^f is the elasticity of MPG with respect to diesel fuel price (in column 2). The resulting ε_i^T's are shown in column (3) of Table 1.8.

The elasticity of fuel use with respect to fuel price, ε_i^F can be derived as follows:

$$\varepsilon_i^F = \varepsilon_i^T + \varepsilon_i^f \tag{1.26}$$

The results are shown in column (4) of Table 1.10. The detailed derivations of equation (1.25) and equation (1.26) are documented in A.6.3.

I adopt Parry (2008)'s assmption that passenger-car equivalent, e_i, is 2.2 for combination trucks, and 1.9 for vocational vehicles. The congestion offset, β_i, is 0.6 for urban areas and 0 for rural areas. As there is no information in VIUS to distinguish between operations in rural and urban areas, two assumptions are made based on Parry (2008) and FHWA (2000). First, elasticity of VMT in urban areas is assumed to be 70% of the estimate in rural areas for the same type of vehicles. Second, the ratio of VMT in rural areas versus those in urban areas is 60%:40% for

Table 1.9: Marginal External Costs

		Fuel related MEC (cents/gallon)				Mileage related MEC (cents/mile)				
		Local air pollution	Global air pollution	Oil dependency	Sum	Road	Congestion	Accidents	Noise	Sum
Combination trucks										
GVWR 7	Rural	26.9	14.0	16.0	56.9	3.3	1.9	0.9	0.2	6.2
	Urban	24.1	14.0	16.0	54.1	10.5	18.4	1.2	2.8	32.8
GVWR 8	Rural	23.4	14.0	16.0	53.4	12.7	2.2	0.9	0.2	16.0
	Urban	21.0	14.0	16.0	51.0	40.9	20.1	1.2	3.0	65.2
Vocational vehicles										
GVWR 3	Rural	15.6	14.0	16.0	45.6	0.0	0.8	1.0	0.0	1.8
	Urban	14.0	14.0	16.0	44.0	0.1	7.7	1.2	0.1	9.1
GVWR 4	Rural	31.0	14.0	16.0	61.0	0.5	1.6	0.7	0.1	2.9
	Urban	27.9	14.0	16.0	57.9	1.6	16.1	1.0	0.8	19.5
GVWR 5	Rural	29.3	14.0	16.0	59.3	0.5	1.6	0.7	0.1	2.9
	Urban	26.3	14.0	16.0	56.3	1.6	16.1	1.0	0.8	19.5
GVWR 6	Rural	23.0	14.0	16.0	53.0	0.5	1.6	0.7	0.1	2.9
	Urban	20.6	14.0	16.0	50.6	1.6	16.1	1.0	0.8	19.5
GVWR 7	Rural	35.0	14.0	16.0	65.0	1.0	2.5	0.5	0.1	4.0
	Urban	31.4	14.0	16.0	61.4	3.1	24.5	0.9	1.5	29.9
GVWR 8	Rural	29.4	14.0	16.0	59.4	5.6	3.3	0.5	0.1	9.5
	Urban	26.3	14.0	16.0	56.3	18.1	32.6	0.9	1.7	53.3
Auto	Rural	22.2	12.0	16.0	50.2	0.0	0.8	1.0	0.0	1.8
	Urban	20.0	12.0	16.0	48.0	0.1	7.7	1.2	0.1	9.1

Note: Parameters of global air pollution and oil dependency are from Parry (2008). Other parameters are from FHWA (2000). Parameters of local air pollution are documented in terms of cents/mile in FHWA (2000). I multiply them with the corresponding fuel economy to convert to cents/gallon.

combination trucks, and 35%:65% for vocational vehicles.

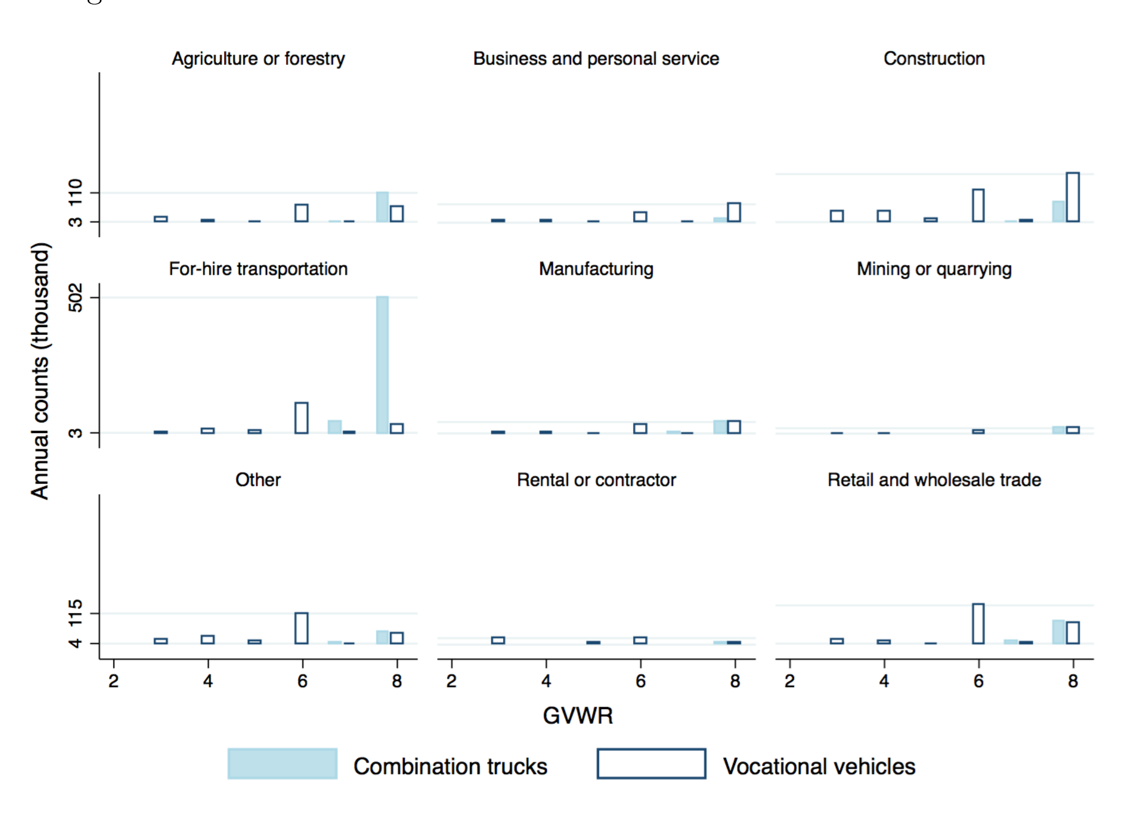
Table 1.9 provides the value of marginal external costs for different weight classes and operation areas, most of which are drawn from the 1997 Federal Highway Cost Allocation Study Final Report and its addendum. Summarizing the MEC of local air pollution, global air pollution and oil dependency gives the fuel-related external cost per gallon. Similarly, the mileage related MEC is computed by adding up the per-mile external effect on road deterioration, congestion, accidents and noise pollution.

In Table 1.9, the MECs in each business sector are derived by taking the weighted average of corresponding MEC, based on the distribution of GVWRs. The weights are derived by taking the ratio of the number of trucks in each weight class and the total. Figure 1.3 shows the distribution of GVWRs in each business sector.

1.6.4 Optimal Taxes

Substituting the parameters above into the optimal tax expression - equation (1.22), I obtain the value of optimal taxes and their corresponding 95% confidence intervals. Tables 1.11 and 1.12 present the results by weight class and business sector, respectively. In general, the optimal tax is higher for the same type of trucks operating in urban areas than those in rural areas as the marginal external cost is often greater in more populated areas. Vehicles with a weight class 6 operating in

Figure 1.3: Truck Count Distribution of GVWRs in Each Business Sector



Note: Truck count data are derived from VIUS (2002).

rural areas have the lowest optimal tax – about 77 cents per gallon. The optimally differentiated tax peaks at 4.76 dollars per gallon for weight class 8 vocational vehicles in urban areas. Compared to differentiated taxes by weight class, optimal taxes by business sector show less variation, especially among vocational vehicles. As presented in Table 1.12, most of the optimal taxes for vocational vehicles operating in rural areas are around one dollar per gallon, and around 2.5 dollars per gallon in urban areas.

To put the calculated optimal taxes in perspective, in 2002, the federal diesel tax was 24.5 cents/gallon (in 2002 US dollars), and the state diesel taxes ranged from 7.5 cents per gallon in Georgia to 31.8 cents per gallon in Pennsylvania. So, even the differentiated optimal taxes on the lower end of the spectrum exceed the actual fuel tax rates in 2002. If I ignore the heterogeneity of trucks' responsiveness to changes in fuel costs and apply the same optimal tax formula, equation (1.22), to average elasticities, shown in Table 1.2, I derive the optimal uniform fuel tax at 2.47 dollars per gallon for combination trucks and 2.07 dollars/gallon for vocational vehicles. These values serve as the baseline in the welfare analysis in section 1.6.5.

Since most of the elasticities of MPG with respect to fuel price are very close to zero and/or cannot be precisely estimated, as shown in Table 1.10, I calculate the 95% confidence interval of the optimal taxes using the Delta method, and present the resulting ranges of optimal taxes in columns (2) and (3) in Tables 1.11 and 1.12.

1.6.5 Welfare Effects

The deadweight loss (or excess burden) from a tax change can be derived by taking the integral of each term in the marginal welfare effect expressed in equation (1.18). It has proven to be more accurate, in some cases, than the "Harberger triangle" approximation (Goulder and Williams, 2003). An additional income effect is incorporated to reduce the deadweight loss in the following mechanism. The income effect increases the labor supply, which leads to a reduction in labor market distortion caused by the substitution effect. Following the approach developed in

Table 1.10: Elasticities of MPG With Respect to Diesel Price

	Combination trucks		Vocational vehicles	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Elasticities by weight class				
GVWR = 3			-0.0749	-0.195***
			(0.0567)	(0.0748)
GVWR = 4			-0.0729	-0.0864
			(0.0604)	(0.112)
GVWR = 5			0.00479	-0.192
			(0.103)	(0.137)
GVWR = 6			0.00116	-0.0146
			(0.0193)	(0.0261)
GVWR = 7	0.0592***	0.0109	0.0713***	0.0114
	(0.0142)	(0.0257)	(0.0210)	(0.0290)
GVWR = 8	0.0111	-0.0305***	-0.000842	-0.0618***
	(0.00819)	(0.00761)	(0.0104)	(0.0164)
Elasticities by business sector				
Agriculture or forestry	-0.0102	0.0161	0.0151	0.0832**
	(0.0182)	(0.0225)	(0.0194)	(0.0339)
Business and personal service	-0.0297	-0.0629	-0.0334	0.143**
	(0.0524)	(0.0564)	(0.0513)	(0.0552)
Construction	-0.0401*	-0.00922	-0.0302	0.0618***
	(0.0204)	(0.0279)	(0.0192)	(0.0235)
For-hire transportation	-0.0496***	0.0575***	-0.034	0.0549*
	(0.0113)	(0.00828)	(0.0283)	(0.0281)
Manufacturing	-0.0595***	-0.0123	-0.0898	-0.00524
	(0.0214)	(0.0254)	(0.0564)	(0.0423)
Mining or quarrying	0.0376	-0.102*	-0.0145	-0.0599
	(0.0354)	(0.058)	(0.0423)	(0.0383)
Rental or contractor	-0.0953***	0.0626	-0.0717	0.0132
	(0.0296)	(0.0574)	(0.0534)	(0.0556)
Retail and wholesale trade	-0.0272**	0.0379*	-0.0451*	0.015
	(0.011)	(0.0156)	(0.0179)	(0.0245)
Other	-0.115	-0.0214	0.0521	0.113**
	(0.0827)	(0.063)	(0.0491)	(0.0568)

Note: $^{*}: p < 0.1$; $^{**}: p < 0.05$; $^{***}: p < 0.01$
Other controls include truck characteristics, business characteristics, state GDP, home state FE. Robust standard errors are clustered at the level of home base states. Instrumental variable is the inflation-adjusted crude oil price.

Table 1.11: Optimal Taxes Differentiated by Weight Class

		Optimal tax (dollar/gallon)	95% confidence interval	
		(1)	(2)	(3)
Combination trucks				
GVWR 7	Rural	0.95	[0.89	1.03]
	Urban	2.04	[1.79	2.36]
GVWR 8	Rural	1.57	[1.48	1.68]
	Urban	4.19	[3.86	4.57]
Vocational vehicles				
GVWR 3	Rural	1.17	[-0.55	0.68]
	Urban	1.14	[-0.55	0.66]
GVWR 4	Rural	1.03	[0.78	10.90]
	Urban	2.35	[1.30	43.75]
GVWR 5	Rural	1.04	[0.79	2.66]
	Urban	2.42	[1.39	9.24]
GVWR 6	Rural	0.77	[0.72	0.83]
	Urban	1.50	[1.31	1.78]
GVWR 7	Rural	0.95	[0.89	1.04]
	Urban	2.29	[1.95	2.79]
GVWR 8	Rural	1.46	[1.29	1.72]
	Urban	4.76	[3.94	6.03]

Goulder and Williams (2003), the deadweight loss due to changes in diesel fuel tax can be expressed as follows.

$$\frac{1}{\lambda}\Delta\tilde{U} = \frac{-(MEC_i^F t_i - \frac{t_i^2}{2})\varepsilon_i^F \frac{F_i}{\tilde{P}_D} - MEC_i^T \varepsilon_i^T \frac{T_i}{\tilde{P}_D} t_i + (MEC_i^A - t_G f_G)\beta_i e_i \varepsilon_i^T \frac{T_i}{\tilde{P}_D} t_i}{1 - \tau_L \epsilon_{LY}}, \tag{1.27}$$

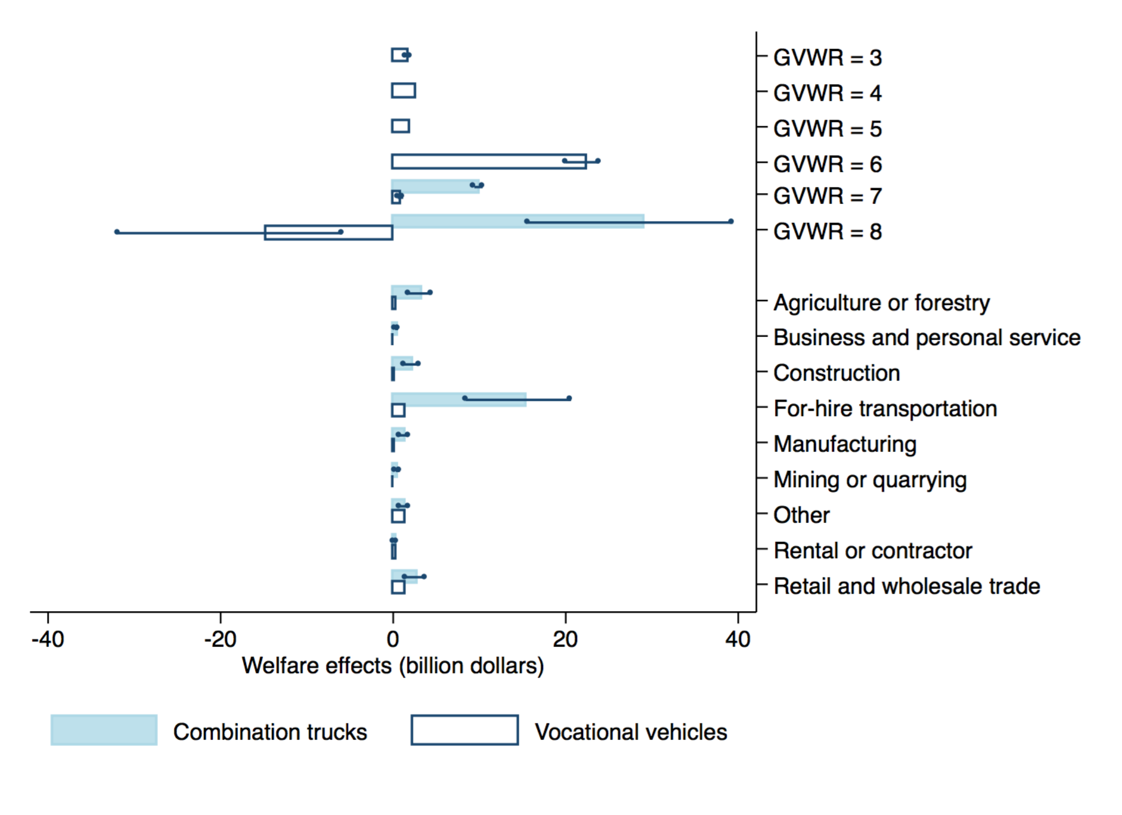
in which $\tilde{P}_D$ is the after tax price for diesel fuel, τ_L is the labor tax, and ϵ_{LY} is the compensated income elasticity of labor supply.

Average fuel use and VMT for each category are drawn from the VIUS 2002 survey. I assume a labor tax of 40 percent and compensated labor supply elasticity of 0.25. The elasticity of labor supply is set to be lower than the midrange estimates in the literature, leading to a more conservative estimate of the welfare effect.

Table 1.12: Optimal Taxes Differentiated by Business Sector

	Location	Optimal tax (dollar/gallon)	95% confidence interval	
		(1)	(2)	(3)
Combination trucks:				
Agriculture or forestry	Rural	1.44	[1.25	1.72]
	Urban	3.72	[3.05	4.73]
Business and personal service	Rural	1.34	[1.12	1.67]
	Urban	3.36	[2.59	4.55]
Construction	Rural	1.37	[1.19	1.65]
	Urban	3.49	[2.85	4.46]
For-hire transportation	Rural	1.59	[1.51	1.69]
	Urban	4.26	[3.96	4.61]
Manufacturing	Rural	1.37	[1.25	1.51]
	Urban	3.47	[3.06	3.98]
Mining or quarrying	Rural	1.04	[0.85	1.51]
	Urban	2.31	[1.62	3.98]
Rental or contractor	Rural	1.69	[1.25	2.87]
	Urban	4.63	[3.05	8.81]
Retail and wholesale trade	Rural	1.51	[1.40	1.66]
	Urban	3.99	[3.57	4.52]
Other	Rural	1.35	[1.02	2.27]
	Urban	3.39	[2.22	6.69]
Vocational vehicles:				
Agriculture or forestry	Rural	1.03	[0.91	1.24]
	Urban	2.70	[2.14	3.66]
Business and personal service	Rural	1.30	[1.01	2.14]
	Urban	3.95	[2.61	7.86]
Construction	Rural	1.04	[0.94	1.21]
	Urban	2.75	[2.28	3.49]
For-hire transportation	Rural	0.92	[0.82	1.11]
	Urban	2.16	[1.71	3.00]
Manufacturing	Rural	0.97	[0.84	1.21]
	Urban	2.42	[1.85	3.53]
Mining or quarrying	Rural	0.81	[0.72	1.09]
	Urban	1.69	[1.25	2.98]
Rental or contractor	Rural	0.80	[0.71	0.99]
	Urban	1.57	[1.22	2.24]
Retail and wholesale trade	Rural	0.98	[0.89	1.12]
	Urban	2.48	[2.07	3.10]
Other	Rural	1.07	[0.84	1.93]
	Urban	2.78	[1.81	6.54]

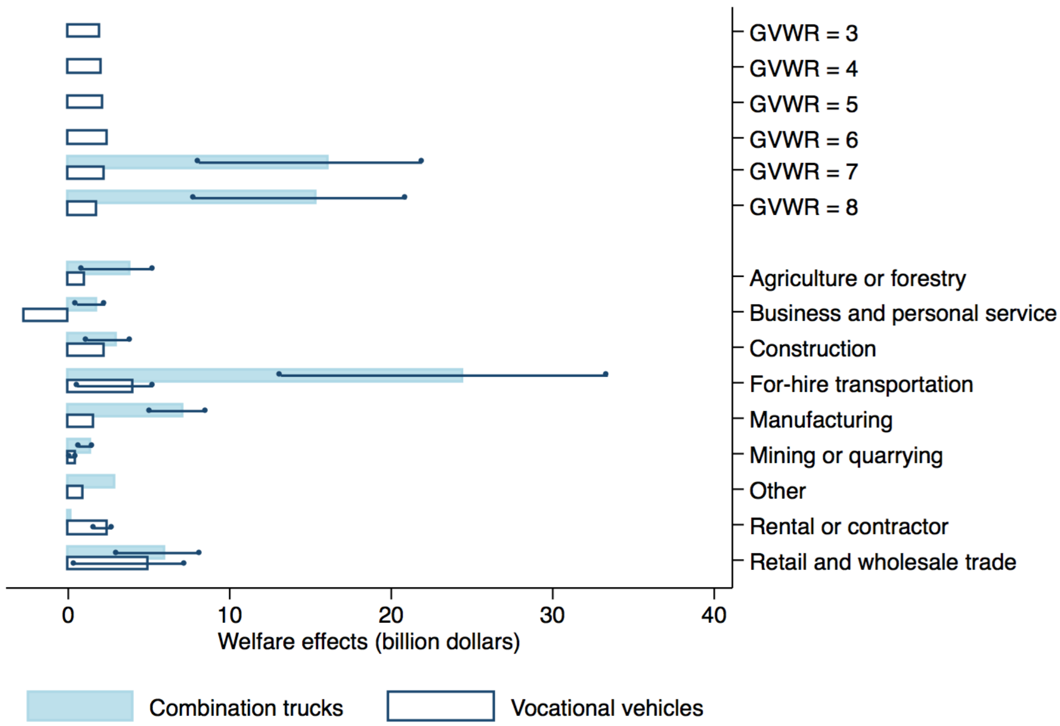
Figure 1.4: Welfare Effects of Imposing Differentiated Fuel Taxes by Vehicle Weight Class (GVWR)



Note: The figure shows the distributional welfare effect of imposing optimally differentiated fuel tax by vehicle weight class on a per-vehicle basis. The baseline scenario is imposing optimal uniform tax and only distinguishing combination trucks and vocational vehicles. The welfare effect is measured in billion dollars in 2002 USD. The lines crossing through some of the bars show the estimation range at 95% significance level. The bars without the lines are lack of statistical significance, and therefore, are not precisely estimated.

The per-vehicle welfare effect for imposing the differentiated fuel taxes is calculated according to equation (1.27), relative to the baseline scenario where uniform optimal taxes are imposed. The total welfare change in each vehicle category is de-

Figure 1.5: Welfare Effects of Imposing Differentiated Fuel Taxes by Business Sector



Note: The figure shows the distributional welfare effect of imposing optimally differentiated fuel taxes by business sector on a per-vehicle basis. The baseline scenario imposes an optimal uniform tax and only distinguishes combination trucks and vocational vehicles. The welfare effect is measured in billion dollars in 2002 USD. Bars without lines lack statistical significance, and therefore are not precisely estimated.

rived from multiplying the per-vehicle welfare effect by the total number of vehicles in that category.[23]

[23]The number of vehicles in each category can be observed in the VIUS surveys. The numbers used in the total welfare calculation are from VIUS 2002.

Figure 1.4 shows the welfare effects of differentiating fuel taxes by vehicle weight class. The solid bars refer to welfare changes in combination trucks, while the white bars refer to those in vocational vehicles. Four important observations can be made from this figure. First, there is a gain in welfare from imposing differentiated taxes on most truck classes compared to taxing all classes at a uniform rate. Second, most welfare gains are from differentially taxing class 8 combination trucks, mainly because differentiated taxes compensate for the large external cost occurred during the operation of this type of vehicle. Third, the variation across vehicle weight classes is greater than across business sectors. In fact, Differentially taxing on most business sectors induces relatively mild welfare changes. This can be explained by the similar distribution of GVWR classes in each business sector, as shown in Figure 1.3 with class 8 combination trucks dominant in every grid. Last, but not least, by adding the dollars saved, it is clearly evident that the total welfare effect of imposing such differentiated taxes is positive. Relative to imposing an optimal uniform tax, differentiated taxes by vehicle weight class create a total welfare gain of 17.5 billion dollars annually.

If optimal fuel taxes are differentiated by business sector, the total welfare gain can be as high as 31.5 billion dollars per year. The distributional effects among GVWRs and business sectors under such a tax regime are shown in Figure 1.5. The majority of the welfare gain is from for-hire transportation, retail and wholesale trade, and manufacturing. The effects are distributed almost evenly across weight classes within each truck type category. Combination trucks in weight class 7 and 8, under optimally differentiated taxation by business sector, experience similar welfare gains at about 15 to 16 billion dollars. The lack of variation in welfare gain among vocational vehicles in each weight class remains true as well, which can be explained by the fact that the distribution of GVWRs is similar across business sectors, as shown in Figure 1.3.

The overall welfare effects of imposing optimal differentiated fuel taxes by weight class is 17.5 billion per annum, and 32.5 billion per annum by business sectors. If I adopt a higher elasticity of labor supply at 0.4, the welfare gains are 18 billion for a weight class based fuel tax and 31 billion for a business sector based fuel tax. If the administration cost of imposing differentiated fuel taxes based on business sectors is high enough, optimal fuel taxes by weight class would be more practical and cost effective.[24] In fact, the welfare gain from such a policy is about 13 times more than the welfare effect estimated by Parry (2008). He suggests that raising diesel fuel tax rate from its current level, 0.45 dollar/gallon, to the uniform optimal level increases welfare by 1.34 billion per annum.

[24]In practice, if the fuel taxes are differentiated based on GVWRs, they can be directly linked with the Vehicles Identification Number (VIN). In this case, although the fuel price at the station appear to be homogeneous, truckers can input their VINs and get the discount instantly at the pump or through mail-in rebates. If the fuel taxes are differentiated based on business sectors, fleets size, or other operational factors, they are likely linked with commercial vehicle's DOT (Department of Transportation) number. The differentiation can be obtained through similar mechanism.

1.6.6 Discussion

Admittedly, realization of the welfare effects in section 1.6.5 rests on the assumption that the following two components remain unchanged once the new fuel tax regime is adopted: characteristics of trucking fleet and parameters of marginal damages. If truckers decide to change the payload category and/or downgrade their vehicles to ones with lighter GVWR in order to avoid high fuel taxes on corresponding categories, the fleet composition and characteristics will be changed, resulting in different total welfare effects. However, per-vehicle welfare gain/loss, as shown in Figures 1.4 and 1.5, is not contingent on this assumption.

The second component is the parameters of marginal damages, which are calculated based on many external factors, such as existing air pollution, demographics, highway infrastructure, growth of economy, and changes in the trucking industry. If higher fuel taxes induce faster technological progress in this industry, it is likely that the marginal damage decreases across the board. For example, more fuel efficient engine design may lead to a reduction in the per-gallon fuel-related externalities (such as local air pollution and oil dependency) for all truck types. It is important to revisit the optimally differentiated fuel taxes and welfare effects if relevant changes are observed.

Lastly, I assume a perfect compliance rate or a perfect monitoring mechanism, which is common in literature when predicting the welfare effects for a hypothetical policy change (for example, Ivaldi and Verboven (2005); Ryan (2012); Wollmann (2014)). Satisfying this assumption is particularly challenging if we differentiate the fuel taxes by business sectors, as trucking fleet can take on payloads in multiple categories. The current categorization encoded in US DOT number may not be sufficient or thorough. It is also necessary to design a monitoring mechanism to prevent intended mislabeling.

1.7 Conclusion

Using truck level micro data, I estimate how fuel cost per mile affects trucking decisions heterogeneously among different weight classes and business sectors. The elasticities of VMT with respect to per-mile fuel cost are about -0.23 for class 7 and 8 combination trucks and -0.27 for class 3 - 8 vocational vehicles. Lighter vehicles tend to be more responsive to changes in per-mile fuel cost. Combination trucks in business and personal transportation, as well as manufacturing, are driven further per annum compared to similar trucks in other business sectors facing the same fuel cost reduction. The VMT choices for vocational vehicles for rental and contractor work are the most elastic among all industries.

I apply the estimated elasticities into a generalized equilibrium model to calculate the optimally differentiated taxes for each vehicle weight class and business sector. Considerations of externalities resulting from truck operations are built into the model, such as local and global air pollution, oil dependency, road damage, congestion, accidents and noise pollution. The optimally differentiated diesel taxes are calculated based on the heterogeneity in their responsiveness to fuel costs, different level of externalities incurred, as well as the operation locations. On one hand, when differentiating taxes by weight class, class 8 vocational vehicles are charged for the highest fuel tax at 4.76 dollars/gallon. On the other hand, less taxes are imposed on lighter trucks in rural areas. It is also possible to differentiate taxes by business sector. In total, there are nine business sectors considered, such as agriculture, construction, for-hire transportation, mining and rental. In general, combination trucks pay higher taxes than vocational vehicles in the same industry and area. Combination trucks in for-hire business and rental/contractor in urban areas face an optimal diesel tax of over 4 dollars/gallon.

Optimally differentiating diesel taxes by vehicle weight class brings in about 17.5 billion dollars per annum, while the welfare gain from differentiating taxes by business sector is about 32.5 billion dollars per annum. These numbers are not sensitive to labor market parameters. Had I adopted a higher elasticity of labor supply, such as 0.4, the total welfare gain would have been 18 billion and 31 billion dollars per annum.[25] Although differentiating by business sector incurs a higher welfare gain, the cost and difficulty of implementation cannot be overlooked. It is sometimes difficult to define business sector clearly, especially when some vehicles are

[25]The total welfare gains calculated with other labor parameters can be found on the author's website: *www.JenEcon.com.*

involved in multiple types of work. Vehicle weight class, however, is clearly labeled on the truck's registration record and can be identified from the vehicle identification number. Setting a tax based on such labels will be less difficult to put in practice.

Chapter 2: Technological Progress in the Commercial Trucking Sector: Empirical Evidence and Implications for Fuel Economy Standards

2.1 Introduction

Heavy-duty trucks are an increasingly important source of greenhouse gas emissions in the transportation sector. In 2011, U.S. Environmental Protection Agency (EPA) and National Highway Traffic Safety Administration (NHTSA) announced the final rule of Phase 1 fuel economy standards for medium and heavy-duty vehicles with model years from 2014 to 2018. The second phase of the regulations calls for a reduction in fuel consumption (gallons/1,000 payload ton-mile) by 24% for combination tractors and 16% for vocational vehicles from 2018 to 2027. This is equivalent to about 3.09% per year improvement in fuel economy for combination trucks, and 1.96% for vocational vehicles. How challenging will such fuel economy improvements be? There is little information about fuel economy from trucks; it is not reported at the time of truck sale or during operation. The Vehicle Inventory and Use Survey (VIUS) is a random sample of the truck fleet in the United States. It provides valuable evidence about the fuel economy of different types of trucks and how fuel economy has changed over time. Our study looks at the evidence about fuel economy, other measures of truck performance and how they changed over the period of the survey. We then use these estimates to draw out the implications for how truck attributes are likely to change in the absence of the regulations during the 2018 to 2030 time period. This approach provides a plausible dynamic baseline that can be used to inform forecasts of the impacts of the Phase 2 regulations on fuel economy and other truck attributes.

In this paper, we take advantage of the detailed vehicle-level dataset (VIUS) to estimate the in-use[1] technological progress in trucking fleet fuel economy. Such progress serves as a dynamic baseline for further evaluating the feasibility of the new fuel economy standards for medium- and heavy-duty trucks. We find that the annual rate of technological progress from 1973 to 2002 is about 0.93% for combination trucks and 0.83% for vocational vehicles. That is to say, absent of regulations, we can expect a business-as-usual improvement in fuel economy by 8.71% for combination trucks and 7.70% for vocational vehicles for every 10 years.

The second objective of the paper is to address this fuel economy challenge by estimating the trade-off effects between fuel economy and other truck attributes. We focus on two vehicle attributes – vehicle weight and engine displacement. We ask: besides technological breakthroughs and adoptions, can we achieve higher fuel economy by changing vehicle attributes? Leard et al. (2015) find the rebound effects

[1]The data sample in VIUS are vehicles registered and operated during the year of survey.

of fuel efficiency to be 30% for combination trucks and 10% for vocational vehicles. Is it possible to offset the rebound effect[2] by changing the other vehicle attributes? Most existing studies that examine the relationship between fuel economy and vehicle attributes focus on light-duty vehicles. Knittel (2011) estimates the trade-offs between fuel economy and vehicle weight for passenger vehicles and finds that fuel economy increases by 4% for every 10% reduction in weight. He also suggests a 2.7% increase in fuel economy for every 10% reduction in horsepower.

Although it is impossible to know with our currently available dataset what vehicle attributes consumers would have chosen had fuel economy been different, we find the revealed trade-offs between fuel economy and other vehicle attributes to be less salient than the trade-off effects in light vehicles. In particular, reducing total vehicle weight by 10% will only result in an improvement in fuel economy by 1.3% for combination trucks and 2.5% for vocational vehicles, all else equal. Sacrificing engine power by 10% can only increase fuel economy by 0.16% for combination trucks and 0.58% for vocational vehicles. The rather marginal trade-off effects between fuel economy and other vehicle attributes imply a great opportunity cost had we improved fuel economy by reducing engine power or total vehicle weight.

The trade-offs between fuel economy and other vehicle attributes may vary depending on the regulations. For example, when vehicle manufacturers face the

[2]The conventional definition of rebound effect is the additional driving and fuel consumption caused by improved fuel efficiency (Small and Van Dender, 2007).

constraints such as engine emission standards, the trade-off between fuel economy and engine displacement tends to change because the constraint affects them disproportionally. If the regulation is on fuel economy itself, for example, the Corporate Average Fuel Economy (CAFE) standards, the realized combination of fuel economy and vehicle attributes is a result of both consumer preference and technical requirement. Previous studies have investigated the effects of policies on the choice of vehicles without considering the trade-off between fuel economy and vehicle attributes. For instance, Goldberg (1998) estimates the equilibrium effect of the CAFE standards for passenger vehicles on vehicle choices for a given set of vehicle attributes. Some recent studies explore the consumer preference in determining the final combination of vehicle attributes. West et al. (2017) suggest that consumers who favor high fuel efficiency are also likely to choose smaller and lower-performance vehicles. The trade-off effect can be different for a different set of vehicle attributes. Therefore, it is crucial to control for vehicle attributes, such as aerodynamic design and truck body type, when estimating the dynamics between fuel economy and other vehicle characteristics.

The rest of the paper is organized as follows. In section 2.2, we discuss the theoretical foundation and introduce the dataset. We also provide a brief introduction of the sources of improvements in truck fuel economy from an engineering point of view. In section 3, we present the empirical strategy and results. In section 4, we explore further explanations for our empirical results by dividing the sample by fleet size. We address the caveats and limitations in section 5 and conclude in section 6.

2.2 Modeling and Measuring Technical Change and Trade-offs in Performance

2.2.1 Theory

We expect heavy-duty truck engine and design to improve over time with continuing technology improvements. It is important to have an idea of the amount of technical progress for these vehicles to both measure improvements in transportation and to evaluate the costs and effectiveness of regulations on fuel economy. We define output, Q_{it}, for truck type i in year t in ton-miles as a function of fuel economy, MPG_{it}, truck weight, $Weight_{it}$, engine displacement, CID_{it}, other attributes related to fuel economy, $\mathbf{MY_{it}}$, and other attributes, $\mathbf{X_{it}}$.

$$Q_{it} = f(MPG_{it}, Weight_{it}, CID_{it}, \mathbf{MY_{it}}, \mathbf{X_{it}}, t) \ . \tag{2.1}$$

We can derive the cost function from the output function, equation (2.1), and write it in an additively separable form(Knittel, 2011):

$$c_{it} = C^1(MPG_{it}, Weight_{it}, CID_{it}, \mathbf{MY_{it}}, t) + C^2(\mathbf{X_{it}}, t) \ . \tag{2.2}$$

The function C^1 captures the components related fuel economy, while function C^2 includes factors that are unrelated to fuel economy, such as interior design. Fuel economy improvement can be modeled as a combined output of changes in vehicle weight, engine displacement, and technological progress. Such function can be derived from equation (2.2) and expressed in terms of the level sets of C^1:

$$MPG_{it} = f(Weight_{it}, CID_{it}, \mathbf{MY_{it}}, t|C^1 = \delta) \ . \tag{2.3}$$

The trade-off between MPG and $Weight_{it}$ (or CID_{it}) can be derived by taking the first order derivatives of equation (2.3).

2.2.2 Data and Evidence

2.2.2.1 Sources of Fuel Economy Improvement

Improvement in load specific fuel consumption (LSFC) can come from improved efficiency in the four-stroke cycle[3] of diesel engine operation. Various technologies that improve heavy-duty trucks' power and fuel economy have been developed and advanced during the period from the 1970s to the early 2000s. For example, common rail direct fuel injection[4] was first introduced on trucks in 1960s,

[3] The operation of a diesel engine can be described by the four-stroke cycle, during which pistons travel between the top dead center and bottom dead center in an engine cylinder. The fuel energy is converted into heat energy, then kinetic energy, along with energy loss in exhausts. In sequence, the four strokes are 1) intake stroke: turbo-boosted air is charged to the engine cylinder; 2) compression stroke: piston is driven upward, compressing and heating the air charged; 3) expansion or power stroke: atomized fuel is injected into the cylinder, igniting once in contact with the heated air; the resulting gas expansion drives the piston downward; 4) exhaust stroke: piston is driven upward, displacing the end gas through the exhaust valves (Bennett, 2012).

[4] Common rail direct fuel injection is a direct fuel injection system for diesel engines. It features a high-pressure fuel rail feeding individual solenoid valves, which provides better fuel atomization.

and it has been further developed by ETH Zurich from 1976 to 1992. In the late 1990s, Bayerische Motoren Werke AG (BMW) combined high performance and better fuel efficiency with a two-liter, four-cylinder diesel engine; Volkswagen introduced three and four-cylinder turbo diesel engines,[5] which improves efficiency by up to 5 percent. Starting in the early 2000s, injector technologies were further enhanced by manufacturers – Bosch, Siemens and Delphi. Modern injection systems[6] reach very high injection pressures, and utilize sophisticated electronic control methods.

Other technological improvements that have been invented and adopted in the past four decades include electrically powered accessories, thermal insulation, aerodynamic design, radial tires, and more. These technological advances, along with the breakthrough of engine designs, are captured in our model as a combined improvement on a yearly basis. As stated above, the improvement in fuel economy due to technological progress in diesel engines has been persistent since the 1970s. Although our data only allow us to estimate the model year fixed effects till 2002, we believe the estimates of the growth rates serve as a good forecast of the dynamic baseline for later years and provide useful information to evaluate the difficulty of

[5] In a turbocharger, the radial exhaust-driven turbine drives the radial compressor to increase the air density going into the engine; therefore, it improves the efficiency of the compressor or turbine. Various sources estimate 0.3 to 5 percent improvement in LSFC from increased supercharging efficiency (EPA, 2015).

[6] The purpose of the fuel injection system is to deliver the correct amount of fuel into the engine cylinders, as discussed previously as the third "stroke". During the process, we need to control the injection timing, fuel atomization, and other parameters.

meeting the regulatory standards.

2.2.2.2 VIUS Data

The Vehicle Inventory and Use Survey (VIUS) was conducted by the Census Bureau from 1963 to 2002. Truck-level microdata was collected every five years from 1977 to 2002.[7] Random samples were generated from registration record on July 1 of each survey year. Surveys were sent out by mail during the second season of the following year. The surveys asked detailed information about trucks' physical and operational characteristics, including average annual vehicle-miles-traveled (VMT), average fuel economy (MPG), typical payload categories and weight, operational class, and more.

Tables 2.1 and 2.2 provide the summary statistics of trucks' physical characteristics for combination trucks and vocational vehicles separately. It is clear that combination trucks, on average, have lower fuel efficiency, higher vehicle weight, and longer lifetime travel distance, compared to vocational vehicles. Most trucks (79% of combination trucks; 74% of vocational vehicles) have the conventional cabin type with the driver sitting behind the engine. All else equal, this cabin type appears to be more aerodynamic (therefore more fuel efficient) than the cab-over-engine type, which features a "flat nose" and the driver's cabin is located on top of the engine.

[7] Data in the survey year 1977 are eliminated from our sample due to its inconsistency with the following survey years.

Table 2.1: Summary statistics - class 7, 8 combination trucks

	Mean (1)	St.d. (2)	Min (3)	Max (4)
MPG	5.75	1.29	0.1	40
Average vehicle weight (including cargo)†	58274.52	14492.28	6000	206360
Engine displacement (cubic inch)	785.36	197.14	200	1050
Engine model year	1989.29	5.71	1980	2002
Air-conditioning (% installed)	71	46	0	100
Odometer reading (100,000 miles)	3.86	2.85	0	91
2 axles; each axle has 2 tires (%)	3	16	0	100
2 axles; front 2 tires; rear 4 tires (%)	13	34	0	100
3 axles (%)	81	39	0	100
4 axles or more (%)	3	18	0	100
Cab forward of engine (%)	1	8	0	100
Cab over engine (%)	20	40	0	100
Conventional cab (%)	79	40	0	100
Other types of cab (%)	0	5	0	100
No. of observations	69,433			

Notes: †: Average vehicle weight is derived from averaging empty vehicle weight and full-loaded vehicle weight based on percent of each type of trip.

Table 2.2: Summary statistics - class 3-8 vocational vehicles

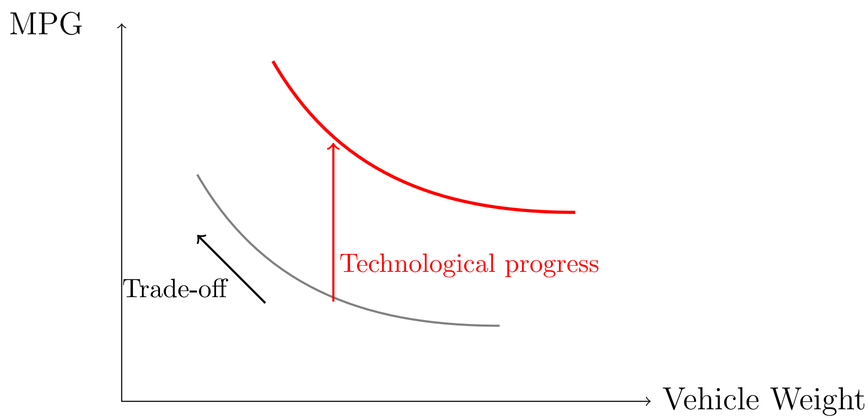
	Mean (1)	St.d. (2)	Min (3)	Max (4)
MPG	7.78	3.43	0.1	40
Average vehicle weight (including cargo)†	30563.37	16162.48	5000	130000
Engine displacement (cubic inch)	533.71	214.07	200	1050
Engine model year	1989.92	5.88	1980	2002
Air-conditioning (% installed)	42	49	0	100
Odometer reading (100,000 miles)	1.65	1.82	0	29
2 axles; each axle has 2 tires (%)	11	31	0	100
2 axles; front 2 tires; rear 4 tires (%)	47	50	0	100
3 axles (%)	31	46	0	100
4 axles or more (%)	11	31	0	100
Cab forward of engine (%)	3	16	0	100
Cab over engine (%)	23	42	0	100
Conventional cab (%)	74	44	0	100
Other types of cab (%)	1	9	0	100
No. of observation	52,675			

Notes: †: Average vehicle weight is derived from averaging empty vehicle weight and full-loaded vehicle weight based on percent of each type of trip.

2.2.2.3 Graphical Evidence for Trade-offs From VIUS Data

In theory, fuel economy is negatively correlated with vehicle weight and engine power (Knittel, 2011).[8] In Figures 2.2 through 2.5 , we illustrate the graphical evidence of trade-off relationships and adopted technological progress from 1982 to 2002. Existing literature has shown that heavier vehicles tend to have lower fuel efficiency (e.g. Boyd and Mellman (1980); Knittel (2011); Anderson and Auffhammer (2014)). Unlike passenger vehicles, the weight of a truck may vary greatly depending on its cargo. As shown in Figures 2.2 and 2.4,[9] the vehicle weight (including cargo) has a negative correlation with MPG. The red line indicating the model year 2002 lies above the blue line for the model year 1982, showing an overall technological improvement in trucking fleet.

Figure 2.1: Theoretical illustration: trade-off between MPG and vehicle weight



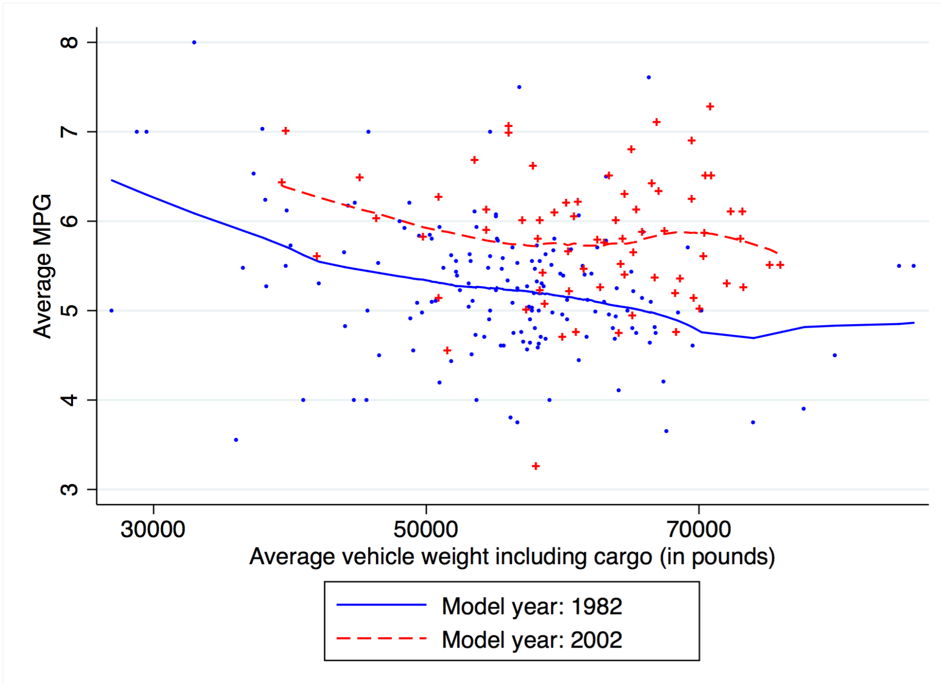
[8] A re-illustration can be found as Figure 2.1.

[9] For the purpose of illustration, the data are aggregated at the levels of truck class (combination vs. vocational), model year, body/trailer type, make.

Engine displacement (CID) is the volume swept by all the pistons inside the cylinders of a reciprocating engine in a single movement from top dead center to bottom dead center. In general, engine displacement measures the volume of the cylinders and loosely suggests the engine's power.[10] Figures 2.3 and 2.5 show the trade-offs between MPG and engine displacement for combination trucks and vocational vehicles respectively. Compared to the trade-off effects of MPG and vehicle weight, there are more overlapping observations between model years 1982 and 2002 in Figures 2.3 and 2.5. There are three reasons: first, engine displacement only explains about 70 percent of the engine power. Second, torque is also an important factor that determines the hauling capability of a truck, as torque measures the rotational force generated by the engine. However, we don't observe this information. Third, the data of engine displacement was collected as a categorical variable, which introduces measurement errors. Nonetheless, the downward shape of the curves in both figures (2.3 and 2.5) indicates negative correlation between engine displacement and MPG. Holding engine displacement constant, the dashed red line (the model year 2002) generally lies above the blue solid line (the model year 1982), showing an increasing trend in MPG while holding the engine displacement constant. This upward trend is present across all ranges of engine displacement for combination trucks. For vocational vehicles, lighter trucks (with an engine displacement under 600 cid) experienced greater improvements.

[10] Detailed discussion can be found in B.1: Engine displacement and horsepower.

Figure 2.2: Trade-off between MPG and vehicle weight for class 7, 8 combination trucks

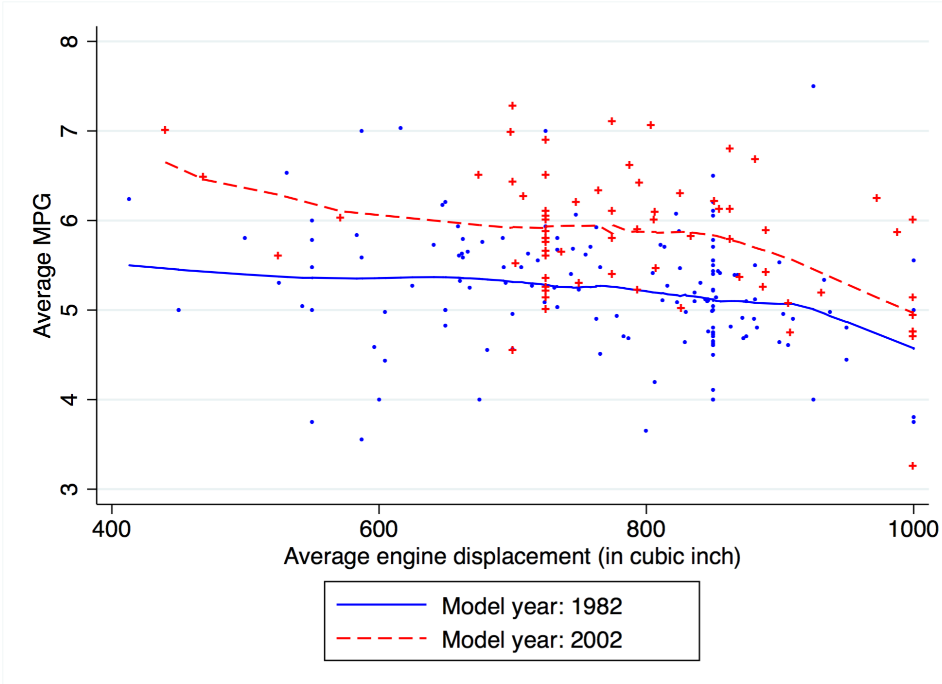


2.3 Empirics

2.3.1 Empirical Specifications

To estimate productivity change over time during the period of the VIUS survey, we identify the shift in the cost function in equation (2.2) above by estimating the year fixed effects accounting for all other changes. We measure the trade-offs in fuel economy and other characteristics by estimating fuel economy as a function of other related variables, as shown in equation (2.3). Prior work has shown that light duty vehicles' weight and engine power are negatively correlated with fuel economy (Knittel, 2011). Such trade-offs for heavy-duty vehicles are likely to be different.

Figure 2.3: Trade-off between MPG and engine displacement for class 7, 8 combination trucks



While engine performance is usually measured by its horsepower and wheel torque, we argue that for heavy duty trucks, engine displacement serves as a good indicator of engine power.[11] Engine displacement, by definition, measures the size of explosion inside the cylinders, which largely determines the power of the engine. The engine torque is the rotational force generated by the engine. Horsepower is a man-made number, and it is defined as the product of engine torque and revolutions per minute (RPM), divided by 5,252. Wheel torque is the combination of engine torque with the force magnification given by the transmission through gearing.

We, therefore, estimate the following equation for fuel economy:

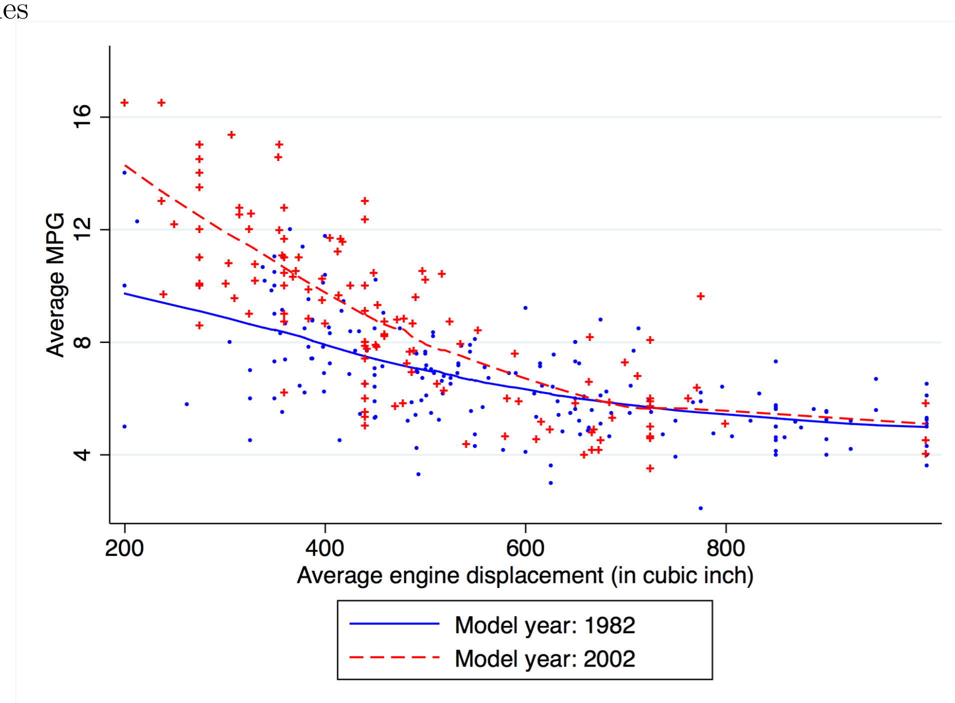
[11] A more detailed discussion can be found in B.1.

Figure 2.4: Trade-off between MPG and vehicle weight for class 3-8 vocational vehicles

$$\ln \text{MPG}_{it} = \alpha_1 \ln \text{Weight}_{it} + \alpha_2 \ln \text{CID}_{it} + \mathbf{MY_{it}}'\gamma + \mathbf{X_{it}}'\beta + t + \epsilon_{it} \tag{2.4}$$

$\mathbf{MY_{it}}$'s are the model year fixed effects. A list of controls, $\mathbf{X_{it}}$, include the body/trailer type, the number of axles on the power unit, the cab type, whether equipped with air-conditioning, natural log of odometer reading, main cargo type, vehicle make, fuel type (interacting with model years), survey year fixed effects and region fixed effects.

Figure 2.5: Trade-off between MPG and engine displacement for class 3-8 vocational vehicles



2.3.2 Empirical Strategies and Results

We estimate equation (2.4) using the VIUS data. We first look at the results of the trade-offs between fuel economy and other variables, and then at the implications of our estimates for changes in productivity over time.

The estimated trade-off effects for combination trucks are shown in column (1) in Table 2.3, and for vocational vehicles in column (3). The factors that are not captured by the included control variables are absorbed by the model year fixed effects, which indicate a lump-sum shift in fuel economy that is due to technological change. We convert the estimated coefficients of model year fixed effects, γ, into percentage changes in MPG over time. They represent the combined effects of adopting fuel-efficient technologies and designs, *i.e*, technological progress. Table 2.4 presents the estimates for combination trucks in column (1) and for vocational vehicles in column (4).

One common concern when using survey data is measurement error: outlier observations may bias the OLS estimation results. If the measurement error tends to appear in the sample randomly, aggregating the sample can cancel out the bias. In the second model, we aggregate the data by survey year, fuel type, model year, body/trailer type, vehicle make, the number of axles on the power unit, and cab type to recover the average fuel economy at the truck model level. We compute the probability weights based on the distribution of truck models in the original dataset and apply the probability weights to the regression with aggregate data. The estimated trade-off effects, along with the estimated coefficients of vehicle attributes, are shown in Table 2.3 in column (2) for combination trucks and in column (4) for vocational vehicles. Estimated technological progress, measured in percentage changes in MPG, is presented in Table 2.4 column (2) for combination trucks and column (5) for vocational vehicles.

In OLS estimation, the underlying assumption is that the estimated coefficient for an independent variable represents the average impact of all observations. To relax this assumption and allow the coefficients to vary in different periods, we apply the Oaxaca/Blinder method of decomposition to estimate the technological progress.

The base period is model years 1973 to 1975. We run the regression as specified in equation (2.4) only for observations from the base period, and use the estimated parameters from the base period to fit the fuel economy in each of the following model years. This method is equivalent to holding the coefficients of the trade-off variables, $Weight$ and CID, constant. The difference between actual and fitted fuel economy can be decomposed into an explained part and an unexplained part. The explained part is the effect of changes in trade-off variables; the unexplained part reflects the technological progress. The estimated progress for combination trucks can be found in column (3) in Table 2.4 and for vocational vehicles in column (6).

The empirical results show similar trends of MPG improvement using the three estimation methods. For combination trucks, the technological progress is about 30 percent over a period of 30 years from 1973 to 2002. The improvement in MPG is estimated at 25 to 28 percent for vocational vehicles. Both truck groups have a much lower annual rate of improvement than expected in the Phase 2 proposed regulation.

2.4 Fuel Economy Improvement

2.4.1 MPG Improvement and Fleet Size

Trucking fleet of different sizes may experience various trajectories of in-use average MPG improvement due to two major reasons. First, large fleets have the capacity to replace and upgrade their vehicles more often than small fleets. Newer

Table 2.3: Estimation Results of the Trade-off Variables

	Class 7, 8 Combination Trucks		Class 3-8 Vocational Vehicles	
	Model 1 (1)	Model 2 (2)	Model 1 (3)	Model 2 (4)
Trade-off variables:				
ln Weight	-0.105***	-0.132***	-0.217***	-0.249***
	(0.00521)	(0.00681)	(0.0132)	(0.00598)
ln Engine displacement	-0.0148***	-0.0157***	-0.0693***	-0.0571***
	(0.00361)	(0.00398)	(0.00879)	(0.00500)
Number of axles: (base: 2 axles, each with 2 tires)				
2 axles, front: 2 tires, back: 4 tires	0.0166***	0.0204***	-0.0363***	-0.0257***
	(0.00545)	(0.00484)	(0.00821)	(0.00424)
3 axles	-0.0339***	-0.0269***	-0.146***	-0.128***
	(0.00839)	(0.00468)	(0.0127)	(0.00565)
4 axles or more	-0.0696***	-0.0751***	-0.187***	-0.183***
	(0.00783)	(0.00627)	(0.0122)	(0.00728)
Cab type: (base: cab forward of engine)				
cab over engine	-0.0117	0.00019	0.0111	0.0333***
	(0.00466)	(0.00754)	(0.0153)	(0.00843)
conventional	0.00789	0.0205***	0.00893	0.0398***
	(0.00571)	(0.00741)	(0.0106)	(0.00810)
other	-0.00287	-0.00384	0.0336***	0.0291**
	(0.0213)	(0.0185)	(0.0105)	(0.0128)
Survey year fixed effects: (base: 1982)				
Survey year 1987	0.00846**	0.00875**	-0.00361	-0.00132
	(0.00270)	(0.00422)	(0.00653)	(0.00467)
Survey year 1992	-0.0215**	-0.0241***	-0.0410***	-0.0321***
	(0.00509)	(0.00458)	(0.00952)	(0.00614)
Survey year 1997	-0.0301***	-0.0288***	-0.0183***	-0.00623
	(0.00760)	(0.00515)	(0.00996)	(0.00630)
Survey year 2002	-0.0617***	-0.0534***	-0.0526***	-0.0192**
	(0.00791)	(0.00662)	(0.0106)	(0.00857)
Other controls:				
Air-conditioning	-0.00624***	-0.0108***	0.0103***	0.00542
	(0.00185)	(0.00395)	(0.00498)	(0.00541)
ln (Odometer reading)	-0.00696***	-0.0125***	-0.00000105	-0.00384
	(0.00186)	(0.00207)	(0.00276)	(0.00247)
Fuel type (gas = 1; diesel = 0)	-0.311***	-0.321***	-0.177***	-0.162***
	(0.0331)	(0.0609)	(0.0165)	(0.0149)
Fuel type × Model years	Yes	Yes	Yes	Yes
Primary Cargo (28)	Yes	No	Yes	No
Body Type (25)	Yes	Yes	Yes	Yes
Manufacturer fixed effects (16)	Yes	Yes	Yes	Yes
Region fixed effects (8)	Yes	No	Yes	No
Adjusted R^2	0.202	0.447	0.352	0.575
No. of observations	99,426	18,583	90,979	31,087

Note: $^{*}: p < 0.1$; $^{**}: p < 0.05$; $^{***}: p < 0.01$
Model 1: main specification, using micro data
Model 2: regression with aggregated data at truck model level
All standard errors (in parentheses) are clustered at the level of manufacturers.

Table 2.4: Technological Progress (in percent)

	Class 7, 8 Combination Trucks			Class 3-8 Vocational Vehicles		
	Model 1 (1)	Model 2 (2)	Model 3 (3)	Model 1 (4)	Model 2 (5)	Model 3 (6)
1974	-0.99	-1.09	-	-1.00	-1.10	-
1975	0.11	-0.30	-	-1.58	-2.13	-
1976	1.33	1.10	1.14	0.34	-0.37	-1.45
1977	2.18	2.04	2.32	2.63	2.32	0.58
1978	3.28	3.32	1.61	2.28	2.19	1.68
1979	3.83	3.74	1.79	5.03	5.41	3.91
1980	5.28	5.13	2.80	5.83	6.07	4.22
1981	8.10	7.93	4.91	10.22	10.26	7.50
1982	8.78	8.57	5.27	8.46	7.83	7.11
1983	10.63	10.85	6.96	9.36	9.63	11.27
1984	12.98	13.88	8.61	13.31	13.77	13.75
1985	14.22	15.03	9.39	14.91	15.14	15.25
1986	15.14	15.60	9.87	17.12	17.94	18.46
1987	16.65	17.23	10.27	17.70	18.06	17.43
1988	17.82	18.41	7.25	18.53	19.12	19.50
1989	18.89	19.36	8.58	19.48	19.96	20.89
1990	20.44	20.92	9.56	18.53	18.77	20.84
1991	22.02	22.51	11.37	18.41	18.18	21.80
1992	23.74	23.74	14.20	19.96	19.96	24.03
1993	23.61	23.99	-0.14	20.92	20.80	22.70
1994	24.61	24.98	1.16	19.84	20.44	22.39
1995	25.73	25.99	2.67	20.68	20.56	23.01
1996	25.61	25.61	2.80	20.80	20.44	20.95
1997	27.38	26.87	3.38	21.41	20.92	22.91
1998	26.24	26.11	22.05	23.12	23.12	25.72
1999	26.62	26.11	22.86	24.86	24.73	29.70
2000	27.25	26.74	24.03	25.48	24.86	29.73
2001	27.76	27.12	23.54	27.89	27.12	31.27
2002	30.87	29.69	29.93	27.00	25.11	27.94

Note: Model 1: main specification, using micro data
Model 2: regression with aggregated data at truck model level
Model 3: estimation applying Oaxaca/Blinder method

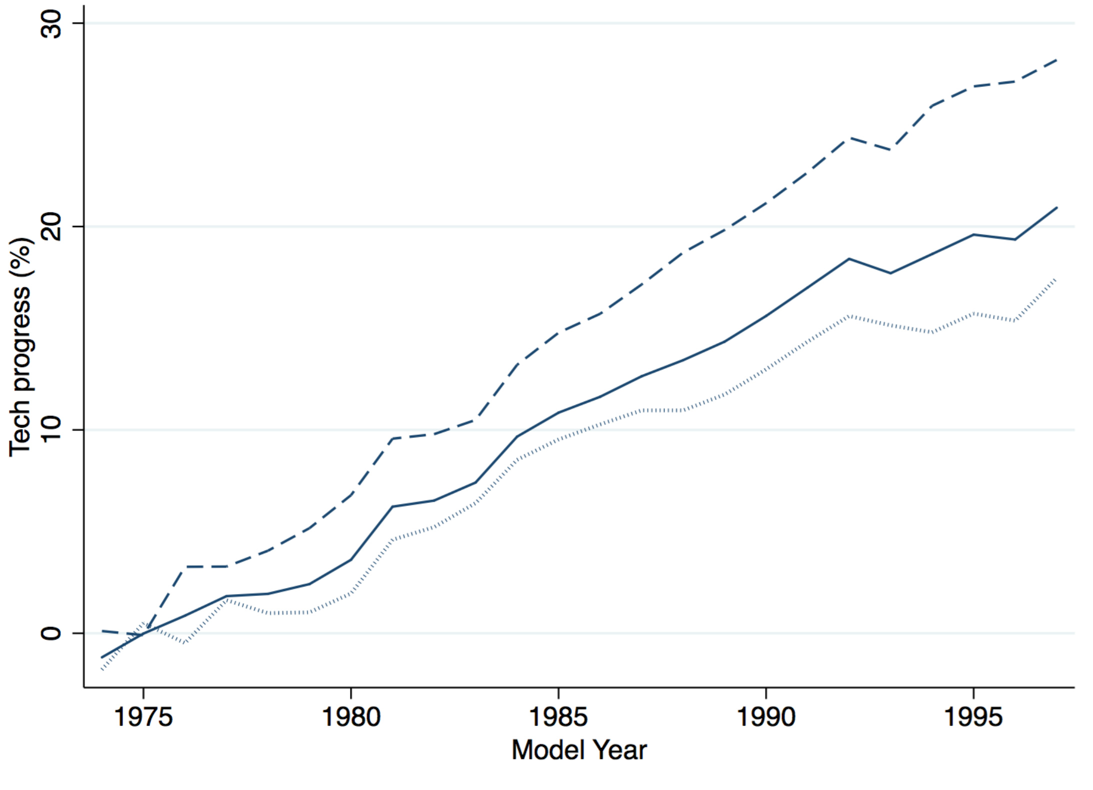
trucks are usually equipped with better aerodynamic devices and technologies; therefore, younger fleets on average should experience a faster growth in in-use MPG. Based on our conversation with the industry, large fleets, such as nationwide shipping companies, purchase from the new vehicle market and sell used trucks at the second-hand market after about four years of use. Second, large fleets usually follow an optimization business model, by which fleet managers assign vehicles to minimize the operational cost. MPG is often built in the optimization business model as a critical input. Therefore, large fleets are incentivized to improve their average MPG in order to lower operation cost.

In our sample, we examine the improvement in average MPG in large and small fleets from the survey year 1982 to 1997.[12] We consider a truck fleet with more than 20 vehicles as a large fleet. We run the baseline OLS regression on each subsample and plot the average in-use MPG improvement as Figure 2.6 for combination trucks and Figure 2.7 for vocational vehicles.

As the Figures 2.6 and 2.7 show, the difference in technological progress between large and small fleets is wider for class 7, 8 combination trucks than that for vocational vehicles. The annual rate of improvement for large combination truck fleets is about 1.04% per annum, and 0.67% for small combination truck fleets. Two possible reasons can explain this gap. First, drivers of large combination truck

[12] The year 2002 is eliminated due to its inconsistency in fleet size categorization with other survey years.

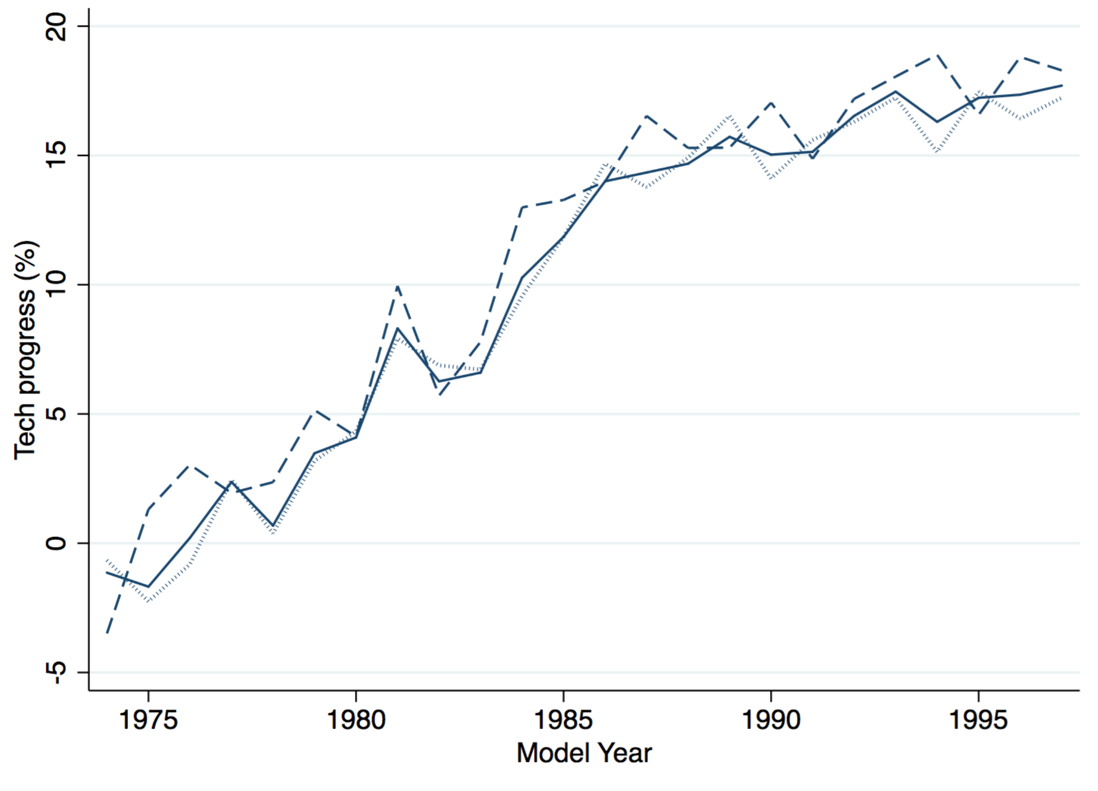
Figure 2.6: Technological progresses of large and small fleets of combination trucks



Note: Solid line refers to the average technological progress; dashed line indicates the estimates of large fleets while tight-dotted line shows the estimates of small fleets.

fleets operate more efficiently due to more training resources and opportunities. Second, large combination truck fleets are equipped with newer and more fuel-efficient vehicles than small fleets. This is entirely possible as trucks are usually highly customized. The second explanation can be further explored by comparing the average vehicle age among large and small combination fleets. The statistics in each survey year are shown in Table 2.5. It is clear that small fleets have greater average age than large fleets in every survey year. The difference is especially large in 1997 when the average age is 4.63 years in large fleets and 8.20 years in small fleets.

Figure 2.7: Technological progresses of large and small fleets of vocational vehicles



Note: Solid line refers to the average technological progress; dashed line indicates the estimates of large fleets while tight-dotted line shows the estimates of small fleets.

2.4.2 Age of Trucks

If the difference in MPG improvement between large and small fleet can be partially explained by uneven distribution of truck age in these two groups, the next question is: Why? On one hand, it can be the fact that older trucks are less fuel efficient due to natural depreciation. On the other hand, new trucks are likely to be equipped with up-to-date technologies. From VIUS dataset, it is impossible to distinguish these two potential sources. Yet, it is still valid to examine MPG im-

Table 2.5: Average ages of combination trucks in large and small fleets

	Large fleets (1)	Small fleets (2)
1982	3.99	4.71
1987	4.41	5.22
1992	4.19	5.25
1997	4.63	8.20

Note: data source: VIUS
Survey year 2002 is not included due to its inconsistency of defining fleet size with other survey years.

Table 2.6: Discounted Lifetime Vehicle-related Costs

	Combination Trucks (1)	Vocational Vehicles (2)
Technology Costs	7994	4600
Compliance Costs	32.4	18.9
Research & Development	302	302
Total	8328.4	4920.9

Source: Regulatory Impact Analysis (EPA)

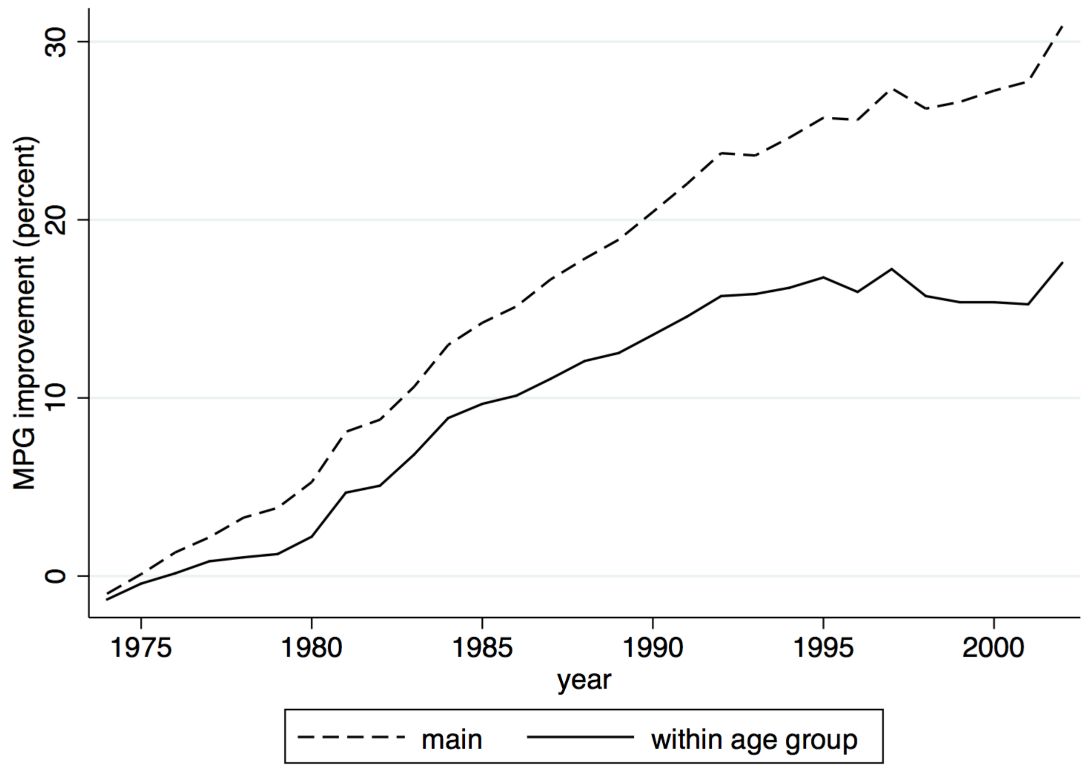
provement within the same age groups.

We add a third-degree polynomial function of truck age to the estimation equation specified in equation (2.4), and estimate the within-age-group MPG improvement to be 17.59% for combination trucks and 16.77% for vocational vehicles from 1973 to 2002. Figures 2.8 and 2.9 show the comparison with the technological progresses estimated in section 2.3.2. For both truck categories, within-age-group MPG improvement is slower than their counterparts.

2.4.3 Is Fuel Price the Driver for MPG Improvement?

A rising fuel price may induce a higher demand for fuel efficient vehicles, which leads to faster technological progress. The seemingly sound "induced innovation" hypothesis was challenged by Newell et al. (1999). They argue that efficiency im-

Figure 2.8: Technological progress within truck age group - combination trucks

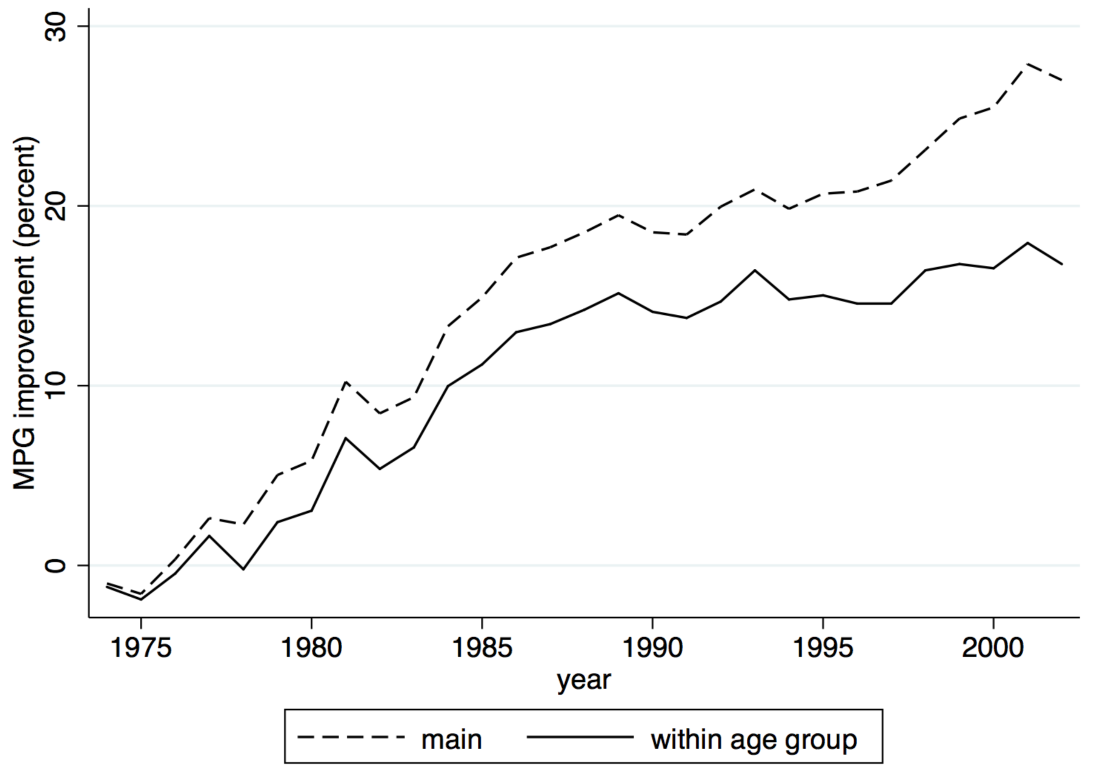


Note: Solid line refers to the average MPG improvement in percentage within truck age group; dashed line replicates the technological progress from the main specification in section 2.3.2.

provements are autonomous and the rate of innovation is independent of energy prices.

To test whether fuel price drives technological progress in heavy-duty trucking industry, we include lagged fuel prices in the main specification (equation 2.4). Since technological innovation takes time, we experiment with fuel prices lagged by one to ten years and watched how their estimated coefficients change. In Table 2.7, we report these coefficients for combination trucks and vocational vehicles. Most of

Figure 2.9: Technological progress within truck age group - vocational vehicles



Note: Solid line refers to the average MPG improvement in percentage within truck age group; dashed line replicates the technological progress from the main specification in section 2.3.2.

the coefficients are not statistically significant. A few precisely estimated are close to zero, indicating a lack of causal relationship between fuel price and MPG.

2.4.4 Discussion

Admittedly, there are three main caveats to our results. First, there are limitations to our dataset. VIUS is the only publicly available dataset that documents detailed trucking decisions and fleet characteristics. Unfortunately, it was discontin-

Table 2.7: Is Fuel Price the Driver for MPG Improvement?

	Combination Trucks (1)	Vocational Vehicles (2)
fuel price - 1	0.00190	0.00908**
	(0.00230)	(0.00333)
fuel price - 2	0.000519	-0.00166
	(0.00221)	(0.00328)
fuel price - 3	-0.000266	0.00547**
	(0.00128)	(0.00193)
fuel price - 4	0.00224	0.00131
	(0.00236)	(0.00278)
fuel price - 5	0.00281*	0.00670**
	(0.00138)	(0.00288)
fuel price - 6	0.00620***	0.00457
	(0.00167)	(0.00272)
fuel price - 7	0.00119	0.00159
	(0.00123)	(0.00241)
fuel price - 8	0.00281*	0.00439
	(0.00145)	(0.00335)
fuel price - 9	0.00192*	0.00332
	(0.000967)	(0.00398)
fuel price - 10	0.00227	0.00735
	(0.00264)	(0.00421)

Note: * : $p < 0.1$; ** : $p < 0.05$; *** : $p < 0.01$. This table shows a collection of estimated coefficients for lagged fuel price variables from 10 regressions for combination trucks and 10 regressions for vocational vehicles.

ued in 2002. Although we believe that the estimated trade-off effects and the rate of MPG improvement remain relatively unchanged since 2002, a natural continuation of our project is to apply the same methodology to more current data. There is a pilot survey conducted in California that resembles VIUS. We are excited to seek collaboration opportunity to work on the full-blown survey data collection. Second, most of the data collected by VIUS are self-reported, which introduces measurement errors in our estimation. In one of our specifications, we aggregate the data at the truck model level to partially address the measurement error issue; yet, the imperfection remains. Third, the business-as-usual MPG improvement can only indicate the adopted technological progress, as the observations are for in-use trucks. We believe the production frontier lies further above the dynamic baseline estimated in this paper. With the current data, estimating the production frontier is out of our reach; however, it is certainly on our future research agenda.

2.5 Conclusion

In this study, we examine the trade-off relationship between fuel economy and vehicle attributes (weight and engine displacement, in particular). We also explore a dynamic baseline in fuel economy improvements by estimating the technological progress in the absence of regulations. We find that technological progress in MPG for combination trucks is about 30.87% from 1973 to 2002. It can be translated to 23.59% reduction in fuel consumption (gallons/1,000 ton payload mile). The annual rate is about 0.92%.

In the recent decade, engine technologies have continued improving in order to achieve higher efficiency and to meet stricter engine emission standards. Low-temperature exhaust gas recirculation (EGR), or advanced EGR cooling, increases engine efficiency by reducing peak combustion temperatures and thus cooling the exhaust gas before it returns to the engine intake manifold. Additionally, a bottoming cycle, acting as a secondary engine, uses exhaust energy to develop additional power. Such technology is shown to reduce fuel consumption by up to 10% (to Assess Fuel Economy Technologies for Medium-and Heavy-Duty Vehicles, 2010).

If the progress of business-as-usual stays the same from 2018 to 2027, approximately 8.01% reduction in fuel consumption can be expected in the absence of fuel economy regulation. While the Phase II standards call for a 24% reduction in fuel consumption, 15.99% will have to come from either more technological advances or changes in trade-off attributes, such as vehicle weight and engine power. For vocational vehicles, the technological progress in MPG is about 27% within 30 years, equating to a 21.26% reduction in fuel consumption. If technological advances remain the same from 2018 to 2027, fuel consumption will be reduced by 7.15% without any regulation, which represents half of the target.

Our findings suggest that it is important to account for the business-as-usual technological progress in improving fuel economy when analyzing the impacts of the new fuel efficiency standards for heavy-duty trucks. In the Regulatory Impact Analysis published by EPA, vehicle-related cost (vehicle program cost) associated with the standards consists of technology cost, compliance cost, research and development cost. The summary of these costs relative to a static baseline is presented in Table 2.6. If we believe fuel efficiency improvement is roughly proportional to technological investment and compliance enforcement, failing to consider the business-as-usual increases in average MPG causes an overestimation of vehicle-related costs by 2.78 billion dollars for combination trucks and 2.20 billion dollars for vocational vehicles.

Failing to include these improvements in the baseline will also mean that fuel savings from the regulations are overestimated. According to EPA's analysis, the fuel savings from the Phase II rules are 60.6 billion dollars for combination trucks and 13.0 billion dollars for vocational vehicles, compared to the static baseline. However, including fuel savings from business-as-usual MPG improvement in the baseline, which are 30% for combination trucks and 45% for vocational vehicles results, results in lower fuel savings from the standards - 40.4 billion dollars for combination trucks and 5.81 billion dollars for vocational vehicles.

We recommend that the agencies consider a dynamic baseline in the final rule of phase 2 standards, as ignoring it may result in a large overestimation of both the cost of the regulation, as well as the fuel consumption savings and greenhouse gas emissions reductions due to the new rules.

Chapter 3: Revealed Compliance to the Environmental Regulation: Evidence from the Heavy-duty Trucking Industry in California

3.1 Introduction

According to the California Air Resources Board emissions inventories, heavy-duty transportation makes up over 20% of the greenhouse gas emissions and over 50% of the emissions of nitrogen oxides from on-road sources.[1,2] As one of the biggest on-road polluting sectors, the heavy-duty trucking industry has been targeted by Environmental Protection Agency (EPA) with various policies. Most of the policies target truck manufacturers, such as engine emission standards for new vehicles. As regulations on new truck models become stricter, manufacturers need to invest more into technology, which leads to higher prices for new trucks. An unintended consequence is that people hold onto their old vehicles longer.[3] Facing this dilemma, in 2008, California Air Resources Board (ARB) adopted the "Statewide Truck and Bus Regulations" (TBR) to reduce emissions of diesel particulate matter (PM), ox-

[1]https://www.arb.ca.gov/cc/inventory/data/tables/ghg_inventory_sector_sum_2000-14.pdf

[2]https://www.arb.ca.gov/ei/emissiondata.htm

[3]See a detailed discussion in Jacobsen and Van Benthem (2015).

ides of nitrogen (NO_x) and other criteria pollutants from heavy-duty diesel-fueled vehicles, and to encourage a faster turnover of the truck fleet. This policy sets deadlines for truckers operating in California to retrofit or upgrade their engines based on the model year and body type of their vehicles. What are truckers' responses to such regulation? In this paper, we estimate the effects of the retrofit deadlines on 1) truck population, 2) vehicle-miles traveled, 3) fuel-consumption and 4) NO_x emissions. The estimates are particularly important to approximate the cost of this regulation, as well as the expected benefit in terms of reduced pollution.

To assess truckers' response to TBR, we use data aggregated at the level of truck model, county and year from EMFAC 2014 Web Database, which are available on the public domain.[4] Compliance with the regulations should be reflected in a decline in truck population in targeted vehicle models in the year of the deadline. In addition to truck population, we also observe average daily travel distance and vehicle-miles traveled (VMT). If the old vehicles are scrapped in lieu of replaced, we may expect VMT to decrease less compared to the changes in truck population.

The earliest deadline specified in the Truck and Bus Regulation requires heavy-duty trucks with model years 1996 to 1999 to be retrofitted or replaced by January 1, 2012. The arbitrary choice of the cutoff model year 1996 suggests that we can

[4]The data can be downloaded from California ARB's website: https://www.arb.ca.gov/emfac/2014/

investigate the effect of the regulations using regression discontinuity (RD) design.[5] We compare the outcome variables for vehicles with model years just below and above 1996. If other factors affecting people's decision of replacement are similar around the cutoff model year, 1996, RD designs control for those factors and the difference in outcome variables can be attributed to the effect of the regulation. Since this regulation was announced in December 2008, MY 1996 truck owners' initial purchase decisions should not be influenced. We find that the truck population is reduced by 71% once the regulation becomes binding. Fuel consumption and NO_x emission are reduced by around 80% for the targeted group of trucks.

We take advantage of the fact that only a subset of the model years are subject to the 2012 deadline, and further identify the effect using a difference-in-difference (DD) estimation method. This method is often used in the literature to estimate the effect of a shock (for example, a sudden change in regulation) by comparing the changes in pre- and post- outcomes for treatment groups and control groups. One of the first and well-cited examples using a DD method is Card et al. (1994). They compare the changes in employment in Pennsylvania and New Jersey to identify the effect of a minimum wage raise in New Jersey. Cutter and Neidell (2009) use a DD method as an extension to a RD design to reveal people's transportation choices in response to a public voluntary program intending to reduce pollutant emissions. In this paper, we set the control group as the trucks with the same attributes as

[5]RD designs are increasingly being used to assess the impacts of regulations. See Cook (2008) for a summary in statistics and economics.

the targeted group but with different model years; therefore, these trucks are not subject to the 2012 deadline. The DD results show that in 2012, the targeted truck populations were reduced by 58%. Total VMT and fuel consumption were reduced by 71% and NO_x emission from the targeted truck group dropped by 76%.

The rest of the paper is organized as follows: we introduce the "Truck and Bus Regulation" in more details in section 2. In section 3, we summarize the data and present graphical evidence, which gives an intuitive grasp of our hypothesis. In section 4, we elaborate on the estimation methods – regression discontinuity design and difference-in-differnce method, followed by the estimation results. In section 5, we apply the difference-in-difference estimation model to a subsample of the data and calculate the percentage of trucks that are exempt from the 2012 deadline. We conclude with policy implications in section 6, and discuss the possible extension from this paper.

3.2 California's Engine Model Year Schedule

3.2.1 The Regulation

The California Truck and Bus Regulation (2014) requires targeted heavy-duty trucks to either retrofit, by installing PM filters, or replace existing engines with 2010 model year engines or newer to meet the emission standards. TBR specifies a schedule for truck fleet to comply based on their truck types, engine model years (MY), operation areas and compliance choices.

Table 3.1: Engine Model Year Schedule for Heavier Trucks

Engine Model Year	Replacement Date (from January 1)
Pre-1994	No requirements until 2015, then 2010 engine
1994-1995	No requirements until 2016, then 2010 engine
1996-1999	*PM filter from 2012 to 2020, then 2010 engine*
2000-2004	PM filter from 2013 to 2021, then 2010 engine
2005-2006	PM filter from 2014 to 2022, then 2010 engine
2007-2009	No requirements until 2023, then 2010 engine
2010 or newer	Meets final requirements

Note: This table is a replication of the table in "Truck and Bus Regulation Model Year Schedules and Options" published by California ARB on web page https://www.arb.ca.gov/msprog/onrdiesel/onrdiesel.htm.

The schedule for retrofit and replacement deadlines for heavy-heavy duty trucks (GVWR greater than 26,000 lbs) is shown in Table 3.1. The earliest deadline requires engine model year 1996 to 1999 vehicles to be equipped with a PM filter by January 1, 2012 in order to operate in California and meet PM and NO_x emissions requirements. Alternatively, an operator of the targeted vehicle group could retire the vehicle or replace it with a newer model.[6] In this paper, we restrict our attention to the 2012 deadline and investigate the effects on truck population, other trucking decisions, and emissions.

[6]This schedule can be adjusted with credits for early action or adding advance technology vehicles to delay compliance until January 1, 2017. To be more specific, a trucking firm can get credits for downsizing the heavier trucks fleet, and/or adding alternative fueled or hybrid vehicles. Early installation of PM filters and/or addition of vehicles with originally equipped PM filters are also rewarded with credits. Excess PM filter credits in the Truck and Bus regulation may be exchanged with those in the in-use off-road diesel vehicle regulation until January 1, 2017.

3.2.2 NO_x-exempt Areas

According to California Air Resources Board (ARB), vehicles operated solely within defined NO_x-exempt areas "can meet PM filter requirements on a delayed schedule from 2015 to 2020 and do not need to be replaced after they are equipped with PM filters." Truck owners are required to report their fleet information and identify their truck(s) that is(are) eligible for this flexible compliance program in each January or within 30 days of purchasing. The NO_x-exempt counties include Alpine, Colusa, Del Norte, Glenn, Humboldt, Lake, Lassen, Mendocino, Modoc, Monterey, Plumas, San Benito, San Luis Obispo, Santa Barbara, Santa Cruz, Shasta, Sierra, Siskiyou, Trinity, Tehama, and Yuba.[7] The NO_x-exempt areas are typically those that are outside of the Clean Air Act non-attainment counties and those where downstream emissions would not create added burden on non-attainment counties.

3.3 Data

3.3.1 Summary Statistics

Our main data source is the Emission FACtors (EMFAC) Web Database. EMFAC is a model developed by the California ARB to calculate vehicle emissions, in-

[7] Details regarding this exemption can be found in the staff report https://www.arb.ca.gov/regact/2008/truckbus08/tbisor.pdf. Subsequent amendments to TBR have included more counties.

ventories, and rates. The publicly available data that are based on historical records span from 2000 to 2013.[8] The data are aggregated at the level of county, calendar year, vehicle class, fuel type and model year.

The heavy duty vehicle inventory for EMFAC is generated from the vehicle registration data provided by the California Department of Motor Vehicles and California International Registration Plan. ARB staff processed the data to determine vehicle class designations and populated the EMFAC database with vehicle counts and vehicle activity.

We observe vehicle population (in each aggregation unit), average daily vehicle-miles-traveled (VMT), fuel consumption, and emissions rates. Tables 3.2 and 3.3 provide the summary statistics of the dataset. *Targeted* group in columns (1) and (4) represents the heavy-duty trucks with model years from 1996 to 1999 in regulated counties. They are subject to the 2012 deadline. The other two groups - *NO_x-exempt* group and *Other MY* group - are not subject to this particular deadline. *NO_x-exempt* group in column (2) and (5) includes trucks with model year from 1996 to 1999 operating in NO_x-exempt counties. From Table 3.2, we can see that there are fewer heavy-duty trucks in NO_x-exempt counties: counties outside of non-attainment areas are generally smaller and less urban. However, vehicle-level activities are similar on average between these two groups, and daily VMT per ve-

[8]The data from 2014 onwards are generated from the EMFAC model for the purpose of forecasting; therefore, we exclude them from our analysis.

hicle looks comparable across all years. *Other MY* group in columns (3) and (6) refers to heavy-duty trucks with model years before 1996 or after 1999 in regulated counties. Column (3) in Table 3.2 shows that the truck population didn't change much from 2000 to 2012, while the number of trucks in *Targeted* group (column 1) was reduced by more than 30% from 2011 to 2012. Similarly, Table 3.3 implies a lack of variation in fuel consumption and NO_x for *Other MY* group, compared to those in *Targeted* group.

3.3.2 Graphical Evidence

Figure 3.1 provides an illustration of the changes in truck population from 2011 to 2012. Each dot on the line indicates the percentage change in population from 2011 to 2012 for a specific model year truck group. The number of trucks in the targeted truck group in regular counties is shown by the blue solid line. The red dashed line traces the percentage change in population for trucks with the same body type and model years as those in the targeted group but registered in NO_x-exempt counties. As explained in section 3.2.1, the 2012 deadline applies to heavy-duty trucks with model years from 1996 to 1999. The reason why we see a decrease not only for trucks in regular counties but also in NO_x-exempt counties is because the exemption only applies to trucks that are operated solely in NO_x-exempt counties. Many vehicles registered within a NO_x-exempt county occasionally operate outside the counties boundaries. In other words, some trucks in our dataset, although

Table 3.2: Summary Statistics: Truck Population and Vehicle-miles Traveled

	Truck population (millions)			**VMT (miles/day, vehicle)**		
	Targeted	NO_x-exempt	Other MY	Targeted	NO_x-exempt	Other MY
Calendar year	(1)	(2)	(3)	(4)	(5)	(6)
2000	17.12	3.02	8.62	180.75	187.01	91.57
	(41.44)	(6.02)	(28.11)	(135.29)	(139.27)	(68.53)
2001	17.61	3.06	8.46	175.49	181.59	92.72
	(39.14)	(5.32)	(28.08)	(137.39)	(141.53)	(75.28)
2002	18.58	3.2	7.79	169.76	174.98	95.66
	(40.87)	(5.53)	(25.85)	(125.05)	(128.52)	(78.24)
2003	21.08	3.61	8.55	152.32	156.79	91.18
	(46.73)	(5.91)	(28.97)	(112.18)	(115.11)	(79.01)
2004	22.43	3.55	8.25	141.50	145.52	90.4
	(49.18)	(6.15)	(29.24)	(98.34)	(100.86)	(77.36)
2005	22.00	3.34	8.81	128.96	131.68	88.96
	(49.34)	(5.73)	(32.46)	(82.31)	(84.33)	(74.5)
2006	23.11	3.44	9.43	113.98	115.3	84.65
	(53.4)	(5.79)	(34.48)	(68.7)	(70.31)	(70.84)
2007	22.36	3.37	9.42	107.27	108.39	85.01
	(52.89)	(5.5)	(33.85)	(63.48)	(64.92)	(73.04)
2008	21.84	3.3	9.16	99.77	100.25	84.28
	(54.48)	(5.55)	(32.24)	(57.96)	(59.13)	(73.76)
2009	18.65	2.92	8.59	92.95	92.93	83.86
	(46.37)	(4.91)	(30.25)	(51.91)	(52.73)	(73.74)
2010	17.32	2.92	9.99	85.04	84.53	80.25
	(46.04)	(5.12)	(39.32)	(43.3)	(43.49)	(71.49)
2011	15.93	2.68	10.14	80.45	79.77	81.72
	(43.24)	(4.76)	(38.45)	(39.78)	(39.73)	(72.39)
2012	10.01	1.9	10.98	70.54	69.67	76.99
	(25.08)	(3.29)	(41.71)	(33.18)	(32.26)	(65.27)
Total	19.08	3.1	9.12	122.77	124.7	86.42
	(46)	(5.41)	(33.08)	(95.22)	(97.95)	(73.55)

Note: Columns (1) and (4) are for targeted group – heavy-duty trucks with model years from 1996 to 1999 operating in non NO_x-exempt counties. They are subject to Truck and Bus Regulation. Columns (2) and (5) are for NO_x-exempt group – heavy-duty trucks with model year from 1996 to 1999 operating in NO_x-exempt counties; therefore, they are not subject to the regulation. Columns (3) and (6) are for other MY group – heavy-duty trucks with model years either older than 1996 or younger than 1999, operating in non NO_x-exempt counties. They are not required to retrofit by 2012.

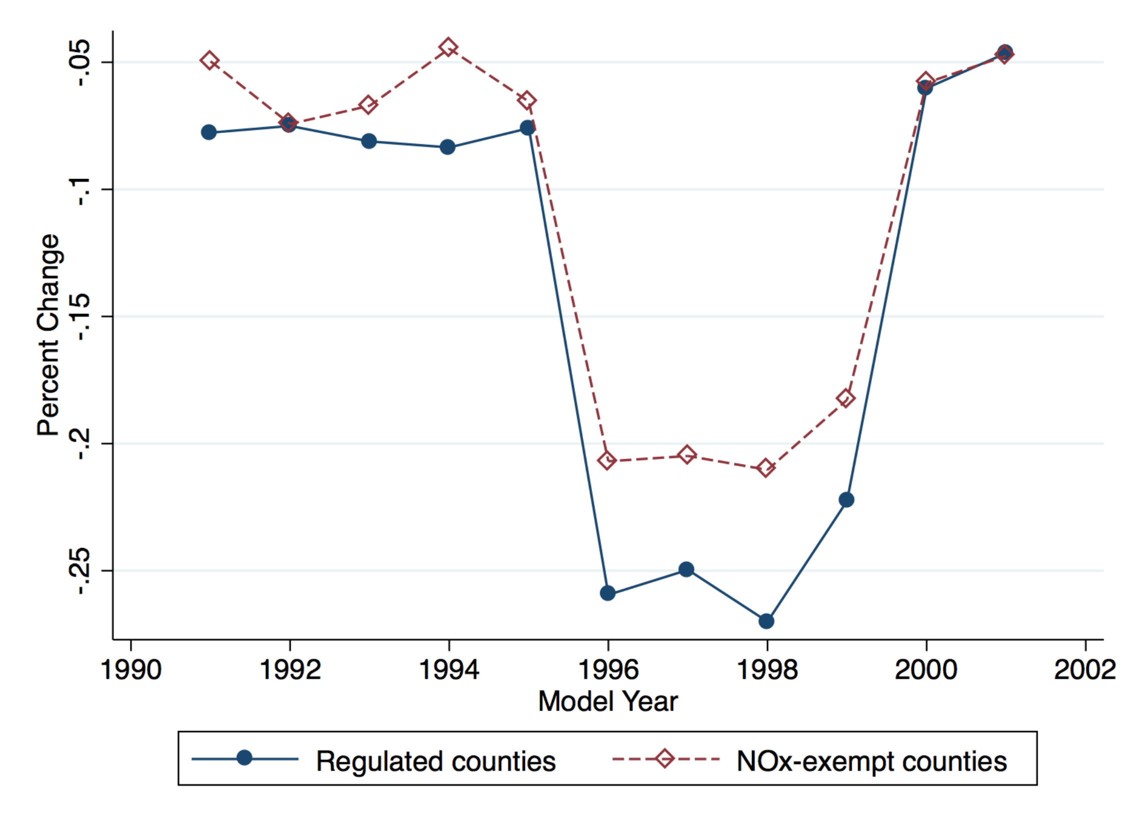
Table 3.3: Summary Statistics: Fuel Consumption and CO_2 Emission

	Fuel consumption (gallons/mile)			**NO_x emissions (1000 tons/day)**		
	Targeted	NO_x-exempt	Other MY	Targeted	NO_x-exempt	Other MY
Calendar year	(1)	(2)	(3)	(4)	(5)	(6)
2000	0.82	0.14	0.23	0.11	0.02	0.03
	(2.69)	(0.42)	(1.1)	(0.38)	(0.06)	(0.15)
2001	0.79	0.14	0.23	0.11	0.02	0.03
	(2.3)	(0.35)	(1.15)	(0.33)	(0.05)	(0.16)
2002	0.81	0.14	0.23	0.12	0.02	0.03
	(2.31)	(0.35)	(1.14)	(0.34)	(0.05)	(0.16)
2003	0.78	0.14	0.23	0.11	0.02	0.03
	(2.18)	(0.33)	(1.14)	(0.33)	(0.05)	(0.15)
2004	0.77	0.12	0.23	0.11	0.02	0.03
	(2.11)	(0.31)	(1.25)	(0.32)	(0.05)	(0.15)
2005	0.65	0.1	0.25	0.09	0.01	0.03
	(1.75)	(0.23)	(1.49)	(0.26)	(0.03)	(0.17)
2006	0.59	0.09	0.26	0.08	0.01	0.03
	(1.58)	(0.2)	(1.44)	(0.23)	(0.03)	(0.16)
2007	0.53	0.08	0.26	0.07	0.01	0.03
	(1.46)	(0.17)	(1.44)	(0.21)	(0.03)	(0.15)
2008	0.46	0.07	0.24	0.06	0.01	0.02
	(1.3)	(0.14)	(1.23)	(0.19)	(0.02)	(0.11)
2009	0.36	0.05	0.22	0.05	0.01	0.02
	(1.02)	(0.11)	(1.13)	(0.15)	(0.02)	(0.1)
2010	0.30	0.05	0.24	0.04	0.01	0.02
	(0.89)	(0.1)	(1.26)	(0.13)	(0.01)	(0.1)
2011	0.26	0.04	0.25	0.03	0.01	0.02
	(0.79)	(0.09)	(1.24)	(0.11)	(0.01)	(0.09)
2012	0.13	0.02	0.27	0.02	0	0.02
	(0.37)	(0.05)	(1.34)	(0.05)	(0.01)	(0.09)
Total	0.56	0.09	0.24	0.08	0.01	0.03
	(1.74)	(0.25)	(1.27)	(0.25)	(0.04)	(0.14)

Note: Columns (1) and (4) are for targeted group – heavy-duty trucks with model years from 1996 to 1999 operating in non NO_x-exempt counties. They are subject to Truck and Bus Regulation. Columns (2) and (5) are for NO_x-exempt group – heavy-duty trucks with model year from 1996 to 1999 operating in NO_x-exempt counties; therefore, they are not subject to the regulation. Columns (3) and (6) are for other MY group – heavy-duty trucks with model years either older than 1996 or younger than 1999, operating in non NO_x-exempt counties. They are not required to retrofit by 2012.

registered in NO_x-exempt counties, are still subject to the regulation. The wedge between these two lines infers the proportion of trucks that are solely operated in NO_x-exempt counties over the ones registered in these counties. This estimate will be furthered discussed in section 3.5.

Figure 3.1: Percentage change in truck population from 2011 to 2012



3.4 Empirical Analysis

3.4.1 Regression Discontinuity (RD) Design

In theory, RD design only uses the sample that is relevant to the policy. We restrict our sample to include only HD trucks with relevant model years in regulated counties (non NO_x-exempt counties) in calendar year 2012. The benefits of using RD designs include 1) post-policy functional form does not have to be the same as pre-policy; 2) MYs that are further away from the cutoff (model years 1996 to 1999) have less weight in explaining the difference in results. As explained in section 3.2.1, the model year of an HD truck in a non NO_x-exempt county is the only deterministic factor of retrofit requirement; therefore, there is no other confounding variable other than model year. Without the 2012 deadline, we should expect the number of trucks moves smoothly across all model years. As Figure 3.1 suggests, the sudden drop in model year 1996 can be used to estimate the direct impact of the regulation. Suppose x_i denotes the difference between the model year in question and the cutoff model year 1996:

$$x_i = MY_i - 1996 \,. \tag{3.1}$$

The retrofit requirement can be defined as follows:

$$T_i = \begin{cases} 1 & \text{if } x_i \geq 0 \\ 0 & \text{if } x_i < 0 \end{cases} \,. \tag{3.2}$$

We can construct the RD estimates by fitting

$$y_i = f(x_i) + \rho T_i + \xi_i, \tag{3.3}$$

in which y_i represents the outcome variable, truck population and VMT. The regression function can be written as follows:

$$y_i = \alpha + \beta_1 x_i + \beta_2 x_i^2 + \rho T_i + \gamma_1 x_i T_i + \gamma_2 x_i^2 T_i + \xi_i. \tag{3.4}$$

Table 3.4: Estimation Results: Regression Discontinuity Design

Dependent variable: (in log)	Truck population (millions) (1)	VMT (million miles/day) (2)	Fuel consumption (gallons/mile) (3)	NO_x emissions (1000 tons/day) (4)
β_1	0.532**	0.554**	0.628***	0.701***
	(0.233)	(0.234)	(0.234)	(0.234)
β_2	0.0667	0.0672	0.0922	0.117**
	(0.0581)	(0.0582)	(0.0582)	(0.0582)
ρ	-0.714***	-0.745***	-0.795***	-0.846***
	(0.210)	(0.210)	(0.210)	(0.210)
γ_1	-0.375	-0.377	-0.450*	-0.602**
	(0.245)	(0.245)	(0.245)	(0.245)
γ_2	-0.0550	-0.0470	-0.0684	-0.0538
	(0.0626)	(0.0627)	(0.0627)	(0.0628)
N	5697	5697	5697	5697
adj. R^2	0.804	0.807	0.808	0.805

Note: $^*: p < 0.1$; $^{**}: p < 0.05$; $^{***}: p < 0.01$
Vehicle class fixed effects and county fixed effects are included in all regressions.

The trends before and after MY 1996 can be modeled as either binomial functions (Table 3.4) or linear functions (in Appendix Table C.2). The corresponding coefficients can be estimated by β's and γ's. The effect of the policy for trucks with model year 1996 is estimated as ρ.

Table 3.4 shows the results of the RD regression where we restrict the sample to be between model years 1993 and 1999. The main coefficient of interest, ρ, indicates the impact of the regulation for model year 1996 HD trucks. Column (1) in Table 3.4 indicates that trucks with model year 1996 to 1999 experienced a drop in populations of 71% from 2011 to 2012. Column (2) in Table 3.5 indicates that this is reflected in a proportional change in VMT from model year 1996 to 1999 vehicles. Columns (3) and (4) in Table 3.5 indicate a slightly greater reduction in fuel consumption and NO_x emissions at around 80% to 85%.

The coefficients, β's, in Table 3.4 are positive in all columns, showing trends in vehicle retirement and vehicle use. Column (1) indicates that between ages of 13 to 19 years, there is on average a 53% attrition rate in vehicle population. Similarly, columns (2) through (4) reflect how this change in vehicle population translates into changes in VMT, fuel consumption and NO_x emissions.

The coefficients, γ's, provide differences in trends that may differentiate the model year 1996 through 1999 vehicles. Neither of the coefficients for truck population nor those for VMT are statistically significant, suggesting that the trends for these vehicles are similar to the vehicles with model year 1993 through 1995. The estimated γ's are negative and statistically significant for fuel consumption and NO_x emissions, implying that the general trend for these two outcome variables are flatter post-MY 1996 comparing to pre-MY 1996.[9]

3.4.2 Difference-in-difference Model

We apply a difference-in-difference (DD) model to identify the effect of the retrofit/replacement requirements with the 2012 deadline on truck population, VMT, fuel consumption and emission rates, taking advantage of the exogenous choices of targeted model years from 1996 to 1999. Denote the outcome variable (truck population, VMT, fuel consumption or NO_x emissions) of model year i vehicles as y_{it} in

[9]However, such difference in trends between pre- and post-MY 1996 vanishes once we specify them as linear functions. See C.3 for details.

calendar year t. The DD model can be written as follows:

$$y_{it} = \mu_i + \tau_t + \delta D_{it} + g(a_i) + \varepsilon_{it} \ , \tag{3.5}$$

in which μ_i is the model year fixed effects and τ_t represents the calendar year fixed effects. The treatment D_{it} is defined as

$$D_{it} = \begin{cases} 1 & \text{if } i \in [1996, 1999] \ \& \ t = 2012, \\ 0 & \text{Otherwise.} \end{cases} \tag{3.6}$$

Additionally, we include $g(a_i)$, a function of truck age in the model to capture the natural attrition in the truck population. In the empirical estimation, we specify $g(a_i)$ as a third-order polynomial function. We apply the same estimation method to examine the effect on all four outcome variables. The estimation results are presented in Table 3.5. D_{it} denotes the interaction term of vehicles with the targeted model years and calendar year 2012. The coefficients of D_{it}, $\delta' s$, indicate the effects of the retrofit/replacement deadline on the targeted truck groups. The estimation results in column (1) show that for each vehicle class, there are about 58% fewer MY 1996 to 1999 trucks operating in 2012 than similar trucks with other model years. The effect on VMT, fuel consumption and NO_x are above 70%.

DD estimation produces smaller estimates (in absolute value) than the estimation results from RD design. In particular, RD design predicts 71% reduction in truck population due to the retrofit/replacement deadline, while DD results show that the reduction is only 58%. The RD design does not differentiate between vehicle age and model year, attributing the population reduction entirely to the regulation.

Table 3.5: Estimation Results: Difference-in-difference Approach

Dependent variable: (in log)	Truck population (millions)	VMT (million miles/day)	Fuel consumption (gallons/mile)	NO_x emissions (1000 tons/day)
	(1)	(2)	(3)	(4)
δ	-0.578***	-0.711***	-0.708***	-0.760***
	(0.0448)	(0.0461)	(0.0463)	(0.0457)
age	0.150***	0.123***	0.121***	0.129***
	(0.00421)	(0.00473)	(0.00472)	(0.00468)
age^2	-0.0125***	-0.0135***	-0.0134***	-0.0139***
	(0.000248)	(0.000259)	(0.000260)	(0.000257)
age^3	0.000184***	0.000198***	0.000196***	0.000203***
	(0.00000427)	(0.00000429)	(0.00000431)	(0.00000427)
N	260,484	260,484	260,484	260,484
R^2	0.542	0.581	0.573	0.579

Note: $* : p < 0.1$; $** : p < 0.05$; $*** : p < 0.01$

D_{ct} denotes the interaction term of calendar year 2012 and heavy-duty trucks that are subject to the 2012 deadline.

County fixed effects, model year fixed effects and calendar year fixed effects are included in all above regressions.

On the other hand, the DD estimation incorporates additional calendar years, allowing us to consider both trends due to vehicle age and specific patterns that may be present in certain model years. The DD estimate attributes some of the decrease in the affected population from 2011 to 2012 to the natural trends[10] as vehicles age.

The difference may also be explained by the spill-over effect to vehicles in the control group – heavy-duty trucks with model years before 1996 or after 1999. For example, as shown in Table 3.1, vehicles with engine model year from 2000 to 2004 are subject to the 2013 deadline. The enforcement of the 2012 deadline may expedite the vehicle replacement/retirement of trucks with model year after 2000.

[10]The natural business-as-usual attrition of vehicles is illustrated in C.5. An ordinary least squares (OLS) regression reveals the natural rate of replacement is about 9.5%.

3.5 How many trucks were exempted from the regulation?

As introduced in section 3.2.2, trucks that are solely operated in NO_x-exempt counties enjoy a postponed deadline of compliance. EMFAC dataset provides vehicles' registration counties, in lieu of operation location. Registration in a NO_x-exempt county is not a necessary condition for the exemption as trucks may travel outside their registration counties. This is also evident in columns (2) and (5) in Tables 3.2 and 3.3, where trucks registered in NO_x-exempt counties experience a similar change with less magnitude in truck population and other outcome variables as the other two groups. How many of them were truly exempted from the 2012 deadline? This estimate of proportion of trucks that are solely operated within their registration counties is important for the cost and benefit analysis of the TBR program; yet, there is lack of studies to provide such an estimate.

We restrict our sample to those registered in NO_x-exempt counties and repeat the exercise in Section 3.4.2. We estimate the effects of the 2012 deadline on trucks that are registered in these counties. By comparing the effects within and outside of the NO_x-exempt counties, we are able to quantify the proportion of trucks registered in NO_x-exempt counties that are actually exempted from the regulation because they are solely operated in those counties. Such information is crucial to ARB in terms of predicting the compliance rate and evaluating the net benefit of the program.

Table 3.6: The effects of the 2012 deadline in NO_x-exempt counties

Dependent variable: (in log)	Truck population (millions)	VMT (million miles/day)	Fuel consumption (gallons/mile)	NO_x emissions (1000 tons/day)
	(1)	(2)	(3)	(4)
δ'_{it}	-0.455***	-0.600***	-0.598***	-0.650***
	(0.0865)	(0.0872)	(0.0874)	(0.0869)
age	0.0995***	0.0685***	0.0701***	0.0758***
	(0.00718)	(0.00766)	(0.00764)	(0.00761)
age^2	-0.0109***	-0.0118***	-0.0118***	-0.0122***
	(0.000426)	(0.000432)	(0.000432)	(0.000430)
age^3	0.000155***	0.000169***	0.000169***	0.000175***
	(0.00000740)	(0.00000729)	(0.00000730)	(0.00000728)
N	134341	134341	134341	134341
Adj. R^2	0.425	0.480	0.475	0.477

Note: $^*: p < 0.1$; $^{**}: p < 0.05$; $^{***}: p < 0.01$

δ'_{it} denotes the coefficients of the interaction term of calendar year 2012 and heavy-duty trucks that are subject to the 2012 deadline.

County fixed effects, model year fixed effects and calendar year fixed effects are included in all above regressions.

Table 3.6 provides the estimation results using difference-in-difference approach with samples restricted to heavy-duty trucks registered in NO_x-exempt counties. 45.5% of trucks with model years from 1996 to 1999 are replaced in 2012 in these counties. VMT and fuel consumption are reduced by 60%. Column (4) shows that NO_x emissions drop by 65%.

Recall that Section 3.2.1 introduces the regulation and truckers' options – they can comply by either replacing their vehicles or installing PM filters to their existing vehicles. Suppose the percentage of targeted trucks complying by installing PM filters is relatively stable across all counties, we can infer the proportion of trucks registered in NO_x-exempt counties that are solely operated within these counties. Denote this proportion as $x\%$. The assumption can be restated as the replacement rates among trucks that are subject to the 2012 deadline remain the same in regulated counties and NO_x-exempt counties, which can be expressed in the following equation:

$$(1 - x\%)\delta_{it} = \delta'_{it} \ , \tag{3.7}$$

in which δ_{it} is the effect on truck population in regulated counties and the estimates is 57.8%. δ'_{it} is the effect in NO_x-exempt counties, 45.5% (column 1 in Table 3.6). Substitute the numbers into equation 3.7, and we derive $x = 21.3$. That is to say, there are about 21.3% of heavy-duty trucks registered in NO_x-exempt counties are solely operated in those counties; therefore, they are not subject to the 2012 deadline.

3.6 Conclusion

In this paper, we provide a methodology for ex-post evaluation of outcomes from California's State Truck and Bus Regulation. While ARB conducts regulatory impact analyses for all new regulations, this process takes place in regulatory development and assumptions are generally not revisited once regulations have been passed. Using data that is informed by DMV data, this approach allows us to consider the impact on vehicle replacement behavior.

We conduct the empirical analysis using two estimation methods on four changes of outcomes – truck population, vehicle-miles traveled, fuel consumption and NO_x emission. First, using a regression discontinuity design, we focus on the truck group that is subject to the 2012 deadline and find a 71.4% reduction in truck population once the regulation becomes binding. The other three outcome variables experienced slightly more reductions. Second, the exogenous choice of targeted model years allows us to conduct a difference-in-difference estimation. Trucks with model years before or after 1996-1999 are not required to retrofit or replace by 2012; therefore they form a control group. The difference-in-difference analysis provides us a lower estimate of the effects – the number of trucks is reduced by 57.8% and daily VMT aggregated at the truck model level decreases by almost 71.1%. Since the truckers may choose to comply by installing PM filters or replacing the engine, a 57.8% reduction in truck population implies that 42.2% of them chose to retrofit and keep the vehicles. The empirical analyses present evidence of how the industry responds to the engine model year schedule and provide input to revisit the regulatory impact analyses. Both RD and DD estimation results show that the reduction in fuel consumption and NO_x are more substantial than the percentage of truck population decrease. We suggest California ARB to take this positive spill-over effect into account when calculating the local environmental benefit of the regulation.

According to the regulation, trucks that are solely operated in NO_x-exempt counties are not subject to the 2012 deadline. How many trucks registered in these counties are solely driven locally? This is a valuable question because the estimate of it is directly linked to the cost and benefit analysis of this regulation. We restrict our sample to heavy-duty trucks that are registered in NO_x-exempt counties and apply the same difference-in-difference estimation. We find a 45.5% reduction in truck population in 2012. Assuming the percentage of truckers who choose to retrofit stays the same across all counties, we infer from a simple calculation (equation 3.7) that 21.3% trucks solely operated within NO_x-exempt counties.

Additionally, two sources of unintended costs should be raised to attention. First, the replaced trucks will be either sold to other states or kept in NO_x-exempt counties. Both scenarios imply negative externalities and partially offset the benefit of the regulatory program. If most of the old trucks leak to NO_x-exempt counties, the local air quality will take the toll. Second, the sudden change in fleet makeup creates a short-term over demand for newer truck models. This may result in high price premium for newer truck models, which adds more financial burden to small business owners who have to upgrade their trucks.

Appendix A: Appendix for Chapter 1

A.1 Variables omitted from the summary statistics table

- Other axle configurations include "2 axles - 1 axle trailer," "2 axles - 3 or more axle trailer," "2 axles - 3 trailers," "2 axles - two trailers," "3 axles - 1 axle trailer," "3 axles - 3 or more axle trailer," "3 axles - three trailers," "3 axles - two trailers," "4 or more axles," "4 or more axles - 1 axle trailer," "4 or more axles - 2 axle trailer," "4 or more axles - 3 or more axle trailer," "4 or more axles - two trailers" and "4 or more axles - three trailers."

- Other vehicle makes include autocar, other(domestic) and other(foreign).

- Other body/trailer types include automobile transport; beverage truck; concrete mixer; drop frame van; garbage truck; grain bodies; insulated non-refrigerated van; livestock truck; low boy; multistop or step van; oil field truck; open top van; platform with devices permanently mounted on it; pole, logging, pulpwood or pipe truck; service truck or craftsman's vehicle; tank truck for dry bulk; tank truck for liquids or gases; utility truck; winch or crane truck; wrecker; yard tractor; and other.

- Other cab types include cab forward of engine, beside engine or other.

- Other primary cargo include chemicals or drugs; farm products; household goods; live animals; lumber or fabricated wood products; metal products; mining products; miscellaneous products of manufacturing; no load carried; paper, textiles or apparel; petroleum products; plastics or rubber products; processed foods; tools, machinery or equipment; waste or scrap; and other.

- Engine displacement (in cubic inch) are grouped into bins as follows – 1 to 300; 301 to 399; 400 to 499; 500 to 599; 600 to 699; 700 to 799; 800 to 899; 900 or more.

- Number of cylinders are categorized as 4, 6, 8 and more than 8.

A.2 First stage estimation

The instrumental variable used in the main regressions is the per-mile fuel cost in states that do not share a border with home base states. In section 1.5.2, I apply an alternative instrumental variable as a robustness check. The alternative IV is constructed by dividing crude oil price by MPG. The results of the first stage estimation in the 2SLS approach are presented in Table A.1.

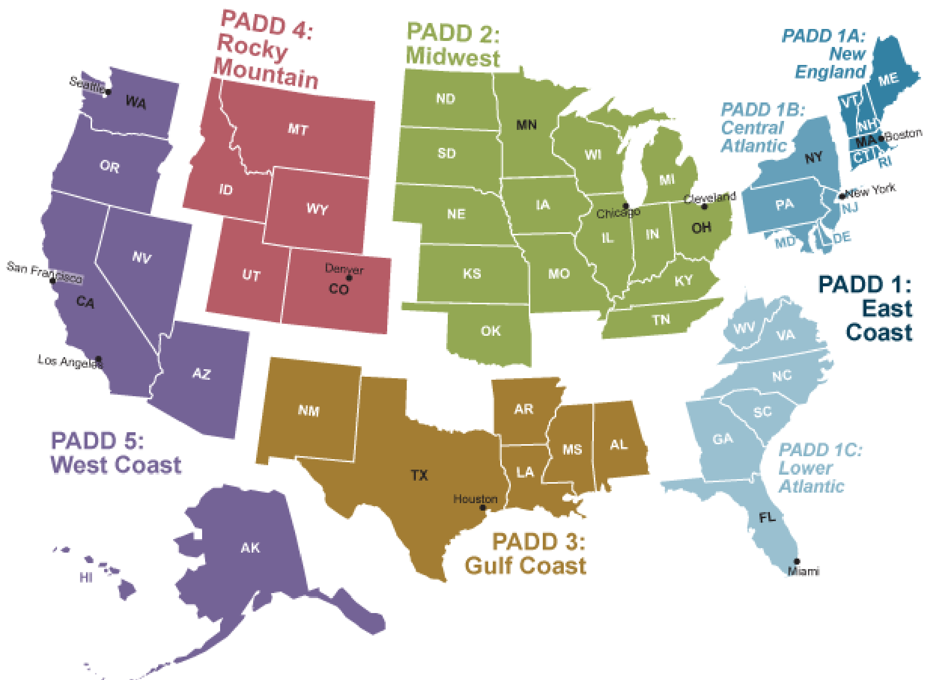
Table A.1: First Stage Estimation Results

IV	Average fuel prices in non-neighboring states		Global crude oil prices	
	Combination	Vocational	Combination	Vocational
	(1)	(2)	(3)	(4)
Coefficients of IV	-5.999***	-8.590***	0.0169***	0.0136***
	(0.0406)	(0.0632)	(0.00197)	(0.000054)
R^2	0.935	0.931	0.916	0.899
p-value of F statistics	< 0.001	< 0.001	< 0.001	< 0.001

Note: *** : $p < 0.01$; robust standard errors are shown in parenthesis.
Dependent variable is ln(fuel cost per mile).
Columns (1) and (2) are first stage estimations corresponding to the IV estimation shown in Table 1.2 and Table 1.3.
Columns (1) and (2) are first stage estimations corresponding to the robustness check using alternative IV shown in Table A.6.

A.3 Regional Division by EIA

Figure A.1: Map of regional division in the U.S.



Source: U.S. Energy Information Administration Form EIA-878

A.4 Heterogeneity of Responsiveness by Other Categories

A.4.1 By operator class

There are generally three operator classes, for-hire, private and rental. *For-hire* trucks are provided by companies or individuals who own the trucks. An individual who not only owns the truck, but also drives it for compensation, is referred as an "owner operator." A for-hire truck is required for a commercial vehicle DOT (Department of Transportation) number. As shown in Figure A.2, about half of the combination trucks in my sample are for-hire trucks, while 85% of the vocational vehicles are operated privately. *Private* trucks are used for business solely for the companies that own the trucks. In some cases, private trucks may remain privately licensed if they are not exclusively for business use. The third operator class is rental. *Rental* trucks only comprise a small percentage of my sample, about 2% for both groups. Typically, these are moving trucks for daily rental. Driving service is usually not provided by truck rental companies.

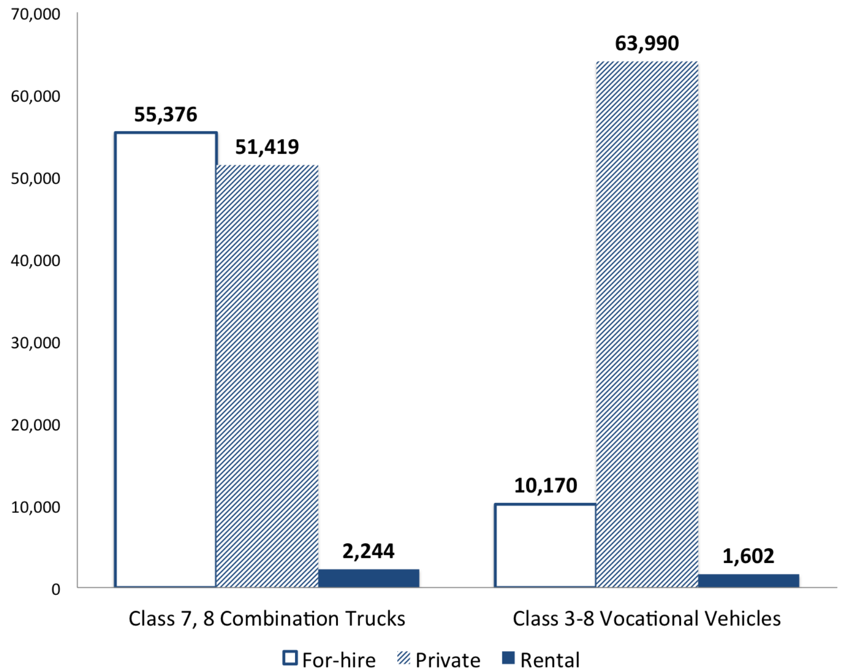
As shown in Table A.2, for combination trucks, for-hire trucks are the most responsive to fuel costs among the three operator classes. In particular, a 10% increase in fuel cost per mile reduces VMT of for-hire trucks by 2.57%, and private trucks by 2.20%. Since for-hire truck owners have the flexibility to choose cargo, schedules and routes, it is not surprising that they are the most responsive to changes in fuel costs. As for vocational vehicles, for-hire vehicles appear to be less sensitive

Table A.2: Estimation Results by Operator Class

Dependent variable:	ln(VMT)		ln(PD)	
	Combination	Vocational	Combination	Vocational
	(1)	(2)	(3)	(4)
Elasticities by operator class:				
For-hire	-0.257***	-0.207***	-0.493***	-0.412***
	(0.0393)	(0.0230)	(0.0330)	(0.0419)
Private	-0.220***	-0.285***	-0.386***	-0.344***
	(0.0346)	(0.0148)	(0.0307)	(0.0167)
Rental	-0.194**	-0.287***	-0.250*	-0.601***
	(0.0827)	(0.0480)	(0.148)	(0.0573)
Control variables				
ln(average vehicle weight)	0.408***	0.239***	2.529***	1.933***
	(0.0223)	(0.0191)	(0.0282)	(0.0398)
ln(odometer reading)	0.484***	0.484***	0.481***	0.510***
	(0.00706)	(0.0174)	(0.00522)	(0.0184)
ln(state GDP)	0.0780*	-0.00331	0.0669**	0.0356
	(0.0406)	(0.0617)	(0.0331)	(0.0723)
Survey year FE?	Yes	Yes	Yes	Yes
Home base state FE?	Yes	Yes	Yes	Yes
Other truck characteristics?	Yes	Yes	Yes	Yes
Business and operational characteristics?	Yes	Yes	Yes	Yes
No. of observation	109039	75762	109039	75762
Adjusted R^2	0.551	0.427	0.681	0.562

Note: $^{*}: p < 0.1$; $^{**}: p < 0.05$; $^{***}: p < 0.01$
All standard errors are clustered at the level of home base regions and shown in parentheses.
In each regression, operator class dummy variables are interacted with ln(fuel cost per mile). The elasticity for a particular operator class is the sum of coefficients of the interaction term and ln(fuel cost per mile); the robust standard error is calculated based on the linear combination correspondingly.

Figure A.2: Distribution of Trucks by Operator Class



to fuel costs than private vehicles. Columns (3) and (4) provide the estimated elasticities of payload distance by operator class. The elasticities are greater in magnitude, showing that payload is also negatively affected by increase in fuel costs. Such effect is even more obvious for for-hire vocational vehicles, as the elasticity of payload distance is almost double the elasticity of VMT.

A.4.2 By Fleet Size

Are truck owners or fleet managers assigning trips strategically to trucks based on their fuel costs? If so, trucks in a large fleet have more flexibility in substitution. I should expect them to be more responsive to changes in fuel costs than those in

Table A.3: Number of Trucks by Fleet Size

	Combination Trucks	Vocational Vehicles
1	22,372	11,288
2 to 5	17,719	23,509
6 to 20	22,236	23,415
21 or more	51,137	25,758
Total	113,464	83,970

Data source: U.S. Vehicle Inventory and Use Survey (1982-2002).

a small fleet. In VIUS, the size of fleet is categorized into four bins.[1] The number of truck counts in each bin is presented in Table A.3. While combination trucks are spread relatively evenly in fleets of different sizes, about 70% of vocational vehicles are in relatively small fleets that have fewer than 20 trucks.

I interact fleet size dummy variables with the natural log of per-mile fuel cost, and add the interaction terms to the estimation equation specified in equations (1.4) and (1.6) to estimate the elasticities of VMT and payload distance with respect to fuel costs. The estimates of interest are listed in Table A.4. In general, both VMT and payload distance are more elastic to fuel cost per mile as fleet size increases. This general trend, with a few exceptions, appears to confirm my expectations. For combination trucks, the elasticity of VMT in a fleet with 21 or more trucks is more than the elasticity in a single-truck fleet by about 75%. Vocational vehicles in a large fleet with more than 21 trucks reduce VMT by about 2.89% when per-mile fuel cost increases by 10%, while a one-vehicle fleet responds only by 2.06%. The estimation results of payload distance tell a similar story. As shown columns (3)

[1]The categorization for fleet size is similar, yet not exactly the same, across the survey years. Some adjustments are made to make the grouping consistent.

Table A.4: Estimation Results by Fleet Size

Dependent variable:	ln(VMT)		ln(PD)	
	Combination	Vocational	Combination	Vocational
	(1)	(2)	(3)	(4)
Elasticities by fleet size:				
1	-0.104**	-0.203***	-0.279***	-0.218***
	(0.0437)	(0.0189)	(0.0528)	(0.0297)
2 to 5	-0.157***	-0.329***	-0.302***	-0.401***
	(0.0281)	(0.0149)	(0.0282)	0.0178
6 to 20	-0.277***	-0.255***	-0.388***	-0.358***
	(0.0316)	(0.0117)	(0.0332)	0.0249
21 or more	-0.313***	-0.271***	-0.577***	-0.425***
	(0.0533)	(0.0238)	(0.052)	0.0338
Control variables				
ln(average vehicle weight)	0.405***	0.216***	2.542***	1.938***
	(0.0224)	(0.0155)	(0.0274)	(0.0384)
ln(odometer reading)	0.487***	0.489***	0.484***	0.512***
	(0.00753)	(0.0168)	(0.00549)	(0.0183)
ln(state GDP)	0.0814*	0.0130	0.0662**	0.0434
	(0.0434)	(0.0618)	(0.0326)	(0.0755)
Survey year FE?	Yes	Yes	Yes	Yes
Home base state FE?	Yes	Yes	Yes	Yes
Other truck characteristics?	Yes	Yes	Yes	Yes
Business and operational characteristics?	Yes	Yes	Yes	Yes
No. of observation	109,039	75,762	109,039	75,762
Adjusted R^2	0.548	0.425	0.679	0.560

Note: $^{*}: p < 0.1$; $^{**}: p < 0.05$; $^{***}: p < 0.01$
All standard errors are clustered at the level of home base regions and shown in parentheses.
In each regression, fleet size dummy variables are interacted with ln(fuel cost per mile). The elasticity for a particular operator class is the sum of coefficients of the interaction term and ln(fuel cost per mile); the robust standard error is calculated based on the linear combination correspondingly.
All estimations use the 2SLS estimation approach to control for the plausible endogeneity of fuel costs.

and (4), elasticities (in absolute values) are the highest in a fleet with more than 21 trucks. All estimates are highly statistically significant.

A.5 Robustness Checks and the Falsification Test: Details

Table A.5: Robustness check 1: estimate with aggregate data

Dependent variable:	ln(VMT)		ln(PD)	
	Combination	Vocational	Combination	Vocational
Overall elasticities	-0.211***	-0.262***	-0.393***	-0.350***
	(0.0316)	(0.0254)	(0.0322)	(0.0312)
Elasticities by GVWR:				
GVWR = 3		-0.271***		-0.543***
		(0.0860)		(0.145)
GVWR = 4		-0.361**		-0.312
		(0.182)		(0.266)
GVWR = 5		-0.452***		-0.571***
		(0.166)		(0.207)
GVWR = 6		-0.281***		-0.287***
		(0.0388)		(0.0543)
GVWR = 7	-0.380***	-0.270***	-0.433***	-0.341***
	(0.0595)	(0.0405)	(0.0719)	(0.0482)
GVWR = 8	-0.184***	-0.199***	-0.385***	-0.285***
	(0.0332)	(0.0291)	(0.0332)	(0.0329)
Elasticities by business sector:				
Agriculture or forestry	0.129*	-0.304***	-0.0852	-0.272***
	(0.0726)	(0.0493)	(0.0728)	(0.0517)
Business and personal service	-0.371**	-0.270***	-0.596***	-0.352***
	(0.148)	(0.0362)	(0.166)	(0.0503)
Construction	-0.258***	-0.232***	-0.368***	-0.336***
	(0.0677)	(0.0359)	(0.0867)	(0.0433)
For-hire transportation	-0.256***	-0.248***	-0.537***	-0.440***
	(0.0350)	(0.0397)	(0.0456)	(0.0476)
Manufacturing	-0.402***	-0.266***	-0.521***	-0.325***
	(0.0594)	(0.0566)	(0.0743)	(0.0759)
Mining or quarrying	-0.231**	-0.081	-0.329***	-0.0297
	(0.112)	(0.0847)	(0.124)	(0.140)
Rental or contractor	-0.325***	-0.312***	-0.392***	-0.376***
	(0.0968)	(0.0476)	(0.142)	(0.0605)
Retail and wholesale trade	-0.249***	-0.271***	-0.432***	-0.381***
	(0.0534)	(0.0302)	(0.0501)	(0.0446)
Other	-0.198***	-0.291***	-0.135	-0.532***
	(0.205)	(0.0415)	(0.167)	(0.0693)

Note: $^{*}: p < 0.1$; $^{**}: p < 0.05$; $^{***}: p < 0.01$
All standard errors, shown in parentheses, are clustered at the level of home base states and survey years.
2SLS estimation method is used in all regressions.

Table A.6: Robustness Check 2: Estimate with Alternative IV

Dependent variable:	ln(VMT)		ln(PD)	
	Combination	Vocational	Combination	Vocational
Overall elasticities	-0.225***	-0.269***	-0.419***	-0.359***
	(0.0313)	(0.0210)	(0.0317)	(0.0256)
Elasticities by GVWR:				
GVWR = 3		-0.172**		-0.366***
		(0.0864)		(0.139)
GVWR = 4		-0.385**		-0.146
		(0.187)		(0.278)
GVWR = 5		-0.462***		-0.689***
		(0.178)		(0.227)
GVWR = 6		-0.263***		-0.281***
		(0.0372)		(0.0553)
GVWR = 7	-0.395***	-0.181***	-0.563***	-0.254***
	(0.0542)	(0.0332)	(0.0625)	(0.0475)
GVWR = 8	-0.200***	-0.239***	-0.395***	-0.322***
	(0.0336)	(0.0236)	(0.0337)	(0.0265)
Elasticities by business sector:				
Agriculture or forestry	0.221***	-0.239***	0.0192	-0.230***
	(0.0753)	(0.0468)	(0.0688)	(0.0524)
Business and personal service	-0.501***	-0.342***	-0.609***	-0.404***
	(0.126)	(0.0309)	(0.163)	(0.0506)
Construction	-0.372***	-0.303***	-0.524***	-0.399***
	(0.072)	(0.0317)	(0.0913)	(0.0360)
For-hire transportation	-0.332***	-0.273***	-0.551***	-0.524***
	(0.0374)	(0.0341)	(0.0443)	(0.0456)
Manufacturing	-0.233***	-0.236***	-0.402***	-0.317***
	(0.0485)	(0.0524)	(0.0630)	(0.0685)
Mining or quarrying	-0.405***	-0.127	-0.513***	-0.152
	(0.131)	(0.0829)	(0.135)	(0.110)
Rental or contractor	-0.248***	-0.342***	-0.410***	-0.476***
	(0.0775)	(0.0469)	(0.113)	(0.0639)
Retail and wholesale trade	-0.235***	-0.207***	-0.493***	-0.274***
	(0.0521)	(0.0270)	(0.0546)	(0.0391)
Other	-0.188	-0.257***	-0.148	-0.473***
	(0.155)	(0.0372)	(0.176)	(0.0573)

Note: $^{*}: p < 0.1$; $^{**}: p < 0.05$; $^{***}: p < 0.01$
All standard errors, shown in parentheses, are clustered at the level of home base states and survey years.
2SLS estimation method is used in all regressions.

Table A.7: Falsification Test: Randomize Fuel Cost per Mile

Dependent variable:	ln(VMT)		ln(PD)	
	Combination	Vocational	Combination	Vocational
Overall elasticities	-0.0124	-0.0176	-0.0157	-0.00546
	(0.00969)	(0.0151)	(0.0119)	(0.0160)
Elasticities by GVWR:				
GVWR = 3		-0.0871*		-0.211**
		(0.0480)		(0.0892)
GVWR = 4		-0.0846		-0.0478
		(0.0851)		(0.137)
GVWR = 5		0.0588		-0.0274
		(0.109)		(0.163)
GVWR = 6		-0.00639		0.0241
		(0.0303)		(0.0416)
GVWR = 7	-0.0216	-0.0255	-0.00869	0.0212
	(0.0377)	(0.0369)	(0.0409)	(0.0508)
GVWR = 8	-0.0116	-0.0142	-0.0162	-0.00702
	(0.0107)	(0.0190)	(0.0129)	(0.0206)
Elasticities by business sector:				
Agriculture or forestry	-0.0222	-0.0355	-0.0266	-0.00551
	(0.0335)	(0.0435)	(0.0373)	(0.0473)
Business and personal service	0.0573	0.0533	0.0697	-0.0185
	(0.0653)	(0.0458)	(0.0835)	(0.0514)
Construction	0.0102	-0.0249	-0.0168	-0.0159
	(0.0399)	(0.0301)	(0.0486)	(0.0338)
For-hire transportation	-0.00293	-0.0554	-0.00819	-0.00792
	(0.00987)	(0.0369)	(0.0133)	(0.0434)
Manufacturing	-0.0256	-0.0761	-0.0215	-0.0195
	(0.0450)	(0.0614)	(0.0493)	(0.0764)
Mining or quarrying	-0.0392	-0.0326	0.0593	0.0337
	(0.0652)	(0.0699)	(0.0827)	(0.0980)
Rental or contractor	-0.0888	-0.00817	-0.0882	-0.0108
	(0.0627)	(0.0479)	(0.0679)	(0.0777)
Retail and wholesale trade	-0.0352	-0.0255	-0.0451	-0.0185
	(0.0238)	(0.0290)	(0.0276)	(0.0298)
Other	-0.0338	0.0852**	0.0185	0.136*
	(0.150)	(0.0411)	(0.141)	(0.0814)

Note: $^{*}: p < 0.1$; $^{**}: p < 0.05$; $^{***}: p < 0.01$

All standard errors, shown in parentheses, are clustered at the level of home base states and survey years.

2SLS estimation method is used in all regressions.

A.6 Derive the Expression of Marginal Welfare Effect and Optimal Taxes

A.6.1 Derive Marginal Welfare Effects

A household chooses R_i, Y, A, subject to time and budget constraints (equation 1.9 and 1.10, to maximize the utility (equation 1.7). The indirect utility function can be written as follows.

$$\tilde{u} = u(R_i, Y, A, \pi A, Z) + \lambda\Big[I + LST - \sum_i p_i R_i - Y - (t_G + P_G) f_G A\Big] \tag{A.1}$$

Write the first order conditions of the household maximization problem.

$$\frac{\partial u}{\partial R_i} = \lambda p_i \tag{A.2}$$

$$u_A = \pi u_\Pi = \lambda(t_G + P_G) f_G \tag{A.3}$$

$$u_Y - \lambda = 0 \tag{A.4}$$

Total differentiating indirect utility with respect to diesel tax t_i yields

$$\frac{1}{\lambda}\frac{d\tilde{u}}{dt_i} = \frac{A}{\lambda} u_\Pi \frac{d\pi}{dt_i} + \frac{u_Z}{\lambda}\frac{dZ}{dt_i} + \frac{dLST}{dt_i} - R_i \frac{dp_i^R}{dt_i} \tag{A.5}$$

Total differentiating equation (1.12) with respect to diesel tax t_i yields

$$\frac{dp_i^R}{dt_i} = q_i + \frac{\omega}{W_i}\frac{d\pi}{dt_i}\ . \tag{A.6}$$

Total differentiating equation (1.14) with respect to diesel tax t_i yields

$$\frac{d\pi}{dt_i} = \pi_{T_i}\frac{dT_i}{dt_i} + \pi_A \frac{dA}{dt_i}\ . \tag{A.7}$$

Total differentiating equation (1.16) with respect to diesel tax t_i yields

$$\frac{dZ}{dt_i} = z^A \frac{dA}{dt_i} + z_i^F \frac{dF_i}{dt_i} + z_i^T \frac{dT_i}{dt_i} \tag{A.8}$$

Total differentiating equation (1.15) and equation (1.17)with respect to diesel tax t_i yields

$$\frac{dLST}{dt_i} = F_i + t_i \frac{dF_i}{dt_i} + t_G f_G \frac{dA}{dt_i} - z_i^L \frac{dR_i}{dt_i} \tag{A.9}$$

Substituting (A.6), (A.7), (A.8) and (A.9) into (A.5) and rearranging terms give the expression of marginal welfare effects shown in (1.18)-(1.21).

A.6.2 Derive Optimal Taxes

Set the marginal welfare effect (equation 1.18) to zero, and rearrange terms.

$$t_i^* = MEC_i^F + MEC_i^T \frac{dT/dt_i}{dF_i/dt_i} + (MEC_i^A - t_G f_G) \frac{dA/dt_i}{dF_i/dt_i} \tag{A.10}$$

Multiplying both the numerator and the denominator of $\frac{dT/dt_i}{dF_i/dt_i}$ by $\frac{T}{P_D+t_i}$, and substituting in the definition of elasticities, congestion offset, and passenger car equivalent give equation (1.22)

A.6.3 Derive ε_i^f and ε_i^F

The elasticity of VMT with respect to per-mile fuel cost η_i^Tcan be decomposed using the chain rule and the definition of per-mile fuel cost.

$$\begin{aligned} \eta_i^T &= \frac{dVMT}{d[(P_D + t_i) \cdot f_i]} \frac{(P_D + t_i) \cdot f_i}{f_i} \\ \frac{1}{\eta_i^T} &= \frac{1}{\varepsilon_i^T} + \frac{\varepsilon_i^f}{\varepsilon_i^T} \end{aligned} \tag{A.11}$$

Rearranging terms gives equation (1.25).

Similarly, the elasticity of fuel use with respect to diesel price can be decomposed into two parts using the chain rule and $F_i = T_i \cdot f_i$ by definition.

$$
\begin{aligned}
\varepsilon_i^F &= \frac{d(T_i f_i)}{d(P_D + t_i)} \frac{P_D + t_i}{T_i f_i} \\
&= \frac{T_i df_i + f_i dT_i}{d(P_D + t_i)} \frac{P_D + t_i}{T_i f_i} \\
&= \varepsilon_i^f + \varepsilon_i^T
\end{aligned}
\tag{A.12}
$$

Appendix B: Appendix for Chapter 2

B.1 Engine displacement and horsepower

Engine displacement (CID) is the volume swept by all the pistons inside the cylinders of a reciprocating engine in a single movement from top dead center to bottom dead center. It is determined by the area of the bore, the length of the stroke and the number of cylinders. The formula is as follows.

$$\text{Displacement} = \tfrac{\pi}{4} \times \text{bore}^2 \times \text{stroke} \times \text{number of cylinders}$$

Generally speaking, engine displacement indicates the volume of the cylinders, which loosely defines the size of explosion inside the cylinders; therefore it suggests the engine's power. While other factors, for example, turbochargers and superchargers, can also affect the size of explosion, engine displacement is an important indicator of engine's power and closely related to the performance of the engine.

Horsepower (HP) is a measurement of power. 1 HP is the equivalent of 33,000 ft/lbfs per minute. It represents the torque at the wheels, *i.e.*, the power to rotate wheels and accelerate the vehicle. Horsepower is a man-made number. It is defined as the product of torque at the engine and revolutions per minute (RPM) divided by

5252. Torque at the engine is the rotational force generated by the engine. Torque at the wheels is the combination of torque at the engine with the torque magnification given by the transmission through gearing. (Note that torque at the engine and torque at the wheels are different concepts.)

In a nutshell, while both horsepower and engine displacement indicate the engine's power, they are different measurements. Engine displacement focuses on the physical size of the engine; horsepower is a performance indicator. They are closely related, as horsepower is largely determined by the torque (at the engine), which is generated by the engine; and the engine's power is largely determined by the size of explosion inside the cylinders'engine displacement.

From 1977 to 2002, there are 6 years of data from Vehicle Inventory and Use Survey (VIUS) that are publicly available. Information regarding engine displacement is documented in all years of survey; however, data of horsepower are available only in survey year 1977, 1982 and 1987. The questions asked in the survey about these two variables are as follows.

- Engine displacement: What is the displacement of the engine in cubic inches?
- Horsepower: What is the horsepower rating of your engine?

The format of the data is either numerical or categorical. In particular,

Survey year	1977	1982	1987
Engine displacement	Numerical	Categorical	Categorical
Horsepower	Numerical	Numerical	Categorical

In survey year 1977, the correlation between engine displacement and horsepower is about 0.67. If we aggregate the data by model year and vehicle make, the correlation goes up to 0.81.

In survey year 1982, engine displacement divides the range of 0 to 1500 into 21 bins. I replace the CID with the mid point of each bin and derive its correlation with the numerical horsepower reported in the data. The correlation is about 0.86. If we aggregate the data by model year and vehicle make, the correlation is 0.98.

In survey year 1987, both CID and horsepower are documented categorically. The categories of CID are the same as in 1982, while the data of horsepower are shown in 7 bins, with the rating ranging from 0 to 475. Again, I replace these two variables with the mid point of each bin and calculate the correlation at about 0.59. The correlation with aggregated data is about 0.91.

In each survey year, I plot the LOWESS smoothing graph for CID and horsepower against vehicle model year for class 7,8 combination trucks. As the graphs show, CID and horsepower move closely together, indicating a strong positive correlation between these two variables.

Figure B.1: Relationship between CID and horsepower - data from survey year 1977

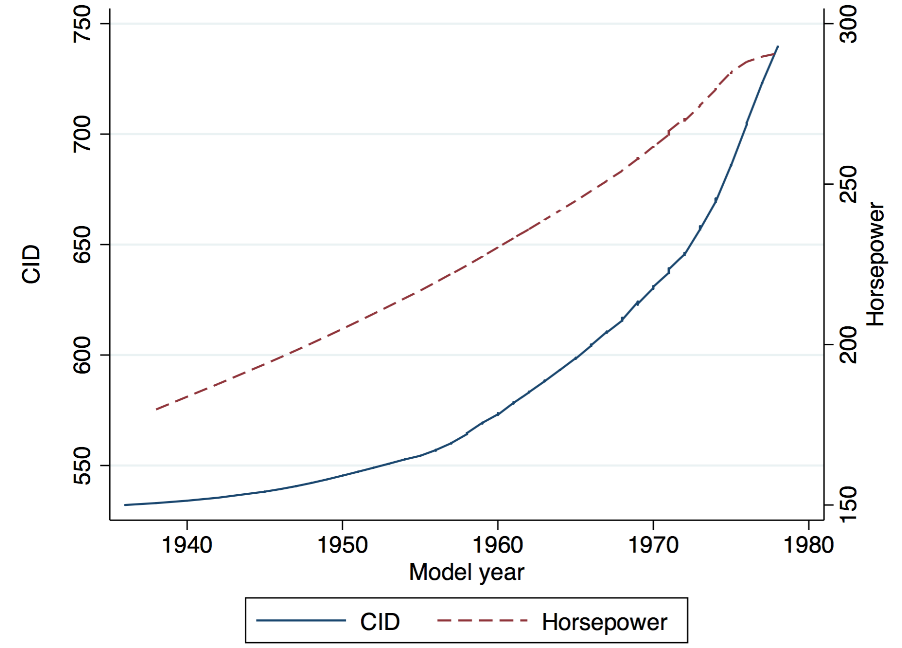


Figure B.2: Relationship between CID and horsepower - data from survey year 1982

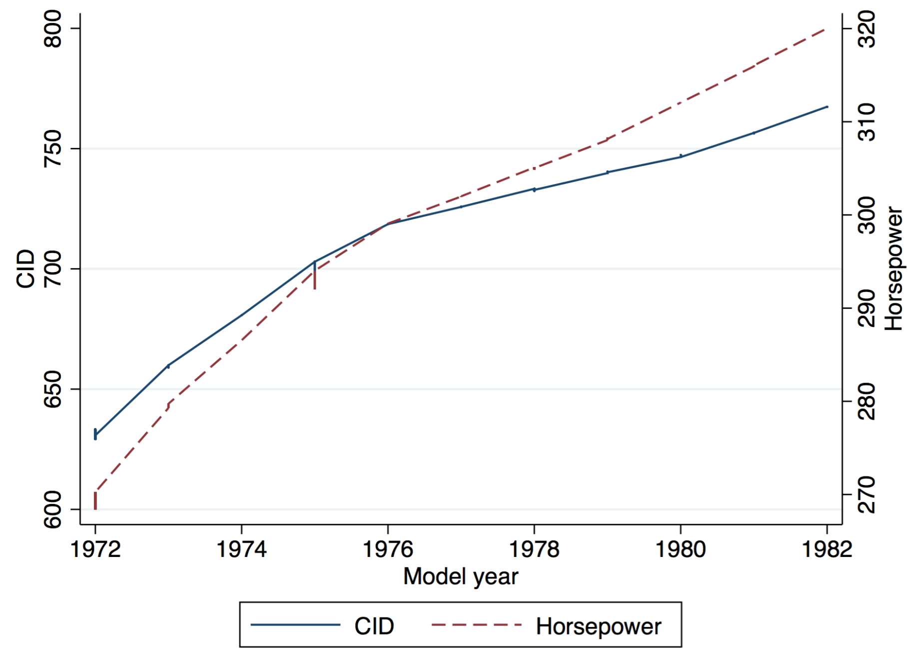
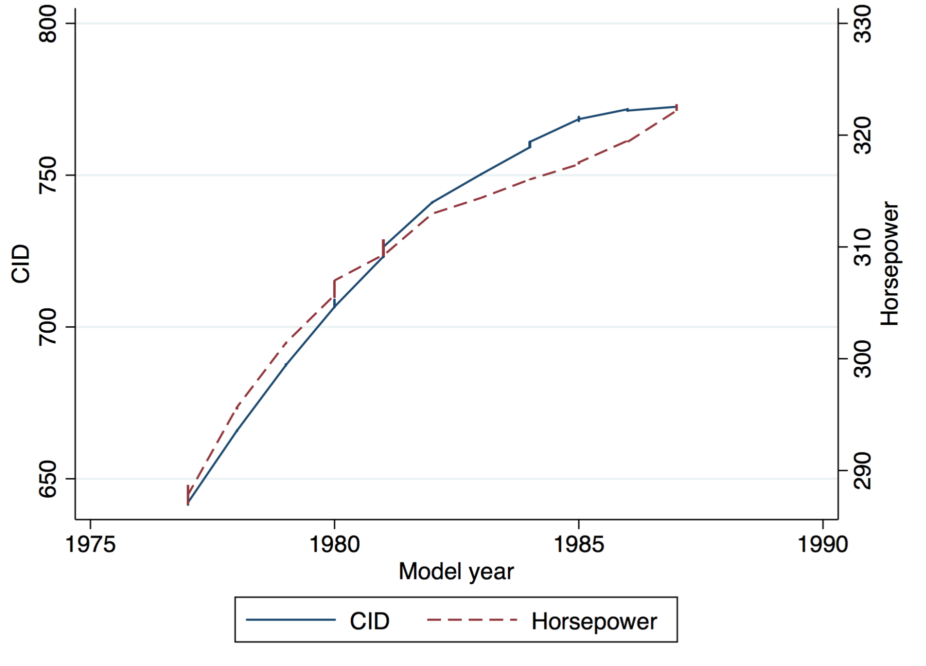


Figure B.3: Relationship between CID and horsepower - data from survey year 1987



To conclude, although it would make our study more comprehensive had we known the horsepower and torque in all survey years, we believe engine displacement serves as a good approximate to engine power given the strong correlation between CID and horsepower as explained above.

Appendix C: Appendix for Chapter 3

C.1 Engine Model Year Schedule for Light-duty Vehicles

Table C.1: Engine Model Year Schedule for Lighter Trucks

Engine Model Year	Replacement Date
1995 and older	January 1, 2015
1996	January 1, 2016
1997	January 1, 2017
1998	January 1, 2018
1999	January 1, 2019
2003 and older	January 1, 2020
2004-2006	January 1, 2021
2007-2009	January 1, 2023

C.2 Enforcement

In California, the emission regulation to trucking firms are enforced through two programs – Heavy-Duty Vehicle Inspection Program (HDVIP or roadside program) and Periodic Smoke Inspection Program (PSIP or fleet program). The roadside program was first became operative in November 1991. Heavy-duty vehicles are tested by CARB inspectors at various roadside locations to identify vehicles that emit excessive smoke or have defective or tampered emission control system. This program was interrupted from October 1993 to February 1996 due to technical reasons. The Periodic Smoke Inspection Program (the fleet program) was became operative in January 1996 with a 15-month phase-in schedule.[1] Starting July 1, 1998, all trucks are required to take this annual inspection.[2]

[1]First 25% of an operator's fleet have to be tested by July 1, 1996.

[2]This inspection is currently conducted by California Highway Patrol.

C.3 RD Design Results With Linear Specification

Table C.2: Estimation Results: Regression Discontinuity Design With Linear Specification

Dependent variable: (in log)	Truck population (millions) (1)	VMT (million miles/day) (2)	Fuel consumption (gallons/mile) (3)	NO_x emissions (1000 tons/day) (4)
β_1	0.267***	0.287***	0.261***	0.236***
	(0.0342)	(0.0343)	(0.0343)	(0.0343)
ρ	-0.506***	-0.543***	-0.514***	-0.522***
	(0.0822)	(0.0824)	(0.0824)	(0.0825)
γ_1	-0.0749*	-0.0496	-0.0126	0.0540
	(0.0401)	(0.0402)	(0.0402)	(0.0402)
N	5697	5697	5697	5697
Adj. R^2	0.804	0.807	0.807	0.804

Note: $^{*} : p < 0.1$; $^{**} : p < 0.05$; $^{***} : p < 0.01$
Vehicle class fixed effects and county fixed effects are included in all regressions.

C.4 Additional graphical evidence

C.5 Business-as-usual Replacement of Vehicles Over Time

Naturally, vehicles are replaced over time. In figure C.4, we provide evidence of heavy-duty trucks with model year from 1996 to 1999 being replaced from calendar year 2004 to 2011. The business-as-usual attrition rate, illustrated as the slope, can be estimated using an OLS approach.

Figure C.1: Percentage change in VMT from 2011 to 2012

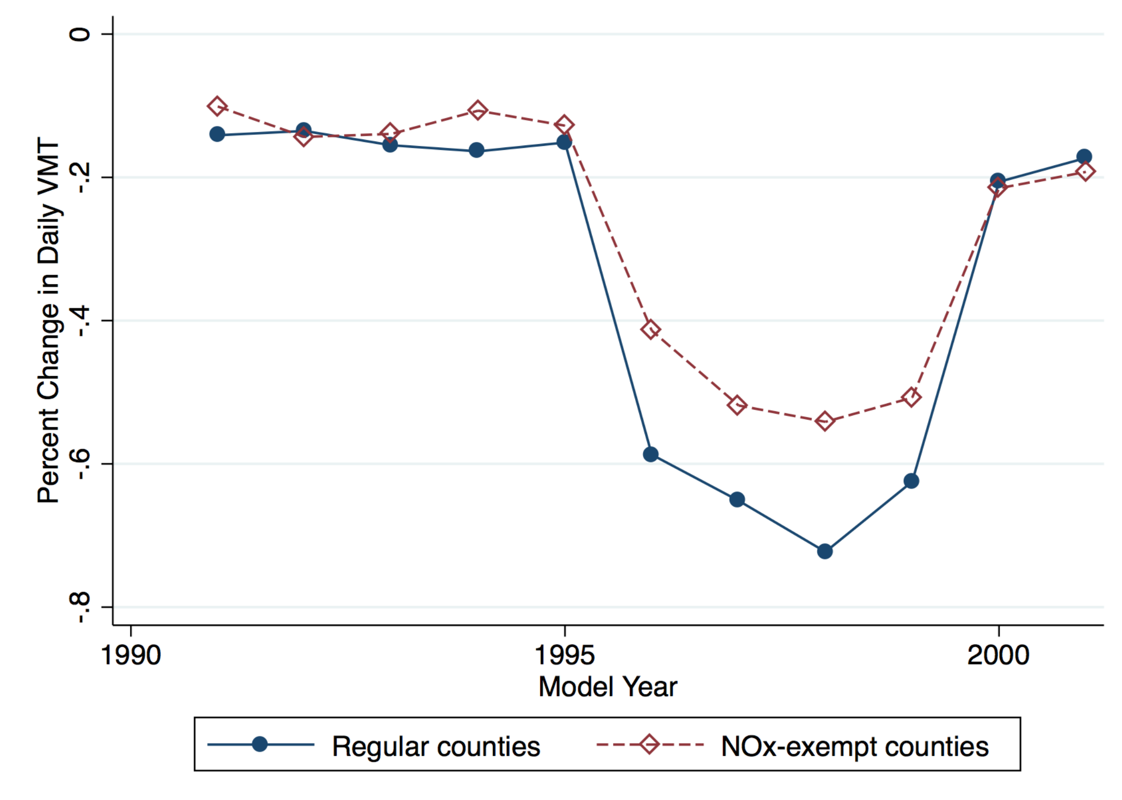


Figure C.2: Percentage change in fuel consumption from 2011 to 2012

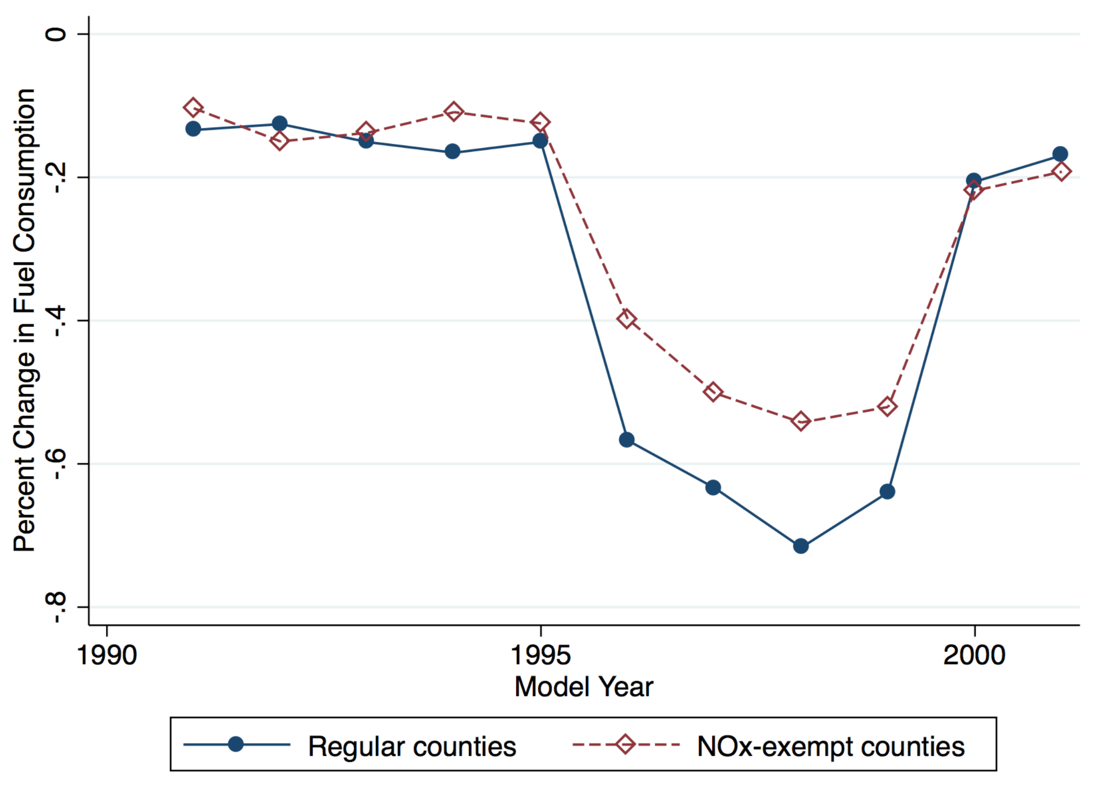


Figure C.3: Percentage change in CO_2 emission from 2011 to 2012

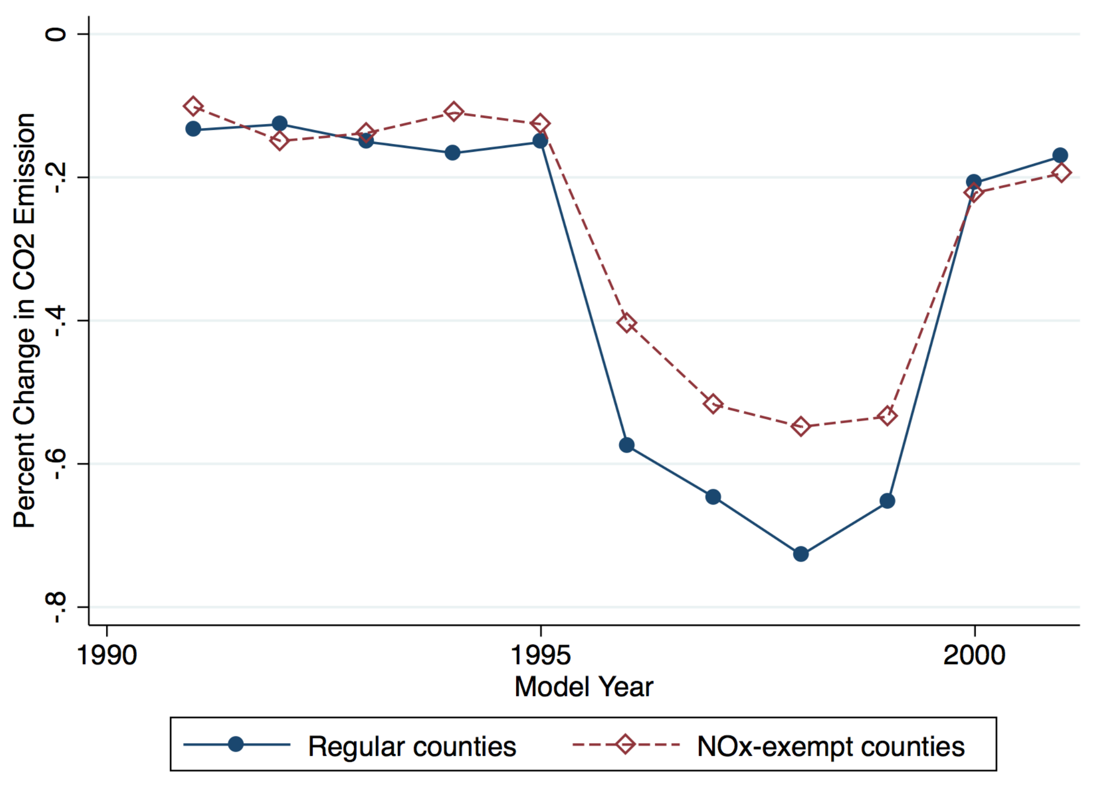
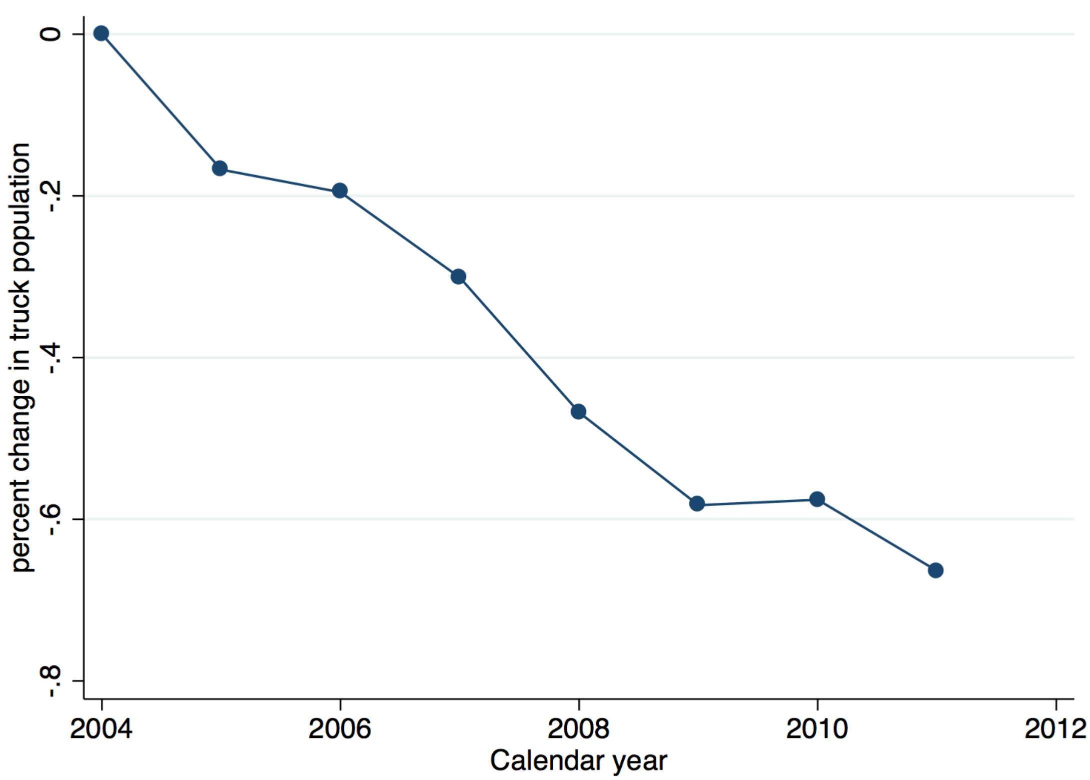


Figure C.4: Business-as-usual Replacement



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