Heterogeneous responses and differentiated taxes: evidence from the heavy-duty trucking industry in the U.S.

Jen Z. He*

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Abstract

In this paper, I exploit a rich vehicle-level micro dataset of U.S. heavy-duty trucking fleet to examine how truckers differentially respond to changes in per-mile fuel cost. The empirical results show that the medium-run elasticities of vehicle-miles-traveled are -0.23 for combination trucks and -0.27 for vocational vehicles; the 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, in particular, 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 of 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. The total tax paid by the trucking industry is reduced by 33 billion dollars.

*Jen Z. He: University of Maryland, Department of Agricultural and Resource Economics, 2200 Symons Hall, College Park, MD 20742. E-mail: zhenghe@umd.edu. My deepest gratitude is to my advisor, Dr. Sébastien Houde, for his support, encouragement and excellent suggestions. I thank Drs. Anna Alberini, Maureen Cropper, Andrew Sweeting, and Roberton C. Williams III from University of Maryland; Dr. Mathieu Dufour from Université du Québec en Outaouais; Drs. Virginia McConnell, Joshua Linn and Benjamin Leard from Resources for the Future; conference participants at 2015 AAEA Annual Meetings, 33rd USAEE/IAEE North American Conference, AREC Environmental-Resource Economics Workshop and AREC Graduate Student Poster Forum. I also benefit from discussion with Enoch Lee and Angela Harmon to improve the manuscript. All errors are mine.

1 Introduction

The trucking industry hauls about 70% of all freight in the United States. Although medium- and heavy-duty trucks only account for 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 stands, have been mostly technology-based and targeted at manufacturers. Emissions pricing policies have rarely been considered as policy instruments to reduce greenhouse gas emissions (Decker and Wohar, 2007; Knittel, 2011). Emission taxes provide a combination of incentives with flexibility - a merit lacked 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 cost. 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 (Dahl, 2012; Barla et al., 2014; Ramli and Graham, 2014). At the regional level, Greene (1984) finds that diesel fuel consumption is inelastic to fuel cost. 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) applies a Partial Adjustment Model to national diesel fuel data in Canada and finds the elasticities at -0.43 for the short run and -0.80 for the long run. Adenbaum et al. (2015) takes advantage of disaggregated data and finds 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) uses truck-level survey data to estimate the effect of higher fuel economy on driving distance, and suggests 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 per-mile fuel cost. 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 per-mile fuel cost) 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 heavy-duty trucking industry as both driving distance and payload weight contribute to total fuel consumption.

An important goal of this paper to calculate 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. It 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 extends such 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 by a factor of 10 or more (Goulder and Williams, 2003). Calthrop et al. (2007) applies 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 offset effect by automobiles is adopted by Parry (2008), in which he estimates the optimal uniform diesel tax for heavy-duty trucks in the U.S with parameters of elasticities drawn from the 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 distributional effects of fuel taxes. For example, West (2004) estimates the effects of gasoline taxes among different income groups using a discrete-continuous choice model; Bento et al. (2009) investigate the distributional effects of gasoline taxes among not only income, but also 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 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. Section 2 explains the data and provides descriptive analysis. Section 3 discusses the empirical model and the identification strategy. Section 4 presents the estimation results and the heterogeneity in responsiveness. Section 5 provides robustness and falsification checks. Section 6 discusses the optimal taxes and welfare analysis. Section 7 concludes.

2 Data

2.1 Data sources

The primary source of data is Vehicle Use and Inventory 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 trucks' weights and body types. In 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 to truck owners if they failed to respond in the first round. Both sample size and response rate stayed relatively stable across all survey years.[2]

VIUS provides detailed information of the U.S. trucking fleet for both physical characteristics of the trucks and their operational features. 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

[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.

[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%.

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 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*[4] refer to straight trucks with gross vehicle weight greater than 10,000 pounds. 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 are missing critical variables after imputation[6], or 7) the data are miscoded.[7]

The fuel cost of per-mile driving, measured in dollars/mile, is derived from taking

[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.

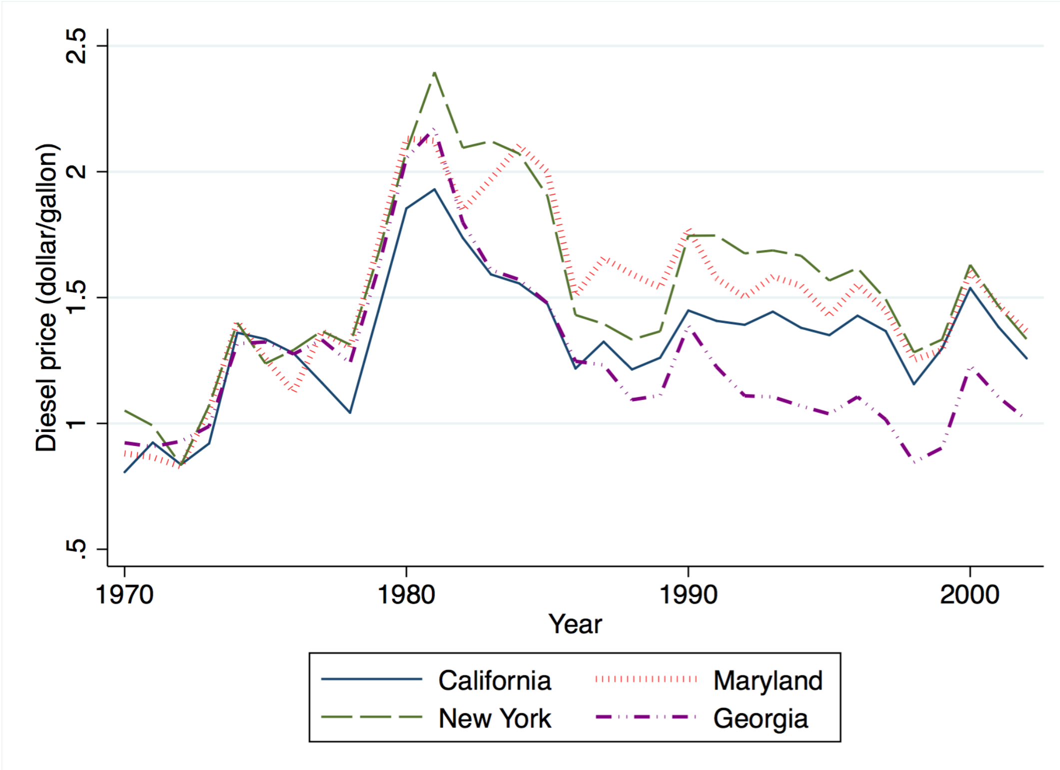
[4] Class 2b (gross vehicle weight from 8,501 pounds to 10,000 pounds) straight trucks are also classified as heavy-duty vocational vehicles in RIA. Unfortunately, I cannot separate Class 2b from Class 2 in the data set.

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

[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 5000 pounds for combination trucks or 1000 pounds for vocational vehicles.

Figure 1: Diesel fuel price (in 2002$) for selected states

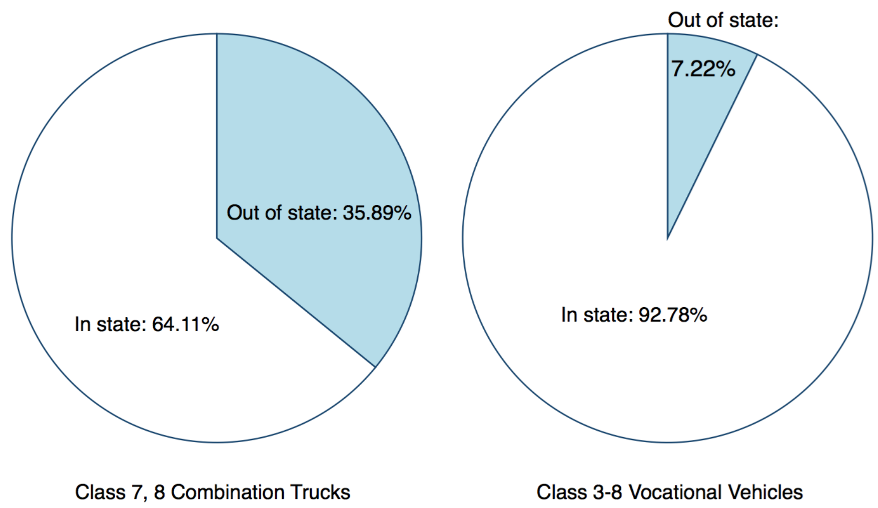


the ratio of diesel price and the fuel economy.[8] Annual diesel prices at the state level are approximated by the inflation adjusted distillate fuel prices published by the United States Energy Information Administration (EIA), as well as federal and state fuel tax rates published in Highway Statistics by 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; the other is mostly determined by the difference in travel distance among truckers. Figure 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 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.

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

Figure 2: Allocation of trips between in-state and out-of-state



The trip-based diesel fuel price is the average of these two situations weighted by the percentage of trips. Figure 2 shows the average percentage of these two situations for combination trucks and vocational vehicles. The solid bars represent the average percentage of in-state trips, and the white bars show the percentage of out-of-state ones. While vocational vehicles mostly stay in their home base states, 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 vehicles.

2.2 Summary Statistics

Table 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 of that for 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.

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 aerody-

Table 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 (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
Other	0.15	0.36	0.11	0.31

Notes: 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 Appendix A. Other characteristics not presented in the table include number of cylinders and engine displacement.

namic 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 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 a 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.

3 Estimation strategy

3.1 Model

The decision of VMT can be considered as an optimal outcome of a profit-maximizing problem. Suppose a driver with truck i in state s in year t receives a marginal revenue of P_b for each mile (or ton-mile as discussed below) of delivery services in business b. The cost of operation includes fuel cost and maintenance cost. The per-mile fuel cost c_i can be derived from dividing fuel price p_i by the average MPG (note 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,

$$\text{VMT}_i = F(c_i, \boldsymbol{X_i}, \boldsymbol{Z_i}, \theta_s, \tau_t, \phi_b) \ . \tag{1}$$

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 stable.

Suppose function F takes the parametric form as follows.

$$\text{VMT}_i = c_i^{\gamma} \exp(\beta_0 + \boldsymbol{X_i}'\boldsymbol{\beta_X} + \boldsymbol{Z_i}'\boldsymbol{\beta_Z} + \theta_s + \tau_t + \phi_b + \epsilon_i), \tag{2}$$

in which c_i is the fuel cost of per-mile driving, derived from the following calculation.

$$c_i = \frac{p_i}{MPG} \tag{3}$$

ϵ_i is assumed to be a mean-zero stochastic error term. Taking the natural logarithm on both sides of equation (2), I derive the specification for empirical estimation.

$$\ln \text{VMT}_i = \beta_0 + \gamma \ln c_i + \boldsymbol{X_i}'\boldsymbol{\beta_X} + \boldsymbol{Z_i}'\boldsymbol{\beta_Z} + \theta_s + \tau_t + \phi_b + \epsilon_i \tag{4}$$

γ can be interpreted as the medium-run elasticity of VMT with respect to fuel cost of per-mile driving.

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.

$$\text{PD}_i = \text{VMT}_i \cdot w_i \cdot \xi_i \tag{5}$$

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 fuel cost of per-mile travel, I follow the same specification as in equation (4).

$$\ln \text{PD}_i = \alpha_0 + \delta \ln c_i + \boldsymbol{X_i}'\boldsymbol{\alpha_X} + \boldsymbol{Z_i}'\boldsymbol{\alpha_Z} + \theta_s + \tau_t + \phi_b + \varepsilon_i \tag{6}$$

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

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 inverse causality between truck i's VMT and its own fuel efficiency (MPG_i), using individual MPG_i in equation (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, 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 expectation of VMT and factor such anticipation 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 boom or bust in a particular industry during the year in question. If, for example, construction industry is booming in California in 2002, it should increase demand for trucking on the west coast. Such shocks will be absorbed by the interaction terms. In fact, as shown in Table 2 and 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. 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 the 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. Clearly global oil price is correlated with local diesel fuel prices; however, it is unlikely that an individual trucker's operational decision would affect the global oil price. I provide the estimation results with the alternative instrument variable in section 5.2.

[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.

[10]In regressions, the instrument 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 B1 in Appendix B.

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 cost. 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 the 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]

4 Empirical results

4.1 Primary estimation results of elasticities

The primary results from estimating equation (4) are shown in Table (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 elasticities of VMT with respect to fuel cost of driving, estimated using ordinary least square (OLS) approach. To address the plausible endogeneity of fuel cost, I show the elasticities using two-stage least square approach in columns (2) and (5), with the instrumental variables (IV) being the average costs of per-mile driving in states that are not bordering with the home base states. The estimated medium-run elasticities of VMT are highly statistically significant. In general, vocational vehicles are more responsive to changes in cost of per-mile driving. To put the results in context, a 10% increase in fuel cost 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 are shown in the expected signs and remained relatively stable across specifications, serving as evidence of robustness. Interaction terms among business sectors, survey years and regions are included in columns (3) and (6). These specifications address concerns that as a group, drivers with similar trucks may experience similar expectations regarding driving which may affect vehicle choice, particularly regard-

[12] I adopt the regional division provided by the U.S. Energy Information Administration. See the map shown in Figure C1 in Appendix C.

[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.

Table 2: Primary estimation results of ln(VMT)

	Combination Trucks			Vocational Vehicles		
	OLS	IV	IV	OLS	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)
ln(cost of per-mile driving)	-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	83242
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 standard errors (in parentheses) in (1) and (4) are clustered at the level of home base states.

Standard errors in (2), (3), (5) and (6) are clustered at the level of home base 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.

ing 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 nearly the same. The robustness of the results ensures that the anticipation effect due to local and temporary boom or bust of an industry is small.

Table (3) presents the primary estimation results of elasticities of payload distance with respect to per-mile fuel cost. A 10% increase in 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 weight of

Table 3: Primary estimation results of payload distance

	Combination Trucks			Vocational Vehicles		
	OLS	IV	IV	OLS	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)
ln(cost of per-mile driving)	-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 standard errors (in parentheses) in (1) and (4) are clustered at the level of home base states.

Standard errors in (2), (3), (5) and (6) are clustered at the level of home base 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 decreases as cost of per-mile driving 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 the increase in fuel cost.

4.2 Heterogeneity in responsiveness

It is important to understand the heterogeneity in responsiveness to changes in fuel cost 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 the difference 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 cost, 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 cost. 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, there is no luxury for such substitution. 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 policy and compliance strategy accordingly. In the rest of this section, I explore the heterogeneity in responsiveness of VMT and payload distance to fuel cost 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 Appendix D.

4.2.1 Weight class

Gross vehicle weight rating (GVWR) is the most common method of 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 3, with additional interaction terms of GVWR dummies and fuel cost variables. 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 4, lighter combination trucks are generally more responsive to changes in fuel cost of per-mile driving. Facing a 10% increase in 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 business and with less flexibility in choice of routes and schedules.

Table 4: Estimation results 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 and operational characteristics?	Yes	Yes	Yes	Yes
No. of observation	113464	83970	109047	75829
Adjusted R^2	0.548	0.426	0.679	0.562

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

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

Table 5: Distribution of business sectors in 2002

Business sector	Combination trucks	Vocational vehicles
	(1)	(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

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 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 cost differently from one another. To examine such heterogeneity among business sectors, I estimate equation (4) and equation (6) with interaction terms of the nine business sector dummy variables with 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 6. All of these regressions apply IV approach to control for the plausible endogeneity of fuel cost. 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 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 due to the relatively rigid demand for truck transportation at mines. Surprisingly, combination trucks in agriculture or forestry are driven more as fuel cost rises. Columns (3) and (4) provide the hetero-

Table 6: Estimation results by business sector

Dependent variable:	ln(VMT)		ln(PD)	
	Combination	Vocational	Combination	Vocational
	(1)	(2)	(3)	(4)
Elasticity 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 and operational 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 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(cost of per-mile driving). The elasticity for a particular operator class is the sum of coefficients of the interaction term and ln(cost of per-mile driving); the robust standard error is calculated correspondingly based on the linear combination.

Table 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 standard errors (in parentheses) are clustered at the level of home base states and survey years.

geneous 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) in both VMT and PD than the averages shown in Table 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%.

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. Second, I construct an 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 two variations of specifications. Following the robustness checks, I conduct a falsification test by randomizing the observations of fuel cost to eliminate the possibility that my estimation results might be driven by factors outside of the model.

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.[14] I apply the same methods as discussed in section 3. Column (2) in Table 7 presents the estimated overall elasticities using the IV approach.[15] The estimates look similar to the primary estimation results, shown in section 4 and repeated in column (1) in Table 7. The similarity in results indicates that the primary estimation outcomes are not driven by individual outliers or measurement errors.

5.2 Alternative instrumental variables

Global crude oil is the source of all distillate products. Its price is often used as an instrumental variable to control for the plausible endogeneity of fuel price (Gillingham, 2014). My alternative instrumental variable is constructed as the ratio of crude oil price and truck model-level fuel efficiency. Diesel prices in each state are clearly correlated with the price of their upstream product, crude oil. Such correlation is also clear from the first-stage estimation results shown in Appendix B. The alternative 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 7.[16] The estimates are within or identical to the 95% confidence interval of the primary results shown in column (1). This suggests that my main results are robust to the alternative instruments for fuel prices.

5.3 Falsification test

I conduct a falsification test by randomizing the cost of per-mile driving variable 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 (4) in Table 7, none of the estimated elasticities is significantly different from zero. This suggests that the negative effects of fuel cost on VMT and payload distance are valid.

6 Differentiated fuel taxes

The estimated heterogeneous elasticities for trucks of different weight classes and business sectors provide important input for calculating the optimally differentiated fuel taxes. It is evident in both theory and empirics that implementing differentiated fuel

[14]The data aggregation method in general does not affect the robustness of my results.
[15]Detailed estimation results using aggregate data can be found in Table E5.
[16]The heterogeneity in elasticities in different subgroups of trucks are presented in Table E6.

taxes achieves higher welfare gain than traditional average taxes. Based on the framework built by Parry and Small (2005) and Parry (2008), I develop a general equilibrium among the households, production sectors, trucking fleet, and the government. The main difference from Parry (2008) is three-fold. First, shipping-intensive goods[17] are priced at the per-ton-mile level, in lieu of per-mile level as in Parry (2008). Such setup is more realistic for the heavy-duty trucking industry and is more 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 at the point when the welfare is highest. The numerical calculation of the optimal tax relies upon the estimates in this study, parameters from the existing literature, and a number of assumptions.

6.1 The analytical framework

(i) Household

Suppose a representative household's utility function can be written as follows. All terms are expressed in per capita per year.[18]

$$u = u\{R_i, Y, A, M, Z\} \tag{7}$$

R_i, measured in ton-mile, denotes consumption of a market good whose production and/or distribution involves nontrivial shipping cost; index i indicates a GVWR class.[19] R_i is defined by the product of vehicle-miles-traveled, T_i and cargo weight, W_i.

$$R_i \equiv T_i \cdot W_i \tag{8}$$

All other consumption is denoted by Y. A is the household's VMT of passenger vehicles. M denotes the total travel time. Z represents all the 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 $u_{MM}, u_{ZZ} < 0$.

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

[18] 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.

[19] 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, as shown in equation (9) and equation (10) respectively.

$$M = \sum_i \pi A \ , \tag{9}$$

in which π is the inverse of the average road speed.

$$I + LST = \sum_i p_i R_i + Y + (t_G + P_G) f_G A \ , \tag{10}$$

in which I denotes the household's 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.

$$p_i = p_i^0 + p_i^R \ . \tag{11}$$

Per-unit production cost is denoted as 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 of freight R_i as given, 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 equals to the operation cost at per-ton-mile basis.

$$p_i^R = (t_i + P_D) q_i + \frac{1}{W_i} \big(\omega \pi + k_i \{a_i\} \big) \ , \tag{12}$$

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's vintage a_i. Solving the fleet manager's cost minimization problem yields the following equation.

$$(t_i + P_D - \frac{k_i'}{f_i^2})T_i = -[\omega\pi + k_i + (t_i + P_D)f_i]\frac{dT_i}{df_i} \ . \tag{13}$$

(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, shown in equation (14).

$$\pi = \pi(T_i, A) \ . \tag{14}$$

The negative externality on pavement L is proportional to the shipping intensity R_i, and can be written as follows. Define z_i^L as the per ton-mile damage to the pavement caused by truck operation.

$$L = \sum_i z_i^L R_i \ . \tag{15}$$

Other externalities Z induced by both truck and auto driving include local and global air pollution, energy security, noise, and accidents.

$$Z = z^A A + \sum_i (z_i^F F_i + z_i^T T_i) \ , \tag{16}$$

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.

$$LST + L = \sum_i t_i F_i + t_G f_G A \ . \tag{17}$$

6.2 The formulation of the optimal taxes

If it were possible to levy a tax that captures i's marginal external damage, it would 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. (Derivation detail can be found in Appendix F.1)

$$\frac{1}{\lambda}\frac{d\tilde{u}}{dt_i} = (MEC_i^F - t_i)(-\frac{dF_i}{dt_i}) + MEC_i^T\big(-\frac{dT_i}{dt_i}) - (MEC_i^A - t_G f_G)\frac{dA}{dt_i} \ , \tag{18}$$

in which

$$MEC_i^F = z_i^F(-\frac{u_Z}{\lambda}) \ , \tag{19}$$

$$MEC_i^T = z_i^T(-\frac{u_Z}{\lambda}) + z_i^L W_i + (\omega T_i - \frac{A}{\lambda}u_\pi)\pi_{T_i} \ , \tag{20}$$

and

$$MEC_i^A = z^A(-\frac{u_Z}{\lambda}) + \Big[(\omega T_i - \frac{A}{\lambda}u_\pi)\pi_A\Big] \ . \tag{21}$$

As shown in equation (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 (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 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 (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. Detailed derivation can be found in Appendix F.2.

$$t_i^* = MEC_i^F + MEC_i^T\Big(\frac{1}{f_i}\Big)\Big(\frac{\varepsilon_i^T}{\varepsilon_i^F}\Big) - (MEC_i^A - t_G f_G)e_i\beta_i\Big(\frac{1}{f_i}\Big)\Big(\frac{\varepsilon_i^T}{\varepsilon_i^F}\Big) \ , \tag{22}$$

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

$$\beta_i = -\Big(\frac{\partial \pi}{\partial A}\frac{dA}{dt_i}\Big)/\Big(\frac{\partial \pi}{\partial T_i}\frac{dT_i}{dt_i}\Big) \tag{23}$$

and

$$e_i = \frac{\partial \pi / \partial T_i}{\partial \pi / \partial A} \quad . \tag{24}$$

6.3 Parameters

Table 8 provides estimates of elasticities and mean values of fuel efficiency in each category of weight class and business sector. Column (1) shows the 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 10. The elasticity of VMT with respect to diesel fuel price, ε_i^T, can be derived as follows. The outputs are shown in column (3) of Table 8.

$$\varepsilon_i^T = \eta_i^T(\varepsilon_i^f + 1) \ , \tag{25}$$

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 elasticity of fuel use with respect to fuel price, ε_i^F can be derived as follows. The results are shown in column (4).

$$\varepsilon_i^F = \varepsilon_i^T + \varepsilon_i^f \tag{26}$$

The detailed derivations of equation (25) and equation (26) are documented in Appendix F.3.

I adopt the assumption made in Parry (2008) 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 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 combination trucks, and 35%:65% for vocational vehicles.

Table 9 provides the value of marginal external costs for different weight classes

Table 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
Other	-0.27	0.11	-0.30	-0.19	7.95
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

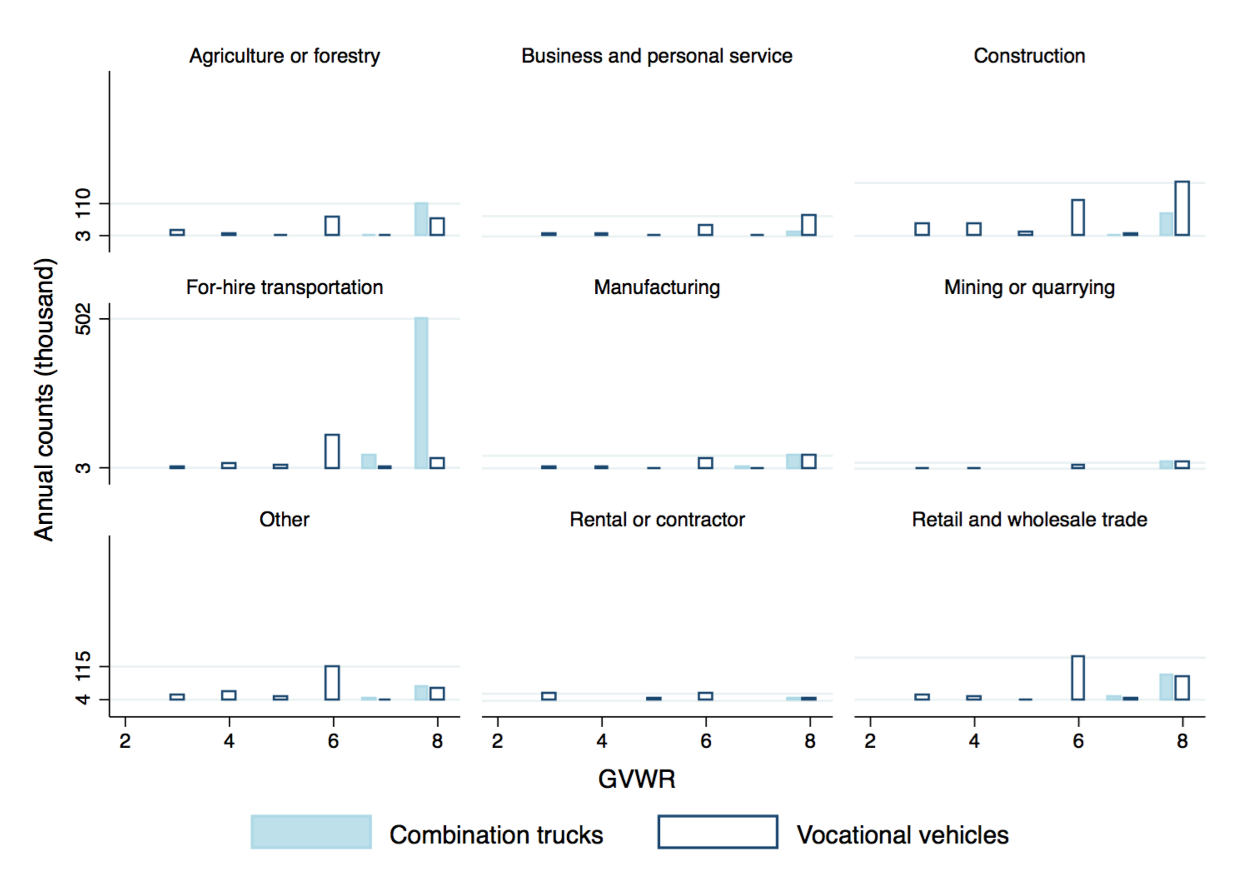
Note: η_i^T: elasticity of VMT with respect to per-mile fuel cost; ε_i^f: elasticity of inverse of MPG with respect to fuel price; ε_i^T: elasticity of VMT with respect to fuel price; ε_i^F: elasticity of fuel use with respect to fuel price.

Table 9: Parameters of 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.

Figure 3: Truck count distribution of GVWRs in each business sector



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

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 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 3 shows the distribution of GVWRs in each business sector.

6.4 Optimal taxes

Substituting the parameters above into the optimal tax expression - equation (22), I obtain the value of optimal taxes and their 95% confidence interval correspondingly.

Tables 11 and 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 weight class 6 operating in 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 12, most of the optimal taxes for vocational vehicles operating in rural areas are around 1 dollar per gallon, and around 2.5 dollars per gallon for thise operating 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 cost and apply the same optimal tax formula, equation (22), to average elasticities, shown in Table 2, I derive the optimal uniform fuel tax for combination trucks at 2.47 dollars per gallon, and for vocational vehicles at 2.07 dollars/gallon. These values serve as the baseline in the welfare analysis in section 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 10, I calculate the 95% confidence interval of the optimal taxes using the Delta method, and present the resulting ranges of optimal taxes in column (2) and (3) in Table 11 and Table 12.

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 (18). It has proven to be vastly more accurate 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 Goulder and Williams (2003), the deadweight loss due to changes in diesel fuel tax can be expressed as follows.

Table 10: Estimate elasticities of MPG with respect to diesel price

	Combination trucks		Vocational vehicles	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Elasticity 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)
Elasticity 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. Standard errors are clustered at the level of home base states. Instrumental variable is the inflation-adjusted crude oil price.

Table 11: Optimal tax 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]

Table 12: Optimal tax 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]
Other	Rural	1.35	[1.02	2.27]
	Urban	3.39	[2.22	6.69]
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]
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]
Other	Rural	1.07	[0.84	1.93]
	Urban	2.78	[1.81	6.54]
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]

$$\frac{1}{\lambda}\Delta\tilde{U} = \frac{-(MEC_i^F t_i - \frac{t_i^2}{2})\varepsilon_i^F \frac{F_i}{\tilde{P}_D} - MEC_i^T \varepsilon_i^T \frac{T_i}{\tilde{P}_D} t_i + (MEC_i^A - t_G f_G)\beta_i e_i \varepsilon_i^T \frac{T_i}{\tilde{P}_D} t_i}{1 - \tau_L \epsilon_{LY}}, \tag{27}$$

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 lower than the midrange estimates in the literature, leading to a more conservative estimate of the welfare effect.

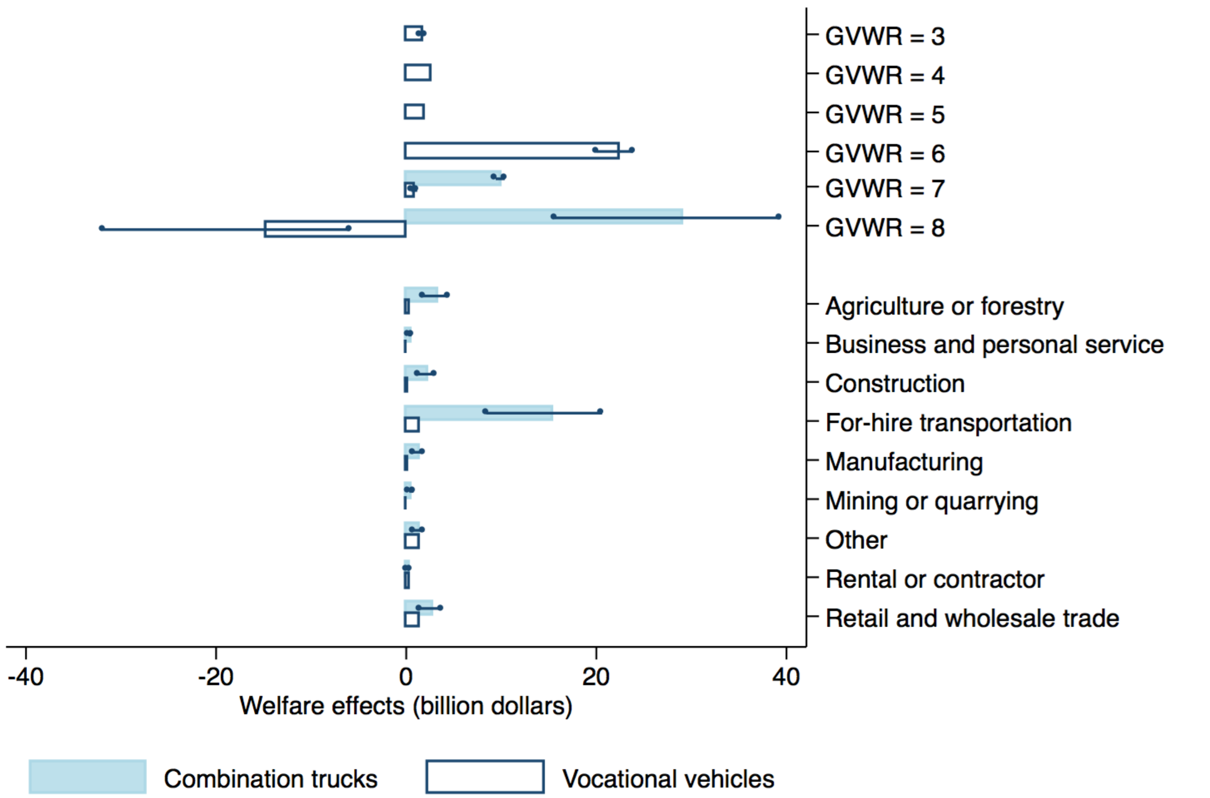
The per-vehicle welfare effect for imposing the differentiated fuel taxes is calculated according to equation (27), relative to the baseline scenario where uniform optimal taxes are imposed. The total welfare change in each vehicle category is derived by multiplying the per-vehicle welfare effect by the total number of vehicles in that category.[20]

Figure 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, most truck groups experience positive welfare effects upon switching from uniform to differentiated taxes. Second, most welfare gains are from class 8 combination trucks, mainly because differentiated taxes compensate for the large external cost occurred due to the operation of this type of vehicles. Third, the variation across vehicle weight classes are more obvious than that across business sectors. In fact, all business sectors experience relatively mild welfare changes, except combination trucks in for-hire transportation. This can be explained by the similar distribution of GVWR classes in each business sector, as shown in Figure 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

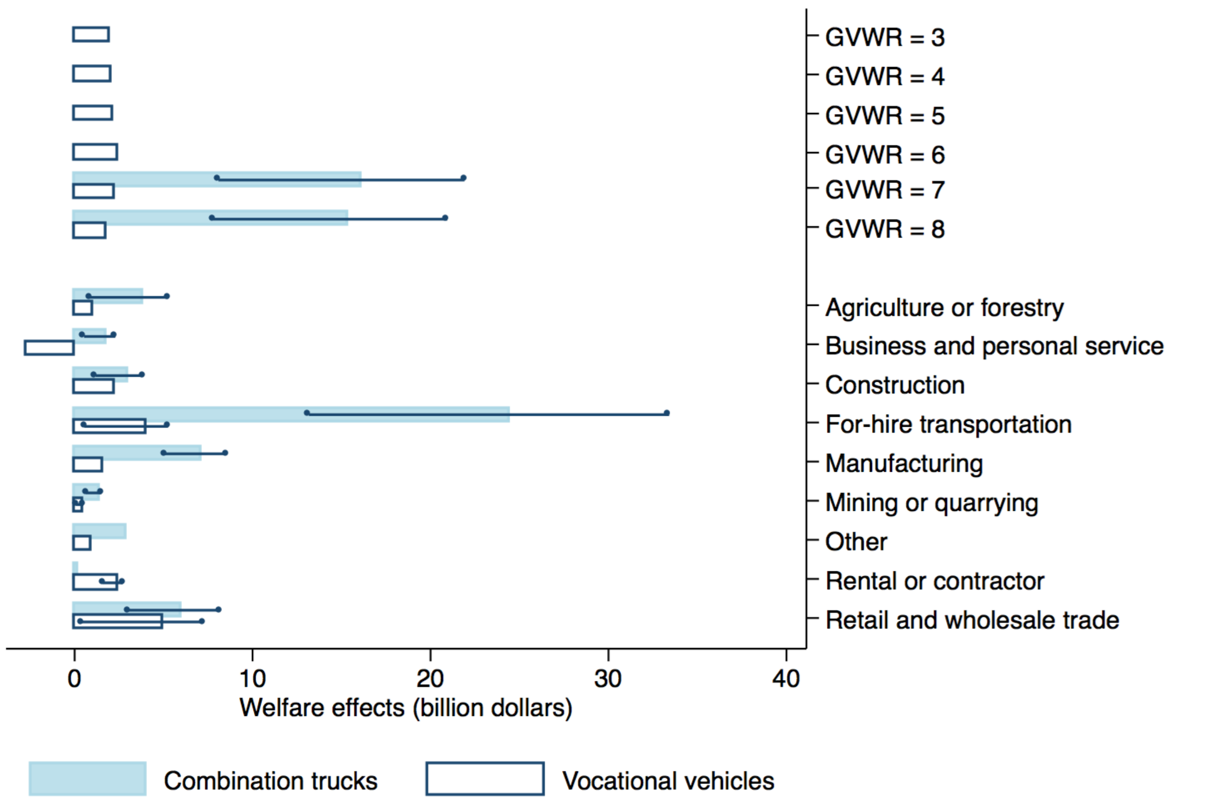
[20] The number of vehicles in each category can be observed in the VIUS surveys. The numbers used in the total welfare calculation are from VIUS 2002.

Figure 4: Welfare effect of imposing differentiated fuel tax 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.

Figure 5: Welfare effect of imposing differentiated fuel tax 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.

and business sectors under such a tax regime are shown in Figure 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 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. 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.

7 Conclusion

Using truck level micro data, I estimate how fuel cost affects trucking decisions heterogeneously among different weight classes and business sectors. The medium-run elasticities of VMT with respect to per-mile fuel cost are about -0.23 for class 7, 8 combination trucks and -0.27 for class 3 - 8 vocational vehicles. Lighter vehicles tend to be more responsive to fuel cost changes. 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 differentiated optimal 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. When differentiating taxes by weight class, class 8 vocational vehicles are charged for the highest fuel tax at 4.76 dollar/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, including agriculture, construction, for-hire transportation, mining, rental, *etc.* In general, combination trucks pay higher taxes than vocational vehicles in the same industry and same area. Combination trucks in for-hire business and rental/contractor in urban areas face an optimal diesel tax over 4 dollar/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.[21] 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 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.

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

Appendix A 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”, “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.

Appendix B First stage estimation

The instrument 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 5.2, I apply an alternative instrument 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 B1.

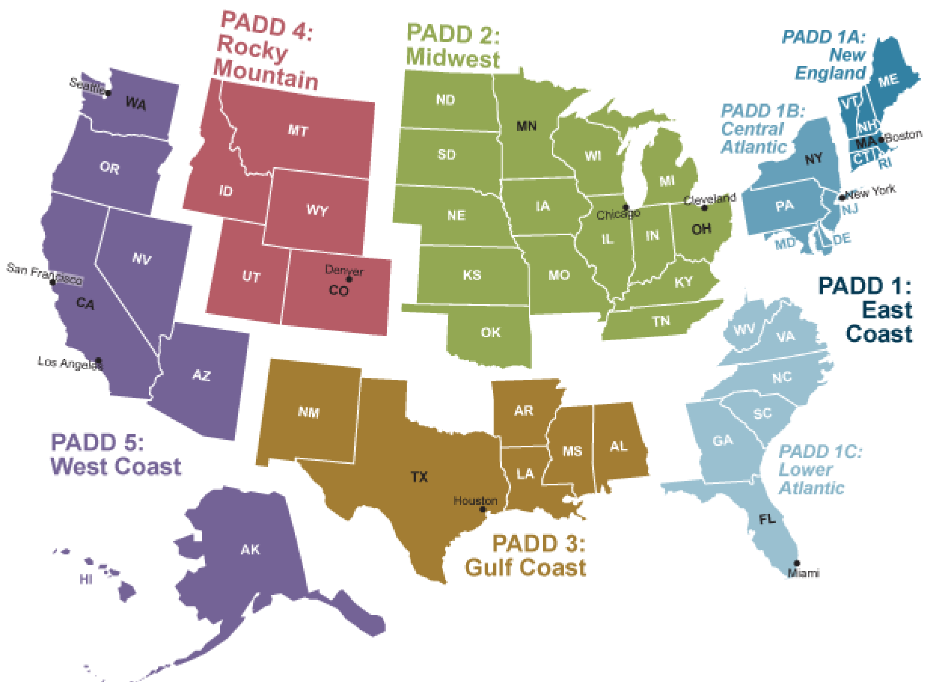
Table B1: First stage estimation results

IV	Average fuel prices in non-neighboring states		Global crude oil prices	
	Combination	Vocational	Combination	Vocational
	(1)	(2)	(3)	(4)
Coefficients of IV	0.997***	0.999***	0.999***	1.000***
	(0.00201)	(0.00119)	(0.00197)	(0.00110)
R^2	0.966	0.988	0.968	0.988
Robust F statistics	246,341	246,341	258,257	833,974

Note: *** : $p < 0.01$; all standard errors (in parenthesis) are clustered at the level of home base regions.
Dependent variable is ln(fuel cost of per-mile driving).
Columns (1) and (2) are first stage estimations corresponding to the IV estimation shown in Table 2 and Table 3.
Columns (1) and (2) are first stage estimations corresponding to the robustness check using alternative IV shown in Table E6.

Appendix C Regional division by EIA

Figure C1: Map of regional division in the U.S.



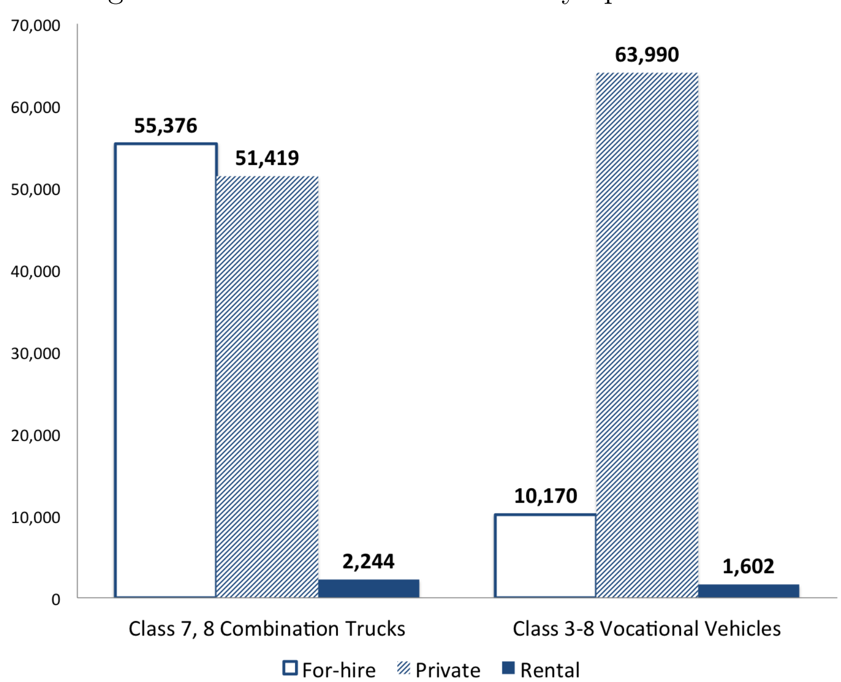
Source: U.S. Energy Information Administration Form EIA-878

Appendix D Heterogeneity of responsiveness by other categories

Appendix D.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 D2, 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.

Figure D2: Distribution of trucks by operator class



As shown in Table D2, for combination trucks, for-hire trucks are the most responsive to fuel cost among the three operator classes. In particular, a 10% increase in

Table D2: 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(cost of per-mile driving). The elasticity for a particular operator class is the sum of coefficients of the interaction term and ln(cost of per-mile driving); the robust standard error is calculated based on the linear combination correspondingly.

Table D3: 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).

the fuel cost of per-mile driving 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 cost. As for vocational vehicles, for-hire vehicles appear to be less sensitive to fuel cost 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 cost. Such effect is even more obvious for for-hire vocational vehicles, as the elasticity of payload distance is almost double the elasticity of VMT.

Appendix D.1.1 By fleet size

Are truck owners or fleet managers assigning trips strategically to trucks based on their fuel cost of per-mile driving? If so, trucks that belong to a large fleet clearly have more flexibility in substitution; thus, I should expect them to be more responsive to changes in the fuel cost of driving compared to those belong to a small fleet. In VIUS, the size of fleet is categorized into four bins.[22] The number of truck counts in each bin is presented in Table D3. 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 equation (4) and equation (6) to estimate the elasticities of VMT and payload distance with respect to fuel cost respectively. The estimates of interest are listed in Table D4. In general, both VMT and payload distance are more elastic to the cost of per-mile driving as

[22] 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 D4: Estimation results by fleet size

Dependent variable:	ln(VMT)		ln(PD)	
	Combination	Vocational	Combination	Vocational
	(1)	(2)	(3)	(4)
Elasticity 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(cost of per-mile driving). The elasticity for a particular operator class is the sum of coefficients of the interaction term and ln(cost of per-mile driving); 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 cost.

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

Appendix E Robustness checks and the falsification test: details

Table E5: 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)
Elasticity 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 E6: 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)
Elasticity 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 E7: Falsification test: randomize the fuel cost of per-mile driving

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.

Appendix F Derive the expression of marginal welfare effect and optimal taxes

Appendix F.1 Derive marginal welfare effect

A household chooses R_i, Y, A, subject to time and budget constraints (equation 9 and 10, to maximize the utility (equation 7). The indirect utility function can be written as follows.

$$\tilde{u} = u(R_i, Y, A, \pi A, Z) + \lambda\Big[I + LST - \sum_i p_i R_i - Y - (t_G + P_G) f_G A\Big] \tag{28}$$

Write the first order conditions of the household maximization problem.

$$\frac{\partial u}{\partial R_i} = \lambda p_i \tag{29}$$

$$u_A = \pi u_\Pi = \lambda (t_G + P_G) f_G \tag{30}$$

$$u_Y - \lambda = 0 \tag{31}$$

Total differentiating indirect utility with respect to diesel tax t_i yields

$$\frac{1}{\lambda}\frac{d\tilde{u}}{dt_i} = \frac{A}{\lambda} u_\Pi \frac{d\pi}{dt_i} + \frac{u_Z}{\lambda}\frac{dZ}{dt_i} + \frac{dLST}{dt_i} - R_i \frac{dp_i^R}{dt_i} \tag{32}$$

Total differentiating equation (12) with respect to diesel tax t_i yields

$$\frac{dp_i^R}{dt_i} = q_i + \frac{\omega}{W_i}\frac{d\pi}{dt_i}\ . \tag{33}$$

Total differentiating equation (14) with respect to diesel tax t_i yields

$$\frac{d\pi}{dt_i} = \pi_{T_i}\frac{dT_i}{dt_i} + \pi_A \frac{dA}{dt_i}\ . \tag{34}$$

Total differentiating equation (16) with respect to diesel tax t_i yields

$$\frac{dZ}{dt_i} = z^A \frac{dA}{dt_i} + z_i^F \frac{dF_i}{dt_i} + z_i^T \frac{dT_i}{dt_i} \tag{35}$$

Total differentiating equation (15) and equation (17)with respect to diesel tax t_i yields

$$\frac{dLST}{dt_i} = F_i + t_i \frac{dF_i}{dt_i} + t_G f_G \frac{dA}{dt_i} - z_i^L \frac{dR_i}{dt_i} \tag{36}$$

Substituting (33), (34), (35) and (36) into (32) and rearranging terms give the expression of marginal welfare effects shown in (18)-(21).

Appendix F.2 Derive optimal taxes

Set the marginal welfare effect (equation 18) to zero, and rearrange terms.

$$t_i^* = MEC_i^F + MEC_i^T \frac{dT/dt_i}{dF_i/dt_i} + (MEC_i^A - t_G f_G)\frac{dA/dt_i}{dF_i/dt_i} \tag{37}$$

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 (22)

Appendix F.3 Derive ε_i^f and ε_i^F

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

$$\begin{aligned} \eta_i^T &= \frac{dVMT}{d[(P_D+t_i)\cdot f_i]}\frac{(P_D+t_i)\cdot f_i}{f_i} \\ \frac{1}{\eta_i^T} &= \frac{1}{\varepsilon_i^T} + \frac{\varepsilon_i^f}{\varepsilon_i^T} \end{aligned} \tag{38}$$

Rearranging terms gives equation (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.

$$\begin{aligned} \varepsilon_i^F &= \frac{d(T_i f_i)}{d(P_D+t_i)}\frac{P_D+t_i}{T_i f_i} \\ &= \frac{T_i df_i + f_i dT_i}{d(P_D+t_i)}\frac{P_D+t_i}{T_i f_i} \\ &= \varepsilon_i^f + \varepsilon_i^T \end{aligned} \tag{39}$$

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