How does fuel cost affect heavy-duty truckers' decisions?

Jen Z. He*

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 the on-road vehicles, they contribute 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 have been mostly technology-based and targeted to manufacturers, whereas fuel price oriented policies, such as fuel taxes, have been rarely considered (Decker and Wohar, 2007; Knittel, 2011). The U.S. Environmental Protection Agency (EPA) announced the fuel efficiency standards for medium- and heavy-duty trucks for the first time in 2014. The effectiveness of such policies heavily depends on how trucking decisions respond to changes in fuel cost.

In this study, I focus on two trucking decisions in particular, vehicle-miles traveled (VMT) and payload distance (PD), which are influenced by fuel cost of per-mile driving. VMT measures the total distance a vehicle travels within a year. The value of payload distance is

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derived from multiplying VMT by the average cargo weight. The changes in fuel cost of per-mile driving come from two sources. One is variation in diesel fuel prices, and the other is fuel economy at truck model level. Fuel cost of per-mile driving is calculated by taking the ratio of fuel price and fuel economy. To quantify the responsiveness of VMT and payload distance to fuel cost, I estimate the elasticities of both decisions with respect to per-mile fuel cost, using truck level micro data. Trucking decisions, vehicle characteristics, fleet characteristics, operational features, location of home base states and prices of diesel fuel are all observed. Along with a careful research design, the rich dataset allows me not only to identify heavy-duty truckers' responsiveness to fuel cost of per-mile driving, but also to explore the heterogeneity among different operational and fleet characteristics.

The topic of how fuel cost affects drivers' decisions have been explored extensively for passenger vehicles, including the effect of Corporate Average Fuel Economy (CAFE) standards (Goldberg, 1998; Allcott and Wozny, 2014), the extent of rebound effect (Small and Van Dender, 2007; Hymel et al., 2010), the decision of VMT at household level (Gillingham, 2014), *etc.* The focus is usually either VMT or fuel economy, while payload distance is less relevant to passenger vehicles market. The empirical evidence from the passenger cars market has shown that condition on the choice of vehicle, how much people drive is fuel price inelastic (Goldberg, 1998); while in the medium run to long run, elasticity of VMT lies about -0.22 (Gillingham, 2014).

While the merits of using micro data have shown in the literature of the passenger vehicle market, only a few recent studies in the trucking industry have taken advantage of detailed vehicle-level dataset to examine truckers' decisions. Adenbaum et al. (2015) finds truck owners undervalue the expected lifetime fuel savings from better fuel economy and supports the policy of introducing fuel efficiency standards in the heavy-duty trucking industry. Leard et al. (2015) estimates the effect of fuel economy on driving distance, the rebound effect, and suggests cautious evaluation of the benefit of such policy.

For the few studies that have considered trucking decisions, the estimation was 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 -0.8 for the long run.

The primary contribution of this study is to quantify the responsiveness of VMT and payload distance to changes in per-mile fuel cost. It is the first attempt to answer such question for heavy-duty commercial vehicles using truck level micro data. It complements the studies of how fuel economy affects individual truckers' decision of VMT (Leard et al., 2015) and their purchase decision of trucks (Adenbaum et al., 2015). I find that 10% increase in per-mile fuel cost reduces VMT by 2.32% for combination trucks and 2.76% for vocational vehicles. The decision of payload distance responds to the same change in fuel cost in a more dramatic fashion; the reduction reaches 4.2% for combination trucks and 3.6% for vocational vehicles.

This paper connects to a sizable literature of fuel tax (Bovenberg and Goulder, 1996; Calthrop et al., 2007; Parry, 2008; Li et al., 2014). Parry (2008) suggests the optimal (second-best) diesel fuel tax for the trucking industry to be $1.12 per gallon, while the most efficient tax structure is a combination of fuel tax at 69 cents per gallon and mileage tax between 7 and 33 cents per mile. The estimation results in this study provide necessary parameters that can be used to derive the optimal diesel fuel tax and potentially suggest welfare gains or loss .

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 identification strategy. Section 4 presents the estimation results and the heterogeneity in responsiveness. Section 5 provides robustness and falsification checks. Section 6 concludes.

2 Data

2.1 Data sources

The primary source of data is Vehicle Use and Inventory Survey (VIUS). It was conducted by the Census Bureau every five years from 1967 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 fleets on 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 GVWR from class 2b to 8, or gross vehicle weight greater than 8,500 pounds,

[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 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%.

are classified as heavy-duty vehicles. I restrict my sample to heavy-duty vehicles, which account for about 70% in the original dataset.

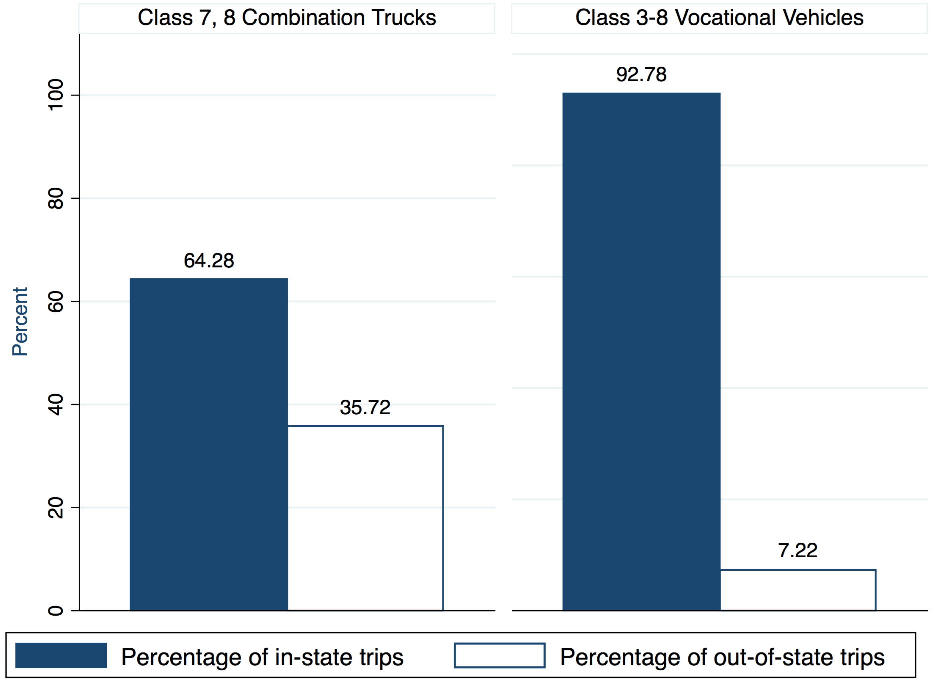
Consistent with the classification published in the regulatory impact analysis (RIA) by the EPA, I examine the heavy-duty fleets in two distinct categories – combination trucks and vocational vehicles. *Combination trucks* refer to tractor trailers[3] with GVWR of class 7 or 8 (gross vehicle weight greater than 26,000 pounds). Most of the combination trucks are meant for hauling cargo on highways for a long distance. The body type of a trailer is typically either an enclosed box or a basic platform. These two types account for more than 50% of the combination truck fleets 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. 94% of the dump trucks operate within their home base states for more than 80% of the time. Besides hauling cargo, vocational vehicles are used for various purposes. 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 further eliminate trucks from the sample if 1) the truck is acquired before 1972 (inclusive), or 2) the engine model year is earlier than 1972 (inclusive), or 3) the truck uses fuel

[3]A truck tractor is a motor vehicle designed primarily for drawing truck trailers. It usually doesn't have a load area. Instead, it has 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.

Figure 1: Allocation of trips between in-state and out-of-state



other than diesel, or 4) the truck spends most time of the year not in use, or 5) the truck is used for personal transportation, government operations or transporting passengers, or 6) there is missing critical variables after imputation[5], or 7) the data is miscoded[6].

The fuel cost of per-mile driving, measured in dollars/mile, is derived from taking the ratio of diesel price and the fuel economy[7]. Annual diesel prices at 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 Department of Transportation. All prices are in 2002 U.S. dollars.

[5]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.

[6]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.

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

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. Truckers in interstate business are 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 essentially useful to construct trip-based fuel prices to approximate the actual diesel fuel prices truckers encountered at the pump. Suppose that truckers face the diesel prices in their home base states while driving within the home base state, and the national average diesel price while driving out of home base states. The trip-based diesel fuel price is the average in these two situations weighted by the percentage of trips. Figure 1 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 states. This allocation implies 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 tripled of 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. Comparing the truck characteristics between these two groups, on average, combination trucks have lower fuel efficiency, greater lifetime mileage and heavier total vehicle weight.

Some truck characteristics are relevant to trucking behaviors and performance. Truck

Table 1: Summary statistics

	Combination Trucks		Vocational Vehicles	
	Mean	St.d.	Mean	St.d.
	(1)	(2)	(3)	(4)
VMT (1,000 miles)	63.74	45.25	20.16	20.64
Payload distance (10,000 ton-miles)	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
Whether install with radial tires?	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 regression. 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.

body/trailer type and axle configuration determine the business use as well as its carrying capacity. A good design of the cabin (or cab) can reduce the aerodynamic drag substantially, and therefore improve its fuel efficiency. Conventional cab is most commonly seen in North America. In such cabin, the driver is seated behind the engine, as in most passenger vehicles. Another type is "cab over engine" – the cabin is 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 the combination trucks and 77% of the vocational vehicles have conventional cabs. Radial tires also contribute to better fuel efficiency. The cored plies are arranged perpendicularly to the direction of travel, so that the tires experience longer tread life, better steering characteristics and less rolling resistance. Although bias tires have the merit of weight carrying ability, radial technology has become a standard design. In my sample, about 69% of the combination trucks and 62% of the 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 f_i by average fuel efficiency ω (note ω is the average MPG of all trucks with the same type as i). Maintenance cost is a function of truck characteristics $\boldsymbol{X_i}$ and fleet operational characteristics $\boldsymbol{Z_i}$. Equating the marginal revenue with the marginal cost gives the optimal solution of VMT,

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

The state-level fixed effects θ_s capture the time-invariant factors. For example, if the fact that an intrastate driver in California drives more on average than a driver with the same truck in Rhode Island is 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 identify time-specific influences on VMT, such as macroeconomic factors, nationwide demand shocks, and measurement errors systematically to a specific survey year. ϕ_b represents the business sector of the cargo delivery, such as agriculture or farming, construction, for-hire transportation, forestry or lumbering. The business fixed effects capture any industry-specific shocks that may affect the 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.

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

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

$$c_i = \frac{f_i}{\omega} \tag{3}$$

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.

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

γ can be interpreted as the medium-run elasticity of VMT with respect to the 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.

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

where w_i denotes the weight of payload (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).

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

δ is interpreted as the medium-run elasticity of payload distance with respect to the 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 economy ω and fuel price f_i are exogenous. Given the possibility of inverse causality between truck i's VMT and its own fuel economy (ω_i), using ω_i in equation (3) would be problematic. Instead, I use the mean ω of all trucks that share the same characteristics as truck i. Since fuel economy of a vehicle is largely determined by its engineering characteristics, the mean ω represents the fuel economy at the truck model level. Thus, it is exogenous to truck i's VMT in a specific survey year. This adjustment also distinguishes the estimation from the discussion about rebound effect, which emphasizes on the endogeneity of fuel economy on driving decisions (Leard et al., 2015).

The assumption that individual drivers are price-takers with respect to the 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 drives up the local fuel prices temporarily. Another scenario which may bias the estimates stems from truckers' forecast of future fuel prices. To control for the plausible endogeneity of fuel prices, I instrument the fuel prices with the inflation adjusted average of prices in states that are not bordering with the home base states. As the fuel prices across states are correlated, the relevance condition of a valid instrument is satisfied[8]. The exclusion condition that a valid instrument has to satisfy relies on a rather strong assumption in this context. I assume that a driver in home base state s is not affected by fuel prices changes in states further than his neighboring states when he/she makes decisions regarding VMT or payload distance. 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 individual trucker's operational decision would affect the global oil price. I provide the estimation results with the alternative IV in section 5.2.

The exclusion restriction holds once I control for some important unobservables captured by 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 of VMT. Furthermore, I include a list of truck characteristics to mimic the experiment in which two identical trucks are driven differently only due to the difference in fuel costs. I also control for model year, make, body/trailer type, cab type, axle configuration, average vehicle weight (in natural log), odometer reading (in natural log), engine displacement, whether installed with

[8]First stage estimation results shown in Table B1 in Appendix B.

Table 2: Primary estimation results of ln(VMT)

	Combination Trucks		Vocational Vehicles	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
ln(cost of per-mile driving)	-0.181***	-0.232***	-0.267***	-0.276***
	(0.0256)	(0.0332)	(0.0148)	(0.0131)
Control variables				
ln(average vehicle weight)	0.406***	0.408***	0.237***	0.238***
	(0.0239)	(0.0223)	(0.0208)	(0.0191)
ln(odometer reading)	0.483***	0.484***	0.484***	0.484***
	(0.00758)	(0.00706)	(0.0187)	(0.0174)
ln(state GDP)	0.0776	0.0778*	-0.00316	-0.00300
	(0.0431)	(0.0406)	(0.0662)	(0.0619)
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	109039	75762	75762
Adjusted R^2	0.551	0.551	0.427	0.427

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.
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 whether installed radial tires.
Business and operational characteristics include operator class, business sector of the shipment, fleet size, and main cargo product.

radial tires, 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. Given the mobility of trucking business, the unobserved factors should affect trucks in the same region (broader than states) in a similar way. I cluster the standard errors in all the estimations at the level of home base region[9].

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 of the fixed effects and controls discussed above are included. Column (1) and (3) present the elasticities of VMT with respect to the 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 column (2) and (4), 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 change in cost of per-mile driving. To put the results in context, 10% increase in fuel cost results in 2.32% reduction in distance of driving for combination trucks and 2.76% for vocational vehicles. For both categories of heavy-duty trucks, IV results are slightly higher in absolute value than OLS results. This is a comforting results, as I suspect the elasticities would be underestimated by OLS in both hypothetical scenarios (inverse causality due to local VMT shocks and drivers' adjustment in VMT based on their forecast of future fuel prices), had I not controlled for the endogeneity of fuel cost. The estimated coefficients of other control variables are shown in the expected signs and remained relatively unchanged across specifications. This serves as one evidence that my results are robust.

Table (3) presents the primary estimation results of elasticities of payload distance with respect to the per-mile fuel cost. 10% increase in fuel cost induces a reduction in payload distance by about 4.20% for combination trucks and 3.56% for vocational vehicles once I control for the endogeneity of fuel prices, as shown in column (2) and (4). The estimates

[9] I adopt the regional division provided by the U.S. Energy Information Administration.

Table 3: Primary estimation results of payload distance

	Combination Trucks		Vocational Vehicles	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
ln(cost of per-mile driving)	-0.362***	-0.420***	-0.351***	-0.356***
	(0.0173)	(0.0276)	(0.0195)	(0.0179)
Control variables				
ln(average vehicle weight)	2.527***	2.530***	1.933***	1.933***
	(0.0303)	(0.0283)	(0.0427)	(0.0396)
ln(odometer reading)	0.481***	0.481***	0.510***	0.510***
	(0.00566)	(0.00520)	(0.0196)	(0.0184)
ln(state GDP)	0.0658	0.0661**	0.0379	0.0380
	(0.0351)	(0.0328)	(0.0785)	(0.0734)
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	109,039	75,762	75,762
Adjusted R^2	0.681	0.681	0.562	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.
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 whether installed radial tires.
Business and operational characteristics include operator class, business sector of the shipment, fleet size, and main cargo product.

are highly statistically significant. The fact that they are even higher than elasticities of VMT in absolute terms implies that the average weight of 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 for per ton-mile shipping to compensate the increase in fuel cost.

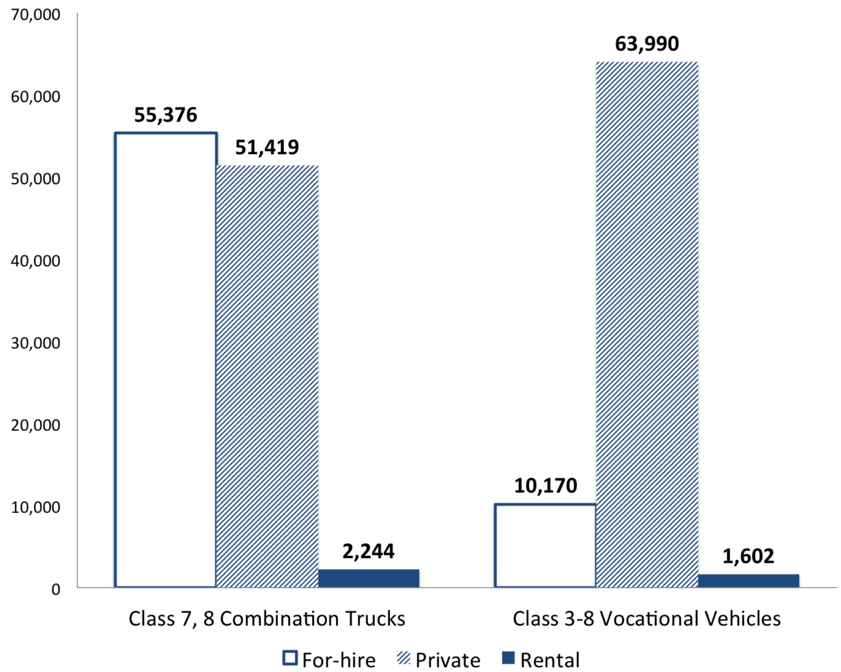
4.2 Heterogeneity in responsiveness

It is important to understand the heterogeneity in responsiveness to changes in fuel cost for three 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 the shipping demand. For such reason, trucks for business or personal services are likely to be more responsive than those in mining or forestry. Second, the possibility of substitution is likely to affect the decisions of VMT and payload distance. Long distance shipment may be assigned to trucks with relatively low per-mile fuel cost. Such substitution is more likely to appear in large fleets. As for owner operators, there would be no luxury for such substitution. Third, because of potential variation in responsiveness, some trucks may encounter more difficulties than others to comply with policies that result in an increase in fuel prices. It is thus essential to realize the heterogeneity of elasticities among various truck groups, and design the policy and compliance strategy accordingly. For the rest of this section, I explore the heterogeneity in responsiveness of VMT and payload distance to fuel cost by operator class, fleet size and business sector.

4.2.1 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. If an individual not only owns

Figure 2: Distribution of trucks by operator class



the truck, but also drives it for compensation, such situation is referred as "owner operator". A for-hire truck is required for a commercial vehicle DOT (Department of Transportation) number. As shown in Figure 2, about half of the combination truck fleets in my sample are for-hire trucks, while 85% of the vocational vehicles are operated as private. *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 consist a small percentage in my sample, about 2% for both groups. Typically, they are moving trucks for daily rental. Driving service is usually not provided by the truck rental companies.

As shown in Table 4, for combination trucks, for-hire trucks are the most responsive to fuel cost among the three operator classes. In particular, 10% increase in 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, schedule and routes, it is not surprising that they are the most responsive ones to changes in fuel cost. As for vocational

Table 4: 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 5: Number of trucks by fleet size

	Combination Trucks	Vocational Vehicles
1	21,106	9,944
2 to 5	16,856	21,193
6 to 19	21,521	21,350
20 to 99	21,427	13,536
100 to 499	15,099	4,899
500 or more	13,030	4,840
Total	109,039	75,762

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

vehicles, for-hire vehicles appear to be less sensitive to fuel cost than private vehicles are. Column (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 doubled of elasticity of VMT.

4.2.2 By fleet size

Are truck owners or fleet managers assign trips strategically to trucks based on their fuel cost of per-mile driving? If so, trucks belong to large fleets clearly have more flexibility in substitution; thus, I should expect them to be more responsive to changes in fuel cost of driving compared to those belong to small fleets. In VIUS, the size of fleets is categorized into six bins. The number of truck counts in each bin is presented in Table 5. While combination trucks spread relatively evenly in fleets of different sizes, about 70% of the vocational vehicles are in relatively small fleets that have less 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.

Table 6: Estimation results by fleet size

Dependent variable:	ln(VMT)		ln(PD)	
	Combination	Vocational	Combination	Vocational
	(1)	(2)	(3)	(4)
Elasticity by fleet size:				
1	-0.139***	-0.208***	-0.310***	-0.224***
	(0.0480)	(0.0205)	(0.0523)	(0.0281)
2 to 5	-0.140***	-0.336***	-0.541***	-0.318***
	(0.0254)	(0.0149)	(0.0830)	(0.0411)
6 to 19	-0.276***	-0.252***	-0.313***	-0.391***
	(0.0355)	(0.0130)	(0.0270)	(0.0136)
20 to 99	-0.337***	-0.265***	-0.535***	-0.373***
	(0.0410)	(0.0233)	(0.0401)	(0.0265)
100 to 499	-0.330***	-0.233***	-0.535***	-0.578***
	(0.0762)	(0.0408)	(0.0869)	(0.101)
500 or more	-0.156*	-0.391***	-0.404***	-0.350***
	(0.0874)	(0.0370)	(0.0307)	(0.0224)
Control variables				
ln(average vehicle weight)	0.408***	0.239***	2.529***	1.933***
	(0.0223)	(0.0191)	(0.0281)	(0.0398)
ln(odometer reading)	0.485***	0.484***	0.482***	0.510***
	(0.00719)	(0.0175)	(0.00529)	(0.0183)
ln(state GDP)	0.0772*	-0.00398	0.0646**	0.0361
	(0.0399)	(0.0616)	(0.0326)	(0.0720)
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	0.551	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, 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 2SLS estimation approach to control for the plausible endogeneity of fuel cost.

The estimates of interest are list in Table 6. In general, both VMT and payload distance are more elastic to cost of per-mile driving as fleet size increases. This general trend, although with exceptions, appears to confirm my expectation. For combination trucks, the elasticity of VMT in fleets with 20 to 499 trucks is more than twice as the elasticities in fleets with less than 5 trucks. Vocational vehicles in large fleets with more than 500 trucks reduce VMT by about 3.91% when per-mile fuel cost is raised by 10%, while the drivers with one vehicle in their fleets respond only by half as much. The estimation results of payload distance tell a similar story. As shown Column (3) and (4), elasticities (in absolute values) are the highest in fleets with size of 100 to 499 trucks. All estimates are highly statistically significant.

4.2.3 By business sector

Business sector for a truck is referred to the industry of either its shipment cargo or its primary task. The distribution of truck counts in my sample across the 10 business sectors are given in figure 3 and figure 4 for combination trucks and vocational vehicles respectively. The majority of combination trucks are used for for-hire transportation. Other main 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 10 business sector dummy variables with the natural log of per-mile fuel cost. The elasticities of interest are derived from 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 7. All the 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 -0.259 to -0.464, and for vocational vehicles from -0.226 to -0.349. Business

Figure 3: Distribution of trucks by business sector (combination trucks)

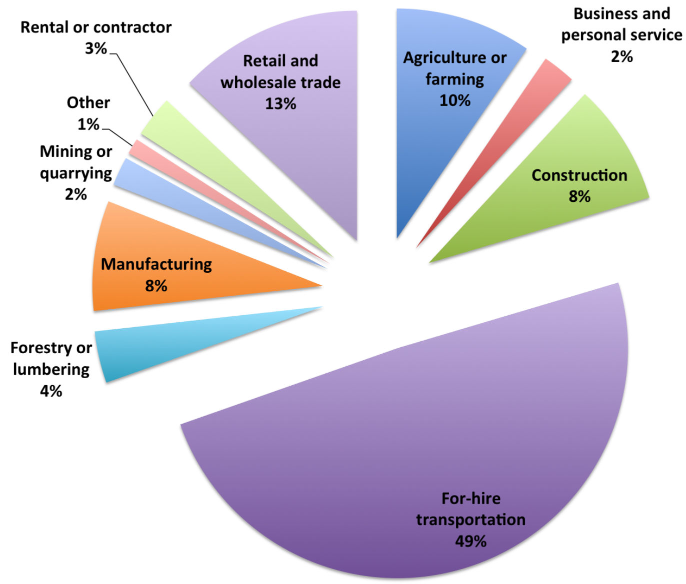


Figure 4: Distribution of trucks by business sector (vocational vehicles)

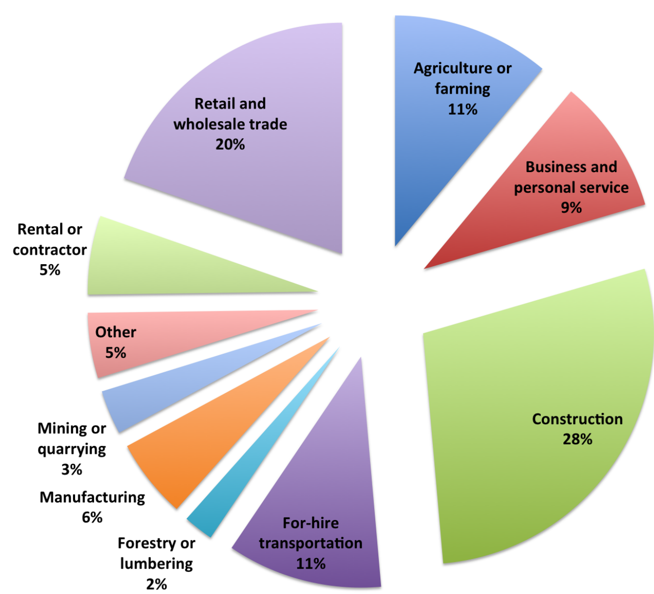


Table 7: Estimation results by business sector

Dependent variable:	ln(VMT)		ln(PD)	
	Combination (1)	Vocational (2)	Combination (3)	Vocational (4)
Elasticity by business sector:				
Agriculture or farming	0.245***	-0.313***	0.0335	-0.345***
	(0.0603)	(0.0473)	(0.0667)	(0.0525)
Business and personal service	-0.464***	-0.309***	-0.665***	-0.373***
	(0.170)	(0.0262)	(0.207)	(0.0374)
Construction	-0.259***	-0.264***	-0.384***	-0.354***
	(0.0698)	(0.0352)	(0.108)	(0.0403)
For-hire transportation	-0.279***	-0.226***	-0.518***	-0.446***
	(0.0394)	(0.0235)	(0.0296)	(0.0489)
Forestry or lumbering	-0.282***	-0.252***	-0.425***	-0.299**
	(0.0260)	(0.0815)	(0.0536)	(0.117)
Manufacturing	-0.406***	-0.268***	-0.571***	-0.322***
	(0.0569)	(0.0556)	(0.0751)	(0.0700)
Mining or quarrying	-0.180	-0.0430	-0.285*	-0.0737
	(0.124)	(0.0965)	(0.152)	(0.0930)
Rental or contractor	-0.321***	-0.349***	-0.412**	-0.431***
	(0.121)	(0.0699)	(0.184)	(0.0572)
Retail and wholesale trade	-0.313***	-0.263***	-0.523***	-0.282***
	(0.0502)	(0.0304)	(0.0435)	(0.0368)
Other	-0.329**	-0.340***	-0.223**	-0.541***
	(0.131)	(0.0215)	(0.0907)	(0.0338)
Control variables				
ln(average vehicle weight)	0.407***	0.239***	2.529***	1.934***
	(0.0222)	(0.0193)	(0.0282)	(0.0399)
ln(odometer reading)	0.483***	0.484***	0.481***	0.509***
	(0.00708)	(0.0175)	(0.00517)	(0.0185)
ln(state GDP)	0.0735*	-0.00594	0.0624*	0.0347
	(0.0392)	(0.0620)	(0.0321)	(0.0735)
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	0.552	0.427	0.682	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, 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 based on the linear combination correspondingly.

and personal services, as well as manufacturing, are more responsive to changes in per-mile fuel cost than combination trucks in other sectors are. 10% increase in fuel cost of per-mile driving induces reduction in VMT by 4.64% and 4.06% respectively. 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 the mines. Surprisingly, combination trucks in agriculture or farming are driven more as fuel cost rises. Column (3) and (4) provide the heterogenous estimates of elasticities of payload distance in different business sectors. Except for agriculture or farming sector, elasticities for combination trucks in other business sectors are negative and statistically significant. In particular, trucks in business and personal service, for-hire transportation, forestry or lumbering, manufacturing, retail and wholesale trade have higher elasticities in absolute values than the primary estimation results in Table 3. The reduction in payload distance ranges from 2.82% to 5.41% across the 10 business sectors when per-mile fuel cost increases by 10%.

5 Robustness and Falsification Checks

Two robustness checks are conducted. First, I aggregate the data at the truck model level to address 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 in estimation. Following the robustness checks, I conduct a falsification test by randomizing the observations of fuel cost to eliminate the possibility that my estimation results are driven by factors outside of the model.

5.1 Aggregate Data

To minimize the potential effect of measurement errors or any odd behavior of individual trucks, I aggregate the data at the level of survey year, home base state, body/trailer type,

Table 8: Robustness checks and falsification test

	Primary results	Aggregate data	Alternative IV	Falsification test
	(1)	(2)	(3)	(4)
Combination Trucks:				
Elasticity of VMT	-0.232***	-0.220***	-0.229***	-0.00679
	(0.0332)	(0.0219)	(0.0332)	(0.00637)
Elasticity of PD	-0.420***	-0.408***	-0.418***	-0.00538
	(0.0276)	(0.0263)	(0.0276)	(0.00917)
Vocational Vehicles:				
Elasticity of VMT	-0.276***	-0.253***	-0.276***	0.00991
	(0.0131)	(0.0122)	(0.0131)	(0.00965)
Elasticity of PD	-0.356***	-0.341***	-0.355***	0.0176
	(0.0179)	(0.0202)	(0.0178)	(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 regions.

make axle configuration, business sector and operator class[10]. The sample size is reduced in half. I apply the same methods as discussed in section 3. The estimates are almost identical to the primary estimation results, shown in section 4. It indicates that the primary estimation results are not driven by individual outliers or measurement errors.

5.2 Alternative instrumental variables

Crude oil price is often used as an instrumental variable to control for the plausible endogeneity of fuel price (Gillingham, 2014). My alternative instrumental variable is derived by taking the ratio of crude oil price and truck level fuel economy. Global crude oil is the source of supply for all distillate products. Diesel prices in each state are clearly correlated with the price of their upstream product, crude oil. Such correlation can be further proved by the first stage estimation results shown in Appendix B. The alternative instrument also satisfy 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 8[11]. The estimates are within the 95% confidence interval

[10] The way of aggregating the data in general doesn't affect the robustness of my results.
[11] The heterogeneity in elasticities in different subgroups of trucks are presented in **??**.

of the primary results shown in column (1), if not identical. Such desired similarity is evident of robustness in the estimation results.

5.3 Falsification test

A falsification test is conducted by randomizing the variable, cost of per-mile driving, across observations. If the relationships between driving decisions and per-mile fuel cost are driven by unobserved factors outside the model, the estimates would remain significant in the falsification test. The fact that such relationships are completely wiped out once I randomize the fuel cost proves the opposite. As shown in column (4) in Table 8, none of the estimated elasticities is significantly different from zero. It is, thus, evident that the negative effects of fuel cost on VMT and payload distance are valid.

6 Conclusion

Using truck level micro data, I estimate how trucking decisions, VMT and payload distance, are affected by the fuel cost of per-mile driving. Primary results show that the medium-run elasticities of VMT are about -0.232 for class 7,8 combination trucks and -0.276 for class 3-8 vocational vehicles. The decision of payload distance is more responsive. 10% increase in per-mile fuel cost reduces payload distance by 4.20% for combination trucks and 3.56% for vocational vehicles. Further, I explore the heterogeneity of elasticities among three types of operator classes, six groups of fleet size, and ten business sectors.

The estimated elasticities have important implications for the effectiveness of fuel cost related policies, such as fuel tax or carbon tax. Parry (2008) models the externalities for heavy-duty trucks and estimates the optimal (second-best) diesel tax at 1.12 dollars per gallon. The parameters of elasticities used in Parry (2008) are from -0.31 to -0.38 for single-unit (vocational) trucks, from -0.38 to -0.44 for combination trucks, and overall -0.24 on average. If I apply the elasticities estimated in this paper to Parry's method, the second-best diesel tax is around 95.5 cents per gallon.

Admittedly, there are at least two main caveats in this study. First, the diesel prices that truckers actually face are unfortunately unobserved. The trip-based fuel prices used in this study are the best approximation that can be derived from VIUS and state-level diesel prices. Nonetheless, if some trucking companies face different fuel prices through, for example, special discount or bulk-purchase, the trip-based fuel prices would be overstated in those cases, and the elasticities would be underestimated. Second, if rebound effect happens at truck model level, such effect is absorbed in the estimated elasticities. Although I carefully construct the fuel cost of per-mile driving by taking the ratio of fuel price and the *average* MPG at the level of truck model, I cannot eliminate the possibility that the entire group of truckers who drive fuel efficient trucks are in general less responsive to changes in fuel cost, compared to the group of truckers who drive less fuel efficient trucks.

Future work is warranted to extend the scope to current trucking fleets. It is also valuable to apply the estimated elasticities to evaluate the effectiveness of current fuel tax structure, as well as the newly announced fuel efficiency standards for medium- and heavy-duty trucks by EPA and National Highway Traffic Safety Administration in 2015.

Appendix A Omitted variables 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 includeChemicals and/or drugs, Farm products, Household goods, Live animals, Lumber and fabricated wood products, Metal products, Mining products, Miscellaneous products of manufacturing, No load carried, Paper, textiles and apparel, Petroleum products, Plastics and/or rubber products, Processed foods, Tools machinery and equipment, Waste and 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 main regressions is the per-mile fuel cost in states that do not share border with the 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 first stage estimation in 2SLS approach are presented in Table B1.

Table B1: First stage estimation results

	Main instrument variable		Alternative instrument variable	
	Combination (1)	Vocational (2)	Combination (3)	Vocational (4)
Instrument variable	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.
Column (1) and (2) are first stage estimations corresponding to the IV estimation shown in Table 2 and Table 3.
Column (3) and (4) are first stage estimations corresponding to the robustness check using alternative IV shown in Table **??**.

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