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Fuel Costs, Economic Activity, and the Rebound Effect for Heavy-Duty Trucks

Benjamin Leard, Joshua Linn, Virginia McConnell, and William Raich

1616 P St. NW
Washington, DC 20036
202-328-5000 www.rff.org

RESOURCES FOR THE FUTURE

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Abstract

Despite a large literature on the rebound effect for passenger vehicles, few studies attempt to estimate the rebound effect for trucks. We estimate the rebound effect for medium- and heavy-duty vehicles using a pooled cross section of detailed truck-level microdata from six waves of the Vehicle Use and Inventory Survey (VIUS). The microdata allow us to control for many relevant characteristics that influence vehicle miles traveled, thereby allowing us to properly isolate the impact of changing cost per mile on truck utilization. We estimate rebound effects of 29.7 percent for tractor trailers and 9.3 percent for vocational vehicles. We also estimate the effect of economic activity on truck miles driven and find that both tractor trailers and vocational vehicles respond less than proportionally to changes in economic activity. Compared to the agencies' implicit assumption of a proportional response, we estimate an aggregate truck miles elasticity with respect to gross state product of 0.62 for tractor trailers and 0.87 for vocational vehicles. Together these estimates suggest that the agencies regulating fuel economy and greenhouse gas emissions rates from US trucks likely overestimate projected long-run fuel savings and greenhouse gas emissions reductions resulting from the standards. We do, however, find that the short-run rebound effects may be smaller due to significant substitution effects between trucks with different fuel economies. Because the standards regulate new trucks only, the standards will cause miles driven to shift from unregulated older trucks to regulated new trucks, which will result in a greater short-run reduction of fuel consumption.

Key Words: rebound effect, heavy-duty trucks, fuel economy standards

JEL Classification Numbers: Q0, R4, C2

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Introduction

Reducing greenhouse gas (GHG) emissions from medium- and heavy-duty trucks is a central part of U.S. climate policy. Trucks account for about 6 percent of U.S. emissions and by 2030 emissions from trucks are expected to exceed emissions from light-duty passenger vehicles (EPA 2015). To address emissions from this sector, the Environmental Protection Agency (EPA) and the National Highway Traffic Safety Administration (NHTSA) began jointly regulating the greenhouse gas emissions rates and fuel economy of trucks in 2014. The first phase of truck standards began in 2014 and extends through 2018. As fuel economy is inversely proportional to the rate of greenhouse gas emissions per mile traveled, the standards will simultaneously increase fuel economy and reduce emissions per mile driven, with an expected reduction in emissions and fuel consumption per mile from tractor trailers of 9 to 23 percent by 2017.[1] In 2015, the Agencies proposed Phase 2 of the standards, which cover the years 2018 through 2027 and reduce tractor trailer emissions by 24 percent relative to Phase 1 standards.[2]

While the standards target the rate of emissions per miles traveled, the social benefits of the standards depend on how much the trucks are driven. By reducing the rate of fuel consumption, the standards reduce total fuel consumption. Economic theory, however, suggests that the resulting lower fuel consumption rates[3] will lower the cost per mile of driving and thus

* Benjamin Leard, fellow, Resources for the Future (RFF), leard@rff.org; Josua Linn, senior fellow, RFF, linn@rff.org; Virginia McConnell, senior fellow, RFF, mcconnell@rff.org; William Raich, research assistant, RFF, raich@rff.org.

[1] These reductions are relative to 2010. Heavy-duty pick-up trucks and vans are expected to achieve per-vehicle reductions in GHG emissions of 17 percent for diesel fuel vehicles and 12 percent for gasoline vehicles. Vocational vehicles, which include dump trucks, cement trucks, tow trucks, etc., are expected to achieve GHG reductions of six to nine percent (EPA 2011).

[2] Trailers, vocational vehicles and pick-up trucks and vans are expected to experience 8 percent, 16 percent and 16 percent reductions in CO2 emissions and fuel use rates when compared to Phase 1 standards.

[3] For tractor trailers the regulation affects load specific fuel consumption, which is the gallons of fuel consumed per ton-mile. For other truck types the regulation affects fuel economy and fuel consumption rates. For convenience we do not make this distinction in the introduction although we do in the empirical analysis.

increase the number of miles trucks are driven.[4] The resulting increase in trucking miles traveled is commonly referred to as the rebound effect. This effect partially offsets the decrease in fuel use and emissions that would occur from the fuel consumption rate alone.[5] The greater is the expected reduction in fuel intensity from the regulation, the larger the effect on cost per mile of driving and the rebound effect. In the trucking sector, the rebound effect in the short run is likely to be different from the long run rebound effect. Because only new trucks are regulated, the cost of driving new trucks is relatively less costly compared to other trucks in the fleet, and fleet managers may shift miles driven from old trucks to new trucks. This type of substitution can temper the rebound effect in the short-term. This effect disappears in the long run, however, as the cost per mile will fall by the same proportion for all trucks.

In our analysis, we use truck-level microdata from a repeated cross section between the years 1977 and 2002 to empirically estimate a model of truck travel, and to identify the relationship between cost of driving and miles driven. The analysis focuses on tractor trailers and vocational trucks (dump trucks, tow trucks, etc.), which account for 66 and 22 percent of total truck fuel consumption, respectively.[6] Relative to the small set of papers using aggregate data from the trucking sector to estimate rebound, we demonstrate the advantages of the microdata, which allow us to account for the endogeneity of fuel costs, control for temporal changes in truck characteristics, and distinguish between the short and long-run rebound effects. We estimate large substitution effects for tractor trailers but find no evidence of substitution effects for vocational vehicles. Finally, we estimate the relationship between economic activity and total truck miles traveled, which we use to project baseline miles traveled. We find that miles traveled respond somewhat less than proportionately to economic activity, as proxied by gross state product (GSP).

These results have four implications for GHG regulations. First, the rebound effect for tractor trailers is larger than the rebound effect assumed by the EPA and NHTSA in their cost benefit analysis of the standards. We estimate a similar rebound effect for vocational trucks as

[4] Lower fuel consumption rates translate to lower per-mile driving costs, and make trucks more competitive relative to other transportation modes.

[5] The rebound effect can also exacerbate other external costs of trucking such as traffic congestion and non-GHG emissions. These external costs per mile driven are substantial. For example, FHWA (1997) estimates marginal congestion costs in urban areas of 16.8 cents per mile for combination trucks and 14.5 cents per mile for single-unit trucks. In 2010, trucks were driven 140 billion miles in urban areas (FHWA 2012), implying external costs to urban areas of $21 billion (see Parry 2008 for further details).

[6] The GHG truck regulations also cover large pickup trucks and vans. We do not include those vehicles because of their small sample size.

the agencies assume. The larger rebound effect for tractor trailers implies lower benefits of the standards. Second, the agencies assume that miles traveled increase proportionately to economic activity, whereas we find that miles traveled increase less than proportionately. This suggests that future miles traveled will be lower than the agencies assume, and hence the benefits of a particular reduction in the fuel consumption rate will be smaller. Third, the results for baseline miles traveled also imply that future truck GHG emissions will be lower than previously thought. That is, although the first two implications suggest lower net benefits of the regulations, the third implication is that the total external costs from the trucking sector, either with or without the regulation, will be lower than previously thought. Fourth, our estimated substitution effect for tractor trailers implies that short run emissions reductions stemming from the regulation will be larger than expected.

A large literature identified the problem of the rebound effect for fuel economy regulations. Much of the analysis in the transportation area focuses on the rebound effect for light-duty vehicles (as reviewed in Gillingham et al. 2015; see the Appendix for further discussion of the light-duty literature). Only a few studies have investigated either the short or long-run rebound effect for trucks. The light-duty rebound effect arises when households respond to the cost per mile of the vehicles they drive. The decision depends on factors such as household budget constraints and the utility from driving. Multi-vehicle households may also reallocate miles traveled across their vehicles when relative fuel costs change. In contrast, in the truck sector firms choose how much to drive their trucks in response to demand for trucking services and other profit incentives. Fuel costs account for nearly 40 percent of total operation costs per mile, a larger share than driver wages or capital costs, and therefore fuel costs are an important determinant of truck utilization. Furthermore, the substitution effects across trucks that operate in competitive markets are likely to operate differently from substitution across vehicles within households (Greene et al. 1999 and Linn forthcoming). Given these differences, the light-duty literature provides little insight into the truck rebound effect.

Specific to the truck sector, only two papers have investigated the rebound effect, and both focus on European markets. DeBorger and Mulalic (2012) develop a structural model in which shipping firms choose truck characteristics and use to minimize costs. The model is calibrated using aggregate time series data from Denmark. They estimate a short-run rebound effect of about 10 percent and a long-run rebound effect of about 17 percent. Matos and Silva (2011), also using aggregate data but for Portugal, estimate a 24 percent rebound effect from a reduced-form model.

The benefits of the standards also depend on baseline miles traveled, and in most existing models miles traveled depend on economic activity and operating costs relative to other transportation modes. Either GDP or gross output typically serves as a proxy for economic activity and demand for trucking services in these models. Lower operating costs for trucks relative to other transportation modes cause more shipping via trucks. Furthermore, an increase in economic activity typically increases demand for trucking services, such as transporting goods for retail sale. It may be reasonable to assume that shipments respond proportionately to economic activity—in fact, the analysis by EPA and NHTSA implicitly assumes a proportionate relationship—but we are not aware of direct empirical evidence supporting this assumption. Even if the relationship were proportional at one point in time, changes in the structure of the economy, such as a shift in output from manufacturing to services, would likely affect the relationship between overall economic activity, as measured by GDP, and shipping. Likewise, shifts in geographic concentration or imports for specific industries would also affect the relationship between shipping and either industrial output or GDP.

In this paper, to fully exploit the advantages of the microdata, we decompose total trucking miles traveled into the product of two components: miles traveled per truck, and the number of trucks operating in the market. We specify miles traveled per truck as a function of the truck's fuel costs per mile, economic activity, truck and geographic characteristics, and a time trend. Fuel costs are likely to be endogenous both for reasons of reverse causality and omitted variables. When trucks are driven more miles they are likely to be driven with heavier loads, reducing fuel economy. Furthermore, fuel economy is typically correlated with other truck attributes such as carrying capacity, which are typically not observed at the aggregate level. Using truck-level microdata offers three primary advantages over the previous truck rebound literature. First, we account for the endogeneity of fuel costs by using oil prices to instrument for fuel costs. Second, we include an extensive set of controls for truck characteristics to allow for changes in truck type and characteristics over time that are correlated with fuel economy. Finally, we distinguish between the short and long-run rebound effects, in contrast to Matos and Silva (2011). We estimate long run VMT – cost per mile elasticities of 18 percent for tractor trailers and 12 percent for vocational trucks. We use GSP to proxy for economic activity and estimate an elasticity of miles traveled per truck to GSP of 18 percent for both tractor trailers and vocational trucks.

In the second level of analysis, we model the number of trucks by state and business category as a function of average fuel costs per mile, economic activity, average truck characteristics, and a time trend. As in the truck-level estimation, we instrument for fuel costs per mile and use GSP to proxy for economic activity. The effect of fuel costs on truck counts is small and not statistically significant either for vocational trucks or tractor trailers. The elasticity of truck counts to GSP is 43 percent for tractor trailers and 70 percent for vocational trucks. For both the truck-level and truck-count regressions, the results are robust to a range of other specifications including the use of alternate measures of economic activity or instruments for fuel costs.

Estimation Strategy

We model the market for trucking services as having a large number of trucks that are differentiated by multiple characteristics. Trucks take shipping prices as exogenous and compete to transport shipments, where all shipments have identical characteristics; we relax this latter assumption in subsequent empirical analysis. The supply of VMT by truck i in year t is a function of variables that influence the marginal cost of providing each mile of trucking services. These variables include fuel cost per mile (fuel price in year t divided by miles per gallon), vehicle age, physical truck characteristics such as axle configuration, cab type and trailer type, and variables related to region-specific costs.[7] Denoting fuel cost per mile as CPM_{it} and other supply-related truck characteristics by X_{it}, we can express the supply of VMT as

$$VMT_{it}^{s} = S(CPM_{it}, X_{it}). \quad (1)$$

The demand of truck i VMT in year t is a function of variables that influence the willingness-to-pay for miles. These variables include economic activity in the region that the truck operates, measured by gross state product (GSP) in year t, market characteristics including the total number of trucks in operation, products that the trucks carries, business and variables related to regional-specific costs.[8] Denoting GSP in time period t by GSP_{it}, the total number of trucks in operation by N_t all other demand-related characteristics by Y_{it}, we can express demand for truck i VMT as

$$VMT_{it}^{d} = D(GSP_{it}, Y_{it}, N_t). \quad (2)$$

[7] An alternative formulation would be to model the equilibrium quantity of ton miles traveled as a function of cost per ton mile and other characteristics. Modeling ton miles introduces measurement error since the most reliable measure of weight in the VIUS waves is self-reported. We include ton-mile regression outputs for tractor trailers and vocational vehicles as a robustness check.

[8] Demand for truck i in year t vehicle miles traveled also depends on costs per mile of truck i in year t relative to other competing trucks in its market. We define and include this variable in a later section of the paper.

In equilibrium, for each truck i and each year t, the total number of trucks in operation and per truck VMT adjusts until per truck VMT demand equals supply:

$$VMT_{it}^{*} = S(CPM_{it}, X_{it}) = D\left(GSP_{it}, Y_{it,}N_{t}^{*}\right) \tag{3}$$

We assume that the following functions defining equilibrium per truck VMT and truck counts that take the form

$$VMT_{t}^{*} = F(CPM_{it}, GSP_{it}, X_{it}, Y_{it}), \tag{4}$$

$$N_{t}^{*} = G(\{CPM_{it}\}_{i}, \{GSP_{it}\}_{i}, \{X_{it}\}_{i}, \{Y_{it}\}_{i}) = G(CPM_{t}, GSP_{t}, X_{t}, Y_{t}). \tag{5}$$

In Equation (5), we assume that cost per mile, GSP, and other supply and demand related truck characteristics enter as market averages, which we denote by variables with t subscripts. We assume that the functions $F(\cdot)$ and $G(\cdot)$ and can be approximated by the following relationships:

$$VMT_{it}^{*} = F(CPM_{it}, GSP_{it}, X_{it}, Y_{it}) = (CPM_{it})^{\beta}(GSP_{it})^{\gamma} \exp(\alpha + \theta X_{it} + \rho Y_{it} + \varepsilon_{it}), \tag{6}$$

$$N_{t}^{*} = G(CPM_{t}, GSP_{t}, X_{t}, Y_{t}) = (CPM_{t})^{\beta'}(GSP_{t})^{\gamma'} \exp(\alpha' + \theta' X_{t} + \rho' Y_{t} + \varepsilon_{t}), \tag{7}$$

In Equations (6) and (7), ε_{it} and ε_{t} are a mean-zero stochastic error terms. Taking the natural log of both sides of Equations (7) and (8) implies

$$\ln(VMT_{it}^{*}) = \alpha + \beta \ln(CPM_{it}) + \gamma \ln(GSP_{it}) + \theta X_{it} + \rho Y_{it} + \varepsilon_{it}. \tag{8}$$

$$\ln(N_{t}^{*}) = \alpha' + \beta' \ln(CPM_{t}) + \gamma' \ln(GSP_{t}) + \theta' X_{t} + \rho' Y_{t} + \varepsilon_{t}'. \tag{9}$$

The parameters of interest to be estimated, β and β', represent the elasticity of VMT and truck counts with respect to the cost of driving one additional mile. Note that these elasticities represent an equilibrium response to a change in the cost of driving. Fuel economy regulations will require increased fuel economy from new trucks, which shifts the supply curve of VMT and lowers the cost per mile of driving. This lowers the marginal cost of providing one more mile of service, which lowers the equilibrium price per mile and increases the equilibrium quantity of miles demanded. The rebound effect is then equal to the sum of these two coefficients.

This notion of the rebound effect is fundamentally different than the traditional rebound effect typically measured for consumer goods, such as passenger cars and light trucks. For light duty vehicles owned primarily by individual households, the rebound effect is driven by private optimization of household consumption choices and adjustments in household budget constraints (Gillingham et al. 2015, Chan and Gillingham, 2015).[9] As a result, passenger vehicle rebound effects are simply demand elasticities and can be estimated with variables that enter the VMT demand equation. In contrast, we must control for variables that are correlated with cost per mile and that shift the supply for truck VMT, particularly truck characteristics that affect marginal costs.

Above we made the simplifying assumption that all shipments are identical to one another, causing trucks to compete for the number of shipments based on cost per mile. If shipments have heterogeneous weight, size, or other attributes, trucks may compete for ton-miles based on cost per ton mile of driving. Below we report results for tractor trailers and vocational vehicles using ton-miles and cost per ton mile.

Since trucking companies compete for hauling and other service contracts, the demand for miles driven for truck i may not only depend on the per mile operating costs of truck i, but also on operating costs of truck i's competitors. We model this possibility by including an average fuel cost per mile of the set of $J(i)$ trucks competing with truck i for miles, denoted by $CPM_t^{J(i)}$, in the demand for truck i miles. This addition yields:

$$\ln(VMT_{it}^*) = \tilde{\alpha} + \tilde{\beta}\ln(CPM_{it}) + \tilde{\varphi}\ln(CPM_t^{J(i)}) + \tilde{\gamma}\ln(GSP_{it}) + \tilde{\theta}X_{it} + \tilde{\rho}Y_{it} + \tilde{\varepsilon}_{it}. \tag{10}$$

[9] Some policies, such as Corporate Average Fuel Economy (CAFE) standards for light duty vehicles, may induce changes in non-price, non-fuel economy attributes, such as weight and horsepower in addition to increasing fuel economy (Klier and Linn, 2012). As a result, these policies may influence utilization through household utility from changes in product attributes other than fuel economy. For example, West et al. (2015) find that programs that subsidize fuel economy may not increase VMT because fuel economy is negatively correlated with other desirable attributes.

See the Appendix for a derivation of the equation. The coefficient $\tilde{\varphi}$ represents a substitution effect: as the average cost per mile of truck i's competitors increases, we expect that the demand for truck i VMT will increase. Therefore we expect the sign of $\tilde{\varphi}$ to be positive.

This substitution effect creates the potential for fuel economy standards to have a more complex effect on vehicle use across the entire truck fleet in the short run. This is because the standards only reduce the cost per mile of new trucks. As the standards take effect, the cost per mile of new vehicles will decrease, leading to an increase in new truck VMT through the rebound effect. The cost per mile of used vehicles, however, remains fixed as the fuel economy of the existing fleet of trucks remains unchanged. The standards cause used trucks to be less competitive with new trucks, which causes demand to shift toward new trucks and away from used trucks. Because new trucks have higher fuel economy than used, this substitution counteracts the traditional rebound effect.[10]

Data

The Vehicle Inventory and Use Survey (VIUS) is the primary data source, with surveys administered in five year intervals from 1977 through 2002.[11] Each survey year, Census sampled over 100,000 trucks by mailing owners or managers mandatory surveys in the first months of the following year. State registration files were used to categorize trucks into five strata based on body type and weight, and a random sample was generated within each stratum. Using the state registration files to generate total truck counts, VIUS provides sampling weights for creating a representative sample. The dataset includes information on vehicle characteristics, driving behavior, and operational details. Vehicle characteristics include fuel economy, body and trailer

[10] To fix this idea, consider the following stylized example. Suppose that without a fuel economy standard, representative new and used trucks each achieve 5 miles per gallon and are driven 100,000 miles per year, so that total gallons of gasoline consumption is 40,000 gallons by the two types of trucks combined. Consider a fuel economy standard of 10 miles per gallon for new trucks. Without a rebound effect, total gallons consumed falls to 30,000 gallons for a total savings of 10,000 gallons. With a rebound effect of 20%, miles driven by new trucks increases to 120,000 miles and total gallons fall to 32,000 gallons, for a total savings of 8,000 gallons. With a rebound effect and a substitution effect, new truck miles increase to 140,000 miles and used truck miles fall to 80,000 miles, and total gallons consumed falls to 30,000 gallons for a total savings of 10,000 gallons, which is the same savings without a rebound effect.

[11] Early surveys were referred to as the Truck Inventory and Use Survey (TIUS). Survey years prior to 1977 are omitted from this analysis because these microdata are no longer made available by the Census Bureau.

type, make, age, and axle configuration.[12] Driving behavior includes annual VMT, in-state and out-of-state driving percentages, and average trip lengths.[13] Operational details include business, product carried, and operator classification.

Using truck body type and gross vehicle weight rating (GVWR), we assign trucks into one of two truck classes outlined by Phase I of the truck fuel economy regulations: Class 7 and 8 combination tractors and Class 2b – 8 vocational vehicles.[14] Table 1 reports our final vehicle counts for each truck category and weight class.

To arrive at our final sample of 167,354 observations, we eliminate observations with missing data for key variables such as VMT, MPG, state, body type, model year, and acquisition year.[15] We drop the following trucks from our sample: trucks disposed of or purchased in the survey year due to truncated annual VMT; trucks greater than 10 years old due to inconsistent model year and acquisition year information across survey years; trucks using fuels other than diesel or gasoline; and trucks with reported annual VMT over 275,000.[16] In Appendix Table A1 we report the effect of these screens on the benchmark results.

In several instances, we impute missing values to avoid dropping additional observations. For trucks purchased new, we assume acquisition year and model year are equal when one value is missing. For trucks with missing information on in-state and out-of-state driving percentages, we use group means by state, truck category, body type, age, and survey year. For missing axle

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[12] Fuel economy is based on self-reported average miles per gallon during the survey year. Respondents are given the ability to report miles per gallon to the nearest tenth decimal place, e.g. 4.5 miles per gallon. In addition to providing a fuel economy value, in a subset of the surveys, respondents are asked to indicate which fuel economy range the truck represents, where the ranges are in one mile-per-gallon increments.

[13] One alternative to our estimation strategy would be to use lifetime VMT and age to calculate average monthly VMT, as in Gillingham (2014). However, VIUS does not report the date of survey completion, introducing measurement error into this calculation. Further, VMT for trucks declines with age much more quickly than for passenger vehicles, making average lifetime VMT a less appropriate measure of recent miles driven.

[14] While the VIUS does not differentiate between Class 2a and Class 2b, we identify a portion of 2b trucks by using their reported average operating weight. By definition, this weight must be below the maximum operating weight specified by the manufacturer (GVWR), making us confident that trucks with an average operating weight above 8,500 pounds fall into a weight class of 2b or higher.

[15] For detailed observation counts at each stage of the cleaning process, see Table A1 in the Appendix.

[16] Trucks older than 10 years old make up only 20% of the sample and an even smaller percentage of VMT. Figure 1 provides a graphical representation of the relationship between VMT and age. One year old trucks drive roughly four times more than 15 year old trucks and are ten times more common in our sample. Data does not allow us to match up fuel prices to alternative fuel trucks because of both price data availability and fuel mixing. These trucks only make up less than one percent of the initial sample. Annual VMT exceeding 275,000 miles equates to driving every day of the year for at least 10 hours at 75 miles per hour.

configuration, operator class, and cab type, we impute using the group mode for truck category, body type, age, and survey year.

We take advantage of in-state and out-of-state driving information to calculate weighted average values for the fuel prices, GSP, and competitors' cost per mile faced by each truck. For each variable, we calculate both state and national values in the survey year and weight those based on in-state driving percentages.[17] State and national gasoline and diesel price data are from the Energy Information Administration's (EIA) State Energy Data System (SEDS). In Equations (8), (9), and (10), we instrument cost per mile using crude oil acquisition costs by refiners nationally. These data are also from EIA. GSP is retrieved from the Bureau of Economic Analysis We calculate truck counts at the state and national level using sampling weights provided in the VIUS datasets.

Estimation Results

To infer the magnitude of a possible rebound effect from truck fuel economy regulations, we estimate the model described above using the VIUS data. The heavy-duty truck fuel economy standards for both Phase 1 and Phase 2 group trucks into three separate categories: tractor trailers, vocational vehicles and HD pickups and vans. We are able to estimate Equations (8), (9), and (10) for the two largest mutually exclusive subsets of our sample, tractor trailers and vocational vehicles.[18] In Tables 2 through 5 we report coefficient estimates of specifications of Equation (8), (9), and (10) for the two categories of trucks.

In estimating Equation (8), for each truck we assign a group average cost per mile for CPM_{it} as opposed to using truck i's cost per mile. Group averages are assigned based on our method for assigning competition groups. We have two reasons for estimating Equation (8) with

[17]We calculate the average fuel price for an individual truck as:

$$\overline{fp} = [(d_s) * (fp_s)] + [(d_n) * (fp_n)],$$

where $\overline{fp}$ is the average fuel price, d_s and d_n are the fraction of driving in and out of state and fp_s and fp_n are the state and national fuel prices. A similar formula is used for GSP, with the national value being an average of the other states' GSPs.

[18] We exclude heavy duty pick-ups and vans from our analysis for two reasons. First, the VIUS surveys do not distinguish between Class 2a and Class 2b pick-ups and vans. Therefore if we were to include all Class 2 pick-ups and vans in our analysis, we would be including vehicles that are not regulated by the heavy duty standards (and are instead regulated by light duty CAFE standards). Second, the sample size of the pick-ups and vans likely to be Class 2b is much smaller than the sample sizes for tractor trailers and vocational. Our attempts at including this class of vehicles in our analysis resulted in mostly insignificant and economically implausible point estimates of the coefficients of interest.

a group average for CPM_{it}. First, we rely on time series variation in fuel prices for identifying the CPM_{it} coefficient. This variation influences the cost per mile of truck i and its competitor's cost per mile. This means that the changes in truck i's cost per mile are correlated with changes in the cost per mile of truck i's competitors. Therefore, using truck i's cost per mile by itself identifies how fuel price changes of truck i and its competitors influence truck i's VMT. Second, defining CPM_{it} by a group average is appropriate for interpreting this variable's coefficient as a long run effect of reducing cost per mile of truck i and its competitors, which is what fuel economy standards are expected to do. This is because in the long run, freight efficiency of all trucks will be, on average, higher as each used truck unaffected by the standards is eventually scrapped. In our robustness checks section we report estimates of Equations (8) using truck i's cost per mile for CPM_{it} and find that the point estimates are similar and statistically indistinguishable from our base specifications.

Class 7 and 8 Tractor Trailers

Table 2 presents coefficient estimates of Equation (8) for Class 7 and 8 tractor trailers. Column (1) reports estimates with a limited set of controls, included weighted GSP per truck, a set of age fixed effects, a fuel type dummy and a set of state fixed effects.[19] The coefficient of interest is the log of cost per mile, which we instrument using the contemporaneous crude oil price.[20] With the basic set of controls, the coefficient of interest is estimated to be -0.169, implying that a 10 percent reduction in the cost per mile leads to an increase of VMT by 1.69 percent. This estimate is near the middle of the rebound effect estimated for passenger vehicles and it seems plausible given the degree of competition between trucks providing freight services.

In Column (2) of Table 2, we report estimates with a more robust set of controls by adding a set of axle configuration fixed effects, a set of cab type fixed effects, a set of body trailer type fixed effects and a set of make fixed effects. This set of additional fixed effects controls for physical characteristics of each truck which are likely to be correlated with cost per

[19] The set of age fixed effects includes one coefficient per year. The fuel type dummy indicates whether the truck has a gasoline or diesel engine. Axle configuration fixed effects include the number of axles per truck and per trailer. Cab fixed effects control for whether the cab of the truck is above, behind, or to the side of the engine. Body trailer type includes the truck type for many single-unit trucks (tow trucks, garbage trucks, utility trucks) or trailer/van type if applicable (e.g. flatbed, standard trailer, fuel tank). Business includes, for example, for-hire transportation, construction, and agriculture. Operator class includes owner operators, motor carriers, and private companies.

[20] We instrument cost per mile with the crude oil price to avoid a common problem of reverse causality between VMT and fuel efficiency. The reverse causality stems from the possibility that truck buyers that expect to drive many miles may decide to buy a truck with better fuel economy.

mile and VMT. The coefficient on log cost per mile drops to -0.145. Adding additional controls for business characteristics, including a set of product fixed effects, business fixed effects and operator class fixed effects, increases the point estimate of the log cost per mile coefficient. With the full set of fixed effects reported in column (3) of Table 2, we estimate the rebound effect for Class 7 and 8 tractor trailers to be -0.185, implying that a 10 percent reduction in the cost per mile leads to an increase of VMT by 1.85 percent.

In our VMT equation, we precisely identify the effect of economic activity on miles traveled. In our preferred specification found in column (3), the elasticity of VMT with respect to GSP is 0.183, implying that GSP growth of 10 percent increases per truck VMT by 1.83 percent.

We also attempt to estimate how the effect of cost per mile on travel by each truck varies depending on the cost per mile of other trucks in the fleet. This is the competition model described by Equation (10), in which we define average cost per mile of truck i's competitors as the average cost per mile of other trucks in the same survey year, truck category, body type and business. This method for assigning competition both reflects the nature of the trucking industry and minimizes the aggregation to a point where all trucks are considered in competition. Body type is an obvious category for competition: tow trucks will not compete with concrete mixers, nor will delivery vans compete with logging trucks. Business is also necessary, as it separates trucks used, for example, for construction, for-hire transportation, manufacturing, and personal transportation. We have estimated models using other competition definitions and have found them to be generally comparable to our results.[21] To be consistent with how we define own cost per mile and GSP, we compute average competition cost per mile at both the state and national level before weighting.[22]

We present our estimates of Equation (10) for our preferred specification for tractor trailers in column (4) of Table 2. The coefficient on log cost per mile is now -0.620, implying that a 10 percent reduction in the cost per mile of truck i leads to an increase in truck i VMT of 6.2 percent, holding cost per mile of truck i's competitors fixed. The substitution effect is measured by the coefficient on the log of cost per mile (competition). For tractor trailers, we find

[21] With defining competition comes an inherent tradeoff. Defining it too broadly ignores important industry factors and inappropriately models trucks competing with others that do not in reality compete. Defining it too narrowly decreases the observations in each group and may ignore competing trucks' behavior.

[22] In calculating competition cost per mile, we use sampling weights provide in VIUS. Observations that represent many more trucks in the U.S. fleet are given a higher weight in calculating cost per mile of competitors. Our results are similar when we do not use these weights.

that the substitution effect enters with the expected positive sign and is statistically significant with a coefficient estimate of 0.432. Our estimates suggest that a 10 percent reduction in the cost per mile of truck i's competitors leads to a reduction in truck i VMT of 4.32 percent, holding cost per mile of truck i fixed.

This result suggests that the short run impact of fuel economy standards for tractor trailers may not lead to much of a net rebound effect, as VMT of relatively fuel efficient new trucks will substitute for VMT of relatively fuel inefficient used trucks as the standards become binding. In the long run, however, once existing used trucks are scrapped and new truck fuel economy is on average equal to used truck fuel economy, the impact of the standard on total gallons of gasoline consumed is measured by the *sum* of the log cost per mile and log average competition cost per mile, as the standards influence the cost per mile of all trucks by the same proportion, including truck i and truck i's competitors. For tractor trailers, the sum of these two coefficients is -0.188, which is statistically indistinguishable from our rebound effect reported in column (3) of Table 2.

We report estimates of the truck count model for tractor trailers in Table 3. The point estimates for each specification, while economically significant, are statistically insignificant. In our preferred specification in column (3), the truck count elasticity with respect to cost per mile is -0.11 with a standard error of 0.11. Together with our VMT results, we conclude that most of the responsiveness of total VMT to changes in cost per mile stem from VMT changes and not truck count changes.

Turning to the effect of economic activity on truck counts, we find that GSP has a large and statistically significant effect on the number of trucks in operation. The point estimate for the elasticity of truck counts with respect to GSP is 0.433, implying that if GSP grows by 10 percent, truck counts are predicted to increase by 4.33 percent, which is a much larger effect than we find in our VMT model.

Class 2b – 8 Vocational Vehicles

In Table 4, we present coefficient estimates of Equation (8) for Class 2b through 8 vocational vehicles. In our preferred specification in column (3) of Table 4, we find that the elasticity of VMT with respect to cost per mile is -0.122, interpreted as a 10 percent reduction in cost per mile leading to an increase in VMT of 1.22 percent.

Unlike tractor trailers, vocational vehicles display vast differences in their shape and purpose. While nearly half of tractor trailers are for-hire transportation, no one business category makes up more than 20% of all vocational vehicles in our sample. The body types include large delivery vans, garbage trucks, and concrete mixers.[23] As a result, we might expect substantial heterogeneity in the rebound effect for vocational vehicles. We explore this hypothesis in the appendix and find that VMT of different groups of vocational vehicles respond similarly to proportionate changes in cost per mile.

The estimates that include the cost per mile of a truck's competition appear in column (4) of Table 4. We find no evidence that a vocational truck's own VMT responds to the fuel costs of its competitors. This is likely because the purpose of vocational vehicles varies dramatically when compared to the utility of tractor trailers so that competitive effects are likely to be minor.

Across all specifications in Table 4, we find that utilization of vocational vehicles has a modest and statistically significant response to economic activity. In our preferred specification in column (3), the response is an elasticity of 0.175, an effect similar in magnitude to our tractor trailer results.

In Table 5, we report estimates of Equation (9), explaining the number of trucks for vocational vehicles. Across all three specifications, the coefficient on the log average cost per mile is small and statistically insignificant. This suggests that the stock of vocational vehicles is unresponsive to fuel cost changes. Economic activity, as measured by the log of GSP, however, is a large and statistically significant impact on the stock of vocational vehicles. In our preferred specification in equation (3), the elasticity of vocational truck counts with respect to GSP is 0.694, an effect that is much larger than our comparable estimate for tractor trailer counts.

Summary

In Table 6 and 7, we summarize our preferred estimates of the rebound effect and elasticities with respect to economic activity for each category. In Table 6, we report rebound effect estimates and compare them to the assumptions made by the RIA for Phases 1 and 2 heavy-duty truck standards. We report the cumulative rebound effect as the sum of the VMT elasticity and the truck count elasticity. Our VMT elasticity with respect to cost per mile for tractor trailers is 18.5 percent, which is almost four times as large as the assumed rebound effect in Phases 1 and 2 RIAs. The lower bound of the 95 percent confidence interval is 8.9 percent, which is still substantially larger than the five percent assumed by the Agencies.

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[23] Other body types include dump trucks, livestock trucks, oil field trucks, logging trucks, and winch or crane trucks.

While including the effect of cost per mile on truck counts increases the size of the rebound effect for tractor trailers, our cumulative effect is less precisely estimated. Our rebound effect estimate in absolute value for tractor trailers is 29.7 percent, which is about six times as large as the value assumed in the RIAs but has a wider confidence interval primarily due to the truck count coefficient being less precisely estimated. The confidence interval o the cumulative effect, however, does not include the rebound effect assumed by the RIAs.

Our vocational vehicle estimate, on the other hand, is slightly less than the 15% value assumed by the agencies. Moreover, the vocational rebound effect confidence interval includes the RIA's assumption.

The difference between our estimates and those of the agencies is particularly important for the tractor trailer category. Tractor trailers account for nearly 66% of truck emissions of CO2 and are projected to achieve 50% greater reductions in fuel consumption than vocational vehicles during Phase 2.

We summarize VMT and truck count elasticities with respect to GSP in Table 7. We compute a cumulative effect by summing the VMT elasticity and the truck count elasticity. While the cumulative effect for each group is economically and statistically significant, the point estimates are both are less than one. This result has important implications for estimating expected gasoline consumption and emissions reductions which depend on forecasted business-as-usual (BAU) VMT. Elasticities less than one imply that BAU VMT will grow less rapidly than economic activity, so that expected gasoline consumption and emissions reductions stemming from fuel economy standards will be less dramatic than a setting where VMT grows in proportion with economic activity. Another noticeable result is that the elasticity for tractor trailers is substantially less than the elasticity for vocational vehicles. Since tractor trailers represent a large fraction of emissions from heavy duty trucks, the fact that this elasticity is relatively small implies even lower expected fuel and emissions savings as a result of the standards.

Robustness Checks

We perform several robustness checks for our key specifications of Equations (8) and (9). We test the sensitivity of our results to using alternative measures of economic activity, alternative measures of cost per mile, and estimating models of ton miles traveled instead of miles traveled for tractor trailers and vocational vehicles.

Alternative Measures of Economic Activity

In Tables 8 and 9 we report coefficient estimates for models that include alternative measures of economic activity. Each table reports our estimates for both tractor trailers and vocational vehicles. Column (1) in each table is our benchmark set of estimates for tractor trailers where we use the log of weighted GSP per truck as a control for economic activity.

In Table 8, we report the robustness of our VMT elasticity model. In columns (2) and (6), we report estimates for models that include restricted GSP as a control for economic activity, where restricted GSP is the sum of GSP from the following industries that are most likely to be associated with demand for trucking services: Agriculture, forestry, fishing, and hunting; Mining; Utilities; Construction; Manufacturing; Wholesale trade; Retail trade; and Transportation (excluding truck transportation). We see a modest increase in magnitude of the coefficient on fuel cost per mile. We see an even larger increase in magnitude when we use value of shipments (Log weighted average VOS) as a measure of economic activity. These estimates appear in columns (3) and (7). The coefficients may be larger in these specifications because we are not controlling for excluded demand factors that are negatively correlated with fuel costs per mile. As a consequence, omitted variable bias will lead to a larger rebound effect. In general, however, we take comfort that the effect of cost per mile for each truck category is fairly robust across several different measures of economic activity.

Our results in Table 9 for truck count elasticities are similar. Using restricted GSP or VOS increases the rebound effect estimate for both truck categories. For both categories, however, the specifications remain insignificant with the exception of the tractor trailers specification using value of shipments as a control for economic activity. In this case, truck counts respond to cost per mile changes, with an elasticity of -0.226.

Alternative Measures of Cost per Mile

In Tables 10 and 11, we present estimation results using alternative measures of cost per mile. Columns (1) and (5) include our benchmark estimation results for tractor trailers and vocational vehicles, where we instrument for cost per mile using the contemporaneous crude oil price. This cost per mile is an average cost per mile for all trucks within truck *i*'s competition group. In Table 10, we report sensitivity results for our VMT models. In columns (2) and (6) we show that results using only truck *i*'s cost per mile are nearly identical in magnitude and are statistically indistinguishable. Columns (3) and (7) are similar specifications but with a different instrument for cost per mile. Here we use as an instrument the interaction between contemporaneous crude oil prices and a 1970 state fuel price deviation from the national fuel price as an instrument for cost per mile. The interaction of the contemporaneous crude price and the 1970 state price deviation is a valid instrument if pre-sample cross state deviations from the national mean are uncorrelated with within-sample deviations in state prices from the corresponding state means. This instrument is meant to expand upon the initial instrument by taking advantage of exogenous cross-state price variation. Overall, our rebound effect estimates are robust to this alternative instrument. In columns (4) and (8), we estimate an alternative version of Equation (8) by replacing the log of cost per mile with the log of average fuel price, where average fuel price is a weighted average of state and national contemporaneous fuel prices for each truck, weighted by in- and out-of-state driving reported by the respondent. The coefficients on the log of average fuel price coefficients appear to be relatively close to their log of cost per mile counterparts for vocational vehicles. For tractor trailers, however, the fuel price coefficient remains negative but is smaller and statically insignificant.

The sensitivity of our truck count specifications to alternative measures of cost per mile appear in Table 11. In general, the results are consistent to what we see with VMT. Using an alternative instrument or fuel price directly has little effect on the rebound effect estimates or the economic activity elasticities.

Estimating Models of Ton Miles

How far the payload of a truck travels, denoted as ton miles, may be a better measure of trucking activity than miles traveled as the former includes both how far a truck travels and how many goods it hauls. In response to fuel economy regulation, truck operators may respond by hauling different amounts of goods in addition to changing their miles traveled. To model this possibility, we estimate models of ton miles traveled by replacing the dependent variable in Equation (8) with the log of ton miles and by replacing the cost per mile variable with the log of cost per ton mile.

We report coefficient estimates in Table 12. The estimated rebound effects for tractor trailers and vocational vehicles are -0.189 and -0.052, respectively. The estimate for tractor trailers is slightly larger in magnitude than our benchmark rebound effect estimate, suggesting that for most of the response to fuel cost changes is through miles driven. We observe a smaller, insignificant rebound effect for vocational vehicles when using ton miles. We prefer the rebound estimates based on VMT rather than ton miles because the VIUS likely contain substantial measurement error in weight.

Since truck counts may also respond differently to cost per ton mile, we consider this possibility by re-estimating Equation (9) with cost per ton mile replacing cost per mile. Similar to our benchmark results, the point estimates retain their sign and general magnitude and remain statistically insignificant as shown in Table 13.

Conclusion

Our study is the first to leverage detailed microdata on truck level characteristics and utilization in the United States to estimate rebound effects that can be directly used for cost-benefit and emissions impact analyses of fuel economy regulation. We find several striking results that should help guide current and future analysis of these and other possible regulations for the heavy duty fleet. Our rebound effect estimate for Class 7 and 8 tractor trailers is robust to several alternative specifications and is at least three times as large as the rebound effect assumed by NHTSA and EPA in the RIAs for Phases 1 and 2 of the heavy duty standards for fuel economy and greenhouse emissions. Since the GHG emissions savings from Phases 1 and 2 are dominated by the predicted changes in fuel consumption by tractor trailers, our substantially higher rebound effect estimate will dramatically diminish the emissions savings from the policy.[24] Furthermore, we find significant substitution effects between fuel efficient and fuel inefficient trucks, which we speculate will have important short-run implications for diesel consumption.

Our results have policy implications beyond those implied for fuel economy standards. Larger rebound effects imply that increasing diesel taxes are relatively more attractive instrument for reducing fuel use and greenhouse gas emissions. Moreover, our results suggest that to mitigate potentially large social welfare losses associated with increased VMT due to the standards (e.g. traffic congestion, traffic accidents), increased diesel taxes may be an appropriate policy response.

[24] How the size of the rebound effect influences the net benefits from the standards, however, is a controversial question. Larger rebound effects imply more VMT, which likely leads to greater private welfare gains in the form of higher producer profits and lower prices faced by consumers. Without a detailed structural model of the heavy duty fleet and VMT decisions, however, it is difficult to accurately assess the benefits associated with additional VMT.

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Figures and Tables

Figure 1. Average VMT by Age and Truck Category

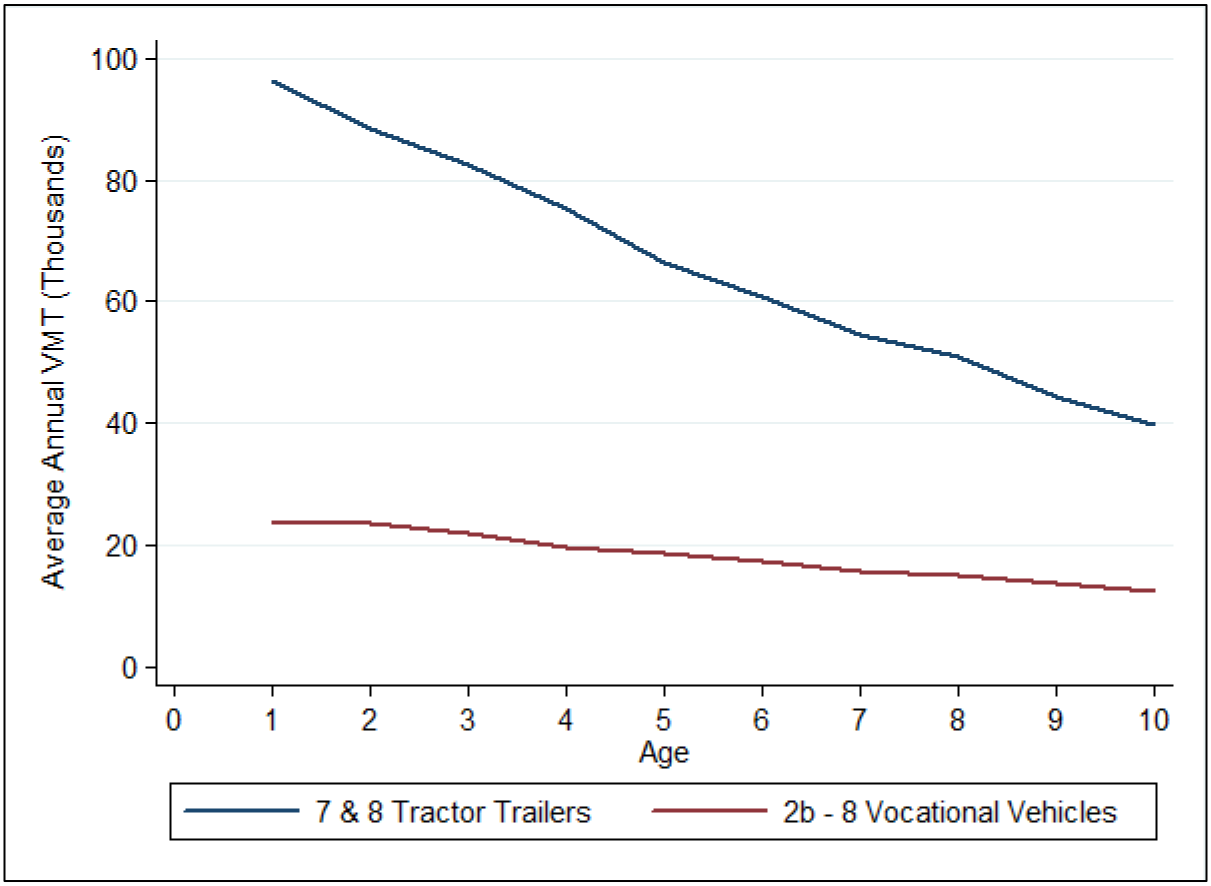

Table 1. Final Observation Count by Weight Class and Truck Category

Class	(2b)	(3)	(4)	(5)	(6)	(7)	(8)	
GVWR (lbs.)	8,501 to 10,000	10,001 to 14,000	14,001 to 16,000	16,001 to 19,500	19,501 to 26,000	16,001 to 33,000	Over 33,000	Total
Tractor Trailers	-	-	-	-	-	6,025	68,706	74,731
Vocational Vehicles	8,007	7,578	4,007	4,729	27,004	10,681	30,617	92,623
Total	8,007	7,578	4,007	4,729	27,004	16,706	99,323	167,354

Notes: Each cell represents the final number of trucks in our data for a given weight class and truck category. The categorical variable gross vehicle weight rating (GVWR) is reported based on de-coded VINs by the VIUS. For each weight class, the associated GVWR range is reported in pounds (lbs.). These counts may not exactly reflect the truck population in a given year. Sampling weights in the VIUS are used to generate state and national truck counts.

Table 2. VMT Elasticities for Tractor Trailers

	(1)	(2)	(3)	(4)
Log cost per mile	-0.169*	-0.145***	-0.185***	-0.620***
	(0.101)	(0.0503)	(0.0488)	(0.158)
Log cost per mile (competition)				0.432***
				(0.150)
Log weighted average GSP	0.348***	0.240***	0.183***	0.186***
	(0.0326)	(0.0261)	(0.0204)	(0.0202)
Constant	5.357***	6.195***	6.795***	6.970***
	(0.331)	(0.250)	(0.264)	(0.277)
Observations	74,731	74,731	74,731	74,538
R-squared	0.217	0.328	0.376	0.355
Age FE	Y	Y	Y	Y
Fuel Type FE	Y	Y	Y	Y
State FE	Y	Y	Y	Y
Axle Configuration FE	-	Y	Y	Y
Cab FE	-	Y	Y	Y
Body Trailer Type FE	-	Y	Y	Y
Make FE	-	Y	Y	Y
Product FE	-	-	Y	Y
Business FE	-	-	Y	Y
Operator Class FE	-	-	Y	Y

Notes: Robust standard errors are clustered by main product and state and are reported in parentheses. Statistical significance is denoted by *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the log of annual VMT. These regressions include only trucks classified as Class 7 & 8 Tractor Trailers. For columns (1) – (3), cost per mile is a weighted average within a truck's competition group, defined as all trucks in a survey year with the same body or trailer type, business, and truck category at the state and national level, each weighted based on in-state driving patterns of each truck. For column (4), the cost per mile is only for truck *i*, and a separate weighted average cost per mile is included for its competition. The first cost per mile term in each column is instrumented using the contemporaneous crude oil price to control for the endogeneity of fuel economy in estimating the VMT of truck *i*. The weighted average GSP per truck is calculated as a weighted average of in-state and out-of-state GSP based on the percent of miles each truck drives in and out of state. Column (1) has a basic set of controls; column (2) adds in truck characteristics; and column (3) represents the exhaustive set of controls, additionally controlling for operational aspects of each truck. Column (4) displays the substitution effect between trucks by including cost per mile for truck *i* and its competitors separately. The lower observation count in column (4) is the result of some trucks having no competitors in our sample.

Table 3. Truck Count Elasticities for Tractor Trailers

	(1)	(2)	(3)
Log average cost per mile	-0.172	-0.0477	-0.112
	(0.162)	(0.106)	(0.113)
Log GSP	0.578***	0.471***	0.433***
	(0.177)	(0.122)	(0.132)
Constant	-0.871	1.647	3.690
	(1.773)	(2.060)	(2.549)
Observations	2,381	2,381	2,381
R-squared	0.831	0.851	0.863
State FE	Y	Y	Y
Business FE	Y	Y	Y
Fuel Type	Y	Y	Y
Axle Configuration	-	Y	Y
Body Trailer Type	-	Y	Y
Cab	-	Y	Y
Make	-	Y	Y
Product	-	-	Y
Operator Class	-	-	Y

Notes: Robust standard errors are clustered by survey year and are reported in parentheses. Statistical significance is denoted by *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the log of the number of trucks in each state-business-year cell. The number of trucks assigned to each state is calculated by using sampling weights provided by Census and in-state and out-of-state driving fractions. Trucks driving entirely in state are assigned to that state, while trucks driving out of state have their out-of-state portion assigned to other states based on the in-state truck populations of each state. State and business fixed effects are used in each specification, while the remaining controls are added to reach our preferred specification (3). The controls are calculated as the percent of trucks in a state-business-year cell that fall into each category (e.g. 10% gasoline, 90% diesel). These percentages are weighted using sampling weights and in-state driving fractions.

Table 4. VMT Elasticities for Vocational Vehicles

	(1)	(2)	(3)	(4)
Log cost per mile	-0.133	-0.120	-0.122***	-0.131
	(0.131)	(0.0896)	(0.0416)	(0.0881)
Log cost per mile (competition)				0.00249
				(0.0494)
Log weighted average GSP	0.203***	0.169***	0.175***	0.175***
	(0.0713)	(0.0444)	(0.0213)	(0.0214)
Constant	6.340***	7.128***	6.585***	6.586***
	(0.662)	(0.415)	(0.285)	(0.290)
Observations	92,623	92,623	92,623	92,292
R-squared	0.188	0.263	0.306	0.305
Age FE	Y	Y	Y	Y
Fuel Type FE	Y	Y	Y	Y
State FE	Y	Y	Y	Y
Axle Configuration FE	-	Y	Y	Y
Cab FE	-	Y	Y	Y
Body Trailer Type FE	-	Y	Y	Y
Make FE	-	Y	Y	Y
Product FE	-	-	Y	Y
Business FE	-	-	Y	Y
Operator Class FE	-	-	Y	Y

Notes: Robust standard errors are clustered by main product and state and are reported in parentheses. Statistical significance is denoted by *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the log of annual VMT. These regressions include only trucks classified as Class 2b - 8 Vocational Vehicles. For columns (1) – (3), cost per mile is a weighted average within a truck's competition group, defined as all trucks in a survey year with the same body or trailer type, business, and truck category at the state and national level, each weighted based on in-state driving patterns of each truck. For column (4), the cost per mile is only for truck *i*, and a separate weighted average cost per mile is included for its competition. The first cost per mile term in each column is instrumented using the contemporaneous crude oil price to control for the endogeneity of fuel economy in estimating the VMT of truck *i*. The weighted average GSP per truck is calculated as a weighted average of in-state and out-of-state GSP based on the percent of miles each truck drives in and out of state. Column (1) has a basic set of controls; column (2) adds in truck characteristics; and column (3) represents the exhaustive set of controls, additionally controlling for operational aspects of each truck. Column (4) displays the substitution effect between trucks by including cost per mile for truck *i* and its competitors separately. The lower observation count in column (4) is the result of some trucks having no competitors in our sample.

Table 5. Truck Count Elasticities for Vocational Vehicles

	(1)	(2)	(3)
Log average cost per mile	-0.0966	0.103	0.0292
	(0.0741)	(0.0920)	(0.120)
Log GSP	0.730***	0.763***	0.694***
	(0.128)	(0.0844)	(0.121)
Constant	-0.0888	1.485	2.777**
	(1.195)	(1.495)	(1.334)
Observations	2,443	2,443	2,443
R-squared	0.832	0.866	0.875
State FE	Y	Y	Y
Business FE	Y	Y	Y
Fuel Type	Y	Y	Y
Axle Configuration	-	Y	Y
Body Trailer Type	-	Y	Y
Cab	-	Y	Y
Make	-	Y	Y
Product	-	-	Y
Operator Class	-	-	Y

Notes: Robust standard errors are clustered by survey year and are reported in parentheses. Statistical significance is denoted by *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the log of the number of trucks in each state-business-year cell. The number of trucks assigned to each state is calculated by using sampling weights provided by Census and in-state and out-of-state driving fractions. Trucks driving entirely in state are assigned to that state, while trucks driving out of state have their out-of-state portion assigned to other states based on the in-state truck populations of each state. State and business fixed effects are used in each specification, while the remaining controls are added to reach our preferred specification (3). The controls are calculated as the percent of trucks in a state-business-year cell that fall into each category (e.g. 10% gasoline, 90% diesel). These percentages are weighted using sampling weights and in-state driving fractions.

Table 6. Summary of Rebound Effect Estimates

Truck Class	7 and 8	2b – 8
Truck Type	Tractor Trailers	Vocational Vehicles
Rebound Effect Assumed in RIAs for Phases 1 and 2	5%	15%
VMT Elasticity	18.5%	12.2%
95% Confidence Interval	8.9 – 28.1%	4.1 – 20.4%
Truck Count Elasticity	11.2%	-2.9%
95% Confidence Interval	-11.1% - 33.4%	-26.4% - 20.6%
Cumulative Effect	29.7%	9.3%
95% Confidence Interval	5.5% - 53.8%	-15.6% - 34.2%
2005 CO2 Emissions from Phase 1 RIA	66%	22%

Notes: Values for the rebound effect assumed in RIAs for Phases 1 and 2 are found on p. 9-10 and p. 8-25, respectively. The cumulative effect is the sum of the VMT elasticity and truck count elasticity, while the cumulative 95% confidence interval is calculated by using a cumulative standard error equal to the square root of the sum of the squared standard errors from each estimate.

Table 7. Summary of GSP Elasticities

Truck Class	7 and 8	2b – 8
Truck Type	Tractor Trailers	Vocational Vehicles
VMT Elasticity	0.186	0.175
95% Confidence Interval	0.146 – 0.226	0.133 – 0.217
Truck Count Elasticity	0.433	0.694
95% Confidence Interval	0.174 – 0.692	0.457 – 0.931
Cumulative Effect	0.619	0.869
95% Confidence Interval	0.358 - 0.881	0.629 – 1.11

Notes: The cumulative effect is the sum of the VMT elasticity and truck count elasticity, while the cumulative 95% confidence interval is calculated by using a cumulative standard error equal to the square root of the sum of the squared standard errors from each estimate.

Table 8. VMT Elasticities Using Alternative Measures of Economic Activity

	Tractor Trailers				Vocational Vehicles			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log cost per mile	-0.185***	-0.256***	-0.287***	-0.217***	-0.122***	-0.176***	-0.196***	-0.154***
	(0.0488)	(0.0462)	(0.0456)	(0.0501)	(0.0416)	(0.0414)	(0.0417)	(0.0472)
Log weighted average GSP	0.183***			0.120***	0.175***			0.0868**
	(0.0204)			(0.0424)	(0.0213)			(0.0362)
Log weighted average restricted GSP		0.198***				0.199***		
		(0.0250)				(0.0147)		
Log weighted average VOS			0.161***	0.0665			0.148***	0.100***
			(0.0196)	(0.0407)			(0.0143)	(0.0260)
Constant	6.795***	6.644***	6.037***	6.359***	6.585***	6.345***	5.961***	5.872***
	(0.264)	(0.278)	(0.319)	(0.343)	(0.285)	(0.221)	(0.259)	(0.258)
Observations	74,731	74,731	74,731	74,731	92,623	92,623	92,623	92,623
R-squared	0.376	0.375	0.375	0.376	0.306	0.306	0.306	0.306
Age FE	Y	Y	Y	Y	Y	Y	Y	Y
Fuel Type FE	Y	Y	Y	Y	Y	Y	Y	Y
State FE	Y	Y	Y	Y	Y	Y	Y	Y
Axle Configuration FE	Y	Y	Y	Y	Y	Y	Y	Y
Cab FE	Y	Y	Y	Y	Y	Y	Y	Y
Body Trailer Type FE	Y	Y	Y	Y	Y	Y	Y	Y
Make FE	Y	Y	Y	Y	Y	Y	Y	Y
Product FE	Y	Y	Y	Y	Y	Y	Y	Y
Business FE	Y	Y	Y	Y	Y	Y	Y	Y
Operator Class FE	Y	Y	Y	Y	Y	Y	Y	Y

Notes: Robust standard errors are clustered by main product and state and are reported in parentheses. Statistical significance is denoted by *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the log of annual VMT. Cost per mile is instrumented using the contemporaneous crude oil price. The weighted averages for GSP, restricted GSP, and VOS are calculated as a weighted average of the state and national values based on the percent of miles each truck drives in and out of state. Restricted GSP includes only the following industries: Agriculture, forestry, fishing, and hunting; Mining; Utilities; Construction; Manufacturing; Wholesale trade; Retail trade; and Transportation (excluding truck transportation). Value of shipments (VOS) is an economic measure retrieved from the Census of Manufacturers. Further measures of economic activity can be found in the Appendix.

Table 9. Truck Count Elasticities Using Alternative Measures of Economic Activity

	Tractor Trailers				Vocational Vehicles			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log average cost per mile	-0.112	-0.162	-0.226**	-0.153	0.0292	-0.0736	-0.0981	0.00986
	(0.113)	(0.122)	(0.105)	(0.122)	(0.120)	(0.115)	(0.102)	(0.109)
Log GSP	0.433***			0.189	0.694***			0.487***
	(0.132)			(0.207)	(0.121)			(0.0938)
Log restricted GSP		0.585***				0.670***		
		(0.0891)				(0.104)		
Log state VOS			0.539***	0.460**			0.491***	0.352***
			(0.132)	(0.205)			(0.0713)	(0.0619)
Constant	3.690	2.275	-0.592	-1.188	2.777**	2.626*	1.588	-0.786
	(2.549)	(1.529)	(1.436)	(1.088)	(1.334)	(1.438)	(1.718)	(1.721)
Observations	2,381	2,381	2,381	2,381	2,443	2,443	2,443	2,443
R-squared	0.863	0.864	0.864	0.864	0.875	0.875	0.875	0.877
State FE	Y	Y	Y	Y	Y	Y	Y	Y
Business FE	Y	Y	Y	Y	Y	Y	Y	Y
Fuel Type	Y	Y	Y	Y	Y	Y	Y	Y
Axle Configuration	Y	Y	Y	Y	Y	Y	Y	Y
Cab	Y	Y	Y	Y	Y	Y	Y	Y
Body Trailer Type	Y	Y	Y	Y	Y	Y	Y	Y
Make	Y	Y	Y	Y	Y	Y	Y	Y
Product	Y	Y	Y	Y	Y	Y	Y	Y
Operator Class	Y	Y	Y	Y	Y	Y	Y	Y

Notes: Robust standard errors are clustered by survey year and are reported in parentheses. Statistical significance is denoted by *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the log of the number of trucks in each state-business-year cell. Columns (1) – (5) display the results for tractor trailers. Columns (6) – (10) display the results for vocational vehicles. The number of trucks assigned to each state is calculated by using sampling weights provided by Census and in-state and out-of-state driving fractions. Trucks driving entirely in state are assigned to that state, while trucks driving out of state have their out-of-state portion assigned to other states based on the in-state truck populations of each state. Restricted GSP includes only the following industries: Agriculture, forestry, fishing, and hunting; Mining; Utilities; Construction; Manufacturing; Wholesale trade; Retail trade; and Transportation (excluding truck transportation). Value of shipments (VOS) is an economic measure retrieved from the Census of Manufacturers.

Table 10. VMT Elasticities Using Alternative Measures of Cost Per Mile

	Tractor Trailers				Vocational Vehicles			
	(1) Crude IV	(2) Crude IV	(3) 1970 FP IV	(4) Fuel Price	(5) Crude IV	(6) Crude IV	(7) 1970 FP IV	(8) Fuel Price
Log cost per mile	-0.185***		-0.163***		-0.122***		-0.347**	
	(0.0488)		(0.0516)		(0.0416)		(0.159)	
Log cost per mile (truck *i*)	-0.167***					-0.129***		
		(0.0530)				(0.0444)		
Log average fuel price				-0.0635				-0.142***
				(0.0631)				(0.0423)
Log weighted average GSP	0.183***	0.187***	0.187***	0.208***	0.175***	0.176***	0.101*	0.188***
	(0.0204)	(0.0205)	(0.0206)	(0.0194)	(0.0213)	(0.0215)	(0.0589)	(0.0200)
Constant	6.795***	6.823***	6.777***	6.743***	6.585***	6.567***	7.013***	6.706***
	(0.264)	(0.263)	(0.262)	(0.286)	(0.285)	(0.290)	(0.468)	(0.296)
Observations	74,731	74,731	74,731	74,731	92,623	92,623	92,623	92,623
R-squared	0.376	0.374	0.376	0.376	0.306	0.304	0.302	0.306
Age FE	Y	Y	Y	Y	Y	Y	Y	Y
Fuel Type FE	Y	Y	Y	Y	Y	Y	Y	Y
State FE	Y	Y	Y	Y	Y	Y	Y	Y
Axle Configuration FE	Y	Y	Y	Y	Y	Y	Y	Y
Cab FE	Y	Y	Y	Y	Y	Y	Y	Y
Body Trailer Type FE	Y	Y	Y	Y	Y	Y	Y	Y
Make FE	Y	Y	Y	Y	Y	Y	Y	Y
Product FE	Y	Y	Y	Y	Y	Y	Y	Y
Business FE	Y	Y	Y	Y	Y	Y	Y	Y
Operator Class FE	Y	Y	Y	Y	Y	Y	Y	Y

Notes: Robust standard errors are clustered by main product and state and are reported in parentheses. Statistical significance is denoted by *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the log of annual VMT. In columns (1) and (5), the log of cost per mile is instrumented using the contemporaneous crude oil price. In columns (2) and (6), the log of cost per mile is only using the cost per mile of truck *i* but is again instrumented using the contemporaneous fuel price. In columns (3) and (7), the instrument is instead the log of the crude oil price interacted with the log of the 1970 deviation in the state fuel price compared to a national average. In columns (4) and (8), the log of truck *i*'s average fuel price is used instead of cost per mile.

Table 11. Truck Count Elasticities Using Alternative Measures of Cost Per Mile

	Tractor Trailers			Vocational Vehicles		
	(1)	(2)	(3)	(4)	(5)	(6)
	Crude IV	1970 FP IV	Fuel Price	Crude IV	1970 FP IV	Fuel Price
Log average cost per mile	-0.112	-0.0544		0.0292	0.107	
	(0.113)	(0.114)		(0.120)	(0.185)	
Log state fuel price			-0.118			0.237
			(0.132)			(0.201)
Log GSP	0.433***	0.451***	0.445**	0.694***	0.715***	0.724***
	(0.132)	(0.131)	(0.139)	(0.121)	(0.129)	(0.136)
Constant	3.690	3.554	10.93***	2.777**	2.736**	2.348
	(2.549)	(2.535)	(1.754)	(1.334)	(1.303)	(1.514)
Observations	2,381	2,381	2,381	2,443	2,443	2,443
R-squared	0.863	0.863	0.863	0.875	0.875	0.875
State FE	Y	Y	Y	Y	Y	Y
Business FE	Y	Y	Y	Y	Y	Y
Fuel Type	Y	Y	Y	Y	Y	Y
Axle Configuration	Y	Y	Y	Y	Y	Y
Cab	Y	Y	Y	Y	Y	Y
Body Trailer Type	Y	Y	Y	Y	Y	Y
Make	Y	Y	Y	Y	Y	Y
Product	Y	Y	Y	Y	Y	Y
Operator Class	Y	Y	Y	Y	Y	Y

Notes: Robust standard errors are clustered by survey year and are reported in parentheses. Statistical significance is denoted by *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the log of the number of trucks in each state-business-year cell. The number of trucks assigned to each state is calculated by using sampling weights provided by Census and in-state and out-of-state driving fractions. Trucks driving entirely in state are assigned to that state, while trucks driving out of state have their out-of-state portion assigned to other states based on the in-state truck populations of each state. In columns (1) and (4), the average cost per mile is instrumented using the contemporaneous crude oil price. In columns (2) and (5), the average cost per mile is instrumented using the log of the crude oil price interacted with the log of the 1970 deviation in the state fuel price compared to a national average. In columns (3) and (6), the state fuel price is used in place of the average cost per mile. This value is not instrumented.

Table 12. Ton Miles Traveled Elasticities

	Tractor Trailers	Vocational Vehicles
Log cost per ton mile	-0.189***	-0.0517
	(0.0474)	(0.0331)
Log weighted average GSP	0.206***	0.177***
	(0.0212)	(0.0198)
Constant	9.003***	8.618***
	(0.339)	(0.273)
Observations	66,811	70,013
R-squared	0.414	0.481
Age FE	Y	Y
Fuel Type FE	Y	Y
State FE	Y	Y
Axle Configuration FE	Y	Y
Cab FE	Y	Y
Body Trailer Type FE	Y	Y
Make FE	Y	Y
Product FE	Y	Y
Business FE	Y	Y
Operator Class FE	Y	Y

Notes: Robust standard errors are clustered by main product and state and are reported in parentheses. Statistical significance is denoted by *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the log of annual ton miles traveled, which we compute by logging the product of reported average weight and reported survey year VMT. Results are reported separately for tractor trailers and vocational vehicles. Cost per ton mile is again calculated at the group level and is instrumented using the contemporaneous crude oil price. Survey year 1977 is excluded from this analysis because of its lack of survey questions relating to vehicle operating weight.

Table 13. Truck Count Elasticities Using Cost Per Ton Mile

	Tractor Trailers	Vocational Vehicles
Log average cost per ton mile	-0.0847	0.151
	(0.168)	(0.109)
Log GSP	0.370**	0.729***
	(0.170)	(0.123)
Constant	3.669*	3.056***
	(2.100)	(0.528)
Observations	1,983	2,035
R-squared	0.865	0.888
State FE	Y	Y
Business FE	Y	Y
Fuel Type	Y	Y
Axle Configuration	Y	Y
Cab	Y	Y
Body Trailer Type	Y	Y
Make	Y	Y
Product	Y	Y
Operator Class	Y	Y

Notes: Robust standard errors are clustered by survey year and are reported in parentheses. Statistical significance is denoted by *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the log of the number of trucks in each state-business-year cell. The number of trucks assigned to each state is calculated by using sampling weights provided by Census and in-state and out-of-state driving fractions. Trucks driving entirely in state are assigned to that state, while trucks driving out of state have their out-of-state portion assigned to other states based on the in-state truck populations of each state. Cost per ton mile is calculated by generating the gallons per ton mile in each cell and multiplying it by the state fuel price. Survey year 1977 is excluded from this analysis because of its lack of survey questions relating to vehicle operating weight.

Appendix

Review of the Rebound Literature

A large literature analyzes the rebound effect from improvements to energy efficiency, not just in the transportation sector but in energy appliances and even industrial applications (Gillingham et al., 2015; Borenstein, 2014). Energy efficiency improvements reduce energy costs and may therefore stimulate more energy use offsetting some of the gains from energy efficiency.

Researchers have spent a great deal of attention to both developing the theory and to empirically estimating the magnitude of the rebound effect for light duty vehicles. CAFE standards for light duty vehicles were binding in the 1980s, and early studies that attempted to look at the effect of these rules on energy using aggregate time series data found the direct rebound effect to between 5 and 15% (Green, 1992). Later studies attempted to improve on measurement and identification issues, including efforts to address endogeneity of vehicle fuel economy and vehicle use (Linn, 2013, Gillingham, 2014), the use of fuel price variation as a proxy for fuel economy changes (Gillingham, 2014), inclusion of fixed effects that account for confounding variation, attempts to distinguish between long run and short run rebound effects (Small and van Dender, 2007, 2015) and addressing the correlation of fuel economy with other vehicle characteristics (Linn, 2013). Most of the studies to date have used aggregate time series data to identify the rebound effect, but some more recent analyses have used micro or individual data (Knittel and Sandler, 2013, Linn, 2013, Gillingham, 2014, Gillingham et al. 2015). Several of these studies have looked at the effect on the rebound effect of evidence of substitution among vehicles in multi vehicle households (Greene, Kahn and Gibson, 1999, Linn, 2013). The results of these studies highlight the importance of substitution among vehicles in determining the magnitude of the rebound effect. We consider in the analysis below the opportunities for substitution among trucks, in estimating the magnitude of the miles travelled rebound.

The more recent studies of the rebound effect in the light duty vehicle market tend to find that the rebound effect is greater than earlier analyses, particularly in the long-run. Linn (2013) finds the long-run rebound effect to be closer to 20-40%. On the other hand, Small and van Dender (2007) and Borenstein (2014) find income effects to be important. If higher incomes mean that drivers are less sensitive to fuel costs, this can reduce the size of the rebound effect.

In contrast, little research to date examines the possible rebound effect from fuel economy improvements in the medium and heavy-duty truck sectors. The factors likely to influence the magnitude of the rebound effect will be different in the heavy-duty truck sector than for light duty vehicles. In the light duty market, the amount of driving is determined by the demand for driving services. In trucking, the amount of driving will be related to both the demand for the goods being carried and the costs of transporting them. Goods shipment should be profit motivated, and we would expect shipping agents to be aware of fuel costs and opportunities for reducing those costs. Therefore, total VMT depends on both fuel costs and economic activity.

In one of the few studies of the trucking industry, DeBorger and Mulalic (2012) develop a structural model based on cost minimizing firm behavior, which they use to examine the effect of exogenous changes in fuel economy and the associated rebound effect. The rebound effect in their model has several components – one is that better fuel economy lowers the cost of production and results in more goods being shipped. The second is a substitution effect, in that for a given amount of freight carried, better fuel economy will mean there can be less effort at schedule logistics, and matching of shipments to existing route networks. The authors then estimate a system of input equations using aggregate annual time series data for Denmark for the years 1980 to 2007. The elements of the rebound effect are derived from the estimated coefficients. They find the rebound effect to be about 9.8% in the short-run and 16.8% in the long-run, where the long-run is defined as allowing the number and type of trucks to change.

Matos and Silva (2011) estimate a reduced form model of the demand for truck freight transport using annual data for Portugal between 1987 and 2006. They look at the effect of changes in energy cost and other variables on the demand for total freight shipments (ton kilometers), accounting for endogeneity of the energy cost variable, using average fuel consumption as the instrument for energy cost. They find that the magnitude of the rebound effect for freight transport in Portugal over this period is about 24%. This is a higher estimate than that found by DeBorger and Mulalic, but it does not account for endogenous changes in the vehicle stock over time as did the DeBorger and Mulalic study.

Our study draws insight from these previous studies but is also different in a number of respects. We use data from surveys of individual truck owners for three separate types of trucks that was collected by the U.S. Census between 1977 and 2002.[25] This is a unique dataset, and contrasts with the aggregate national data that has been used to estimate truck the rebound effect

[25] The VIUS does not categorize trucks into the categories that we separate trucks. We create these categories based on weight and class variables.

in two European countries. Although the data have shortcomings in that we are limited by the questions that were asked, and key variables, such as fuel economy, are self-reported. However, we have detailed data about the trucks, their cargo and where they travel which allows us to control for these determinants of VMT that are omitted in analysis using aggregate data. We also attempt to account for the likely endogeneity between the cost per mile of driving and the miles driven.[26]

Data Cleaning

Table A1. Data Cleaning

Step	Observations Dropped	Resulting Observation Count
Initial count	-	612,302
Not in one of our truck classifications	200,343	411,959
Missing body / trailer type	737	411,222
Personal transportation or not in use	12,378	398,844
Disposed of during or before survey year	18,348	380,496
Fuel other than gas or diesel	6,002	374,494
Missing or zero MPG	27,128	347,366
Missing VMT	5	347,361
Missing acquire year or model year	94,283	253,078
Age < 1	32,148	220,930
Age > 10	53,529	167,401
VMT > 275,000	47	167,354
Final count	-	167,354

[26] Cost per mile is calculated by dividing the fuel price by the fuel economy (MPG) of the truck. Simultaneity bias with this term and VMT is a common issue in the rebound effect literature, as truckers that anticipate driving long distances are more likely to purchase fuel efficient trucks.

Further Robustness Tables

Table A2. Alternative Vocational Classification

VMT Elasticities for Vocational Vehicles		
	(1)	(2)
Log cost per mile	-0.118**	-0.161***
	(0.0486)	(0.0543)
Log weighted average GSP	0.180***	0.162***
	(0.0218)	(0.0358)
Constant	6.577***	6.274***
	(0.309)	(0.427)
Observations	61,553	31,070
R-squared	0.328	0.275
Age FE	Y	Y
Fuel Type FE	Y	Y
State FE	Y	Y
Axle Configuration FE	Y	Y
Cab FE	Y	Y
Body Trailer Type FE	Y	Y
Make FE	Y	Y
Product FE	Y	Y
Business FE	Y	Y
Operator Class FE	Y	Y

Notes: Robust standard errors are clustered by main product and state and are reported in parentheses. Statistical significance is denoted by *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the log of annual VMT. These regressions include only trucks classified as Class 2b - 8 Vocational Vehicles. Cost per mile is a weighted average within a truck's competition group, defined as all trucks in a survey year with the same body or trailer type, business, and truck category at the state and national level, each weighted based on in-state driving patterns of each truck. Cost per mile is instrumented using the contemporaneous crude oil price. The weighted average GSP per truck is calculated as a weighted average of in-state and out-of-state GSP based on the percent of miles each truck drives in and out of state. To investigate the heterogeneity within the Class 2b – 8 Vocational vehicles, we separate concrete mixers, garbage trucks, dump trucks, oil field trucks, service trucks, utility trucks, crane trucks, tow trucks, and yard tractors from this category and estimate their VMT in column (2). Results for the remaining trucks, primarily box and platform trucks, are displayed in column (1).

Table A3. Additional Measures of Economic Activity

VMT Elasticities Using Alternative Measures of Economic Activity						
	Tractor Trailers			Vocational Vehicles		
	(1)	(2)	(3)	(5)	(6)	(7)
Log cost per mile	-0.185***	-0.371***	-0.260***	-0.122***	-0.170**	-0.168***
	(0.0488)	(0.0878)	(0.0779)	(0.0416)	(0.0681)	(0.0431)
Log weighted average GSP	0.183***			0.175***		
	(0.0204)			(0.0213)		
Log national GDP		-0.0537			0.0911	
		(0.102)			(0.0762)	
Annual national GDP growth			0.630			0.591
			(0.538)			(0.407)
Constant	6.795***	9.324***	8.571***	6.585***	6.864***	8.267***
	(0.264)	(1.583)	(0.225)	(0.285)	(1.169)	(0.181)
Observations	74,731	74,731	74,731	92,623	92,623	92,623
R-squared	0.376	0.370	0.371	0.306	0.304	0.304
Age FE	Y	Y	Y	Y	Y	Y
Fuel Type FE	Y	Y	Y	Y	Y	Y
State FE	Y	Y	Y	Y	Y	Y
Axle Configuration FE	Y	Y	Y	Y	Y	Y
Cab FE	Y	Y	Y	Y	Y	Y
Body Trailer Type FE	Y	Y	Y	Y	Y	Y
Make FE	Y	Y	Y	Y	Y	Y
Product FE	Y	Y	Y	Y	Y	Y
Business FE	Y	Y	Y	Y	Y	Y
Operator Class FE	Y	Y	Y	Y	Y	Y

Notes: Robust standard errors are clustered by main product and state and are reported in parentheses. Statistical significance is denoted by *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the log of annual VMT. Cost per mile is instrumented using the contemporaneous crude oil price. The weighted averages for GSP is calculated as a weighted average of the state and national values based on the percent of miles each truck drives in and out of state. Columns (1) – (3) display the results for tractor trailers, while columns (4) – (6) display the vocational vehicle results. Further measures of economic activity can be found in Table 8.

Table A4. Additional Measures of Economic Activity

Truck Count Elasticities Using Alternative Measures of Economic Activity				
	Tractor Trailers		Vocational Vehicles	
	(1)	(2)	(3)	(4)
Log average cost per mile	-0.112	-0.155	0.0292	-0.101
	(0.113)	(0.121)	(0.120)	(0.121)
Log GSP	0.433***		0.694***	
	(0.132)		(0.121)	
Annual GSP growth		1.224***		0.318
		(0.421)		(0.293)
Constant	3.690	7.936***	2.777**	9.309***
	(2.549)	(1.441)	(1.334)	(1.232)
Observations	2,381	2,381	2,443	2,443
R-squared	0.863	0.862	0.875	0.869
State FE	Y	Y	Y	Y
Business FE	Y	Y	Y	Y
Fuel Type	Y	Y	Y	Y
Axle Configuration	Y	Y	Y	Y
Cab	Y	Y	Y	Y
Body Trailer Type	Y	Y	Y	Y
Make	Y	Y	Y	Y
Product	Y	Y	Y	Y
Operator Class	Y	Y	Y	Y

Notes: Robust standard errors are clustered by survey year and are reported in parentheses. Statistical significance is denoted by *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the log of the number of trucks in each state-business-year cell. Columns (1) and (2) display the results for tractor trailers. Columns (3) and (4) display the results for vocational vehicles. The number of trucks assigned to each state is calculated by using sampling weights provided by Census and in-state and out-of-state driving fractions. Trucks driving entirely in state are assigned to that state, while trucks driving out of state have their out-of-state portion assigned to other states based on the in-state truck populations of each state.

Derivation of Substitution Equation (10)

We include an average fuel cost per mile of the set of $J(i)$ trucks competing with truck i for miles, denoted by $CPM_t^{J(i)}$, in the demand for truck i miles:

$$VMT_{it}^{d} = \widetilde{D}\left(CPM_t^{J(i)}, GSP_{it}, Y_{it}\right). \tag{11}$$

Equilibrium miles driven by truck i is now obtained by equating Equations (1) and (11):

$$VMT_{it}^{s} = S(CPM_{it}, X_{it}) = \widetilde{D}\left(CPM_t^{J(i)}, GSP_{it}, Y_{it}\right) = VMT_{it}^{d}. \tag{12}$$

Therefore observed truck i VMT in year t will be a function of supply and demand variables:

$$VMT_{it}^{*} = \tilde{F}\left(CPM_{it}, CPM_t^{J(i)}, GSP_{it}, X_{it}, Y_{it}\right). \tag{13}$$

We assume that the function $\tilde{F}(\cdot)$ can be approximated by the following relationship:

$$VMT_{it}^{*} = \tilde{F}\left(CPM_{it}, CPM_t^{J(i)}, GSP_{it}, X_{it}, Y_{it}\right) = (CPM_{it})^{\tilde{\beta}} (CPM_t^{J(i)})^{\tilde{\varphi}} (GSP_{it})^{\tilde{\gamma}} \exp(\tilde{\alpha} + \tilde{\theta}\, X_{it} + \tilde{\rho} Y_{it} + \tilde{\varepsilon}_{it}). \tag{14}$$

In Equation (14), $\tilde{\varepsilon}_{it}$ is a mean-zero stochastic error term. Taking the natural log of both sides of Equation (14) implies

$$\ln(VMT_{it}^{*}) = \tilde{\alpha} + \tilde{\beta}\ln(CPM_{it}) + \tilde{\varphi}\ln(CPM_t^{J(i)}) + \tilde{\gamma}\ln(GSP_{it}) + \tilde{\theta} X_{it} + \tilde{\rho} Y_{it} + \tilde{\varepsilon}_{it}. \tag{15}$$