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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

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

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Abstract

Economic theory suggests that fuel economy standards induce a rebound effect, which is the increase in energy use caused by lower per-mile fuel costs due to the regulation. Despite a large literature on this effect for passenger vehicles, few studies attempt to estimate the rebound effect for heavy-duty trucks. We estimate the magnitude of the rebound effect for medium- and heavy-duty vehicles using a pooled cross section of detailed truck-level microdata that spans 25 years. Our estimates imply an average rebound effect of 30 percent for tractor trailers and 10 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 economic activity; we estimate an aggregate truck miles elasticity with respect to gross state product of 60 percent for tractor trailers and 82 percent for vocational vehicles. These estimates taken together suggest that the agencies regulating US trucks likely overestimate projected long-run fuel savings and greenhouse gas emissions reductions resulting from the standards.

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

JEL Classification Numbers: Q0, R4, C2

Contents

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Introduction

Reducing greenhouse gas (GHG) emissions from medium- and heavy-duty trucks is a central part of US climate policy. Trucks currently account for about 6 percent of US emissions, and by 2030 emissions from trucks are expected to exceed emissions from light-duty passenger vehicles (EPA 2015a). To reduce emissions from this sector, the Environmental Protection Agency (EPA) and the National Highway Traffic Safety Administration (NHTSA) jointly regulate the GHG emissions rates and fuel economy of trucks.[1] As fuel economy is inversely proportional to the rate of GHG emissions per mile traveled, the standards will simultaneously increase fuel economy and reduce emissions per mile. The regulations apply to all trucks not classified as passenger vehicles, of which tractor trailers account for most emissions and fuel consumption. The regulations are expected to reduce tractor trailer emissions and fuel consumption per mile by 9 to 23 percent by 2017.[2] 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.[3]

Whereas 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.[4] Economic theory, however, suggests

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* 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] The first phase of truck standards began in 2014 and extends through 2018.

[2] 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, among others, are expected to achieve GHG reductions of 6–9 percent (EPA 2011).

[3] Tractor trailers, vocational vehicles, and pickup trucks and vans are expected to experience 8 percent, 16 percent and 16 percent reductions, respectively, in CO_2 emissions and fuel use rates when compared to Phase 1 standards.

[4] 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.

that the resulting lower fuel consumption rates reduce the cost per mile of driving and thus increase the number of miles trucks are driven, because trucks are more competitive with other transportation modes. As trucks are driven more, they use more fuel, thereby reducing the total fuel use savings from the standards. This erosion of energy savings is the rebound effect, which partially offsets the decrease in fuel use and emissions that would occur from the lower fuel consumption rate alone.[5] As expected reductions in fuel intensity from the regulation increase, so too does the effect of cost per mile on total miles traveled and the rebound effect.

In addition to estimating the rebound effect, we also estimate the relationship between economic activity and total truck miles traveled. This relationship is important for projecting fuel consumption and emissions in the absence of the regulation, as well as the fuel savings and emissions reductions caused by the regulation. As the economy grows, the effect of economic activity on truck miles traveled grows stronger. Higher fuel consumption and emissions in the absence of regulation correspond with greater fuel savings from the regulation. We jointly estimate this relationship with the rebound effect, which we use to project baseline miles traveled.

In our analysis, we use truck-level microdata from a repeated cross section between the years 1977 and 2002 to estimate a model of truck travel. The analysis focuses on tractor trailers and vocational trucks (e.g., dump trucks, tow trucks, and others), which account for 66 and 22 percent of total truck fuel consumption, respectively (EPA 2011).[6] 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

[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; by comparison, per-mile fuel costs are about 20 cents per mile in our sample. 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.

endogenous both for reasons of reverse causality and omitted variables.[7] 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 elasticities of per truck vehicle miles traveled (VMT) with respect to cost per mile of 20 percent for tractor trailers and 14 percent for vocational trucks. We use gross state product (GSP) to proxy for economic activity and estimate an elasticity of miles traveled per truck to GSP of 18 and 17 percent for tractor trailers and vocational trucks, respectively. Because the regulations target fuel economy of new but not existing trucks, fuel economy standards could induce substitution of miles traveled from existing (unregulated) to new (regulated) trucks. To assess whether this effect is economically meaningful, we test whether the fuel costs of other trucks in the same market affect a truck's miles traveled. We find positive and statistically significant effects for tractor trailers but not for 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, and average truck characteristics. 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 42 percent for tractor trailers and 65 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.

We highlight the relevance of our estimates for the current fuel economy standards by simulating outcomes if the standards had been adopted starting in 1992 and continued for 10 years (during which time the entire fleet would turn over), allowing us to estimate a long-run rebound effect. We find that the rebound effect for tractor trailers after 10 years would have been

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[7] Reverse causality is a common concern in the estimation of the rebound effect for light duty vehicles (Small and Van Dender 2007). Vehicle buyers who expect to drive their vehicles many miles have an incentive to purchase a vehicle with high fuel economy. Therefore, observed miles driven influence observed fuel economy.

When trucks are driven more miles, they are likely to be driven with heavier loads, thus 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.

roughly 30 percent, which is larger than the current estimate of the rebound assumed by the regulatory agencies in their cost–benefit analysis. We compare our simulation outcomes to a simulation where baseline fuel use responds proportionally to economic activity, an assumption implicitly made by the agencies in their analyses of the regulations.[8] We find that the proportionality assumption exaggerates baseline fuel use and expected fuel use savings stemming from the policy. Taken together, our results imply that the regulatory agencies may be overestimating the fuel use savings and emissions reductions from the standards. We more generally highlight the critical importance of accurately estimating behavioral responses to policy and economic conditions.

These results have four implications for GHG regulations. First, the rebound effect for tractor trailers is large and exceeds the rebound effect assumed by EPA and NHTSA in their cost–benefit analysis of the standards. However, our estimate of the rebound effect for vocational trucks is roughly the same as that assumed by the agencies. 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, although we estimate a statistically significant degree of substitution across trucks

[8] The fuel savings and emissions reductions caused by the standards depend on baseline (i.e., unregulated) miles traveled, in addition to the rebound effect. In most existing trucking sector 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 gross output or GDP.

because of variation in relative fuel costs, this substitution effect is not present in the long run, as every truck in the fleet is eventually affected by the regulation.

A large literature identifies the problem of the rebound effect for fuel economy regulations. Much of the analysis focuses on the rebound effect for light-duty vehicles (as reviewed in Gillingham et al. 2015b).[9] Only a few studies have investigated either the short- or long-run rebound effect for trucks, despite the fact that the rebound effects have different underlying mechanisms for light-duty vehicles and 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 (Linn forthcoming).

In contrast to households, firms in the truck sector choose how much to drive their trucks in response to demand for trucking services, competition with other trucks, supply factors, and other profit incentives. Fuel costs account for nearly 40 percent of total operation costs per mile—a larger share than driver wages and other components of operating 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; Linn forthcoming). Because truck vehicle miles traveled are an equilibrium outcome, it is necessary to control for supply factors, other than fuel costs, which affect marginal costs. Given these differences, the light-duty literature provides little insight into the heavy-duty 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. The authors estimate a short-run rebound effect of about 10 percent and a long-run rebound effect of about 17 percent, where the rebound effect is defined as the increase in vehicle kilometers travelled resulting from an improvement in fuel economy. Matos and Silva (2011), using aggregate data from Portugal, estimate a 24 percent rebound effect from fuel economy improvements using a reduced-form model. Our study extends this literature as we use detailed data on individual trucks and regional

[9] See the appendix for further discussion of the light-duty literature.

variation in economic activity over time and estimate a range of elasticities that influence the level of the rebound effect.

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 of truck i); vehicle age; physical truck characteristics such as axle configuration, cab type and trailer type; and variables related to region-specific costs.[10] 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

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

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 GSP in year t, market characteristics including the total number of trucks in operation, the products that the trucks carries, business, and variables related to region-specific costs.[11] Denoting GSP in time period t by GSP_{it}, the total number of trucks in operation by N_t, and all other demand-related characteristics by Y_{it}, we can express demand for truck i VMT as

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

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:

[10] 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 additional measurement error since the most reliable measure of weight in the Vehicle Inventory and Use Survey (VIUS) waves is approximated. We include ton-mile regression outputs for tractor trailers and vocational vehicles as a robustness check.

[11] Demand for vehicle miles traveled by truck i in year t depends on costs per mile of truck i in year t relative to other competing trucks in its market. We include this variable in the empirical analysis.

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

We assume that the functions defining equilibrium per-truck VMT and truck counts 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 $G(\cdot)$ 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 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.[12] These elasticities represent an equilibrium response to the cost of driving. Fuel economy regulations will require increased fuel economy from new trucks, which lowers the cost per mile of driving.[13] This reduction

[12] 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, but we prefer the specifications that do not use weight because of measurement concerns (see data section for further discussion).

[13] Our identification of the rebound effect rests on the common assumption that the VMT response to changes to fuel economy is identical to the VMT response to changes in fuel prices (Small and Van Dender 2007). Recent studies on the light-duty rebound effect suggest that these responses may be different (Linn forthcoming; West et al. 2015). There is no evidence, however, that this response is different for heavy-duty vehicles.

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 sum of these two coefficients, β and β', is an estimate for the elasticity of aggregate VMT with respect to cost per mile and serves as an estimate of the long-run rebound effect.[14]

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 households, the rebound effect is determined by private optimization of household consumption choices and adjustments in household budget constraints (Gillingham et al. 2015a; Chan and Gillingham 2015).[15] 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 operating costs other than fuel costs.[16]

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 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 competitors' costs per mile. This means that truck i's cost per mile is correlated with the cost per mile of truck i's competitors. 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 section on robustness checks, we report estimates of equations (8)

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[14] This is because total fuel use and total VMT are proportional to one another. In the long run, fuel economy standards reduce the cost per mile of every truck, increasing total VMT and proportionally increasing total fuel use.

[15] 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 that are sacrificed when households purchase more fuel efficient automobiles.

[16] Some companies that require trucking services for shipping their products own an in-house fleet of trucks. In the context of our estimation framework, these companies supply and demand their own trucking services.

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.

Because 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 an alternative version of equation (8):

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

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 complex short-run effect on vehicle use across the entire truck fleet. 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. 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 VMT to shift toward new trucks and away from used trucks. Because new trucks have higher fuel economy than used trucks, this substitution may offset some of the traditional rebound effect.[17]

[17] 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 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 fuel consumed falls to 30,000 gallons for a total savings of 10,000 gallons. With a rebound effect of 20 percent, miles driven by new trucks increases to 120,000 and total consumption 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 and used truck miles fall to 80,000, and total fuel consumed falls to 30,000 gallons for a total savings of 10,000 gallons, which is the same savings without a rebound effect (more generally, the traditional rebound and subtitution effects need not cancel one another).

Data

The Vehicle Inventory and Use Survey (VIUS) is our primary data source, with surveys administered in five-year intervals from 1977 through 2002.[18] For each survey year, the US Census Bureau sampled more than 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 type, make, age, and axle configuration.[19] Driving behavior includes annual VMT, in-state and out-of-state driving percentages, and average trip lengths.[20] Operational details include business type, product carried, and operator classification.

Using truck body type and gross vehicle weight rating (GVWR), we assign trucks into one of two truck classes defined in Phase I of the truck fuel economy regulations: Class 7 and 8 combination tractors, and class 2b–8 vocational vehicles.[21] Table 1 reports our final vehicle counts for each truck category and weight class.

To arrive at our final sample of 185,331 observations, we eliminate observations with missing data for key variables such as VMT, MPG, state, body type, model year, and acquisition year.[22] 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

[18] 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 US Census Bureau.

[19] Fuel economy is based on self-reported average miles per gallon during the survey year. Respondents can 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.

[20] 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.

[21] Although 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 of more than 8,500 pounds fall into a weight class of 2b or higher.

[22] For detailed observation counts at each stage of the cleaning process, see table A1 in the appendix.

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.[23] In appendix table A1, we report the effect of these screens on the final sample size.

For some variables and observations, 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 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.[24] State and national gasoline and diesel price data are from the Energy Information Administration's State Energy Data System. In equations (8), (9), and (10), we instrument cost per mile using crude oil acquisition costs by refiners nationally. These data are also from the Energy Information Administration. GSP is retrieved from the Bureau of Economic Analysis. We calculate truck counts at the state and national levels using sampling weights provided in the VIUS datasets.

Summary statistics for the two truck categories are displayed in table 2. Average annual VMT for tractor trailers and vocational vehicles are 71,450 and 18,871, respectively. Fuel prices, expressed in 2005 US dollars, average $1.50, with variation from $1.21 to $2.98. Tractor trailers experience slightly worse fuel economy than vocational vehicles, requiring 0.19 gallons per mile

[23] Trucks older than 10 years old make up 20 percent of the sample and a smaller percentage of VMT. One-year-old trucks drive roughly four times more than 15-year-old trucks and are ten times more common in our sample. Data do 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 1 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.

[24] 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.

versus 0.16. Mean ages for the tractor trailers and vocational vehicles are 4.69 and 5.21 years, respectively.

Estimation Results

To infer the magnitude of a possible rebound effect from truck fuel economy regulations, we estimate equations (8) through (10) using the VIUS data. The heavy-duty truck fuel economy standards for both Phase 1 and Phase 2 define three mutually exclusive truck categories: tractor trailers, vocational vehicles, and heavy-duty pickups and vans. We are able to estimate equations (8), (9), and (10) for the two largest categories, tractor trailers and vocational vehicles.[25] In tables 3 through 6, we report coefficient estimates of specifications of equation (8), (9), and (10) for the two categories of trucks.

Class 7 and 8 Tractor Trailers

Table 3 presents coefficient estimates of equation (8) for class 7 and 8 tractor trailers. Column (1) reports estimates with a limited set of controls, including weighted GSP per truck, a set of age fixed effects, a fuel type dummy, and a set of state fixed effects.[26] The coefficient of interest is the log of cost per mile, which we instrument using the contemporaneous crude oil price.[27] With the basic set of controls, the coefficient of interest is estimated to be -0.206, implying that a 10 percent reduction in the cost per mile results in an increase in VMT of

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

[26] 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.

[27] 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 who expect to drive many miles may decide to buy a truck with better fuel economy. The first stage regressions for our preferred specifications are presented in appendix table A5.

approximately 2 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.

Column (1) omits many truck characteristics that affect marginal costs, and the discussion of the empirical strategy suggests that this specification would yield biased estimates of all coefficients. In column (2) of table 3, we report estimates with a larger set of controls by adding fixed effects for axle configuration, cab type, body trailer, and make. The additional fixed effects control for physical characteristics of each truck, which are likely to be correlated with cost per mile and VMT. The coefficient on log cost per mile drops to -0.169. 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 controls reported in column (3) of table 3, we estimate the elasticity of per-truck VMT with respect to cost per mile for class 7 and 8 tractor trailers to be -0.203. This is the preferred specification because it controls for supply-side factors that may be correlated with cost per mile to the fullest extent possible given the available data.

In our VMT equation, we precisely identify the effect of economic activity on miles traveled. In the preferred specification in column (3), the elasticity of VMT with respect to GSP is 0.179, implying that GSP growth of 10 percent increases per-truck VMT by almost 2 percent.

We also estimate how the cost per mile of other trucks in the fleet affects VMT. 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 reflects the nature of the trucking industry. 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, and manufacturing. We have estimated models using other competition definitions and have found them to be generally comparable to our results.[28] To be consistent with how we define

[28] The definition of competition introduces 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, exacerbating measurement error, and may ignore competing trucks' behavior.

own cost per mile and GSP, we compute average competition cost per mile at both the state and national level before weighting.[29]

We present our estimates of equation (10) for our preferred specification for tractor trailers in column (4) of table 3. The coefficient on log cost per mile is now -0.648, implying that a 10 percent reduction in the cost per mile of truck i leads to an increase in truck i VMT of about 6.5 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 that the substitution effect enters with the expected positive sign and is statistically significant with a coefficient estimate of 0.446. 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 about 4.5 percent, holding cost per mile of truck i fixed.

This result suggests that with binding standards for new trucks, the substitution effect may mitigate some of the rebound effect in the short run, as VMT of relatively fuel efficient new trucks will substitute for VMT of relatively fuel inefficient used trucks. In the long run, however, once existing used trucks are scrapped and replaced by regulated new trucks, the average new truck fuel economy is on average equal to used truck fuel economy. In the long run, 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 -0.202, which is statistically indistinguishable from our estimate reported in column (3) of table 3.

We report estimates of the truck count model for tractor trailers in table 4. For each specification, the point estimates of the cost per mile coefficient, although economically significant, are statistically insignificant. In our preferred specification in column (3), the truck count elasticity with respect to cost per mile is -0.10, with a standard error of 0.12. Together with our VMT results, we conclude that most of the responsiveness of total VMT to cost per mile stem from VMT and not truck counts.

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

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 0.419, implying that if GSP grows by 10 percent, truck counts are predicted to increase by about 4 percent, which is a much larger effect than we find in our VMT model.

Class 2b–8 Vocational Vehicles

In table 5, we present coefficient estimates of equation (8) for class 2b–8 vocational vehicles. In our preferred specification in column (3), we find that the elasticity of VMT with respect to cost per mile is -0.135, interpreted as a 10 percent reduction in cost per mile leading to an increase in VMT of 1 percent.

Unlike tractor trailers, vocational vehicles display vast differences in their shape and purpose. Although nearly half of tractor trailers are for-hire transportation, no one business category makes up more than 20 percent of all vocational vehicles in our sample. The body types include large delivery vans, garbage trucks, and concrete mixers.[30] As a result, we might expect substantial heterogeneity in the responsiveness of VMT to cost per mile 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 5. 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 with the utility of tractor trailers so that competitive effects are likely to be minor.

Across all specifications in table 5, 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 elasticity is 0.167, which is similar in magnitude to our tractor trailer results.

In table 6, 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

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

unresponsive to fuel costs. 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 0.654, an effect that is much larger than our comparable estimate for tractor trailer counts.

Summary

In tables 7 and 8, we summarize our preferred estimates of elasticities for each category. In table 7, we report VMT and truck count elasticities with respect to cost per mile and compare them to the rebound effect assumptions made by EPA and NHTSA in their cost–benefit analysis for Phases 1 and 2 heavy-duty truck standards. We report the cumulative elasticities 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 20 percent, which is almost four times as large as the assumed rebound effect in Phases 1 and 2. The lower bound of the 95 percent confidence interval is 8.9 percent, which is still substantially larger than the 5 percent assumed by the agencies.

While including the effect of cost per mile on truck counts increases the size of the cumulative elasticity for tractor trailers, our cumulative effect is less precisely estimated. Our cumulative estimate in absolute value for tractor trailers is 30 percent, which is about six times as large as the rebound effect assumed in the agencies' cost–benefit analysis but has a wider confidence interval, primarily due to the truck count coefficient being less precisely estimated.[31] However, in this case as well, the lower end of the confidence interval of the cumulative effect is more than the 5 percent rebound effect assumed by the agencies.

Our vocational vehicle estimate, on the other hand, is slightly less than the 15 percent value assumed by the agencies. Moreover, the confidence interval of the cumulative elasticity for vocational vehicles includes the agencies' 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 percent of truck emissions of CO_2 and are projected to achieve 50 percent greater reductions in fuel consumption than vocational vehicles during Phase 2.

We summarize VMT and truck count elasticities with respect to GSP in table 8. We compute a cumulative effect by summing the VMT elasticity and the truck count elasticity.

[31] The cost–benefit analyses appear in the Regulatory Impact Analyses of Phases 1 and 2 (EPA 2011; EPA 2015b).

Whereas the cumulative effect for each group is economically and statistically significant, the point estimates of both are less than 1. This result has important implications for estimating expected gasoline consumption and emissions reductions that depend on forecasted business-as-usual VMT. Elasticities less than 1 imply that business-as-usual 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 in which VMT grows in proportion with economic activity. We quantify this implication at the end of the paper.

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.[32]

Alternative Measures of Economic Activity

In tables 9 and 10, 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 9, we report the robustness of our VMT elasticity model. Columns (2) and (6) report estimates for models that include restricted GSP as a control for economic activity, where restricted GSP is the sum of GSP from industries that are most likely to demand trucking services: agriculture, forestry, fishing, and hunting; mining; utilities; construction; manufacturing; wholesale trade; retail trade; and transportation (excluding truck transportation). We observe a modest increase in magnitude of the coefficient on fuel cost per mile, and an even larger increase in magnitude when we use value of shipments (log weighted average value of shipments [VOS]) as a measure of economic activity. These estimates appear in columns (3) and

[32] We also investigate whether deregulation of the trucking sector affects our rebound estimates. We drop survey year 1977 to isolate the rebound effect after the passage of the Motor Carrier Act of 1980, which had significant impacts on the trucking industry. The VMT and truck count regressions are presented in appendix tables A6 and A7. The cost per mile coefficients in the per-truck regressions change very little. In the truck count regressions, these coefficients increase but remain statistically insignificant.

(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 (in magnitude) elasticity estimate. In general, however, the effect of cost per mile for each truck category is fairly robust across the different measures of economic activity.

Our results in table 10 for truck count elasticities are similar. Using restricted GSP or VOS increases the elasticity of truck counts with respect to cost per mile estimates for both truck categories. For both categories, however, the specifications remain insignificant with the exception of the tractor trailer specification, using VOS as a control for economic activity. In this case, truck counts respond to cost per mile, with an elasticity of -0.215.

Alternative Measures of Cost per Mile

In tables 11 and 12, 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 11, 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 cross-state price variation. Overall, our elasticity 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 12. In general, the results are consistent with the VMT results. Using an alternative instrument or fuel price directly has little effect on the elasticity estimates.

Estimating Models of Ton Miles

The distance a truck's payload travels, denoted as ton miles, may be a better measure of trucking activity than miles traveled. Ton miles capture both how far a truck travels and the weight of the goods it hauls. In response to fuel economy regulation, truck operators may respond by hauling different loads 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 13. The estimated elasticities of per-truck ton miles traveled with respect to cost per ton mile for tractor trailers and vocational vehicles are -0.209 and -0.056, respectively. The estimate for tractor trailers is slightly larger in magnitude than our benchmark per-truck VMT elasticity estimate, suggesting that most of the response to fuel costs is through miles driven. We observe a smaller, less significant elasticity for vocational vehicles when using ton miles. We prefer the elasticity estimates based on VMT rather than ton miles because the VIUS likely contains substantial measurement error in weight.

Because 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 general magnitude and remain statistically insignificant (table 14).

Simulations

We use our estimation results to simulate the effects of hypothetical fuel economy standards assuming they were to take place during our sample period. We simulate the effects of standards that match the stringency of the Phase 1 standards. By 2018, these standards are expected to reduce new vehicle cost per mile of tractor trailers and vocational vehicles by 16 percent and 10 percent, respectively. We assume these percent reductions will be required over our sample period. This simulation exercise has two objectives. First, we want to illustrate how our estimated elasticities affect VMT and gallons consumed when standards are tightened by this magnitude. Second, we want to highlight the importance of our economic activity elasticities for quantifying long-run impacts of the standards.

Because our estimated rebound effects are interpreted as long-run effects, we focus our simulation on the long run. We define the long run as 10 years after the standards are set so that the entire fleet has turned over and every truck on the road has been sold under (and therefore affected by) the regulation. We calibrate our simulation using our 1992 truck sample, as the midpoint of our data set, and we define the long run outcomes to occur in 2001.

To highlight the importance of the cost per mile and GSP elasticity estimates, we construct the baseline 2001 fleet by predicting truck counts and VMT for each truck for that year. We predict these outcomes by plugging in observed 2001 fuel prices and GSP into the estimated truck count and VMT equations and fixing all other truck characteristics to their 1992 levels. This calculation yields predicted truck counts, VMT per truck, and gallons consumed without regulation in 2001, which we report separately for tractor trailers and vocational vehicles in table 15 under the column titled “Baseline.”

We then perform two simulations of regulation beginning in 1992 and remaining through 2001. In the first simulation, we reduce gallons per mile for all tractor trailers and vocational vehicles by 16 percent and 10 percent, respectively, and recalculate the reported outcomes. In this simulation we hold truck counts and VMT per truck fixed to isolate the expected fuel savings of the regulation without a rebound effect. These values appear in table 15 under the column titled “Regulation/No Rebound.” For tractor trailers, the fuel savings without a rebound effect are 2.3 billion gallons of diesel.

In the second simulation, we allow truck counts and VMT per truck to respond to the standards. We predict truck counts and VMT per truck under the standards by substituting the regulated gallons per mile into our prediction equations. We report aggregate outcomes of this simulation in table 15 under the column titled “Regulation/Rebound.” For tractor trailers, both truck counts and VMT per truck are predicted to increase, and the expected fuel savings are substantially lower at 1.6 billion gallons of diesel. Gallons eroded—the unrealized fuel savings resulting from the rebound—are 0.7 billion gallons for tractor trailers, or about 28.5 percent of the intended fuel savings. This erosion is a nontrivial quantity, as it represents about 5 percent of gallons consumed from the entire tractor trailer fleet after the regulation takes place.

We next turn to a final simulation exercise to isolate the importance of our estimated GSP elasticities. This exercise is motivated from the fact that the agencies’ cost–benefit analysis for Phases 1 and 2 implicitly assume a cumulative GSP elasticity equal to 1 for all types of trucks.

As a result, the forecasted level of gallons consumed may be substantially larger than they would be with a lower assumed elasticity. Because the regulation determines a percent reduction in fuel consumption, the level of the projected fuel use savings and associated emissions reductions stemming from the standards may be overstated, as they are achieved from a large baseline level of gallons consumed. We compare the baseline gallons and the gallons reduced using our own GSP estimates with an alternative simulation in which we predict truck counts and VMT per truck in 2001. The simulation assumes that the cumulative GSP elasticity for each truck category equals 1. To perform this simulation, we scale up our estimated truck count and VMT equation GSP elasticities so that they add up to 1.

The results of this exercise appear in table 16. In the first columns under "Cumulative GDP Elasticity" for each truck category, we re-state the simulation outcomes using our own cumulative GSP elasticities of 0.60 and 0.82 for tractor trailers and vocational vehicles, respectively. In the second columns we present simulation results for the case where we predict baseline and regulation outcomes, with the assumption that cumulative GSP elasticities equal 1. For both truck categories, predicted baseline gallons consumed and fuel savings dramatically increase because of the larger predicted aggregate VMT response to GSP growth between 1992 and 2001. This leads to the striking result that the differences between gallons of fuel reduced from the policy—1.0 billion gallons and 0.3 billion gallons for tractor trailers and vocational vehicles, respectively—are larger than the gallons eroded from the rebound effect. The difference of 1.0 billion gallons of fuel reduced represents a 38.5 percent reduction of fuel savings relative to the setting where the cumulative GSP elasticity equals 1. This calculation demonstrates the importance of the elasticity of VMT to economic activity in determining the fuel savings and emissions reductions of the regulation.

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 analyses of these and other possible regulations for the truck fleet. Our elasticity of per-truck VMT with respect to cost per mile 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 for Phases 1 and 2 of the heavy-duty standards for fuel economy and GHG 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 diminish the emissions savings from the policy.[33] Furthermore, we find significant substitution effects between fuel efficient and fuel inefficient trucks, which could have important short-run implications for diesel consumption.

In addition, this paper is the first to estimate the relationship between VMT and economic activity. Most existing models assume an elasticity equal to 1, implying that VMT will grow proportionately to GDP in the coming years. Although the results vary somewhat across specifications, we find evidence of an elasticity less than 1, particularly for tractor trailers. The lower elasticity implies that VMT may not grow as quickly as current forecasts suggest, but, because the truck standards determine percent reductions in fuel consumption and emissions relative to the baseline, the lower elasticity also implies lower net benefits. In fact, our simulations imply that the lower elasticity reduces the estimated fuel savings and emissions of the standards by more than the rebound effect itself. This finding suggests that future empirical research on the transportation sector should place as much emphasis on the relationship between economic and activity and VMT as it does on the rebound effect.

Our results have policy implications beyond the fuel economy standards. Larger rebound effects imply that increasing diesel taxes is a relatively more attractive instrument for reducing fuel use and GHG 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.

[33] 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. A detailed structural model of the heavy-duty fleet and VMT decisions, which is out of the scope of our paper, is necessary to accurately assess the benefits associated with additional VMT.

Tables

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	More than 33,000	Total
Tractor trailers	-	-	-	-	-	6,669	77,361	84,030
Vocational vehicles	8,736	8,508	4,394	5,119	28,857	12,212	33,475	101,301
Total	8,736	8,508	4,394	5,119	28,857	18,881	110,836	185,331

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 vehicle identification numbers by the Vehicle Inventory and Use Survey (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. Summary Statistics by Truck Category

	Tractor Trailers				Vocational Vehicles			
Truck observations	84,030				101,301			
State-business-year observations	2,391				2,444			
	Mean	SD	Minimum	Maximum	Mean	SD	Minimum	Maximum
Annual VMT (thousands)	71.45	43.96	0.00	275.00	18.71	18.88	0.00	270.50
Weighted average fuel price (2005$)	1.59	0.27	1.21	2.98	1.75	0.37	1.21	2.98
Gallons per mile	0.19	0.09	0.02	10.00	0.16	0.12	0.03	10.00
Cost per mile (2005$/mi)	0.30	0.15	0.04	15.16	0.28	0.21	0.04	16.55
Weighted average GSP (2005$, thousands)	197.09	176.31	11.18	1,574.55	189.79	204.50	11.18	1,574.55
Age	4.69	2.66	1.00	10.00	5.21	2.75	1.00	10.00

Notes: Trucks with annual vehicle miles traveled (VMT) of zero (not in use) are dropped from our study. Several trucks report one mile driven and are kept in the sample. Fuel price and gross state product (GSP) are weighted based on in-state and out-of-state driving patterns. Age is rounded to the closest integer. Trucks less than one year old are dropped due to incomplete annual VMT.

Table 3. VMT Elasticities for Tractor Trailers

	(1)	(2)	(3)	(4)
Log cost per mile	-0.206**	-0.169***	-0.203***	-0.648***
	(0.0977)	(0.0471)	(0.0460)	(0.126)
Log cost per mile (competition)				0.446***
				(0.118)
Log weighted average GSP	0.337***	0.232***	0.179***	0.181***
	(0.0310)	(0.0245)	(0.0191)	(0.0188)
Constant	5.470***	6.340***	6.935***	7.121***
	(0.316)	(0.229)	(0.240)	(0.244)
Observations	84,030	84,030	84,030	83,837
R-squared	0.226	0.340	0.386	0.363
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, and * p<0.1. The dependent variable is the log of annual vehicle miles traveled (VMT). These regressions include only trucks classified as Class 7 and 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 gross state product (GSP) per truck is calculated as a weighted average of in-state and out-of-state GSP based on the percentage 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 4. Truck Count Elasticities for Tractor Trailers

	(1)	(2)	(3)
Log average cost per mile	-0.200	-0.0184	-0.1000
	(0.162)	(0.0976)	(0.118)
Log gross state product	0.541***	0.479***	0.419***
	(0.174)	(0.0973)	(0.118)
Constant	-0.677	1.185	0.782
	(1.776)	(1.589)	(2.374)
Observations	2,391	2,391	2,391
R-squared	0.830	0.847	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, and * 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 in the VIUS data and in-state and out-of-state driving fractions. Trucks driving entirely in state are assigned to that state, whereas 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 percentage 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 5. VMT Elasticities for Vocational Vehicles

	(1)	(2)	(3)	(4)
Log cost per mile	-0.145	-0.130	-0.135***	-0.169*
	(0.128)	(0.0857)	(0.0396)	(0.0867)
Log cost per mile (competition)				0.0268
				(0.0506)
Log weighted average GSP	0.198***	0.164***	0.167***	0.169***
	(0.0695)	(0.0437)	(0.0202)	(0.0202)
Constant	6.448***	7.228***	6.660***	6.631***
	(0.641)	(0.398)	(0.276)	(0.281)
Observations	101,301	101,301	101,301	100,994
R-squared	0.191	0.267	0.310	0.308
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, and * p<0.1. The dependent variable is the log of annual vehicle miles traveled (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 gross state product (GSP) per truck is calculated as a weighted average of in-state and out-of-state GSP based on the percentage 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 6. Truck Count Elasticities for Vocational Vehicles

	(1)	(2)	(3)
Log average cost per mile	-0.0319	0.0582	0.0300
	(0.0824)	(0.124)	(0.132)
Log gross state product	0.684***	0.740***	0.654***
	(0.113)	(0.0829)	(0.108)
Constant	0.506	2.408**	2.386**
	(1.023)	(0.983)	(0.968)
Observations	2,444	2,444	2,444
R-squared	0.833	0.857	0.865
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 *** $p<0.01$, ** $p<0.05$, and * $p<0.1$. 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 the US Census Bureau and in-state and out-of-state driving fractions. Trucks driving entirely in state are assigned to that state, wheras 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 percentage 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 7. Summary of Cost per Mile Elasticity Estimates

Truck Class	7 and 8	2b–8
Truck Type	Tractor Trailers	Vocational Vehicles
Rebound Effect Assumed in RIAs for Phases 1 and 2 (EPA 2011; EPA 2015b)	5%	15%
VMT Elasticity	-0.203	-0.135
95% Confidence Interval	(-0.281, -0.089)	(-0.213, -0.057)
Truck Count Elasticity	-0.100	0.030
95% Confidence Interval	(-0.331, 0.131)	(-0.229, 0.299)
Cumulative Effect	-0.303	-0.105
95% Confidence Interval	(-0.551, -0.055)	(-0.375, 0.165)
2005 CO_2 Emissions (EPA 2011)	66%	22%

Notes: Values for the rebound effect assumed in RIAs for Phases 1 and 2 are found on pp. 9–10 in EPA (2011) and pp. 8–25 in EPA (2015b), respectively. The 2005 CO_2 emissions can be found on page 25 of the Phase 1 Regulatory Impact Analysis.The cumulative effect is the sum of the vehicle miles traveled (VMT) elasticity and truck count elasticity, whereas 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. Summary of Gross State Product Elasticity Estimates

Truck Class	7 and 8	2b–8
Truck Type	Tractor Trailers	Vocational Vehicles
VMT Elasticity	0.179	0.167
95% Confidence Interval	(0.142, 0.216)	(0.127, 0.207)
Truck Count Elasticity	0.419	0.654
95% Confidence Interval	(0.188, 0.650)	(0.442, 0.866)
Cumulative Effect	0.598	0.821
95% Confidence Interval	(0.364, 0.833)	(0.606, 1.04)

Note: The cumulative effect is the sum of the vehicle miles traveled (VMT) elasticity and truck count elasticity, whereas 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 9. VMT Elasticities Using Alternative Measures of Economic Activity

	Tractor Trailers				Vocational Vehicles			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log cost per mile	-0.203***	-0.275***	-0.303***	-0.231***	-0.135***	-0.186***	-0.205***	-0.170***
	(0.0460)	(0.0435)	(0.0428)	(0.0462)	(0.0396)	(0.0391)	(0.0394)	(0.0447)
Log weighted average GSP	0.179***			0.123***	0.167***			0.0718**
	(0.0191)			(0.0378)	(0.0202)			(0.0338)
Log weighted average restricted GSP		0.191***				0.194***		
		(0.0238)				(0.0139)		
Log weighted average VOS			0.156***	0.0586			0.147***	0.108***
			(0.0188)	(0.0375)			(0.0130)	(0.0238)
Constant	6.935***	6.807***	6.218***	6.552***	6.660***	6.388***	5.969***	5.894***
	(0.240)	(0.257)	(0.295)	(0.318)	(0.276)	(0.216)	(0.249)	(0.251)
Observations	84,030	84,030	84,030	84,030	101,301	101,301	101,301	101,301
R-squared	0.386	0.385	0.385	0.386	0.310	0.310	0.310	0.310
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, and * p<0.1. The dependent variable is the log of annual vehicle miles traveled (VMT). Cost per mile is instrumented using the contemporaneous crude oil price. The weighted averages for gross state product (GSP), restricted GSP, and value of shipments (VOS) are calculated as a weighted average of the state and national values based on the percentage 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). VOS is an economic measure retrieved from the Census of Manufacturers. Further measures of economic activity can be found in the appendix.

Table 10. 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	-0.1000	-0.154	-0.215**	-0.152	0.0300	-0.0870	-0.110	0.0172
	(0.118)	(0.127)	(0.108)	(0.123)	(0.132)	(0.117)	(0.112)	(0.122)
Log gross state product	0.419***			0.153	0.654***			0.464***
	(0.118)			(0.179)	(0.108)			(0.0847)
Log restricted GSP		0.594***				0.615***		
		(0.0708)				(0.0878)		
Log state VOS			0.574***	0.508***			0.461***	0.328***
			(0.108)	(0.176)			(0.0704)	(0.0616)
Constant	0.782	-0.999	-4.122***	-4.597***	2.386**	2.213**	1.147	-0.842
	(2.374)	(1.850)	(1.340)	(1.208)	(0.968)	(1.041)	(1.229)	(1.120)
Observations	2,391	2,391	2,391	2,391	2,444	2,444	2,444	2,444
R-squared	0.863	0.864	0.864	0.865	0.865	0.864	0.865	0.867
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, and * 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 the US Census Bureau and in-state and out-of-state driving fractions. Trucks driving entirely in state are assigned to that state, whereas 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 gross state product (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 and in years ending in 2 and 7, the Economic Census.

Table 11. VMT Elasticities Using Alternative Measures of Cost per Mile

	Tractor Trailers				Vocational Vehicles			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Crude IV	Crude IV	1970 FP IV	Fuel Price	Crude IV	Crude IV	1970 FP IV	Fuel Price
Log cost per mile	-0.203***		-0.189***		-0.135***		-0.321**	
	(0.0460)		(0.0486)		(0.0396)		(0.128)	
Log cost per mile (truck *i*)		-0.204***				-0.142***		
		(0.0457)				(0.0422)		
Log average fuel price				-0.0961				-0.155***
				(0.0584)				(0.0395)
Log weighted average GSP	0.179***	0.180***	0.181***	0.203***	0.167***	0.168***	0.105**	0.182***
	(0.0191)	(0.0189)	(0.0193)	(0.0181)	(0.0202)	(0.0204)	(0.0481)	(0.0185)
Constant	6.935***	6.984***	6.921***	6.909***	6.660***	6.630***	7.025***	6.789***
	(0.240)	(0.239)	(0.238)	(0.259)	(0.276)	(0.281)	(0.411)	(0.283)
Observations	84,030	84,030	84,030	84,030	101,301	101,301	101,301	101,301
R-squared	0.386	0.384	0.386	0.386	0.310	0.308	0.307	0.310
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, and * p<0.1. The dependent variable is the log of annual vehicle miles traveled (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 only uses 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. The weighted average gross state product (GSP) per truck is calculated as a weighted average of in-state and out-of-state GSP based on the percentage of miles each truck drives in and out of state.

Table 12. 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	-0.1000	-0.0258		0.0300	0.0325	
	(0.118)	(0.125)		(0.132)	(0.190)	
Log state fuel price			-0.128			0.236
			(0.121)			(0.209)
Log gross state product	0.419***	0.443***	0.428**	0.654***	0.655***	0.689***
	(0.118)	(0.119)	(0.125)	(0.108)	(0.108)	(0.117)
Constant	0.782	0.548	-1.630	2.386**	2.383**	1.763
	(2.374)	(2.396)	(2.958)	(0.968)	(1.039)	(0.996)
Observations	2,391	2,391	2,391	2,444	2,444	2,444
R-squared	0.863	0.863	0.863	0.865	0.865	0.866
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, and * 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 the US Census Bureau and in-state and out-of-state driving fractions. Trucks driving entirely in state are assigned to that state, whereas 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 13. Ton Miles Traveled Elasticities

	Tractor Trailers	Vocational Vehicles
Log cost per ton mile	-0.209***	-0.0564*
	(0.0437)	(0.0317)
Log weighted average GSP	0.203***	0.177***
	(0.0198)	(0.0177)
Constant	9.058***	8.593***
	(0.311)	(0.261)
Observations	75,254	76,960
R-squared	0.426	0.484
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, and * 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 vehicle miles traveled (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. The weighted average gross state product (GSP) per truck is calculated as a weighted average of in-state and out-of-state GSP based on the percentage of miles each truck drives in and out of state.

Table 14. Truck Count Elasticities Using Cost per Ton Mile

	Tractor Trailers	Vocational Vehicles
Log average cost per ton mile	0.0275	0.171
	(0.154)	(0.115)
Log gross state product	0.448***	0.677***
	(0.161)	(0.113)
Constant	0.503	2.385**
	(2.687)	(1.160)
Observations	1,992	2,036
R-squared	0.865	0.875
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 *** $p<0.01$, ** $p<0.05$, and * $p<0.1$. 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 the US Census Bureau and in-state and out-of-state driving fractions. Trucks driving entirely in state are assigned to that state, whereas 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.

Table 15. Rebound Effect Simulation Results

	Class 7 & 8 Tractor Trailers			Class 2b–8 Vocational Vehicles		
		Regulation			Regulation	
	Baseline	No Rebound	Rebound	Baseline	No Rebound	Rebound
Truck Count (Thousands)	1,126.0	1,126.0	1,145.8	3,784.9	3,784.9	3,773.0
VMT per Truck (Thousands)	70.1	70.1	72.7	16.9	16.9	17.1
Aggregate VMT (Billions)	79.0	79.0	83.3	63.9	63.9	64.6
Aggregate Gallons (Billions)	14.3	12.0	12.6	8.9	8.0	8.1
Aggregate Reduction in Gallons (Billions)	-	2.3	1.6	-	0.9	0.8
Rebound Effect:						
Aggregate Reductions Eroded (Billion Gallons)		0.6			0.1	
Aggregate Reductions Eroded (Percent)		28.5%			10.0%	

Notes: Simulation results displayed in this table use the long-run specifications for per-truck vehicle miles traveled (VMT) and truck counts. The displayed results are annual estimates for 2001 using the 1992 truck sample. The year 2001 marks the 10th year of a supposed fuel economy standard imposed in 1992, enough time to cover every truck in our sample (maximum age of 10 years). In the “Baseline” scenario, the trucks’ fuel economy is left unchanged. Under the “Regulation” scenarios, fuel economy improvements for tractor trailers and vocational vehicles are 16 and 10 percent, respectively. Under the “No Rebound” scenario, truck counts and per-truck VMT are assumed to be unchanged from these fuel economy improvements. Note, however, that aggregate gallons in this case is different from the baseline due to the standards. The rebound effect is calculated as the percentage of the intended reductions in energy use that are not realized due to increases in truck counts and utilization.

Table 16. GSP Elasticity Simulation Results

	Class 7 & 8 Tractor Trailers			Class 2b–8 Vocational Vehicles		
	Cumulative GSP Elasticity			Cumulative GSP Elasticity		
	0.60	1.00	Difference	0.82	1.00	Difference
Baseline Gallons of Fuel Consumed (Billions)	14.3	22.3	8.0	8.9	11.9	2.0
Gallons of Fuel Reduced (Billions)	1.6	2.6	1.0	0.8	1.1	0.3

Notes: Simulation results displayed in this table use the long-run specifications for per-truck vehicle miles traveled (VMT) and truck counts. The displayed results are annual estimates for 2001 using the 1992 truck sample. The year 2001 marks the 10th year of a supposed fuel economy standard imposed in 1992, enough time to cover every truck in our sample (maximum age of 10 years). In the “Baseline” scenario, the trucks’ fuel economy is left unchanged. Under the “Regulation” scenarios, fuel economy improvements for tractor trailers and vocational vehicles are 16 and 10 percent, respectively. The fuel reductions displayed in this table refer to the regulation scenario including our estimated rebound effect. We conduct this simulation using both our gross state product (GSP) elasticities from table 8 and the implicit 1:1 relationship between GSP and VMT assumed by the agencies. Baseline fuel consumption is a scenario with no regulation in place. Fuel consumption reductions are the difference between this scenario and a scenario with the regulation in place, accounting for our estimated rebound effect. To simulate these scenarios using an elasticity of 1, our GSP elasticities for per-truck VMT and truck counts are scaled up proportionally to sum to 1.

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. 2015b; 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. Corporate Average Fuel Economy (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 be between 5 and 15 percent (Green 1992). Later studies attempted to improve on measurement and identification issues, including efforts to address endogeneity of vehicle fuel economy and vehicle use (Gillingham 2014; Linn forthcoming), 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 forthcoming). 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; Gillingham 2014; Gillingham et al. 2015a; Linn forthcoming). Several of these studies have looked at the effect on the rebound effect of evidence of substitution among vehicles in multi-vehicle households (Greene et al. 1999; Linn forthcoming). 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 showed, particularly in the long run. Linn (forthcoming) finds the long-run rebound effect to be 20–40 percent. 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 in 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 is 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. They use this model 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 reduce the effort at schedule logistics and the 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 percent in the short run and 16.8 percent 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 percent. 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 collected by the US Census Bureau from surveys of individual truck owners between 1977 and 2002. We separate the trucks into three types.[34] This is a unique dataset, and it contrasts with the aggregate national data that has been used to estimate the truck rebound effect in two European countries. The data have shortcomings—they are limited by the questions that were asked by the survey, 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 those 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.[35]

Data Cleaning

Table A1 provides information on the data cleaning process. Beginning with an initial observation count of 612,302, we clean the data and arrive at a final observation count of 185,331 trucks.

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	13,519	239,559
Age > 10	54,172	185,387
VMT > 275,000	56	185,331
Final count	-	185,331

[34] The VIUS does not categorize trucks into the categories that we separate trucks. We create these categories based on weight and class variables.
[35] Cost per mile is calculated by dividing the fuel price by the fuel economy (MPG) of the truck. Simultaneity bias with this term and vehicle miles traveled (VMT) is a common issue in the rebound effect literature, as truckers who 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, and * p<0.1. The dependent variable is the log of annual vehicle miles traveled (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 gross state product (GSP) per truck is calculated as a weighted average of in-state and out-of-state GSP based on the percentage 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

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, and * 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 gross state product (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 9.

Table A4. Additional Measures of Economic Activity – Truck Counts

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 gross state product	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, and * 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 the US Census Bureau and in-state and out-of-state driving fractions. Trucks driving entirely in state are assigned to that state, whereas 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.

Table A5. First Stage Regression for VMT per Truck Estimation

	Tractor Trailers	Vocational
	(1)	(2)
Log crude price	0.545***	0.641***
	(0.0107)	(0.0205)
Log weighted average GSP	-0.0288***	-0.0937***
	(0.00600)	(0.0103)
Constant	-0.565***	-0.274**
	(0.0900)	(0.129)
Observations	84,030	101,301
R-squared	0.790	0.709
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, and * p<0.1. The dependent variable is the log of group cost per mile. Regressions are the first stage of the instrumental variable regressions in column (3) of tables 3 and 5. The weighted average gross state product (GSP) per truck is calculated as a weighted average of in-state and out-of-state GSP based on the percentage of miles each truck drives in and out of state.

Table A6. Post-1977 Survey Year Vehicle Miles Traveled per Truck Regressions

	Tractor Trailers	Vocational
	(1)	(2)
Log average cost per mile	-0.188***	-0.167***
	(0.0462)	(0.0323)
Log gross state product	0.173***	0.149***
	(0.0201)	(0.0172)
Constant	7.151***	6.934***
	(0.235)	(0.250)
Observations	75,258	76,972
R-squared	0.372	0.289
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 survey year and are reported in parentheses. Statistical significance is denoted by *** p<0.01, ** p<0.05, and * p<0.1. The dependent variable is the log of the number of trucks in each state-business-year cell. Survey year 1977 is excluded to test whether our estimates change post deregulation of the trucking industry. For both tractor trailers and vocational vehicles, we use our preferred specifications, column (3) in tables 3 and 5.

Table A7. Post-1977 Survey Year Truck Count Regressions

	Tractor Trailers	Vocational
	(1)	(2)
Log average cost per mile	0.0261	0.154
	(0.146)	(0.112)
Log gross state product	0.447***	0.663***
	(0.157)	(0.111)
Constant	0.415	2.338**
	(2.880)	(1.106)
Observations	1,992	2,036
R-squared	0.865	0.876
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, and * p<0.1. The dependent variable is the log of the number of trucks in each state-business-year cell. Survey year 1977 is excluded to test whether our estimates change post deregulation of the trucking industry. For both tractor trailers and vocational vehicles, we use our preferred specifications, column (3) in tables 4 and 6.

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

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

References

Borenstein, Severin (2014). Microeconomic Framework for Evaluating Energy Efficiency Rebound and Some Implications. Energy Institute at Haas Working Paper 242R.

Chan, Nathan W., and Kenneth Gillingham (2015). The Microeconomic Theory of the Rebound Effect and Its Welfare Implications (with Nathan W. Chan) *Journal of the Association of Environmental & Resource Economists* 2(1): 133–159.

De Borger, Bruno, and Ismir Mulalic (2012). The Determinants of Fuel Use in the Trucking Industry—Volume, Fleet Characteristics and the Rebound Effect. *Transport Policy* 284–295.

EPA (2011). Final Rulemaking to Establish Greenhouse Gas Emissions Standards and Fuel Efficiency Standards for Medium- and Heavy-Duty Engines and Vehicles—Regulatory Impact Analysis. Office of Transportation and Air Quality US Environmental Protection Agency and National Highway Traffic Safety Administration US Department of Transportation. EPA-420-R-11-901. http://www3.epa.gov/otaq/climate/documents/420r11901.pdf

EPA (2015a). EPA and NHTSA Propose Greenhouse Gas and Fuel Efficiency Standards for Medium- and Heavy-Duty Trucks: By the Numbers. Regulatory Announcement. EPA-420-F-15-903. http://www3.epa.gov/otaq/climate/documents/420f15903.pdf

EPA (2015b). Proposed Rulemaking for Greenhouse Gas Emissions and Fuel Efficiency Standards for Medium- and Heavy-Duty Engines and Vehicles—Phase 2—Draft Regulatory Impact Analysis. Office of Transportation and Air Quality US Environmental Protection Agency and National Highway Traffic Safety Administration US Department of Transportation. EPA-420-D-15-900. http://www3.epa.gov/otaq/climate/documents/420d15900.pdf

FHWA (1997). 1997 Federal Highway Cost Allocation Study: Final Report. Federal Highway Administration. U.S. Department of Transportation, Washington, DC.

FHWA (2012). Highway Statistics Series: Highway Statistics 2010. Annual Vehicle Distance Traveled in Miles and Related Data—2010 by Highway Category and Vehicle Type. U.S. Department of Transportation Office of Highway Policy Information. http://www.fhwa.dot.gov/policyinformation/statistics/2010/vm1.cfm

Gillingham, Kenneth (2014). Identifying the Elasticity of Driving: Evidence from a Gasoline Price Shock in California. *Regional Science & Urban Economics* 47(4): 13–24.

Gillingham, Kenneth, Alan Jenn, and Inês Lima Azevedo (2015a). Heterogeneity in the Response to Gasoline Prices: Evidence from Pennsylvania and Implications for the Rebound Effect. Forthcoming in *Energy Economics*.

Gillingham, Kenneth, David Rapson, and Gernot Wagner (2015b). The Rebound Effect and Energy Efficiency Policy. *Review of Environmental Economics & Policy*, conditionally accepted.

Greene, David (1992). Vehicle Use and Fuel Economy: How Big Is the "Rebound" Effect? *The Energy Journal* 13(1): 117–143.

Greene, David, James Kahn, and Robert Gibson (1999). Fuel Economy Rebound Effect for U.S. Household Vehicles. *Energy Journal* 20(3): 1-31.

Klier, Thomas, and Joshua Linn (2012). New-Vehicle Characteristics and the Cost of the Corporate Average Fuel Economy Standard. *The RAND Journal of Economics* 43(1): 186–213.

Knittel, Chris, and Ryan Sandler (2013). The Welfare Impact of Indirect Pigouvian Taxation: Evidence from Transportation. Working Paper.

Linn, Joshua (forthcoming). The Rebound Effect for Passenger Vehicles. *The Energy Journal*.

Matos, Fernando J.F., and Francisco J.F. Silva (2011). The Rebound Effect on Road Freight Transport. Empirical Evidence from Portugal. *Energy Policy* 39: 2833–2841.

Parry, Ian (2008). How Should Heavy-Duty Trucks Be Taxed? *Journal of Urban Economics* 63(2): 651–668.

Small, Kenneth, and Kurt Van Dender (2007). Fuel Efficiency and Motor Vehicle Travel: The Declining Rebound Effect. *The Energy Journal* 28(1): 25–51.

——— (2015). The Rebound Effect for Automobile Travel: Asymmetric Response to Price Changes and Novel Features of the 2000s. *Energy Economics* 49: 93–103.

U.S. Census Bureau. *Vehicle Inventory and Use Survey, 1977-2002*. https://www.census.gov/svsd/www/vius/products.html

U.S. Census Bureau. *Economic Census*. http://www.census.gov/econ/census/

West, Jeremy, Mark Hoekstra, Jonathan Meer, and Steven L. Puller (2015). Vehicle Miles (Not) Traveled: Why Fuel Economy Requirements Don't Increase Household Driving. NBER Working Paper No. 21194.