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# Pigouvian Taxes at Odds: Freight Trucks, Externalities, and the Dispatch Effect

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## Abstract

External costs of freight trucks include air pollution, highway damage and congestion. We show that diesel taxes reduce both the pollution and congestion externalities, but worsen highway damage: an increase in the fuel price causes trucks to adjust dispatch decisions so as to reallocate their loads to fewer but heavier trucks. Even with the associated decline in total demand for cargo, the dispatch effect leads to a net increase in road damage. We investigate the relationship between diesel fuel prices and freight truck activities using individual truck data recorded by road sensors in California and New York between 2011 and 2015. The dual use of diesel fuel in New York for transportation and home heating enables an IV approach to estimate price elasticities for fuel demand, cargo dispatching, road damage, and vehicle-ton miles traveled. We use the estimates to inform assessments of diesel tax increases and fuel economy standards for heavy trucks.

## 1. Introduction

A substantial literature discusses the need for multiple instruments in the presence of multiple externalities.<sup>1</sup> The focus, however, has been on the inadequacy of a single Pigouvian instrument – say, a carbon tax – to deal with a second problem such as insufficient technological innovation, rather than the possibility that, in isolation, the first instrument may worsen the second externality. This is the issue we investigate. We show that an increase in the tax on diesel fuel leads to heavier trucks and, in the absence of a second instrument addressing truck weight

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<sup>1</sup> See, e.g., Jaffe, Newell and Stavins, 2005; Bennear and Stavins, 2007; Goulder and Parry, 2008. Our concern is when a “first best” instrument such as a carbon tax, is available but flawed. Much of the multiple-instruments literature has analyzed second best options, assuming that use of a Pigouvian tax is restricted by politics, or considered how multiple instruments work at cross purposes to undermine efficiency. See e.g., Fankhauser et al (2010)

externalities, more road damage. Our calculations suggest that the increased external costs due to the diesel tax from road damage offset its benefits from lower carbon emissions.

This finding is perhaps ironic because these taxes are often levied to repair roads. While economists generally discourage taxation of intermediate goods (Diamond and Mirrlees, 1971),<sup>2</sup> policy discussions of diesel fuel taxes often focus on how the revenues can be dedicated to highway infrastructure and the contribution of such infrastructure to economic growth (CBO, 2015; Durranton, Morrow, and Turner, 2014).<sup>3</sup> We find that an increase in the diesel tax to raise revenues for road maintenance increases the need for maintenance. Approximately 10% of the revenue from a diesel tax increase is lost to additional road damage due to cargo reallocation.

The relationship between fuel price and truck weight arises from dispatch decisions faced by trucking firms. Freight shippers bundle price and quality, where a key dimension of quality is the frequency of shipment. More frequent deliveries lower inventory costs for the freight customers or the waiting costs of the final customers. Indeed, absent transportation costs, it would be optimal to move individual goods between origin-destination pairs at exactly the time the good was demanded. As transportation costs increase, it becomes profitable to spatially and temporally aggregate loads. Heavier trucks use more fuel overall, but fuel consumption per ton of cargo—the relevant measure for the commercial trucking industry—is lower. Thus manufacturers face a tradeoff between inventory and transportation costs (De Vany and Saving, 1983; Shirley and Winston, 2003; Shah and Brueckner, 2012).<sup>4</sup> *Ceteris paribus*, an increase in fuel prices will further aggregate loads.<sup>5</sup>

If road damage were linear in total weight, such redistribution would be of little consequence, but road damage sharply increases in weight per truck axle (Small and Winston, 1986). Adding 1,000 pounds to an already fully loaded 5 axle truck generates 38 times more damage than adding 1,000 pounds to an empty one. Because truck weight generates nearly all road non-weather related road damage, understanding the determinants of truck weight is key to

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<sup>2</sup> Except in cases, like that of trucking, where the good generates externalities (Sandmo, 1975).

<sup>3</sup> For example President Obama's 2014 State of the Union Address promoted infrastructure spending stating that, "In today's global economy, first-class jobs gravitate to first-class infrastructure..."

<sup>4</sup> Shirley and Winston's analysis of the external costs and benefits of infrastructure spending is very similar to what we attempt here with respect to marginal costs for freight trucks.

<sup>5</sup> The aggregation results in savings in labor and capital costs as well as fuel; changes in the cost of any component changes dispatching. This paper addresses only fuel.

understanding infrastructure damage. Thus, the dispatch effect of a fuel price increase—the distribution of an equivalent weight in cargo among fewer trucks—is consequential.

We investigate the impact of fuel prices on cargo shipments using a unique data set and a novel instrument for diesel prices. We obtained sensor readings on over 1.4 billion vehicle events from weigh-in-motion data collected in New York and California. These data allow us to track daily changes in the weight and number of trucks at specific locations. Most importantly, these data allow for sophisticated identification. Our primary identification concern relates to the close link between trucking, trade, and economic activity. Diesel fuel prices are expected to be endogenous to cargo weight because changes in economic conditions will affect both the world oil price, a major determinant of the price of diesel fuel, and demand for goods and services that involve hauling freight.<sup>6</sup> To identify the price effect, we exploit weather-related fuel differences between New York and California. In New York, sales of distillate fuel oil for residential heating purposes average 70% of the quantity sold for on-highway transportation.<sup>7</sup> Cold weather—particularly unexpected cold weather—increases demand for heating oil and the price of diesel fuel in New York relative to California, whereas an unanticipated warm spell decreases the differential.

We therefore explain the weight differential between New York and California as a function of the diesel price differential using unexpected weather as an instrument. We find that when fuel prices increase 10 percent, fuel use by heavy trucks declines 2.7 percent and average truck weight increases 3 percent. While total truck traffic decreases by around 1 percent, on net there is 18 percent more road damage.

The dispatch effect changes the welfare comparison of using fuel taxes versus efficiency standards to control carbon emissions. For automobiles, economists have overwhelmingly favored fuel taxes over efficiency standards (Parry et al., 2007, Bento et al. 2009, Jacobsen 2013) because the standards, by reducing the cost of driving, induce an increase in vehicle miles traveled (the “rebound” effect) which undermines some of the fuel savings as well as

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<sup>6</sup> If world oil price is used as an instrument for price in a trucking demand analysis, we expect the estimated demand elasticity to be biased down. See, e.g., Winebrake et al (2015), whose estimate is much lower than ours.

<sup>7</sup> Sales of Distillate Fuel Oil by End Use, U.S. Energy Information Administration, [http://www.eia.gov/dnav/pet/pet\\_cons\\_821dst\\_dcu\\_SNY\\_a.htm](http://www.eia.gov/dnav/pet/pet_cons_821dst_dcu_SNY_a.htm). Even if some sales of home heating oil may in fact wind up in the tanks of trucks—the only difference between home heating oil and diesel fuel is the tax—residential demand is significant.

exacerbating other externalities like congestion. Similar rebound driving is expected for trucks (De Borger and Mulalik, 2012; Leard et al., 2015).<sup>8</sup> But we find that a reduction in per-mile shipping cost from the standard causes freight to be reallocated across more trucks so that schedules are enhanced—that is, the rebound occurs on both a quality and a quantity dimension. In consequence, road damage declines. While there is considerable uncertainty about the cost of external congestion and safety of trucks, we find that fuel efficiency standards dominate fuel taxes as a policy to reduce carbon emissions for a wide range of parameter estimates.<sup>9</sup>

Broadly, our analysis supports the use of axle-weight taxes that have been championed by transportation economists (Winston, 1991). A single heavy truck generates more road damage than 1000 passenger vehicles, yet heavy trucks contribute only 36 percent of the taxes that generate the highway trust fund.<sup>10</sup> Despite the benefits of axle-weight taxes, states have gradually repealed them in the face of political and judicial headwinds. However, the failure to implement axle-weight taxes undermines the ability of regulators to enact other policies.

The remainder of the paper is organized as follows. The next section discusses some relevant features of the heavy truck industry and the market for diesel fuel. Section 3 presents a stylized model that motivates our empirical analysis. Section 4 addresses some data construction issues and section 5 goes into the validity of our instrument. Sections 6 and 7 contain estimation results and policy simulations, and section 8 concludes.

## II. Heavy Trucks and Diesel Fuel: Background

### A. Heavy Trucks and Cargo Weight

Trucks are classified by axle count, weight, and size. There are three broad classes of heavy-duty trucks: heavy-duty pickups, tractor-trailers, and vocational vehicles.<sup>11</sup> While all of these

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<sup>8</sup> The work on the relationship between fuel economy standards and rebound for automobiles is extensive (Jacobsen, 2013; Small and Van Dender, 2007). An excellent discussion of the rebound effect for both automobiles and other consumer goods is contained in Borenstein, 2013.

<sup>9</sup> Sathaye et al (2010) also consider how policies intended to improve welfare by reducing truck externalities may be undone by road damage – in their case, regulations requiring increased load factors so as to reduce the VMT-related externalities of trucks.

<sup>10</sup> See Joint Committee on Taxation, 2015. Diesel taxes generate \$8.9 billion and other taxes on trucks generated \$4.9 billion of the \$37.9 billion highway trust fund. If roads are not optimally maintained, they will cause an additional external cost in damage to other vehicles. See Winston, 2013.

<sup>11</sup> Examples of heavy-duty trucks include the Ram 2500-3500, Silverado 2500-3500. Vocational vehicles generally have fewer than 5 axles and are tailored to a specific task with examples including garbage trucks, cement trucks, busses, and fire trucks.

vehicles could conceivably be used to haul freight and are likely to burn diesel, we focus on tractor-trailers, which dominate long-haul freight moved by road.

Tractor-trailers have seen large growth between 1990 and 2010 when vehicle miles traveled (VMT) grew by 87 percent and ton-miles by 47 percent.<sup>12</sup> Together these trends suggest that the average load has grown lighter over time. While some of these changes are likely due to overall growth of trade and the economy, this time period also saw low oil prices and the rise of ‘just-in-time’ manufacturing (Kamakate and Schipper, 2009). From the cargo recipient’s perspective, more frequent deliveries, of perhaps smaller loads, lowers inventory costs for manufacturers, wholesalers or retailers, or (in the absence of inventory) waiting times of consumers.<sup>13</sup> For operators, the cost of scheduling also increases with the size of the load. Not only is there a cost of finding additional freight to fill a vehicle to capacity, but there is also a cost of finding cargo for the return trip. We refer to combined scheduling and inventory costs, which may fall on either the consumers or the operators, as logistics costs.

The growth of trucking miles and ton-miles is of policy importance beyond its indication of economic transformation and expansion. Tractor-trailers are the second largest and fastest growing source of carbon emission in transportation. They are also, along with weather, the predominant source of damage to roads. Both of these concerns are closely tied to vehicle weight. Engineers define a unit of damage to a road based on the cumulative axle-weight of vehicles. One equivalent single axle load (ESAL) is the amount of wear caused by a single axle bearing 18,000 pounds. Because road damage as measured by ESALs rises to the third or fourth power of axle weight, an 80,000 pound, 5-axle truck causes 1000 to 1500 times more damage than a passenger vehicle and most states, including California and New York, limit the maximum total weight of a vehicle to 80,000 lbs.<sup>14</sup> Larger loads are only allowed for ‘non-divisible’ loads and require special permits issued by the state.<sup>15</sup>

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<sup>12</sup> For comparison, light-duty vehicle miles grew by 34 percent.

[http://www.rita.dot.gov/bts/sites/rita.dot.gov/bts/files/publications/national\\_transportation\\_statistics/index.html](http://www.rita.dot.gov/bts/sites/rita.dot.gov/bts/files/publications/national_transportation_statistics/index.html)

<sup>13</sup> See DeVany and Saving (1983) for an early discussion of the cost of quality expressed as wait-time to receive a product.

<sup>14</sup> Weights and axle configurations are also governed by the FHWA ‘bridge-formula’ which sets the maximum allowable weight for a given axle configuration on the interstate system, but for the standard 5-axle tractor-trailer that is 51 feet between its first and final axle it is capped at 80,000 lbs.

<sup>15</sup> These permits are rarely denied but are often required to use particular routes that avoid bridges or sensitive infrastructure. States also encourage operators to use vehicles with more than five axles to minimize damage.

Aggregating cargo is a key way to lower freight costs because it reduces capital costs (if fewer trucks are needed), driver costs, and fuel costs. Although trucks with heavier loads use more fuel, the fuel use per ton declines with total vehicle weight (Franzese and Davidson, 2011). The industry is thus characterized by both a private and public conflict. For the private market there is a tradeoff between the cost of delivery per ton, in both fuel, equipment, labor and maintenance,<sup>16</sup> and the frequency of delivery with its attendant dispatch costs. In the public sphere, the tradeoff is between road damage and the pollution generated by fuel use as well as other externalities associated with greater truck traffic.

The carbon emissions of these vehicles has come under the scrutiny of the Environmental Protection Agency in recent years.<sup>17</sup> To reduce petroleum consumption in this sector it has instituted efficiency standards. The standards, beginning with model year 2014, require a maximum fuel consumption per brake-horsepower-hour for engines, which, as a measure of an engine's ability to do work, essentially regulates the gallons of diesel fuel consumed per ton-mile. Increasing fuel taxes, the standard economists' tool for dealing with carbon emissions, are also the subject of current policy debates, although usually in the context of infrastructure funding. The federal tax has been constant (and not indexed for inflation) at 24.4 cents since 1993; increasing it was the focus of extensive discussions during the congressional debates over the 2016 Transportation Act. While ultimately a tax increase was not included in the bill, between 2013 and 2016 seventeen states increased their diesel taxes.<sup>18</sup> As we show in Section 7, efficiency standards and taxes have different impacts on the private costs of dispatch and delivery; as such, they also have a different impact on the public costs of the related externalities.

## B. No. 2 Distillate.

Certain features of petroleum markets drive our identification strategy. Petroleum refining converts crude oil, a complex mixture of hydrocarbons, into a variety of products ranging from methane gas to asphalt. Two of the most important are gasoline and distillate. While gasoline is

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<sup>16</sup> The American Trucking Research Institute breaks down per-mile motor carrier costs in 2013 as 38% fuel, 34% labor, and 28% other vehicle-based expenses including purchase payments and maintenance (Torrey and Murray, 2014).

<sup>17</sup> An growing literature addresses fuel consumption of trucks and options to enhance fuel efficiency. See, e.g., National Research Council 2010; 2014, whose studies were influential in the debates over the recent changes in heavy truck efficiency standards.

<sup>18</sup> "Recent Legislative Actions Likely to Change Gas Taxes," National Conference of State Legislatures, 2/9/2016, at <http://www.ncsl.org/research/transportation/2013-and-2014-legislative-actions-likely-to-change-gas-taxes.aspx>;

primarily used in cars, distillate fuel oil is used in several applications and is further categorized.<sup>19</sup> No. 2 distillate fuel oil is primarily used as diesel fuel in automobiles, railroads, and trucks. It is also used as home heating oil (No. 2 fuel oil), although this use is highly regional with nearly 88% of all No 2. fuel oil being used in the Northeast. A single home may use between 850 and 1,200 gallons in a season, which is stored in tanks holding several hundred gallons. With the exception of quality/pollution standards and taxation, the fuel used for home heating and powering diesel vehicles is identical. In the United States, refineries are optimized for gasoline production, but on net the U.S. imports gasoline and exports diesel to countries with a higher share of diesel transportation demand.

No. 2 distillate is also distinguished on the basis of intended use. ‘Off-road’ distillate is exempt from road taxes and is used not only in home heating but also in vehicles used for farming, construction, and in locomotives. ‘On-road’ diesel is used by trucks on highways. The first comprehensive regulations on diesel for both on- and off-road purposes were phased in starting in 2006 and required the use of ultra-low sulfur diesel (<15 ppm). Ultra-low sulfur home heating oil has been phased in more gradually on a state-by-state basis, with New York first to adopt the standard in 2012. While consumers cannot legally switch fuels between home heating and on-road use, the two uses compete with one another.<sup>20</sup> In the mid-Atlantic region, including New York, highway use accounts for about 55% of distillate use and residential heating is 23%.<sup>21</sup> One result of the competition is that diesel prices follow an overall seasonal pattern opposite to gasoline. Whereas gasoline prices (and gasoline imports) rise in the summer, diesel prices routinely rise in the winter, accompanied by a decline in diesel exporting, particularly in the Northeast.<sup>22</sup> In addition to seasonal shifts, unusual winter weather is credited with increasing or decreasing diesel prices.<sup>23</sup> We explore this relationship below.

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<sup>19</sup> Distillate No. 1 is typically used on vehicles such as city buses, which are excluded from our analysis, while higher numbered residuals (No. 5 and 6) are generally used for steam powering in electric generation or maritime freight.

<sup>20</sup> Off-road diesel is dyed red to aid in the detection of fraud. But despite both the color and some quality variations, off-road diesel is apparently diverted frequently to road-using vehicles (Marion and Muehlegger 2008).

<sup>21</sup> The fuel statistics all come from the Energy Information Administration.

<sup>22</sup> Marion and Muehlegger (2011) use this variation to examine pass-through rates of taxes, exploiting the seasonal variation in demand elasticity for diesel fuel.

<sup>23</sup> See, e.g., “Strong El Nino helps reduce U.S. winter heating demand and fuel prices,” *Today in Energy*, U.S. Energy Information Administration, April 25, 2016, at <http://www.eia.gov/todayinenergy/detail.cfm?id=25952>. (accessed August 12, 2016); “Diesel Average Increases 3.1 cents to \$3.904 as Cold Weather Lifts Seasonal

### III. Model of the Freight Trucking Market

#### A. A stylized model of freight trucking

Our analysis unpacks the impact of fuel prices on freight truck activities into two components: the change in weight per truck-mile, and the change in the total cargo-miles, or vehicle ton-miles.<sup>24</sup> We focus on several issues that are omitted from similar models for light-duty vehicles. First, truck operators can influence their per mile costs.<sup>25</sup> Second, total vehicle miles traveled can change without necessarily changing total cargo demand. Lastly, we are interested in identifying changes in vehicle weight and their associated road damage, which are justifiably ignored in models of light-duty vehicles.

The following stylized model describes the relationship between vehicle weight and fuel price. Consider the market for hauling freight where  $Q$  is total demand for cargo measured in ton-miles. A representative tractor-trailer operator will choose a cargo of size  $w$  (per mile). Given  $Q$ , the choice of  $w$  determines two costs. The first is a fuel cost which depends on the price of diesel,  $p$ , and the quantity of fuel required to ship the one ton of cargo one mile,  $f(w)$ , where  $f'(w) < 0$  and  $f''(w) > 0$ . The fuel use per truck-mile is  $wf(w)$  and total fuel use in the industry is  $Qf(w)$ . The model captures the fuel consequence of dispatching: total fuel use declines when cargo is aggregated into fewer, heavier loads.<sup>26</sup>

We call the second cost determined by  $w$  the logistical cost,  $l$ , which is a quality of service characteristic associated with the frequency of deliveries.<sup>27</sup> It may include inventory costs for the customers of freight services when less frequent deliveries mean that they have to store goods; alternatively, it may be the waiting costs for their customers if inventory is unavailable. Finally, it may include the cost to shippers of organizing a load of freight. In each case, for a constant level of total demand,  $Q$ , an increase in per-truck cargo weight  $w$  implies less frequent

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Demand,” *Transport Topics*, 2/3/2014, at

<http://www.ttnews.com/gateclient/premiumstorylogin.aspx?storyid=34064>, (accessed August 12, 2016).

<sup>24</sup> The ratio of the two yields vehicle miles traveled, or the number of trucks on the road.

<sup>25</sup> Similar capability exists for light-duty vehicles either by purchasing a different vehicle (Li, Timmins, and von Haefen 2009), or by changing driving speed and acceleration patterns (Burger and Kaffine, 2009) but these changes are generally ignored in VMT demand (rebound) models.

<sup>26</sup> Aggregation will also result in savings in capital and labor costs of trucking. These factors are excluded as we observe no changes in them in our data; however, extending the model to include other costs is straightforward.

<sup>27</sup> This model is closest to (although simpler than) the price/frequency freight model in De Vany and Saving (1983). More sophisticated market conditions are considered in Shah and Brueckner (2010) and references cited therein.

delivery and higher logistic costs. Given  $Q$ , the frequency of delivery is  $N = Q/w$ .  $N$  is also the number of trucks on the road (per mile), and, under the model's assumption of identical trucks, the number of truck-miles driven. For mathematical convenience, we model logistical costs as a function of infrequency, or  $l(1/N) = l(w/Q)$ , where  $l'(\cdot) > 0$  and  $l''(\cdot) > 0$ .<sup>28</sup> The logistical costs may be shared between the shippers and customers or borne entirely by either side of the market.

Total cost for delivering cargo  $Q$  is:<sup>29</sup>

$$(1) \quad TC = pQf(w) + Ql\left(\frac{w}{Q}\right)$$

De Vany and Saving (1983) show that if a market of this type is competitive, two conditions hold: first, the total shipping price to final customers – including any quality-related costs external to the transaction price – will equal marginal total costs. Second, in equilibrium, average total costs are minimized. The freight trucking industry is competitive<sup>30</sup>, so in equilibrium  $w$  will minimize average total cost:

$$(2) \quad pf'(w) + \frac{1}{Q}l'\left(\frac{w}{Q}\right) = 0$$

Equation (2) states that, in equilibrium, per truck cargo  $w$  is set to equate the marginal fuel savings and the marginal logistics/inventory penalty.

The relationship between cargo weight and fuel price is derived from equation (2):

$$(3) \quad \frac{dw}{dp}A + \frac{dQ}{dp}B = 1$$

where

$$(4) \quad A = \frac{\left[ pf''(w) + \frac{1}{Q^2}l''\left(\frac{w}{Q}\right) \right]}{-f'(w)} > 0 \text{ and } B = \frac{\left[ -\frac{1}{Q^2}l'\left(\frac{w}{Q}\right) - \frac{w}{Q^3}l''\left(\frac{w}{Q}\right) \right]}{-f'(w)} < 0$$

The first term in (3) is the dispatch effect. Note that if demand is inelastic, or  $Q$  unaffected by changes in the diesel price,  $1/A$  measures the extent to which cargo is reallocated among trucks

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<sup>28</sup> This model assumes that the economy is not strictly constant returns to scale. An increase in aggregate demand,  $Q$ , allows the industry to improve transportation along both the quality dimension (more frequent deliveries) and price (lower costs per ton from upweighting the cargo per truck). Under constant returns to scale, the number of trucks would double and average cost remain unchanged.

<sup>29</sup> All values are per mile, an annotation that we drop for concision. Costs are for delivering cargo one mile, as are the marginal costs.

<sup>30</sup> We ignore heterogeneity among customers; alternatively, suppose the industry is separated into unrelated submarkets, each of which is competitive.

when fuel costs increase so as to take advantage of the fuel savings from aggregation. The second term in equation (3) is the freight demand effect. Absent dispatch changes (that is, if  $dw/dp = 0$ ), this term would measure the extent that an increase in fuel cost raises total freight cost, and the consequent drop in demand. Efficiency gains from a change in dispatch reduces the demand response. The demand response in turn modifies dispatching, as lower demand means that for a given cargo  $w$ , frequency is reduced, changing the relative marginal costs for fuel and quality. For modest demand elasticity, per-truck cargo weight will increase with an increase in fuel cost. But for sufficiently elastic demand, an increase in fuel costs could be associated with lower weight per-truck cargos. It is, however, straightforward to show that frequency will never increase when, *ceteris paribus*, the fuel price increases.

### B. The elasticity of demand and the rebound effect

The elasticity of fuel use turns on both the dispatch effect and the freight demand effect. Let  $F(p)$  be the total fuel use for fuel price  $p$ :

$$(5) \quad F(p) = Q(p)f(w(p))$$

We derive an expression for the diesel demand elasticity by differentiating (5) with respect to  $p$ :

$$(6) \quad \varepsilon_{F,p} = \varepsilon_{Q,p} + \varepsilon_{f,w}\varepsilon_{w,p}$$

Where the terms in (6) are elasticities of total fuel use with respect to fuel price, quantity with respect to fuel price (the freight demand effect), fuel use with respect to weight (an engineering relationship) and weight with respect to fuel price (the dispatch effect).

Fuel economy regulations are evaluated relative to the “rebound effect,” or the extent to which the standards, by lowering fuel use, reduce the cost of driving and hence increase freight activity. To calculate the rebound effect of fuel economy regulations, we follow the prior literature and assume that regulators impose a standard  $\gamma$  with no capital costs.<sup>31</sup> The rebound effect compares the fuel savings under the naive model  $F^0 = \gamma[w(p)N(p)]f(w(p))$  with a model

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<sup>31</sup> More precisely, capital costs are fixed costs and assumed to be small enough that they do not dissuade anyone from buying a car –but more importantly that they do not change the cost of driving a mile. For freight, this assumption is less sound: we would expect operators to pass through all capital costs that increase transportation costs, affecting aggregate demand  $Q$  and truck hauling choices in line with the analysis in Section III. The calculations here should then be viewed as upper bounds for the extent of rebound and the associated calculations.

that acknowledges the price change for hauling freight,  $F^l = \gamma[w(\gamma p)N(\gamma p)]f(w(\gamma p))$ . The rebound effect is calculated as  $1 - \frac{\partial F^0 / \partial \gamma}{\partial F^1 / \partial \gamma}$ , which can be simplified to

$$(7) \text{ Rebound Effect} = \varepsilon_{N,p} + \varepsilon_{w,p} + \varepsilon_{f,w} \varepsilon_{w,p}$$

Expression 7 is identical to the demand elasticity in equation (6) as  $Q = Nw$ . It extends prior examinations of the rebound question by including the change in efficiency that occurs when freight aggregation changes. Prior work has only accounted for the change in miles (the first term) or ton-miles (the first two terms).

### C. Empirical Strategy

We are interested in the effect of changing diesel prices on vehicle weight. Although our data are observations of individual trucks, our diesel prices and weather data are at the daily and weekly level by region. Therefore we aggregate to the day-by-state level. An initial approach is laid out in the following system of equations

$$(8) \quad y_{st} = \beta P_{st} + X'_{st}\gamma + \varepsilon_{st}, \quad \varepsilon_{st} = \theta_t + u_{st}$$

and

$$(9) \quad P_{st} = X'_{st}\delta + \eta_{st} \quad \eta_{st} = \lambda_t + v_{st}$$

where  $y_{st}$  is average truck weight in state  $s$  on date  $t$ ,  $P_{st}$  is state level diesel price,  $X_{st}$  is other determinants of truck weight and  $\varepsilon_{st}$  and  $\eta_{st}$  are the unobserved determinants of truck weight and diesel prices.<sup>32</sup> Additional regressions replace  $y_{st}$  with the daily average count of trucks, ESALs, and speed. One condition for the OLS regression of truck weight on price to be a consistent estimate of  $\beta$  is that  $E[\varepsilon_{st}\eta_{st}] = 0$ . If there are omitted transitory shocks at the national ( $\theta_t$  and  $\lambda_t$ ) or state level ( $u_{st}$  and  $v_{st}$ ) that covary with diesel prices and truck weight, the OLS estimator will be biased. In particular, we are concerned that local, national, or international economic activity may change demand for freight movement and the cost of freight logistics simultaneously with diesel prices or world oil prices.

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<sup>32</sup> Measurement error of prices would represent another type of error that would result in attenuation bias. Because of the long distances that tractor-trailers can drive before refueling, our diesel price may be measured with error. This is another benefit of our instrumental variables approach.

We use data on daily average truck weight in New York and California, discussed in Section 4, below. A differencing approach will absorb any national level shocks<sup>33</sup> and dispose of  $\theta_t$  and  $\lambda_t$ .

$$(10) \quad y_{NYt} - y_{CAt} = \beta (P_{NYt} - P_{CAt}) + (X_{NYt} - X_{CAt})' \gamma + (u_{NYt} - u_{CAt})$$

and

$$(11) \quad (P_{NYt} - P_{CAt}) = (X_{NYt} - X_{CAt})' \delta + (v_{NYt} - v_{CAt})$$

For unbiased estimation of  $\beta$ ,  $E[(u_{NYt} - u_{CAt})(v_{NYt} - v_{CAt})] = 0$ . This condition may not be satisfied. For example, if local demand for one-way trips increases, average cargo weight will fall and the demand for diesel will increase.

Consistent estimation requires an instrumental variable,  $Z_t$ , that causes changes in the diesel price spread between regions but does not change truck weight. We propose the use of random fluctuations in temperature as measured by excess heating degree days over the prior month. The assumption is that abnormally cold weather will result in an excess number of heating degree days and the demand for heating oil will compete for stocks of No. 2 distillate fuel oil.<sup>34</sup>

Equation (11) then becomes:

$$(12) \quad (P_{NYt} - P_{CAt}) = (X_{NYt} - X_{CAt})' \delta_X + Z_t \delta_Z + (v_{NYt} - v_{CAt})$$

where  $Z_t$  is a rolling sum of excess heating degree days (EHDD) in the Northeast over the prior 30 days. One benefit of this instrument is that it will raise diesel prices in a region as large as the driving range of a truck. Another benefit is that the mechanism can be partially observed by examining demand for residential distillate. Because our diesel price data is weekly, we cluster our standard errors at the week level.

There are some exclusion concerns with our instrument. First, truck drivers may avoid traveling on days with bad weather. This can be addressed by directly including measures of daily temperature, snowfall, and rainfall. Our assumption is that weather may affect travel on the

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<sup>33</sup> The shocks eliminated by this differencing will also include world oil prices. Because refinery contracts are often many months in duration, lags of world oil prices are often occasionally included in regressions using high frequency data. An additional benefit of this differencing approach is that it allows us to remove the effect of lagged world prices avoiding the need for a second instrument.

<sup>34</sup> Heating Degree Days alone are also correlated to diesel prices, as these are anticipated and, together with seasonal variations in cargo demand, in part determine export decisions, they may but may not be independent of cargo demand. We use a seasonal dummy variable to account for the anticipated weather changes.

date of travel but temperature during the prior weeks does not directly influence trucking decisions. This assumption may be violated if extremely cold weather depresses economic activity. If cold weather reduces freight shipments of retail goods, EHDD may measure a demand rather than a supply shift of diesel. We can examine the robustness of our result by using autumn and spring subsamples when heating is still required but the absolute temperature is milder than in winter. Furthermore in the autumn residential inventories of heating oil are likely to be high and demand will not (initially) respond, while in the spring even relatively small temperature changes will affect demand as heating oil inventories are depleted. In section V, below, we show that there is an asymmetric response between these seasons, which suggests that our instrument is shifting supply rather than demand.

#### IV. Data

*Weigh-in-Motion Data.* The data documenting trucks is collected from weigh-in-motion (WIM) sensors on major interstates, US highways, and state roads in New York and California. WIM sensors automatically measure the axles, spacing, weight, and speed of all trucks passing a point in the road. These sensors are used by states to enforce weight restrictions, monitor road demand, and to flag potential weight restriction violators for inspection at static weigh stations. WIM sensors are typically a strip embedded across all lanes of the roadway that detect characteristics of trucks at high speed.

WIM files contain only a few measures for a given truck as well as the date, time, and location of detection, but as a census of all vehicles passing over a point, they provide an unusually large amount of data. We have at least one recorded truck for 126 detectors in California and 33 detectors in New York. The records for California and New York detail 1.28 billion and 0.2 billion truck records respectively. We restrict our analysis to 5-axle tractor trailers.<sup>35</sup> WIM data are noisy, and we delete some observations as errors, in accord with

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<sup>35</sup> This restriction eliminates the possibility that fuel prices generate substitution across vehicles of different axle count. We make this restriction because, of all vehicles with more than two axles, five axle trucks are more than 78 percent of all vehicles. We also believe vehicles with more or less than five axles to be less relevant to our study. Vehicles with fewer axles are often vocational vehicles that do not haul freight. Vehicles with more axles are often used to haul invisible loads and are more likely to be data errors. When passing trucks generate large pavement vibrations, WIM detectors can erroneously detect multiple ‘ghost axles’ with extremely light weight. Expanding our analysis to include vehicles with more than 5 axles would only further increase the road damage generated as fuel prices increase because fuel use is increasing in axle count.

standard procedures for this data.<sup>36</sup>

We use the WIM data on vehicle weight, axles, and axle spacing to calculate per vehicle Equivalent Standard Axle Loads (ESAL), the standard measure used to characterize road damage caused by vehicles. Our procedure for calculating ESALS is contained in the appendix. ESALS cannot be estimated from average truck weights and vehicle miles traveled because they are nonlinear in truck weight. Individual truck-level data are required to estimate ESALS; this is a key advantage of using WIM data.

From the truck level data we generate daily measures for each state of average truck weight, total ESALS, total vehicle count, average speed, and the average cargo weight of a truck (truck weight less 23,000 lbs.<sup>37</sup>). Some detectors have dates with missing data resulting in an unbalanced panel. We drop detectors with less than 75 percent data coverage and impute the remaining missing observations.<sup>38</sup> Once all relevant detectors are imputed, we average across all detectors to the state level to generate 1,822 daily observations for each of New York and California. As is discussed further below, we assume that the average values across detectors per state is proportionate to highway traffic within the state so that we can interpret the regression coefficients as applying to vehicle ton miles traveled, ESALS per mile, cargo per truck mile, and so on.

Figure 1 maps the location of the detectors and the weight distribution of 5-axle vehicles (before aggregation) used in our analysis. The maps show that detectors are widely dispersed and are not exclusively on the largest freeways. The bottom panels show the weight distribution. The bimodal distribution demonstrates the prevalence of empty trucks on the road, which introduces considerable slack in the system to reorganize loads as the marginal cost per mile changes.

*Weather data.* Daily weather data come from the National Climatic Data Center's Global

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<sup>36</sup> Quinley (2010). See the Appendix for more details. We tried several different cleaning strategies, which made no difference to our results. As most of our analysis is based on average daily values per state, we expect these estimates are affected little by the kinds of errors found in WIM data. The exception is for the regressions that estimate total traffic. While these coefficients are measured imprecisely, the point values are robust to our different choices for cleaning.

<sup>37</sup> The Department of Energy identifies the empty vehicle weight range for tractor-trailers (combination trucks; class 8b) at 20,000 to 26,000 lbs. See *Gross Vehicle Weight vs. Empty Vehicle Weight*, DOE, Office of Energy Efficiency & Renewable Energy, Fact #621, May3, 2010, at <http://energy.gov/eere/vehicles/fact-621-may-3-2010-gross-vehicle-weight-vs-empty-vehicle-weight>, accessed 8/12/2016.

<sup>38</sup> See Appendix for further details on the imputation.

Historical Climatology Network-daily, which provides daily minimum and maximum temperature and total rainfall and snowfall for weather stations in the United States. This database collects and performs quality control for weather data. Because households with heating oil are primarily concentrated in upstate New York we use the average readings of weather stations centered at Albany.<sup>39</sup>

Daily weather data is used directly as a control in our regressions and also to form the instrument of excess heating degree days (EHDD). Heating degree days (HDD) are a commonly used measure that reflects the demand for heating energy. Using a base of 65 F, a day spent at 64 F will be one HDD. Temperatures above 65 F are not counted.<sup>40</sup> We proportionally assign the temperature to the range between the minimum and maximum temperature recorded. To calculate the expected number of HDD, we average the number of HDD during that day over the forty-year period between 1975 and 2015. To calculate the EHDD, we take the difference between the realized HDD days for a given day and the expected HDD days on that date. These values are then summed over the prior 30 days. This 30-day EHDD measure is positive (negative) when winter weather is unusually cold (warm). In summer, EHDD is usually zero.<sup>41</sup>

## V. The Effect of Cold Weather in the Northeast on Diesel Price

Diesel prices vary between regions of the US. Differences in taxation, environmental standards, distance from refineries, and retail competition all contribute to baseline variation.<sup>42</sup> The most important for our analysis concerns the regional use of diesel as heating oil.

For our instrument of EHDD to be relevant it should increase the price gap between New York and California diesel prices. Figure 2 plots the kernel smoothed EHDDs, the diesel price spread, and the weight difference. The top panel displays the daily average heating degree days.

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<sup>39</sup> We use inverse distance weighting of these stations up to 200km.

<sup>40</sup> Rather than assign the HDD days as the difference of the mean of min and max temperature from 65 F, we proportionally assign the temperature to the range between the min and max temperature recorded.

<sup>41</sup> Sources for other data used in the regressions are: The Energy Information Administration for weekly crude oil prices (WTI), weekly regional diesel prices (California is available by itself; we use PADD 1b for New York), weekly residential distillate demand (available nationally; but over 88% is consumed in the Northeast). Truck tonnage information is from the Bureau of Transportation Statistics and information of real GDP from the Bureau of Economic Analysis.

<sup>42</sup> Diesel taxes did not change in New York or at the federal level over the sample period. In California, the structure of taxes changed in a complicated “tax swap” that allowed the State to use revenues to pay a highway bond. Rates are now calculated on a quarterly basis. California diesel fuel tax varied between \$.335 and \$.395 during the sample period. See <https://www.boe.ca.gov/sutax/strf.htm>

The two coldest time periods are in early 2014 and 2015, while the winter of 2011-2012 was mild.

The second panel plots the difference in diesel prices between the two regions. Differencing removes any shocks, trends, or seasonality in diesel prices that are common to both locations, but may not remove seasonality that differentially affects each location. One of the largest price differentials occurs in early 2014 and a second differential occurs in early 2015 when temperatures were abnormally cold. The price differential remains relatively stable throughout the mild winter of 2011-2012.

To more rigorously examine the patterns suggested by Figure 2, it is useful to remove the trend and seasonality using a regression. To quantify the effect of excess HDD on the diesel price differential between New York and California, we estimate regressions of the form

$$(12) \quad P_{NY,t} - P_{CA,t} = \alpha + \beta EHDD_t^{30} + X_t' \gamma + \varepsilon_t$$

where  $EHDD_t^{30}$  is our measure of excess heating degree days on date  $t$  over the prior 30 days, which we scale dividing by 100. The term  $X_t'$  includes a trend, monthly fixed effects, and other potential controls such as GDP, monthly freight, and the world oil price in some regressions. Because our diesel price data is weekly, we cluster standard errors at the week level.

Table 1 reports the estimates of the effect of EHDD on diesel price. Column 1 reports results for our simplest specification indicating that 100 EHDD in the past month increases the price spread by roughly 4 cents. The next column 2 includes controls for GDP, monthly freight, and the WTI oil price, which we generally omit due to endogeneity concerns. The addition of these regressors decreases the magnitude of the effect to 2.5 cents but it remains statistically significant at the 0.1% level.

The next set of regressions include controls for daily weather, which are important controls in later regressions on truck weight, but which are insignificant and minimally affect the estimates in Table 1. Column 4 uses all data price starting in 2007. While this is earlier than the time period for which we have WIM data, it shows that the relationship is robust to the addition of more years of data. Columns 5 and 6 examine the data from August through November and March through June, respectively. In the autumn, when retail stockpiles of heating oil are high, we would expect little effect of EHDD on the diesel price differential. The point estimate on

EHDD in column 5 is small and statistically insignificant. In the spring, when stock piles are low, we would expect a response and the coefficient on EHDD in column (6) similar response as the specifications in columns 3 and 4. The final column replaces the diesel price spread with the gasoline prices spread between New York and California. Heating oil does not directly compete with gasoline, and consequently the price gap should not increase with cold weather.<sup>43</sup> The coefficient on EHDD in column 7 is smaller than that of diesel and statistically insignificant.

Lastly, we provide additional evidence that heating oil is the mechanism by which cold weather affects diesel prices. If consumers have sufficient reserves such that they do not require additional heating oil during cold periods, weather is unlikely to influence diesel prices. Table 2 provides evidence that excess HDD increases demand for residential distillate. The coefficient on EHDD in column 1 indicates that for every 100 excess HDDs in the prior month, demand for residential distillate increase by 15,000 barrels per day. This suggests that heating oil demand responds to unusually winter weather and that we adequately capture unusual weather in New York, and the Northeast more generally.

## VI. The Effect of Diesel Prices on Trucking

This section examines the relationship between diesel prices and 5-axle truck behavior. We begin with vehicle weight. Table 3 panel A presents these results using IV-estimation. For comparison, the OLS results are presented in column 1. The OLS estimate of the vehicle weight-diesel price elasticity is 0.10. The specification in column 2 estimates equation 8 using the EHDD instrument. This specification estimates that the vehicle weight-diesel price elasticity is 0.33, suggesting that the OLS estimate is downward biased by roughly two thirds. The logged specification changes the units on the first stage but presents a similar picture to the prior section. The F-test is statistically significant at conventional levels.

One potential concern with the estimates in column 2 is that cold weather may affect demand for diesel for trucks rather than demand for heating oil. For example, suppose unusually cold weather over the previous month depresses the local economy and lowers total demand for goods. Trucking companies might respond by parking the empty backhauling trucks, as they will

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<sup>43</sup> Gasoline is coproduced with diesel and cold weather may depress the price in New York if excess gasoline is refined to keep pace with demand for distillate. In some robustness regressions using a longer period of data or other controls we find a marginally significant decrease in the price gap in response to cold weather, consistent with coproduction.

not be needed soon for a full load. This would imply that the average weight of trucks on the road would increase, together with a reduction in overall demand for cargo.<sup>44</sup> We can directly test this hypothesis by estimating the IV regression using data restricted to August through November (column 3) and March through June (column 4). These months are generally mild compared with December through February, removing extreme events.

In the autumn, no effect is found because of a weak first stage, as discussed in section V. Alternatively, in the spring, shown in column 4, we find a highly significant F-test and a positive estimated effect of diesel prices on truck weight. Inventories are depleted in the spring so that EHDD shocks are more likely to require additional heating oil deliveries and abnormal weather is less likely to directly change demand for freight services. These results support our interpretation that we are observing a supply side shock in the instrumented diesel price variation.

In Panel B we explore the changes in trucking behavior in more depth. Although our data do not provide a measure of vehicle cargo weight, we estimate cargo by removing the average weight of empty trucks of 23,000 lbs. Column 1 contains the estimated fuel price elasticity for cargo. Column 2 displays IV estimates for total truck traffic (the count of observations). Although the total traffic regression is imprecisely measured,<sup>45</sup> the point estimates imply that a 10 percent increase in fuel price is associated with 5.69 percent more cargo per truck, which is loaded onto 6.57 percent fewer trucks: that is, our results suggest that total cargo declines by 0.88 percent. In the short run at least, the reduction in traffic is consistent with fewer vehicle miles travelled by heavier trucks. But the reduction in vehicle miles traveled is associated more with dispatch changes—perhaps fewer deliveries per day or week, or otherwise less convenient scheduling—than mode-shifting.

Assessing road damage requires knowledge of how the additional cargo weight is distributed. Redistributing a given amount of cargo to moderate-weight vehicles will produce significantly

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<sup>44</sup> Note that our instrument for price depends on temperatures over the previous month; our daily weather measures will capture changes in demand from snowfall, for example, but we do not expect snow or rain to factor into the instrumented diesel price.

<sup>45</sup> The imprecision is likely because detectors occasionally have lane outages which introduces noise into the count of vehicles at any station. Outages are only noted in our data by the disappearance of observations from a particular lane, and while there is no definitive way to confirm outages, they can be recognized on busier roads. These outages will introduce error into our measures of vehicle weight and speed if outages are correlated with the lanes tractor-trailer drivers chose. We see no evidence that these outages are more likely in any particular lane.

less damage than redistributing it to the heaviest vehicles. As is discussed in Section 4, the ESAL calculations are derived directly from raw (disaggregated) WIM data so as to account for the redistribution of truck weights in addition to the average change in weight. We conclude (column 3) that increasing the diesel price results in a statistically significant increase in ESALs. The point estimate indicates that a 10 percent increase in diesel price raises road damage by 18.98 percent. Because of the quartic relationship between axle weight and road damage, even small average upweighting can greatly increase road damage.

The final column examines the recorded speed of vehicles. Burger and Kaffine (2009) show that light-duty vehicle drivers reduce speed in uncongested traffic when gasoline prices are high and some studies have shown that tractor-trailers may have a similar ability to reduce fuel use by driving slower.<sup>46</sup> In column 4 we find that tractor-trailers reduce speed in response to higher diesel prices consistent with this conjecture. Although we are less confident in assigning a value to the amount of fuel saved by this action, slower speed may represent a second dimension in which scheduling suffers when marginal costs per mile increase.

## VII. Discussion

### A. Demand elasticity and the change in vehicle ton-miles

The estimates in section VI allow us to evaluate the welfare implications of a carbon or diesel tax and a fuel efficiency standard. The parameters used in this simulation are given in Table 4 with further discussion in Appendix II. Calculation of the carbon externalities in these simulations requires estimating the diesel fuel consumption response to a change in fuel price using the demand elasticity (or rebound effect) derived in equation (6), while other externalities including congestion, accidents and local pollutants are modeled as a function of ton-miles hauled.<sup>47</sup>

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<sup>46</sup> The results are very sensitive to road grade. On-road measurements are further complicated as slower average driving is associated with road congestion rather than a sustained speed (Franzese and Davidson 2011).

<sup>47</sup> The standard calculations for passenger vehicles use vehicle-miles traveled (VMT) for congestion, safety, and local pollution externalities. Externalities for heavy duty trucks are usually evaluated on ton-miles: heavier trucks accelerate and decelerate more slowly, causing more congestion and are plausibly less safe. Local pollutants vary with engine features as well as fuel consumption. A combination of VMT, fuel consumption and ton-miles are implicated in these externalities. Our use of ton-miles is driven by available estimates for external costs of trucks, which are priced per ton-mile in most sources. The appendix contains simulations that employ a range of estimates for these costs.

As is derived in section III, the elasticity of ton-miles with respect to price, or the “ton-miles rebound effect” is the sum of the change in per-truck tons (cargo weight) plus the change in vehicle miles traveled. Table 3 panel B column 1 reports the elasticity of per-truck cargo weight  $\varepsilon_{w,p}$ . We do not directly measure the elasticity of vehicle-miles traveled, but by assuming that vehicle miles travelled by freight trucks are proportionate to the measured traffic at WIM detectors we can use the estimate of the count elasticity,  $\varepsilon_{N,p}$ , also reported in Table 3, for this factor.<sup>48</sup> Thus the sum of  $\varepsilon_{N,p}$  and  $\varepsilon_{w,p}$  is the ton-miles rebound effect at -0.088. The imprecision with which we estimate  $\varepsilon_{N,p}$  cautions against placing much weight on the point estimate, but we note that the ton-mile value is similar to that used by the EPA (2015), -.05, as well as the short-run estimates by Leard et al. (2015), -0.189 and De Borger and Mulalic (2015), -.10.

To estimate the demand elasticity (fuel rebound effect) for diesel requires that the ton-mile elasticity be modified by the difference in fuel efficiency per ton-mile due to the cargo weight change (equation 6), which we denote by  $\varepsilon_{f,w}$ , and base on measures from the engineering literature (ORNL, 2011). Together these estimates imply a demand elasticity and short-run fuel rebound effect of -0.30.

Both elasticities will presumably differ in the long run, but the direction of change is unclear. The long run allows more scheduling flexibility, which would imply that greater weight changes would be observed over time. Alternatively, during the short run empty trucks may only be dispatched when diesel is cheap, consistent with the observed increase in average weight and decrease in traffic existing only in the short-run. Our ESAL estimates are not consistent with dispatch changes only in backhaul strategies, as it would imply no ESAL increase, but, if partly responsible for the observed changes, the implication is that the short run fuel response is more elastic than the long run. Lastly, demand for cargo is more elastic in the long run: if deliveries remain inconvenient, customers may shift to another mode of transportation, leaving the truckers to either further reduce operations or enhance services, albeit at a cost, and a more elastic long-run elasticity of demand for fuel and ton-miles.

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<sup>48</sup> Specifically, this assumes that upweighted trucks do not shift their driving to roads that disproportionately lack or, alternatively, are rife with traffic sensors.

## B. Diesel Taxes, Short Run Carbon Emissions Reductions, and Road Damage

Diesel taxes are discussed most often as a revenue generating mechanism but also, in recent years, as part of a comprehensive carbon tax policy. As a correction for external carbon damage, these taxes are broadly popular with economists. However, the presence of other unpriced externalities means the tax is, at best, second-best. We consider here whether it may come in third, after a fuel efficiency standard.

We begin by imposing a diesel tax of \$0.37 per gallon as part of a carbon tax policy. This level of taxation corresponds to a carbon price of \$36 per metric tonne of CO<sub>2</sub> (Interagency Working Group, 2015). Applying our estimated demand elasticity to annual diesel sales, this diesel tax results in 800 million fewer gallons of diesel consumption and generates \$292.4 million in carbon benefits.

A diesel tax, because it reduces ton-miles, will reduce other associated externalities. We apply our ton-miles rebound estimate to the total ton-miles shipped in the US, which implies that 21.7 billion fewer ton-miles reduced congestion, accidents, local pollution, and noise externalities generating \$576.3 million in benefits.

To evaluate the potential increase in road damage from raising diesel taxes, we apply our ESAL elasticity to the typical detector in the New York sample and extrapolate the increase in road damage to the national network of interstates. The increase of 8.5 billion ESALs nationwide generates \$1,172.9 million in additional damage.

Because the road damage externality overwhelms the carbon and ton-mile based externalities, the diesel tax on net costs of \$304.2 million annually. While the revenue raised is not included in this calculation as it is a transfer from consumers of trucking services to the government, it could offset other taxes, such as labor taxes introducing additional benefits. More commonly, diesel taxes are dedicated towards funding road repairs and are not set to maximize consumer surplus; however, even from an infrastructure funding perspective, the road damage erodes more than 10 percent of the increased revenue. As a second best strategy, the diesel tax is problematic.

### C. Fuel Efficiency Standards and Road Damage

Policy makers often attempt to improve efficiency through fuel efficiency standards. Particularly in the case of automobiles, economists stress that fuel efficiency standards, by lowering the price per mile of driving, may increase driving related externalities and reduce the carbon emissions saved by the policy. For automobiles, exacerbating the congestion, accident and pollution externalities associated with driving may be so large as to make fuel economy standards welfare reducing (Anderson et al., 2011). The welfare effects for trucks are likely to differ significantly. The reduced per ton-mile cost of shipping freight will lead to higher frequency (quality) shipments so that while vehicle ton-miles increase, the cargo weight per truck, and associated weight externality of tractor-trailers will decline.

In our simulation, we consider an exogenous improvement in fuel efficiency per ton-mile, such that the standard translates the weight-efficiency frontier of trucks outward, that is, at every weight, fuel use declines by an equal factor. First we examine the primary welfare benefit—the reduction in carbon net rebound diesel consumption. When using our estimated rebound effect, we follow the prior literature and assume that regulators impose this standard with no capital costs.<sup>49</sup> We choose a 4 percent improvement in efficiency to generate the same carbon reductions as the diesel tax in the prior section: a reduction of 800 million gallons that generates \$292.4 million in carbon benefits.

Next we examine the secondary costs of increased ton-miles and miles that occurs when efficiency is improved. Using our ton-miles rebound effect, the standard will generate 9.3 billion additional ton-miles resulting in \$246.6 million in congestion, accident, local pollution, and noise costs. The comparison of welfare at this intermediate step reveals a result familiar in the context of automobiles—carbon benefits are nearly entirely offset by increased ton-mile related externalities (Fischer, Harrington, and Parry, 2007). The net welfare at this step is \$45.8 million. Because fuel economy standards exacerbate these externalities, economists have criticized standards as not only sub-optimal, but also possibly even welfare reducing.

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<sup>49</sup> More precisely, capital costs are fixed costs and assumed to be small enough that they do not dissuade anyone from buying a car –but more importantly that they do not change the cost of driving a mile. For freight, this assumption is less sound: we would expect operators to pass through these capital costs increasing transportation costs apart from the fuel saving component incorporated in our estimate, affecting aggregate demand  $Q$  and truck hauling choices in line with the analysis in Section III. The calculations here should then be viewed as upper bounds for the extent of rebound and the associated calculations.

Because fuel economy standards lower the cost per ton-mile, we expect a dispatch as well as price response with higher frequency deliveries in lower weight freight vehicles. The resulting reduction of 3.7 billion ESALs in damage to the interstate system yields an additional \$501.9 million in benefits, resulting in a net benefit of \$547.7 million for the fuel efficiency standard.

#### D. Comparison of Two Policy Instruments

The simple analyses presented in the prior two sections are far from comprehensive but highlight the importance of the dynamics posited and estimated in this paper. Stated simply, using typical estimates of the ton-mile rebound effect and reasonable external cost estimates, the dispatch effect has the capacity to flip the preference for fuel taxes over fuel economy standards. We find that diesel taxes generate net costs of \$304 million while fuel economy standards generate net benefits of \$548 million.

There are, of course, assumptions that reverse this conclusion. Assumptions that increase ton-mile externalities will favor diesel taxes. For example a more elastic ton-mile response to price also favors the diesel tax policy, as it will exacerbate the driving-associated externalities. An elasticity of at least -0.19 flips the welfare preference for the two policies.<sup>50</sup> This is outside the range in the current literature with most negative at -0.189 from Leard et al. (2015). Using higher costs per ton-mile will also favor diesel taxes. If we use the upper bounds given by the GAO for external cost of congestion, accidents, and local pollution, both policies will exhibit net benefits and the difference between them narrows, but the efficiency standard continues to dominate the tax. Assumptions that lower the dispatch effect also shift the preference towards diesel taxes. An ESAL elasticity less than one, which is within the 95 percent confidence interval, also reverses the preference. However, because we omit damage to non-interstate roads, the per-ESAL damages are likely to be much larger than the value used in the simulations so that the fuel efficiency standard advantage is likely to survive each of these scenarios.

Effects beyond our simple simulation may also change the preference ordering. For example, we omit potential tax efficiency benefits from using diesel tax revenue for reducing distortionary taxation (Parry and Oates, 2000). Conversely, the ‘internal’ benefits of fuel economy standards for myopic consumers (Busse, Knittel, Zettelmeyer, 2013), which dominate the EPA’s cost-

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<sup>50</sup> See Appendix Tables A.1 and A.2 for these scenarios.

benefit analysis of heavy-duty-truck fuel economy standards,<sup>51</sup> are not included here.<sup>52</sup> Our data do not allow us to comment on the magnitude of such benefits, but we note that the benefits of reduced road damage discussed in this paper are not included in the EPA analysis. Imposing such a standard would also generate capital costs that would be reflected in average costs (Borenstein, 2015). It is unclear how inclusion of capital costs would change the relative comparison between policies as an offset in the standard's reduced ton-mile costs drives both the dispatch effect and ton-miles rebound towards zero so that both external benefits and external costs of the efficiency standard decline.

Another caveat is that these estimates are short-run responses, and do not account for long-run changes in engine technology choice in response to a diesel tax. Such a dynamic would increase carbon benefits and decrease road damage costs from a diesel tax, shifting the preference towards diesel taxes.

Lastly, we note that the preference for fuel economy standards is dependent on the failure of policy makers to implement and courts to allow for comprehensive axle weight taxes. In the presence of an axle-weight tax, operators would only aggregate loads where the fuel savings were greater than the tax penalty.<sup>53</sup> With a lower incentive to aggregate in the presence of a fuel price increase, particularly on the heaviest trucks, the road damage penalty from a tax versus standard will be correspondingly lower so that other external costs, as with automobiles, will dominate the comparison.

## VIII. Conclusions

Evaluating the effects of taxes and regulations on intermediate goods is challenging. Policies that change the price of fuel, or cost per ton-mile, for freight trucks change the market for cargo on two dimensions: directly, in the price per ton-mile, and indirectly, through the change in

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<sup>51</sup> The EPA finds benefits of \$175.1 billion in fuel savings compared with a technology cost of \$25.4 billion. Overall total cost of the standard is estimated at \$31.1 billion compared with a benefit of \$275 billion (Table 8-38, EPA 2015). The magnitudes in the EPA evaluation cannot be directly compared with ours as the EPA models a standard for multiple classes of vehicles that is changing over a longer time horizon. See Gayer and Viscusi (2013) for further discussion.

<sup>52</sup> While engineers and policy makers often include benefits for consumers who do not recognize the full value of reduced fuel costs when buying more efficient vehicles, economists have been skeptical of these claims (Gillingham and Palmer, 2012; Allcott and Wozny, 2014; Sallee, West, and Fan, 2016). Intuitively, myopia seems even less plausible for profit-maximizing firms in a competitive industry such as trucking than for consumers of automobiles

<sup>53</sup> Of course, even with axle-weight taxation, a diesel tax would still result in a cargo weight response and more road damage. Optimal taxation requires joint optimization of the two instruments, recognizing their interdependency.

delivery schedules. The choices along the price/quality margin depend on, and in turn affect, the structure of the manufacturing, wholesale, retail and trade markets that purchase cargo services.

This paper focuses on how fuel prices affect dispatch decisions and the resulting change in truck loads. We find that a 10 percent increase in diesel prices increases vehicle weight by 3 percent. The relationship between fuel price and truck weight imposes an additional cost of increased road damage whenever fuel taxes are increased but confers added benefits to a fuel efficiency standard. Of course, neither approach yields an optimal outcome for controlling both highway use externalities and pollution externalities. Instead, multiple instruments are needed.

Critical to generating optimal outcomes would be the imposition of axle-weight-mile taxes. The American Trucking Association has resisted any axle-weight use taxes, and the courts have largely agreed with their argument that the axle-weight taxes in most states have been implemented in a way that imposed unfair burdens on the freight truck industry.<sup>54</sup> Much of the information required to impose trip specific axle-weight taxes already exists as trucks already extensively document their driving. An interesting feature of state diesel fuel taxes in the United States is that, unlike gasoline, diesel is taxed by the state of use rather than purchase. Through a process moderated by the International Fuel Tax Agreement (IFTA), truckers pay tax in the state where diesel is purchased, but then keep track of where it is used by recording miles driven by state. The IFTA organization keeps track of net tax over- and under-payments by state, collects payments from truckers or issues them rebates, and arranges transfers between states. Many states, including New York and California, also have highway use taxes, levied on truckers based on the vehicle-miles-traveled within the state, with collection and disbursements organized by IFTA. Use taxes vary by class, but are insensitive to the weight changes analyzed here.<sup>55</sup> Given the growth in trucking, the importance of infrastructure for economic activity, and the potential for benefits, we suggest revisiting the structure of taxes on heavy trucks to explore the value of a mix of fuel and weight use taxes.

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<sup>54</sup> As of 2016, Oregon has most successfully resisted court challenges to its tax but it imposes no diesel fuel tax. Other states have run afoul of the dormant commerce clause in their attempts to tax axle-weights. See Pitcher, 2014; ATA Litigation Center, 2010.

<sup>55</sup> These use taxes are levied annually and are based on the vehicles' maximum weight but do vary with the weight of any particular trip, and indeed appear to give an incentive for firms to increase weight per axle. An analysis of their effects is beyond the scope of this paper. The information collected for IFTA raises the potential for taxes that are road and time specific and thus address congestion externalities as well (Parry, 2008).

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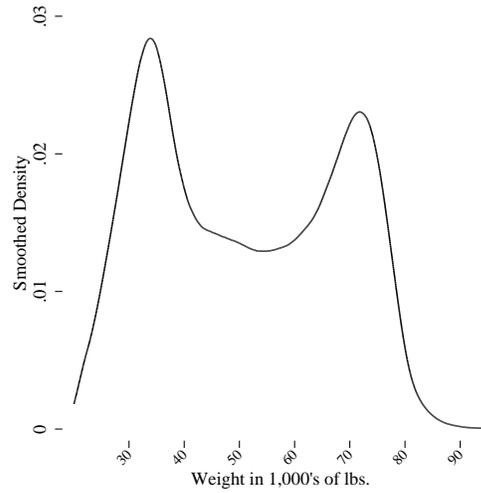
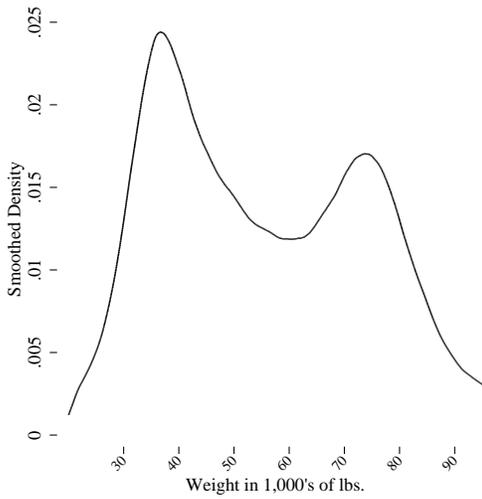
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New York Detectors

California Detectors



New York WIM Distribution

California WIM Distribution

Figure 1: Weight-in-Motion Data

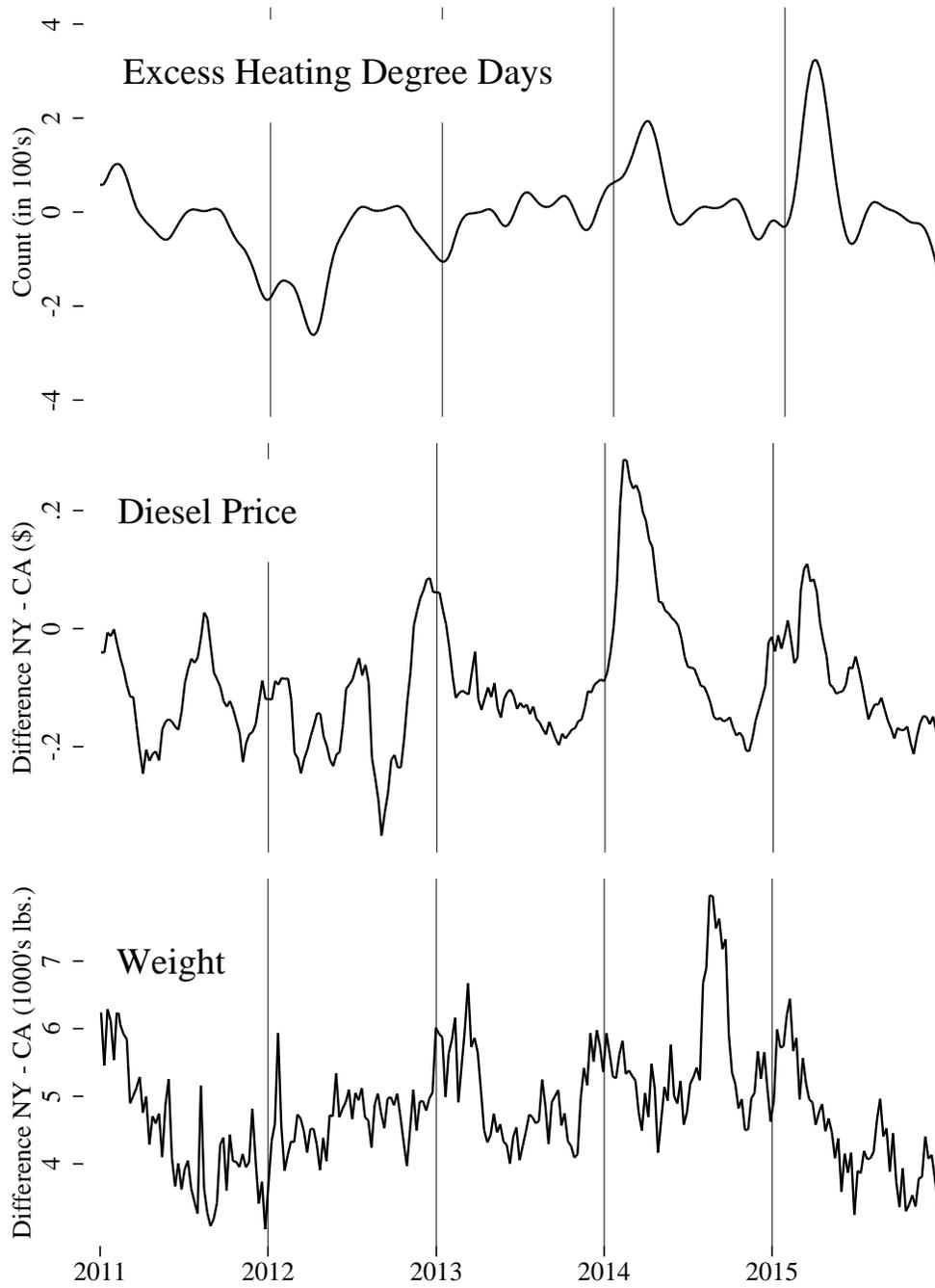


Figure 2: Weight, Diesel Price, & Heating Degree Days

Table 1: Heating Degree Days and Diesel Prices

Dep. Var.: NY Price - CA Price	Diesel						Gasoline (Placebo)
	(1)	(2)	(3)	(4)	(5)	(6)	
EHDD	0.042*** (0.005)	0.025*** (0.005)	0.040*** (0.005)	0.033*** (0.006)	-0.007 (0.008)	0.037*** (0.007)	0.018 (0.012)
Rain (cm)			0.005 (0.004)	0.004 (0.004)	0.007 (0.004)	-0.001 (0.005)	-0.000*** (0.000)
Snow (cm)			0.000 (0.003)	-0.003 (0.004)	-0.001 (0.005)	-0.001 (0.005)	-0.003*** (0.001)
Temp. (°F/1000)			-0.604 (0.445)	-0.504 (0.585)	-0.810 (0.533)	-0.862 (0.660)	0.008 (0.007)
GDP		-0.046*** (0.009)					
Monthly Freight		-0.635* (0.315)					
WTI Oil Price		-0.009 (0.041)					
R-squared	0.44	0.52	0.44	0.22	0.14	0.68	0.46
N	1822	1731	1822	3258	610	610	1822
Sample	2011-2015	2011-2015	2011-2015	2007-2015	Aug.-Nov. 2011-2015	Mar.-Jun. 2011-2015	2011-2015

*Notes:* The estimates are from seven regressions of the listed daily fuel price or daily fuel price differential on the listed regressands. EHDD is 100 excess heating degree days in the 30 prior days. Trend and fixed effects for month are included in all regressions. Standard errors, clustered on week, are given in parentheses with \* indicating significance at 5%, \*\* at 1%, and \*\*\* at <1%

Table 2: Heating Degree Days and Distillate Consumption

Dep. Var.: Monthly Average Daily Residential Distillate Consumption (1000s)	(1)	(2)	(3)	(4)
	EHDD	18.082*** (3.840)	14.902*** (4.173)	15.813*** (3.891)
Total Monthly Rain (cm)		-0.450 (0.714)	-0.474 (0.704)	-0.874 (0.641)
Total Monthly Snow (cm)		0.612* (0.289)	0.500 (0.283)	0.625* (0.249)
GDP				0.065*** (0.008)
WTI Oil Price				0.021 (0.161)
R-squared	0.86	0.86	0.86	0.89
N	358	358	358	358
Sample	1986-2015	1986-2015	1986-2015	1986-2015
Quadratic Trend	N	N	Y	Y

*Notes:* Values shown are the coefficients of four regressions of the daily residential distillate consumption in thousands of barrels averaged at the monthly level on the regressands. EHDD is 100 excess heating degree days in the 30 prior days. Monthly average temperature is omitted because, at a monthly aggregation, it is highly correlated with our measure of EHDD. Trend and fixed effects for month are included in all regressions. Robust standard errors are given in parentheses with \* indicating significance at 5%, \*\* at 1%, and \*\*\* at <1%

Table 3: 5-Axle Vehicles

<i>Panel A: Average Vehicle Weight</i>				
Dependent Variable: log(NY Weight)-log(CA Weight)				
	OLS	IV		
	(1)	(2)	(3)	(4)
<i>Second Stage</i>				
log(\$NY)-log(\$CA)	0.103*** (0.029)	0.331*** (0.063)	0.000 (0.050)	0.157* (0.068)
Rainfall (cm)	-0.005*** (0.001)	-0.006*** (0.001)	-0.005*** (0.001)	-0.007*** (0.001)
Snowfall (cm)	0.004*** (0.000)	0.004*** (0.000)	0.003 (0.002)	0.004*** (0.001)
Temperature (°F/1000)	-0.226** (0.075)	-0.070 (0.085)	-0.447 (0.465)	0.004 (0.105)
R-squared	0.18	0.12	0.10	0.12
N	1822	1822	610	610
Month Restriction	None	None	Aug.-Nov.	Mar.-Jun.
<i>First Stage</i>				
EHDD		0.011*** (0.001)	0.002 (0.002)	0.010*** (0.002)
<i>Kleibergen-Paap F-Stat.</i>		17.26	7.81	20.87
<i>Panel B: Other Outcomes</i>				
Dependent Variable:				
	Cargo	Daily Count	ESALs	Speed
	(1)	(2)	(3)	(4)
<i>Second Stage</i>				
log(\$NY)-log(\$CA)	0.569*** (0.108)	-0.657 (0.547)	1.898** (0.730)	-0.201*** (0.042)
Rainfall (cm)	-0.009*** (0.001)	0.001 (0.005)	-0.013 (0.008)	-0.001* (0.001)
Snowfall (cm)	0.007*** (0.001)	-0.021*** (0.004)	-0.002 (0.005)	-0.009*** (0.001)
Temperature (°F/1000)	-0.123 (0.144)	0.223 (0.707)	-0.717 (0.854)	0.110 (0.059)
R-squared	0.14	0.12	0.05	0.38
N	1822	1822	1822	1822
<i>First Stage</i>				
EHDD	0.011*** (0.001)	0.011*** (0.001)	0.011*** (0.001)	0.011*** (0.001)
<i>Kleibergen-Paap F-Stat.</i>	17.26	17.26	17.26	17.26

*Notes:* The estimates in Panel A are from four regressions of daily average vehicle weight on the listed regressands. The estimates in Panel B are from our regressions of daily average daily vehicle count, ESALS, cargo (weight - 23,000 lbs.), and vehicle speed on the listed regressands. EHDD is 100 excess heating degree days in the 30 prior days. Trend and fixed effects for month are included in all regressions. Standard errors, clustered on week, are given in parentheses with \* indicating significance at 5%, \*\* at 1%, and \*\*\* at <1%

Table 4: Simulation Parameters

Parameter	Value	Source
$\varepsilon_{g,c}$	-0.32	Franzese and Davidson (2011) Eq. 1
Annual Diesel Sales	38.5 billion gallons	EIA 2014 Adjusted Sales of Distillate Fuel Oil by End Use
Average Diesel Price 2011-2015	\$3.85 gallon	Authors calculation and EIA PADD1B (2015\$)
Annual ESALs per Lane Mile from Tractor-Trailers	553,340	Authors calculations and NY WIM data
Share of 3+Axle Truck Traffic that is 5 Axle	78 percent	Authors calculations and NY WIM data
Average Vehicle Weight	55,000 lbs.	Authors calculations and NY WIM data
Average Tractor-trailer Fuel Economy	8.67	Franzese and Davidson (2011) Eq. 1 at 55,000 lbs.
Road Damage Cost	\$0.137 per ESAL <sup>a,b</sup>	FHWA (1995)
Miles of Interstate	42,795	FHWA
Ton-miles of Freight in 2011	2.6 Trillion	Bureau of Transportation Statistics
Social Cost of Carbon	\$36 per tonne CO <sub>2</sub>	Interagency Working Group on Social Cost of Carbon (2015)
Congestion cost	\$0.0044 per ton-mile <sup>b,c</sup>	GAO (2011)
Accident Risk	\$0.0121 per ton-mile <sup>b,d</sup>	GAO (2011)
Local Pollution (PM 2.5 and NOx)	\$0.0095 per ton-mile <sup>b,e</sup>	GAO (2011)
Noise	\$0.0005 per ton-mile <sup>b</sup>	GAO (2011)

<sup>a</sup> Lower bound of \$0.087 per ESAL in 1995 dollars. See text for further discussion.

<sup>b</sup> Converted to 2016 dollars.

<sup>c</sup> Range is \$0.0026 to \$0.0062 per ton-mile. Listed value is midpoint.

<sup>d</sup> Range is \$0.0012 to \$0.0230 per ton-mile. Listed value is midpoint.

<sup>e</sup> Range is \$0.0012 to \$0.0179 per ton-mile. Listed value is midpoint.

Table 5: Simulation Outcomes

<i>Simulation A: Diesel/Carbon Tax</i>	
Tax per gallon <sup>a</sup>	\$0.37
Tax Revenue	\$10.8 Billion
Change in Fuel Use <sup>b,c</sup>	-800.1 Million Gallons
Carbon Benefit	\$292.4 Million
Ton-Miles Change	-21.7 Billion Ton-Miles
Congestion, Accidents, Local Pollution, and Noise Benefit <sup>d</sup> <i>Upper and Lower Bound</i> <sup>e</sup>	\$576.3 Million [\$118.5 to \$1,034.1]
ESAL Change	8.5 Billion ESALs
Road Damage <sup>f</sup> <i>95% C.I.</i>	-\$1,172.9 Million [-\$2,075.1 to -\$270.7]
Total	-\$304.2 Million
<i>Simulation B: Fuel Economy Standard</i>	
Increase in Efficiency	4 percent
Change in Fuel Use <sup>c</sup>	-800.1 Million Gallons
Carbon Benefit	\$292.4 Million
Ton-Miles Change	9.3 Billion Ton-Miles
Congestion, Accidents, Local Pollution, and Noise <sup>d</sup> <i>Upper and Lower Bound</i> <sup>e</sup>	-\$246.6 Million [-\$442.5 to -\$50.7]
ESAL Change	-3.7 Billion ESALs
Road Damage <sup>f</sup> <i>95% C.I.</i>	\$501.9 Million [\$115.8 to \$887.9]
Total	\$547.7 Million

<sup>a</sup> Assumed carbon tax of \$36 per metric ton CO<sub>2</sub>.

<sup>b</sup> Assumes no change in technology. In the long run, without a binding fuel economy standard, operators would be expected to purchase vehicles with higher fuel efficiency.

<sup>c</sup> Confidence intervals omitted as the demand elasticity makes use of parameters from the literature and the level of fuel economy standard is chosen to match the carbon saved under the diesel tax.

<sup>d</sup> The GAOs cost of local pollution includes PM2.5 and NO<sub>x</sub>.

<sup>e</sup> Uses the lower or upper bound of all externality prices listed in footnotes to Table 4.

<sup>f</sup> Includes damage/benefit to 42,795 miles of Interstate Highways. Assumes two lanes per direction.