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The Effect of Trucks Dispatch Decisions on Pavement Damage and Other Externalities

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The Effect of Truck Dispatch Decisions on Pavement Damage and other Externalities

A Research Report from the University of California Institute of Transportation Studies

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16. Abstract
External costs of freight trucks include air pollution, highway damage, and congestion. While diesel taxes reduce both the pollution and congestion externalities, we show that they worsen highway damage. We investigate the impact of fuel prices on cargo shipments using weight-in-motion data from New York and California. We obtained sensor readings on over 1.4 billion vehicle events. These data allow us to track daily changes in the weight and number of trucks at specific locations. We explain the average daily 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 3.1 percent and average truck weight increases 3.2 percent. While total truck traffic decreases by around 1 percent, on net there is 19.6 percent more road damage. The dispatch effect changes the welfare comparison of using fuel taxes versus efficiency standards to control carbon emissions. 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.

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Executive Summary

External costs of freight trucks include air pollution, highway damage, and congestion. While diesel taxes reduce both the pollution and congestion externalities, we show that they worsen highway damage. An increase in the tax on diesel fuel leads to heavier trucks and, in the absence of a second tax or policy that addresses truck weight externalities, more road damage. Indeed, our calculations suggest that the increased external costs due to the diesel tax from road damage offset its benefits from lower carbon emissions.

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 optimal 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). Ceteris paribus, an increase in fuel prices will further aggregate loads.

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—road damage increases to the fourth power in axle weight. 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 non-weather related road damage, understanding the determinants of truck weight is key to 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 weight-in-motion data from New York and California. We obtained sensor readings on over 1.4 billion vehicle events. These data allow us to track daily changes in the weight and number of trucks at specific locations. To identify the price effect on vehicle weight, 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. Diesel fuel and home heating oil are largely the same product. 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 average daily 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 3.1 percent and average truck weight increases 3.2 percent. While total truck traffic decreases by around 1 percent, on net there is 19.6 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 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 exacerbating other externalities like congestion. Similar rebound driving is expected for trucks. 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.

Axle-weight-mile taxes, which have been championed by transportation economists, address the truck weight externality directly. We show that in addition to providing an efficient source of support for infrastructure maintenance, in conjunction with a carbon tax such as the current tax on diesel fuel, the weight tax allows for a welfare enhancing optimal environmental policy.

Introduction

A tenet of welfare economics is that multiple policy instruments are needed to fix multiple externalities (Tinbergen, 1952). Rarely is such an outcome possible. Full correction of one out of many market failures may be a substantial policy achievement but in a second best setting may no longer be optimal; indeed, eliminating one distortion alone may lower total welfare (Lipsey and Lancaster, 1956). This is the issue we investigate. Our calculations suggest that an attempt to charge freight truckers for the external costs of their carbon emissions will increase the external costs of road damage to such a degree that total welfare declines.

Links between externalities are not uncommon. Road damage and air pollution in this case are "jointly reinforcing" externalities (Bennear and Stavins, 2007); that is, truckers' actions in response to a Pigouvian tax on one externality exacerbate the other. This finding is ironic because diesel taxes are often levied to repair roads. While economists generally discourage taxation of intermediate goods to raise revenue,[1] policy discussions of diesel fuel taxes often focus on how the revenues can be dedicated to highway infrastructure and how the resulting infrastructure would contribute to economic growth (CBO, 2015). We find that an increase in the diesel tax to raise revenues for road maintenance increases the need for maintenance. Approximately 11% of the revenue from a diesel tax increase is lost to additional road damage.

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 freight customers or waiting costs of final customers. Absent transportation costs, it would be optimal to move individual goods between origin-destination pairs at exactly the time the good was to be used or sold. 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, companies face a tradeoff between inventory and transportation costs. Ceteris paribus, an increase in fuel prices will further aggregate loads.[2]

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. [3] Because truck weight generates nearly all road damage that is not weather related, understanding the determinants of truck weight is key to

[1] See Diamond and Mirrlees, 1971. The exception is cases like trucking, where the good generates externalities (Sandmo, 1975).

[2] Freight aggregation saves labor and capital costs as well as fuel; changes in the cost of any component of transport cost changes dispatching. This paper addresses only fuel.

[3] 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. See Joint Committee on Taxation, 2015. If roads are not optimally maintained, they will cause an additional external cost in damage to other vehicles. See Winston, 2013. Significant revenues are also raised from heavy truck registration fees which are usually based on the maximum loaded weight of trucks but on share of miles driven, rather than actual mileage, within each state. For examples, see http://www.irponline.org/?page=FeeSchedules

understanding infrastructure damage. The dispatch effect of a fuel price increase—how fuel prices affect the distribution of cargo among trucks—is consequential.

We investigate the dispatch effect 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 sensors 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, they allow for sophisticated identification. Diesel fuel prices are likely to be endogenous to cargo weight due to both global and local shocks. 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.[4] Furthermore, a local shock that increases demand for freight services plausibly increases local demand for and the local price of diesel fuel. To identify the price effect, we exploit weather-related fuel differences between New York and California. In New York, sales of diesel fuel for residential heating (where it is usually called heating oil) average 70% of the quantity sold for on-highway transportation.[5] 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 3.1 percent and average truck weight increases 3.2 percent. While total truck traffic decreases by around 1 percent, on net there is 19.6 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 because an efficiency standard, by reducing the cost of driving per mile, induces an increase in vehicle miles traveled (the "rebound" effect), which undermines some of the fuel savings as well as exacerbating other externalities like congestion.[6] Similar rebound driving is expected for trucks (De Borger and Mulalik, 2012; Leard et al., 2015). But we find that the reduction in per-mile shipping cost from an efficiency 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 external costs of truck

[4] 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.
[5] Sales of Distillate Fuel Oil by End Use, U.S. Energy I.nformation Administration, 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 critical difference between home heating oil and diesel fuel is the tax—residential demand is significant.
[6] The work on the relationship between fuel economy standards and rebound for automobiles is extensive; see, e.g., Anderson et al., 2011; Bento et al., 2009; Jacobsen, 2013 and references cited therein. An excellent discussion of the rebound effect for both automobiles and other consumer goods is contained in Borenstein, 2013.

congestion and safety, we find that fuel efficiency standards dominate fuel taxes as a policy to reduce carbon emissions for a wide range of estimates.[7]

Our analysis underscores the importance of investigating linked externalities. Many externalities display "jointly ameliorating" behavior (Bennear and Stavins, 2007) where a tax that corrects one externality reduces welfare losses from other externalities. This is the case for automobiles: a Pigouvian tax on fuel internalizes emissions externalities and, by reducing vehicle use, lowers the congestion and safety externalities of traffic (Parry and Small, 2005). Other examples include taxing a product to correct for the externalities of one production pollutant when the production process produces multiple pollutants (Caplan and Silva, 2005) and using revenue from environmental taxes to reduce preexisting labor and capital taxes. Alternatively, cases of jointly-reinforcing externalities include the tax-interaction effects of pollution taxation examined by Bovenberg and Goulder (1996) and Parry (1997), and the possibility that imposition of a Pigouvian pollution tax can exacerbate market power-related welfare loss (Buchanan, 1969).

Axle-weight-mile taxes, which have been championed by transportation economists (Parry, 2008; Small et al., 1991), address the truck weight externality directly.[8] While these papers advocate a combination of fuel and weight distance taxes to separately address the fuel and weight externalities of trucks, they do not account for the interaction between fuel price and truck weight and hence between the two instruments. Our analysis lends urgency to a dual tax regime, as it shows that an appropriate weight-distance tax allows for is not only addresses the heavy truck road externalities, but also allows for a welfare enhancing optimal environmental policy.

I. Heavy Trucks and Diesel Fuel: Background

Heavy Trucks and Cargo Weight

Tractor-trailers dominate the truck cargo industry. Between 1990 and 2010, this industry grew significantly: vehicle miles traveled (VMT) increased 87 percent and ton-miles increased by 47 percent.[9] Together the trends suggest that the average load has grown lighter. While some of the change is 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).

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

[7] 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 required increased load factors so as to reduce the VMT-related externalities of trucks.

[8] Despite its benefits, a number of states have repealed this tax in the face of political and judicial headwinds. As of 2016, Oregon has a tax that comes closest to addressing heavy truck externalities. See Pitcher, 2014.

[9] 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

growing source of carbon emissions in transportation. They are also, along with weather, the predominant sources 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. ESALs rise by the third or fourth power of axle weight, depending on the type of road. Thus, 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 pounds.[10] Larger loads are only allowed for 'non-divisible' loads and require special permits.[11]

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[12] and the frequency of delivery. 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.

Freight truck carbon emissions have come under the scrutiny of the Environmental Protection Agency in recent years (Harrington and Krupnick, 2012). EPA heavy truck fuel efficiency standards, first implemented in model year 2014, specify a maximum fuel consumption per brake-horsepower-hour for engines, and essentially regulate 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 federal efforts to raise the tax failed, between 2013 and 2016 seventeen states increased their diesel taxes.[13] As we show in Section VI, efficiency standards and taxes have different impacts on the private costs of dispatch and delivery; as such, they also result in different the public costs from the related externalities.

No. 2 Distillate

Certain features of petroleum markets drive our identification strategy. Petroleum refining

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10 Weights and axle configurations are also governed by the FHWA bridge weight regulations which set the maximum allowable weight for a given axle configuration on the interstate system.

11 These permits are rarely denied but often require use of particular routes that avoid bridges or sensitive infrastructure.

12 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).

13 "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.

converts crude oil, a complex mixture of hydrocarbons, into a variety of products ranging from methane gas to asphalt. Among the most important are gasoline and distillate fuel oil. While No. 2 distillate fuel oil, more commonly referred to as diesel fuel, is primarily used in trucks and locomotives, in the United States it is also used as home heating oil. The northeastern United States accounts for nearly 88% of all No 2. fuel oil used for domestic heating.[14] During a heating season, a single home may use between 850 and 1,200 gallons, which is stored in tanks that hold several hundred gallons. Unlike Europe, very few passenger vehicles in the United States are diesel powered (less than 3% of the U.S. new car sales in 2014, as opposed to 50% of the new car sales in Europe).[15] While U.S. refineries are optimized for gasoline production, on net the U.S. imports gasoline and exports diesel to countries with a higher share of diesel transportation demand.

No. 2 diesel has multiple uses. 'Off-road' diesel 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 pollution 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. [16] 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.[17] In addition to seasonal shifts, unusual winter weather is credited with increasing or decreasing diesel prices.[18] We explore this relationship below.

II. Model of the Freight Trucking Market

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-

[14] Distillate No. 1 is used by city buses, which are excluded from our analysis, while higher numbered residuals (No. 5 and 6) are used for steam powering in electric generation or maritime freight.

[15] See https://www.rita.dot.gov/bts/sites/rita.dot.gov.bts/files/publications/bts_fact_sheets/oct_2015/html/entire.html

[16] The fuel statistics in this section all come from the Energy Information Administration. Off-road diesel is dyed red to aid in the detection of fraud, which nevertheless persists to some degree (Marion and Muehlegger 2008).

[17] Marion and Muehlegger (2011) use this variation to examine pass-through rates of taxes, exploiting the seasonal variation in demand elasticity for diesel fuel.

[18] 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 Demand," *Transport Topics,* 2/3/2014, at http://www.ttnews.com/gateclient/premiumstorylogin.aspx?storyid=34064, (accessed August 12, 2016).

miles.[19] We focus on several issues that are omitted from similar models for light-duty vehicles. First, truck operators can influence their per mile fuel costs.[20] Second, by modifying the dispatch schedule, total vehicle miles traveled can change in the absence of any change in ton-miles (total cargo demand). Lastly, we are interested in identifying changes in vehicle weight and the 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 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 $Qf(w)$.[21] The model captures the fuel consequence of dispatching: total fuel use declines when cargo is aggregated into fewer, heavier loads.[22]

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. It may include inventory costs for the customers of freight services; alternatively, it may be their customers' waiting costs if inventory is unavailable. It may also include organization costs, such as the material and labor costs of shifting from uniform packaging that wastes freight space to differentiated packaging allowing for higher weight density. In each case, for a constant level of total demand Q, an increase in per-truck cargo weight w implies less frequent delivery and higher logistic costs. 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 $l''(\cdot) > 0$.[23] 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:[24]

(1) $$TC = pQf(w) + Ql\left({}^{w}/_{Q}\right)$$

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[19] The ratio of the two yields vehicle miles traveled, or the number of trucks on the road.

[20] 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.

[21] Further restrictions on the relative magnitudes of these derivatives are needed so that the total fuel use per truck increases with total truck weight: $wf''(w) < -2f'(w)$; $f(w) + wf'(w) > 0$.

[22] Aggregation will also result in savings in capital and labor costs of trucking. Extending the model to include other costs is straightforward.

[23] 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.

[24] All values are per mile, an annotation that we drop for concision. Costs are for delivering cargo one mile, as are the marginal costs.

De Vany and Saving (1983) show that if a market of this type is competitive, in equilibrium, average total costs—including any quality-related costs external to the transaction price—are minimized. Assuming a competitive freight trucking industry,[25] in equilibrium *w* will minimize average total cost if:

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

Equation (2) implies that, in equilibrium, per truck cargo *w* is set to equate the marginal fuel savings and the marginal logistics/inventory penalty.[26]

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

(3) $$^{dw}\!/_{dp}\, A = 1 - {}^{dQ}\!/_{dp}\, B$$

where

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

and $^{dQ}\!/_{dp}$, the "freight demand effect," is the change in the equilibrium quantity of cargo given how the price of shipping (average total cost of freight shipping) changes with the change in diesel price, *p*.[27]

Equation (3) describes the dispatch effect, and shows that the dispatch effect depends not only on the fuel and logistical costs but also on the elasticity of demand for cargo. If demand is perfectly inelastic, *Q* will be unaffected by changes in the diesel price. In this case, the dispatch effect is unambiguously positive, and 1/*A* measures the extent to which cargo is reallocated among trucks when fuel costs increase so as to take advantage of the fuel savings from aggregation. Per-truck weight increases and frequency declines.   In general, the freight demand effect moderates the extent that trucks upweight. Notwithstanding the best efforts of the trucking company, the increase in fuel cost will typically lower demand for cargo, as some freight price increase is unavoidable. Even were truck weight unchanged, delivery schedules would deteriorate, raising both average and marginal logistical costs. In order to not unduly sacrifice scheduling in the face of a reduction in cargo demand, minimizing total costs will thus

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25 In a competitive market, any increase in shipping cost is fully passed through to consumers. However, the relationship between the fuel price, cargo weight, and frequency is independent of how the logistic costs of shipping are shared between the freight truck industry and its consumers. Shah and Brueckner (2012) derive a similar result for more complex markets. In a differentiated market where otherwise-identical shippers establish reputations, they show that frequency of service declines when either the fixed or variable component of shipping costs increases.

26 Minimum average cost declines with total cargo, Q, which means that the competitive supply curve is declining in output. The existence of an equilibrium thus requires further assumptions on the elasticity of demand for cargo, *Q* relative to supply.

27 The price change incorporates cost changes due to the dispatch effect of fuel price as well as the direct increase in fuel price per gallon.

involve less upweighting than in the inelastic demand case. While scheduling suffers with an increase in fuel price, the change in truck weight may be either positive or negative. Signing the dispatch effect is thus an empirical problem.

The Elasticity of Demand and the Rebound Effect

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

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

Differentiating (5) with respect to *p*:

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

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). The first term is a demand effect while the second measures the efficiency adjustment due to dispatch changes.

Fuel economy regulations are evaluated relative to the "rebound effect." An efficiency standard in part symmetric to a fuel price decrease, that is, a ten percent improvement in fuel efficiency lowers the per mile cost of driving an identical amount to the change in cost from a ten percent decrease in the price of fuel. Ignoring the capital costs of the standard, [28] the elasticity of fuel use with respect to a standard is $-1 - \varepsilon_{F,p}$, while the elasticities of cargo weight and vehicle miles traveled with respect to an efficiency standard are both positive and equal to the opposite of the same elasticities with respect to fuel price.

Empirical Strategy

Consider the following equation:

(7) $$\ln(y_{st}) = \beta \ln(P_{st}) + X'_{st}\gamma + \delta_s + \gamma_t + u_{st}$$

where y_{st} is the outcome of interest (average truck weight, number of trucks per day, or ESALs) in state *s* at time *t*, P_{st} is state-level diesel price, X_{st} is a matrix of other determinants of the outcome variable, and δ_s, γ_t, and u_{st} are unobserved state-level fixed, national-level time

[28] More precisely, the automotive studies assume that 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 IIIA. The calculations here should then be viewed as upper bounds for the extent of rebound and the associated calculations.

varying, and state-level time varying components.[29] β measures the price elasticity of weight, truck count, or ESALs.

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. To correct for national and international shocks, let New York and California denote the states in equation (7) and difference:

$$(8) \ln(y_{NYt}) - \ln(y_{CAt}) = \beta\,(\ln(P_{NYt}) - \ln(P_{CAt})) + (X_{NYt} - X_{CAt})'\gamma + u_{NYt} - u_{CAt}$$

or:

$$(9) \qquad \Delta\ln(y_t) = \beta\,\Delta\ln(P_t) + \Delta X_t{}'\gamma + \eta_t$$

While equation (9) improves upon that of (7), endogeneity remains if state-level demand for freight hauling influences local diesel prices. To address this concern, we use instrumental variables:

$$(10) \qquad \Delta\ln(P_t) = \theta Z_t + \Delta X_t'\gamma + \mu_t$$

where $\Delta\widehat{\ln(P_t)}$ is the predicted diesel price spread between states as estimated in the first stage. Consistent estimates of β require the instrument, *Z*, to satisfy $cov(Z, P|X) \neq 0$ and $cov(Z, \eta|X) = 0$. We propose the use of random fluctuations in temperature as measured by excess heating degree days (EHDD) over the prior month. The assumption is that a spell of abnormally cold weather will increase demand for heating oil, competing for the stock of No. 2 distillate fuel oil and driving up the price of diesel fuel in New York compared with California.[30] 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 heating oil. Because the diesel price data are weekly, standard errors are clustered at the week level.[31]

There are some exclusion concerns with the instrument. First, truck drivers may avoid traveling on days with bad weather. To address this concern we exclude excess heating degree days for the current and two prior days from the instrument and directly include measures of contemporaneous daily temperature, snowfall, and rainfall in the regression. Second, while

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[29] 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.

[30] Heating Degree Days, as opposed to excess heating degree days, are a poor instrument, as these are anticipated and, together with seasonal variations in cargo demand, in part determine export decisions. As such, they may or may not be independent of cargo demand. We use a seasonal dummy variable to account for the anticipated weather changes.

[31] In appendix table A.2 we also consider a time-series framework with a 7-day autocorrelated error structure estimated using GMM. Our preferred estimates of equation 12 use LIML and standard errors clustered at the weekly level because the instrument is weak in the regression that uses only data from the autumn months.

weather may affect travel on the date of travel, the IV model assumes that temperature during the prior weeks does not. The following sections present several robustness checks based on expected seasonal variation during the autumn and spring. There is an asymmetric response between these seasons, which suggests that the instrument is shifting supply of diesel through the proposed channel.

III. Data

Weigh-in-Motion Data. The data documenting trucks are 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.

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 data from 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.[32] WIM data are noisy, and we delete some observations as errors, in accord with standard procedures for this data.[33]

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. Due to the non-linearity of ESALs in truck weight, ESALs cannot be estimated from aggregate vehicle information. 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 and total vehicle count. Detectors with less than 75 percent data coverage are dropped from the sample, while missing values for the remaining detectors are imputed.[34] 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

[32] This restriction eliminates the possibility that fuel prices generate substitution across vehicles of different axle count. We make this restriction because five axle trucks are more than 78 percent of all vehicles with at least 3 axles. 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.

[33] Quinley (2010). We tried several different cleaning strategies, which did not affect the 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.

[34] See Appendix for further details on the imputation.

below, we assume that the average values across detectors are representative of highway traffic within the state so that we can interpret the regression coefficients as applying to vehicle ton miles traveled, ESALs per mile, and cargo per truck mile.

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. While the bimodal distribution demonstrates the prevalence of empty trucks on the road, there are many partially-filled vehicles, 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 Historical Climatology Network-daily, which provides daily minimum and maximum temperature and total rainfall and snowfall for weather stations in the United States. Because New York state households that heat with heating oil are primarily concentrated in upstate New York we use the average readings of weather stations centered at Albany.[35]

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 are a commonly used measure that reflect the demand for heating energy. Using a base of 65 F, a day spent at 64 F will be one heating degree day. Temperatures above 65 F are not counted. We proportionally assign the temperature to the range between the minimum and maximum temperature recorded. To calculate the expected number of heating degree days, we average the number of heating degree days during that day over the forty-year period between 1975 and 2015. To calculate the excess heating degree days, we take the difference between the realized heating degree days for a given day and the expected heating degree days on that date. These values are then summed over the prior period. As is discussed above, we omit the current day's excess heating degree days as well as the prior two days from our measure such that the measure is the sum of dates *t-2* through *t-30*. The excess heating degree day measure is positive (negative) when winter weather is unusually cold (warm). In summer, the measure is usually zero.[36]

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

The use of unusually cold or warm weather during heating season is a legitimate instrument if (1) it generates a price differential in diesel between New York and California; and (2) it is uncorrelated with demand for freight services. We consider both requirements in this section.

Figure 2 plots the kernel smoothed excess heating degree days, the diesel price spread, and the

[35] We use inverse distance weighting of these stations up to 200km.

[36] Sources for other data used in the regressions are: The Energy Information Administration for weekly regional diesel prices (California is available by itself; we use PADD 1b for New York), and monthly residential distillate demand (available nationally; but over 88% is consumed in the Northeast).

weight difference. The top panel displays the daily average heating degree days. 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 quantify the effect of excess heating degree days on the diesel price differential between New York and California, we estimate regressions of the form

$$P_{NY,t} - P_{CA,t} = \alpha + \beta EHDD_t + X_t'\gamma + \varepsilon_t \tag{11}$$

The term X_t' includes a trend, monthly fixed effects, and controls for same-day weather conditions.

Table 1 reports the estimates of the effect of excess heating degree days on diesel price. Column 1 reports results for the simplest specification indicating that 100 excess heating degree days in the past month increases the price spread by roughly 4 cents. 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 3 uses price data starting in 2007. While this is earlier than the time period for which we have WIM data, it shows that the weather-price relationship is robust to the addition of more years of data. These regressions establish a strong relationship between EHDD and the diesel price differential between New York and California.

We next consider some evidence for the exclusion requirement. Columns 4 and 5 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 excess heating degree days on the diesel price differential. The point estimate on excess heating degree days in column 4 is small and statistically insignificant. In the spring, when stockpiles are low, we would expect a stronger response and the coefficient on excess heating degree days in column 5 is indeed similar to that in the specifications in column 2. Together these regressions require that a competing explanation for the relationship between weather and diesel prices must differ by season. The final column considers a placebo test. We replace the diesel price spread with the gasoline price 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.[37] The coefficient on EHDD in column 6 is smaller than that in the diesel regressions 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 heating degree days increase demand for residential distillate fuel. The coefficient on excess heating degree days in column 1 indicates that for every 100 excess heating degree days in the prior month, demand for residential distillate increases by 20,311 barrels per day. These tests lend credibility to the claim that unusually cold or mild winter can instrument for the difference in diesel prices between New York and California.

V. 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 results using IV-estimation. For comparison, OLS results are presented in column 1. The OLS estimate of the vehicle weight-diesel price elasticity is 0.11. The specification in column 2 estimates equation (8) using the EHDD instrument. This specification estimates that the vehicle weight-diesel price elasticity is 0.32, consistent with a downward bias in the OLS estimate. The logged specification changes the units on the first stage but presents a similar picture to section IV. The F-test is statistically significant at conventional levels.

One potential concern with the estimate in column 2 is that cold weather may affect demand for diesel for trucks as well as 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 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.[38] We can provide some evidence against 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 likely to stifle demand for sectors like retail.

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

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[37] 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.

[38] 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.

EHDD shocks are more likely to require additional heating oil deliveries even if the abnormal weather is measured from a more temperate base and is unlikely to directly change demand for freight services. These results support the 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.[39] Column 1 contains the estimated fuel price elasticity for cargo. Column 2 displays IV estimates for total daily truck traffic (the daily count of observations). Although the total daily traffic regression is imprecisely measured,[40] the point estimates imply that a 10 percent increase in fuel price is associated with 5.55 percent more cargo per truck, which is loaded onto 6.67 percent fewer trucks. Thus, total cargo declines by 1.12 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, or less convenient scheduling—than mode-shifting.

Assessing road damage requires data on the distribution of vehicle weight. Redistributing a given amount of cargo to moderate-weight vehicles will produce significantly 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 19.63 percent. If the price increase is due to a diesel tax that, as is usual, is dedicated towards funding road repairs, the estimated additional road damage erodes more than 10 percent of the increased revenue. Because of the quartic relationship between axle weight and road damage, even small average upweighting of moderately heavy trucks can greatly increase road damage.

VI. Discussion

Demand Elasticity and the Change in Vehicle Ton-Miles

The estimates in section V 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

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[39] Midpoint of empty vehicle weight for class 8 trucks Table 5-15 (NRC, 2010).

[40] 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.

demand elasticity derived in equation (6), while other externalities including congestion, accidents and local pollutants are modeled as a function of ton-miles hauled.[41]

The elasticity of ton-miles with respect to price is the sum of the price elasticity of per-truck tons (cargo weight) plus the price elasticity of 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.[42] Thus the sum of $\varepsilon_{N,p}$ and $\varepsilon_{w,p}$ is the ton-miles elasticity at -0.112. 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) of -.05, as well as the short-run estimates by Leard et al. (2015) of -0.189 and De Borger and Mulalic (2015) of -.10.

Estimating the demand elasticity 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 $\varepsilon_{f,w}$. Together these estimates imply a demand elasticity of -0.319.

Presumably, both the ton-mile and the fuel demand elasticities will differ in the long run, but the direction of change is unclear. The long run allows more scheduling flexibility, which would imply a bigger dispatch effect and greater weight changes. Alternatively, during the short run empty trucks may only be dispatched when diesel is cheap, in which case the observed increase in average weight and decrease in traffic would attenuate in the longer run. Note that the ESAL estimates are not consistent with dispatch changes only in backhaul strategies. To observe an increase in ESALs, as we do, the distribution of trucks on the road must shift so that there are more heavy trucks, not merely fewer empty ones. Nevertheless, if the decline in traffic is partly temporary, then the short run fuel response may be more elastic than the long run. Lastly, demand for cargo is likely 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.

Diesel Taxes, Short Run Carbon Emissions Reductions, and Road Damage

Diesel taxes are 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

[41] 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.

[42] Specifically, this assumes that upweighted trucks do not shift their driving to roads that disproportionately lack or, alternatively, are rife with traffic sensors.

come in third, after a fuel efficiency standard.

We consider a diesel tax of $0.37 per gallon. This level of taxation corresponds to a carbon price of $36 per metric tonne of CO_2 (Interagency Working Group, 2015). Applying our estimated demand elasticity to annual diesel sales, the tax yields 850 million fewer gallons of diesel consumption and generates $310.8 million in carbon benefits (see Table 5).

A diesel tax, because it reduces ton-miles, will lower other driving-associated externalities. Applying the ton-miles elasticity estimate to the total ton-miles shipped in the US implies that the tax lowers ton-miles by 27.6 billion. The associated reduced congestion, accidents, local pollution, and noise externalities generate $733.5 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 interstate highways. The increase of 8.8 billion ESALs nationwide generates $1.213 billion in additional damage. Note that the damage estimate is a lower bound (possibly very low) as the trucks also drive on other roads, and these roads are usually more sensitive to increases in ESALs.

Combining the externalities, the diesel tax on net reduces welfare by $168.8 million annually.

Fuel Efficiency Standards and Road Damage

Policy makers often attempt to address emission externalities through fuel efficiency standards. However, in the case of automobiles, economists stress that fuel efficiency standards, by lowering the price per mile of driving, increase driving and may related externalities, and may even be welfare reducing (Anderson et al., 2011). The welfare effects for trucks differ significantly. When a fuel efficiency standard lowers the ton-mile cost of shipping freight, we estimate that firms respond by offering higher frequency shipments. Whereas vehicle ton-miles and the associated externalities increase, the cargo weight per truck, and associated road damage declines.

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. We follow the prior literature and ignore the capital cost of the standard.[43] We choose a 4 percent improvement in efficiency so as to generate the same carbon reductions as the diesel tax in the prior section: a reduction of 850 million gallons that generates $310.8 million in carbon benefits.

Using the estimated ton-miles elasticity, the standard will generate 12.9 billion additional ton-

[43] More precisely, the light duty vehicle analyses require that capital costs are small enough that they do not dissuade anyone from buying a car and that they do not change the cost of driving a mile.

miles, resulting in $342.8 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 of a fuel economy standard are nearly entirely offset by increased ton-mile related externalities.

Finally, consider the dispatch effect and reduction in vehicle weight. The resulting reduction of 4.1 billion ESALs in damage to the interstate system yields an additional $566.9 million in benefits, resulting in a net benefit of $534.9 million for the fuel efficiency standard.

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. Using typical estimates of the ton-mile rebound effect and reasonable external cost estimates, the dispatch effect has the capacity to create a welfare preference for fuel economy standards over fuel taxes. We find that diesel taxes generate net costs of $168.8 million while fuel economy standards generate net benefits of $534.9 million.

There are, of course, assumptions that reverse the conclusion. Assumptions that increase ton-mile externalities will favor diesel taxes. For example, a more elastic ton-mile response to price causes more driving under the fuel efficiency standard and less under the fuel tax. Driving-associated externalities penalize the former. Changing the preference ordering among the policies by this dimension requires a ton-mile elasticity of at least -0.185, which is at the edge of the range in the current literature.[44] Using higher costs for the externalities per ton-mile will also favor diesel taxes. If we simultaneously use the upper bounds given by the GAO (2011) for external costs of, congestion, accidents, and local pollution, both policies will exhibit net benefits and the tax, by a small margin, outperforms the standard. Assumptions that lower the dispatch effect also shift the preference towards diesel taxes. An ESAL elasticity at the bottom of 95 percent confidence interval yields a welfare advantage towards diesel taxes.[45] 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 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, which dominate the EPAs cost-benefit analysis of heavy-duty-truck fuel

[44] Leard et al. (2015) have the smallest of current estimates, at -0.189.

[45] See Appendix Tables A.5 and A.6 for simulations with maximum ton-mile externalities and lower 95 percent confidence interval for our ESAL estimate.

economy standards,[46] are not included here.[47] A third feature, often omitted from the tax-vs.-standards analyses, are the capital costs associated with fuel efficiency technology that increases average driving costs (Borenstein, 2013). It is unclear how inclusion of capital costs would change the relative comparison between policies for commercial trucks. We expect any increase in capital costs to be included in freight fees, offsetting the fuel cost reduction of the standard and modifying the dispatch effect. Thus, both external benefits and external costs of the efficiency standard decline. Fourth, this analysis fails to 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.

VII. Conclusions

This paper examines how fuel prices influence dispatch decisions and the resulting change in truck weight. We find that a 10 percent increase in the price of diesel fuel increases vehicle weight by 3 percent. The redistribution of weight across trucks results in a significant increase in road damage, on the order of 11 percent of the revenues collected from the tax.

In the environmental sphere, a fuel efficiency standard (or other non-market regulatory strategy) is typically called second-best, relative to the assumed first-best Pigouvian tax. We show that for the case of cargo trucks, a fuel efficiency standard obtains a better welfare outcome than a Pigouvian diesel tax, in spite of the additional driving-related externalities that result from cargo demand changes and operational adjustments by trucking firms.

Lipsey and Lancaster (1956) show, in the context of trade and removing tariffs, that the range of outcomes when removing only one constraint is potentially quite large and that it is possible for such a piecemeal change to lower total welfare. While their results are well known, these second-best concerns are often viewed as second order. That appears to not be the case here. Correcting the market failure associated with emissions from diesel use in heavy trucks by imposing a Pigouvian tax removes one constraint. But doing so imposes an efficiency loss due to the presence of a second constraint: the absence of marginal cost pricing for highway damage. Whereas the initial lack of an emission tax is not optimal, its imposition is not even second-best.

For a sector as rich with market failures as transportation, the trade literature may provide other helpful lessons. For example, rather than arbitrarily correcting a market distortion, it may be best to reduce all distortions uniformly, or to focus first on the largest distortion (Hatta,

[46] 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.

[47] 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, these benefits have been the subject of debate between economists (Gillingham and Palmer, 2012; Allcott and Wozny, 2014; Sallee, West, and Fan, 2016).

1977). Carbon is known to be small by comparison to other external costs in the transportation market (Parry and Small, 2005). While fuel taxes provide an attractive public revenue source, taxing road damage instead may be both better for infrastructure use and welfare improving.

Table 1 Heating Degree Days and Diesel Prices

	Diesel Price Gap					Gasoline Price Gap
	(1)	(2)	(3)	(4)	(5)	(6)
Excess HDD	0.044***	0.042***	0.033***	-0.006	0.040***	0.019
	(0.005)	(0.005)	(0.007)	(0.009)	(0.008)	(0.014)
Rain (cm)		0.005	0.004	0.007	-0.001	0.009
		(0.004)	(0.004)	(0.004)	(0.005)	(0.008)
Snow (cm)		-0.000	-0.003	-0.001	-0.001	0.002
		(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
Temp. (F/1000)		-0.603	-0.541	-0.807	-0.821	-2.822**
		(0.446)	(0.587)	(0.529)	(0.648)	(0.905)
R-squared	0.43	0.44	0.21	0.14	0.68	0.46
N	1819	1819	3255	610	610	1819
Sample	2011-2015	2011-2015	2007-2015	Aug.-Nov. 2011-2015	Mar.-Jun. 2011-2015	2011-2015
Month Fixed Effects	Y	Y	Y	Y	Y	Y

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 summed from date t-30 through t-3. 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 Diesel Prices

Dependent Variable: Monthly Average Daily Residential Distillate Consumption (1000s)

	(1)	(2)	(3)
Excess HDD	20.311***	16.989***	18.014***
	(4.139)	(4.549)	(4.261)
Trend	-0.844***	-0.840***	-0.130
	(0.028)	(0.028)	(0.202)
Trend-squared			-0.001***
			(0.000)
Total Monthly Rainfall		-0.418	-0.441
		(0.712)	(0.701)
Total Monthly Snowfall		0.567	0.452
		(0.291)	(0.287)
GDP			
WTI Oil Price			
R-squared	0.86	0.86	0.86
N	358	358	358
Sample	1986-2015	1986-2015	1986-2015
Month Fixed Effects	Y	Y	Y

Notes: Values shown are the coefficients of 4 regressions of the daily residential distillate consumption in thousands of barrels averaged at the monthly level on the regressands. Excess HDD is the sum HDD below 65 degrees over the prior 30 days divided by 100 (approximately one standard deviation). Monthly average temperature is omitted because, at a monthly aggregation, it is highly correlated with our measure of excess HDD. Robust standard errors are given in parentheses. *** Significant at the 1 percent level. **Significant at the 5 percent level. * Significant at the 10 percent level.

Table 3 Five-Axel Vehicles

Panel A: Average Vehicle Weight

Dep. Var: log(NY Wt)-log(CA Wt)	OLS	IV		
	(1)	(2)	(3)	(4)
Second Stage				
log($NY)-log($CA)	0.106**	0.321***	0.000	0.152*
	(0.033)	(0.069)	(0.053)	(0.072)
Rainfall	-0.006***	-0.006***	-0.006***	-0.007***
	(0.001)	(0.001)	(0.001)	(0.001)
Snowfall	0.004***	0.004***	0.003	0.005***
	(0.000)	(0.001)	(0.002)	(0.001)
Temperature	-0.223**	-0.073	-0.438	0.052
	(0.079)	(0.089)	(0.492)	(0.111)
R-squared	0.16	0.11	0.09	0.12
N	1819	1819	610	610
Month Restriction	None	None	Aug.-Nov.	Mar.-Jun.
First Stage				
Kleibergen-Paap F-Stat.		16.51	7.50	20.79

Panel B: Other Outcomes

Dependent Variable	Cargo	Daily Count	ESALs
	(1)	(2)	(3)
Second Stage			
log($NY)-log($CA)	0.555***	-0.667	1.963*
	(0.118)	(0.574)	(0.771)
Rainfall	-0.010***	0.001	-0.014
	(0.002)	(0.005)	(0.008)
Snowfall	0.007***	-0.021***	-0.002
	(0.001)	(0.004)	(0.005)
Temperature	-0.130	0.220	-0.655
	(0.151)	(0.705)	(0.860)
R-squared	0.12	0.12	0.04
N	1819	1819	1819
First Stage			
Kleibergen-Paap F-Stat.	16.51	16.51	16.51

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 summed from date t-30 through t-3. 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

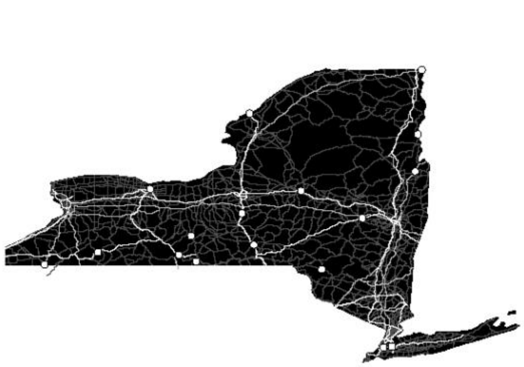
Parameter	Value	Source
$\varepsilon_{g,c}$	-0.372	Franzese and Davidson (2011) Eq. 1
Annual Diesel Sales	38.5 billion gallons	EIA 2014 Adjusted Sales of Distillate Fuel Oil by End Use
Average Diesel Price 2011-2015	$3.85 gallon	Authors calculation and EIA PADD1B (2015$)
Annual ESALs per Lane Mile from 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	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 CO2	Interagency Working Group on Social Cost of Carbon (2015)
Congestion cost	$0.0044 per ton-mile	GAO (2011)
Accident Risk	$0.0121 per ton-mile	GAO (2011)
Local Pollution (PM 2.5 and NOx)	$0.0095 per ton-mile	GAO (2011)
Noise	$0.0005 per ton-mile	GAO (2011)

Table 5 Simulation Outcomes

Simulation A: Diesel/Carbon Tax	
Tax per gallon	$0.37
Tax Revenue	$10.8 Billion
Change in Fuel Use	-850.4 Million Gallons
Carbon Benefit	$310.8 Million
Ton-Miles Change	-27.6 Billion Ton-Miles
Congestion, Accidents, Local Pollution, and Noise Benefit	$733.5 Million
Upper and Lower Bound	[$150.8 to $1,316.1]
ESAL Change	8.8 Billion ESALs
Road Damage	-$1,213.1 Million
95% C.I.	[-$2,165.9 to -$260.2]
Total	-$168.8 Million

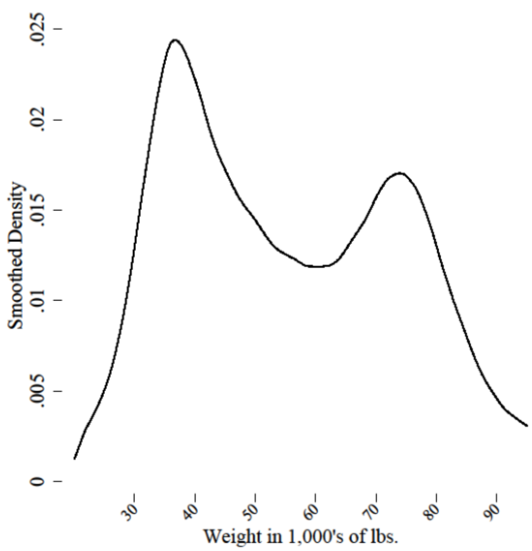
Simulation B: Fuel Economy Standard	
Increase in Efficiency	4 percent
Change in Fuel Use	-850.4 Million Gallons
Carbon Benefit	$310.8 Million
Ton-Miles Change	12.9 Billion Ton-Miles
Congestion, Accidents, Local Pollution, and Noise	-$342.8 Million
Upper and Lower Bound	[-$615.1 to -$70.5]
ESAL Change	-4.1 Billion ESALs
Road Damage	$566.9 Million
95% C.I.	[$121.6 to $1,012.3]
Total	$534.9 Million

Assumed carbon tax of $36 per metric ton CO2. The level of fuel economy standard is chosen to match the carbon saved under
the diesel tax.

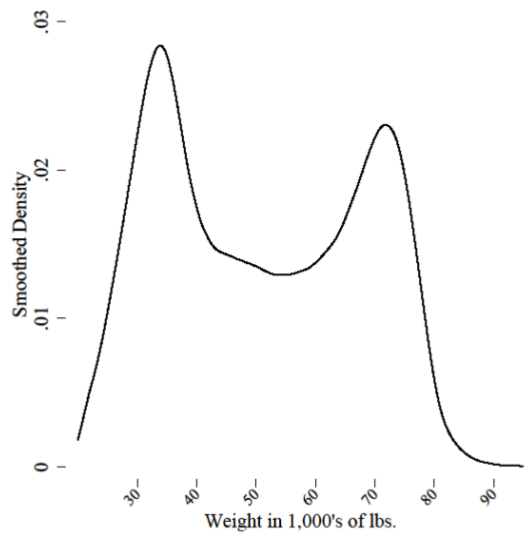


New York Detectors

California Detectors



New York WIM Distribution



California WIM Distribution

Figure 1 Weigh-in-Motion Data

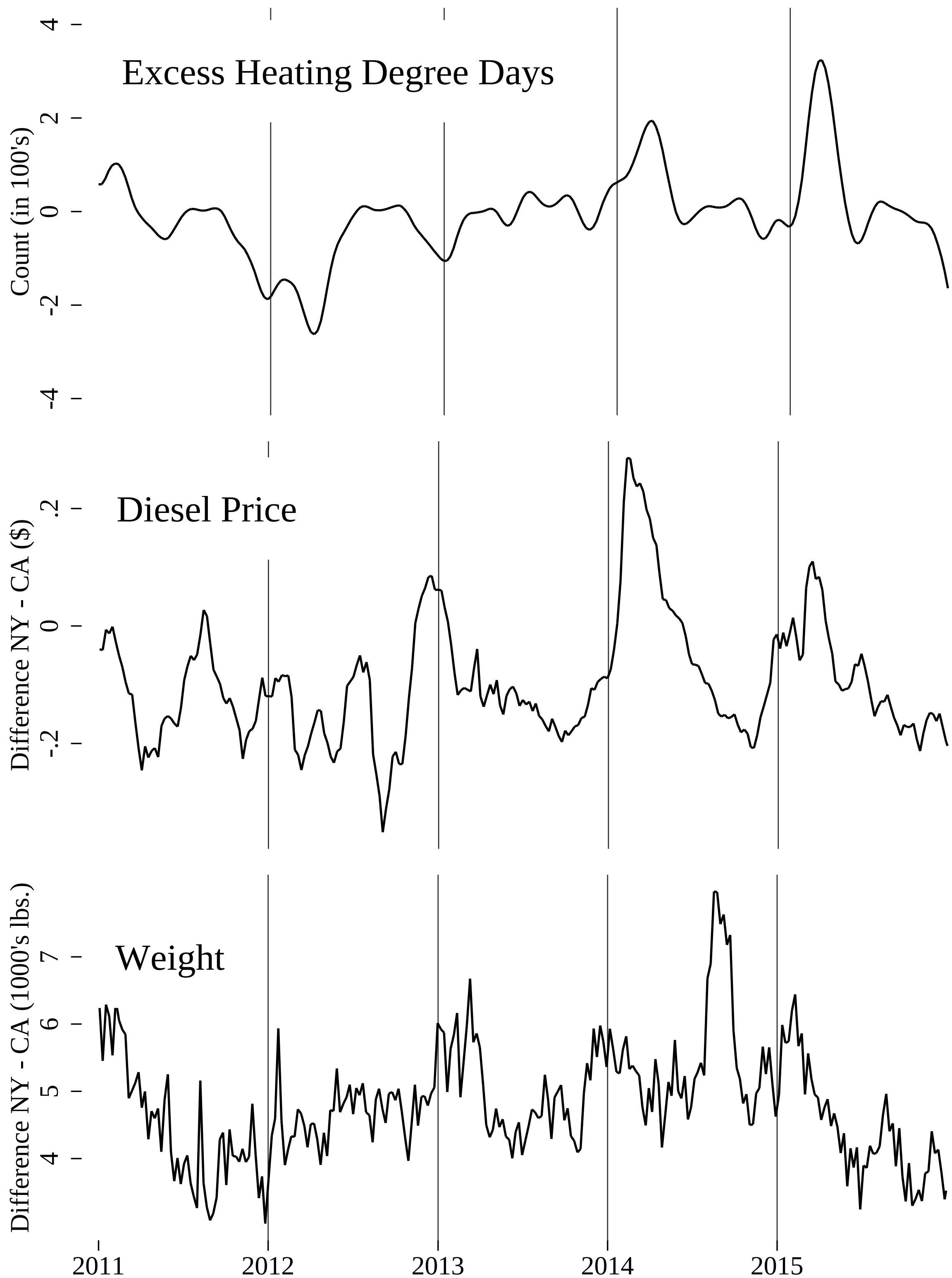


Figure 2 Kernel smoothed excess heating degree days, diesel price spread, and weight difference

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Appendix I: Data issues

A. Calculating per-vehicle ESALs

Equivalent Standard Axle Loads for a particular axle $ESAL_a$ are calculated using the AASHTO rigid pavement formulation using the formula:

$$ESAL_a = \left(\frac{W_a}{SL}\right)^b \tag{A1}$$

Where SL is a standard load factor that varies based on the number of axles in the group, W_a is total weight of the axle group, and b is an exponent taken from the engineering literature.[48] For b we adopt a value of 4, which is the most common in the literature.[49] WIM data includes the spacing between axles. For the ESAL calculation, grouped axles are less than 96 inches apart; otherwise the axles are separate.[50] This calculation is performed for all axle groups and summed to the truck level.

B. Further Details on Data Cleaning

Processing New York WIM data.

WIM sensors occasionally generate errors, most commonly through registering vehicles with implausible characteristics. These errors are cleaned for California data but are not for New York. We followed standard cleaning procedures for the New York data, retaining only 5-axle trucks weight between 26,000 and 120,000 lbs. and removing vehicles with speeds below 10 mph or above 80 mpg, and with implausible axle configurations.[51] In total 741 million vehicles meet our requirements across both data sets.[52]

Generating a Balanced Panel

Detectors, particularly in New York, do not always function. Some detectors appear to start operations during our sample period, others are taken offline for servicing, while others are missing data for unknown reasons. Missing data in some locations (e.g. New York City) will generate large variation in the state level measures. We reduce this variation using several

48 For single axles SL is 18,000, for tandem axles it is 29,000, and for tridem it is 39,000.

49 There is some disagreement in the literature as to the appropriate value of b. Early work suggested this parameter was higher than 4.6. Small and Winston (1986) noted that this regression was censored and that a Tobit model gave values between 3.2 and 3.6. They also suggest that this modeling error may underlie the faster-than-expected deterioration of many roads. This formula, using the 4th power, is commonly referred to as the 'generalized fourth power law.'

50 Where two axles are closer than this distance they are considered tandem; where three axles are closer than 192 inches they are considered tridem.

51 See Quinley (2010) It is fairly standard to have close placement for groups of 2 (tandem) or 3 (tridem) axles but we remove vehicles with 4 or more closely spaced axles, for which we also cannot assign an ESAL measure. For the typical file, this is roughly 1% of all trucks, before any other deletions. For the typical file, before any other deletions, less than 4% of all trucks are eliminated because of speeds that are below 10 mph or above 80 mph.

52 The majority of deletions are for 2-axle vehicles. There are 741 million legitimate 3+ axle vehicles between 26 and 120 thousand lbs., of which 85% are 5-axle vehicles.

methods. Initially we average our data at the detector-day level. We then drop from our analysis all detectors with more than one-third missing data. For the detectors that remain we impute missing observations. In our main specification we impute missing detector-day observations based on a regression where the detector with missing data is the dependent variable and closest detector is the independent variable. Where data is also missing for the closest detector, we repeat the procedure with the next closest detector and so on.[53] Once all missing observations are imputed, we average to the state level. The second imputation method replaces missing observations with the station mean, before averaging to the state level.

Appendix II: Simulation details

To evaluate the external costs of road damage, carbon, congestion, accidents and local pollution requires prices from the literature. Our choices, together with references, are listed in Table 4. Road damage is assessed based on the change in ESALs, which are valued at 13.7 cents per ESAL mile, the minimum value from FHWA (1995), converted to current dollars. There are a wide range of values for this parameter across academic and technical documents. ARTBA (2016) states that the cost of resurfacing a 4-lane highway is 1.25 million per mile, resulting in a per-ESAL cost of 12.7 cents per mile when distributed across a road with a pavement lifetime of 10 million ESALs.[54] Since this value assumes no deeper structural damage, no bridge damage, and no weather costs, it seems a reasonable lower bound. Keeler and Small (1977) find similar marginal costs for medium roads. The annual baseline number of ESALs per highway-mile is 1.1 million, based on the assumption that interstates are 2 lanes and the average ESAL count in our New York data is 553,340 per lane.[55] We apply these measures to the 42,795 miles of the interstate system. We omit all damage to secondary roads, which are not covered by the WIM data but may be substantial.

The carbon cost of $36 per metric tonne of CO_2 is based on the 3% discount rate calculation of the Interagency Working Group on Social Cost of Carbon (2015). For consistency we limit our focus to carbon generated from diesel fuel consumed by 5-axle vehicles. We assume that the fraction of the 38.5 billion gallons of on-road diesel sold to 5-axle vehicles in the US is 73 percent, consistent with the share of 5-axle vehicles in our WIM freight truck data.[56]

Unfortunately, cost estimates for local pollution, accident, congestion, and noise externalities for trucks are infrequently examined and sensitive to assumptions about where and when trucks drive. We adopt measures from the GAO (2011), which give ranges for each external cost

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53 In regressions in the appendix we also perform an imputation with the overall mean of the detector.

54 American Road and Transportation Builders Association [FAQ], Retrieved August 8, 2016, from http://www.artba.org/about/faq/

55 A million ESALs annually per road appears to be a common measure in many state DOT analyses and is the value given for median traffic in Small and Winston (1986).

56 73 percent is the share of 5-axle vehicles out of all vehicles with more than 2 axles in the WIM data. We exclude two-axle vehicles as they often burn gasoline and are likely to drive more frequently on secondary roads that are less frequently monitored by WIM sensors.

and use the range as well as midpoint in the analysis. The extent of the externalities depend on vehicle weight as well as vehicle miles, and thus vary with vehicle-ton-miles. While the relationship is unlikely to be directly proportional to both factors, the published estimates make no correction for non-linearities and are reported on a vehicle-ton-mile, which we adopt in the analysis as well.

Table A.1: Day of Week Fixed Effects

	IV (LIML)			
	Weight	Daily Count	ESALs	Cargo
	(1)	(2)	(3)	(4)
Second Stage				
log($NY)-log($CA)	0.324***	-0.726	1.888*	0.559***
	(0.069)	(0.576)	(0.775)	(0.119)
Rainfall	-0.005***	-0.003	-0.020**	-0.009***
	(0.001)	(0.004)	(0.007)	(0.002)
Snowfall	0.004***	-0.022***	-0.004	0.007***
	(0.000)	(0.004)	(0.005)	(0.001)
Temperature	-0.062	-0.008	-0.975	-0.114
	(0.088)	(0.672)	(0.833)	(0.151)
R-squared	0.17	0.46	0.35	0.16
N	1819	1819	1819	1819
First Stage				
Kleibergen-Paap F-Stat.	76.309	76.309	76.309	76.309

Notes: The estimates are from five regressions of daily average vehicle weight, vehicle count per detector, ESALs, and cargo (weight - 23,000 lbs.) on the listed regressands. EHDD is 100 excess heating degree days summed from date t-30 through t-3. Trend and fixed effects for day of week and month are included in all regressions. Standard errors, clustered on week, are given in parentheses with + indicating significance at 10%, * at 5%, ** at 1%, and *** at <1%.

Table A.2: Time Series Error Structure

	IV (GMM)			
	Weight	Daily Count	ESALs	Cargo
	(2)	(3)	(4)	(5)
Second Stage				
log($NY)-log($CA)	0.321***	-0.667	1.963+	0.555***
	(0.088)	(0.768)	(1.019)	(0.152)
Rainfall	-0.006***	0.001	-0.014+	-0.010***
	(0.001)	(0.005)	(0.007)	(0.001)
Snowfall	0.004***	-0.021***	-0.002	0.007***
	(0.000)	(0.004)	(0.006)	(0.001)
Temperature	-0.073	0.220	-0.655	-0.130
	(0.094)	(0.657)	(0.807)	(0.160)
R-squared	0.11	0.12	0.04	0.12
N	1819	1819	1819	1819
First Stage				
Kleibergen-Paap F-Stat.	81.619	81.619	81.619	81.619

Notes: The estimates are from five regressions of daily average vehicle weight, vehicle count per detector, ESALs, and cargo (weight - 23,000 lbs.) on the listed regressands. EHDD is 100 excess heating degree days summed from date t-30 through t-3. Trend and fixed effects for month are included in all regressions. Heteroskedastic and autocorrelation consistent standard errors with a kernel of 7 days, are given in parentheses with + indicating significance at 10%, * at 5%, ** at 1%, and *** at <1%.

Table A.3: Delete Aug. and Sept. 2014

	IV (LIML)			
	Weight	Daily Count	ESALs	Cargo
	(2)	(3)	(4)	(5)
Second Stage				
log($NY)-log($CA)	0.336***	-0.718	1.957*	0.581***
	(0.067)	(0.577)	(0.767)	(0.115)
Rainfall	-0.005***	-0.000	-0.012	-0.009***
	(0.001)	(0.005)	(0.008)	(0.001)
Snowfall	0.004***	-0.021***	-0.003	0.006***
	(0.001)	(0.004)	(0.005)	(0.001)
Temperature	-0.051	0.122	-0.719	-0.092
	(0.083)	(0.715)	(0.874)	(0.142)
R-squared	0.11	0.12	0.05	0.12
N	1758	1758	1758	1758
First Stage				
Kleibergen-Paap F-Stat.	76.714	76.714	76.714	76.714

Notes: The estimates are from five regressions of daily average vehicle weight, vehicle count per detector, ESALs, and cargo (weight - 23,000 lbs.) on the listed regressands. EHDD is 100 excess heating degree days summed from date t-30 through t-3. Trend and fixed effects for month are included in all regressions. Observations in August and September 2014 deleted because they display abnormally high vehicle weight in summary statistics. Standard errors, clustered on week, are given in parentheses with + indicating significance at 10%, * at 5%, ** at 1%, and *** at <1%.

Table A.4: Impute Missing Detectors with Mean

	IV (LIML)			
	Weight	Daily Count	ESALs	Cargo
	(2)	(3)	(4)	(5)
Second Stage				
log($NY)-log($CA)	0.315***	-0.694	1.839*	0.545***
	(0.068)	(0.573)	(0.763)	(0.117)
Rainfall	-0.006***	0.000	-0.014*	-0.010***
	(0.001)	(0.005)	(0.007)	(0.002)
Snowfall	0.004***	-0.020***	-0.002	0.007***
	(0.001)	(0.004)	(0.005)	(0.001)
Temperature	-0.067	0.255	-0.506	-0.120
	(0.088)	(0.705)	(0.852)	(0.150)
R-squared	0.11	0.11	0.04	0.12
N	1819	1819	1819	1819
First Stage				
Kleibergen-Paap F-Stat.	76.628	76.628	76.628	76.628

Notes: The estimates are from five regressions of daily average vehicle weight, vehicle count per detector, ESALs, and cargo (weight - 23,000 lbs.) on the listed regressands. EHDD is 100 excess heating degree days summed from date t-30 through t-3. Trend and fixed effects for month are included in all regressions. Before aggregation to the state level, detectors with missing data are imputed using the mean value for the detector across all observations. Standard errors, clustered on week, are given in parentheses with + indicating significance at 10%, * at 5%, ** at 1%, and *** at <1%.