Fuel Efficiency, Mode Choice and the Rebound Effect in U.S. Freight Transportation

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Abstract

Energy efficiency improvements can create rebound effects that increase energy use. We study rebound in U.S. freight transportation and show substitution across transportation modes can be an important rebound channel. The sign of the rebound effect depends on whether improved efficiency induces substitution to more or less fuel-efficient modes. We use detailed U.S. micro data to model shippers' freight mode choices and simulate how these choices change under energy efficiency standards. Under a policy approximating U.S. heavy duty truck fuel economy standards, we find rebound can be positive or negative in individual market segments. However, the overall effect substantially reduces gains from improved truck fuel efficiency. Energy savings are reduced by approximately 19% because shipments switch from rail service to improved, but still less fuel-efficient, truck service. Similar substitution rebound effects could occur in other settings where producers choose between technologies with different energy efficiencies.

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Main

An extensive literature has examined the extent to which rebound could undermine the benefits of increased energy efficiency[1–5]. In this literature, the rebound effect typically describes the increase in energy consumption due to the perceived lower cost, induced by improved efficiency, of using of an energy-intensive good. For instance, when air conditioners become more efficient, cooling costs decrease. Rebound occurs if consumers lower their thermostats in response, partially off-setting the efficiency gains.

There is a related but distinct form of rebound that has received considerably less attention in both the academic and policy communities: the substitution from other production technologies, modes or appliances. In many settings, firms or consumers can choose not only the intensity of use but also the technologies to deploy. For example, when air conditioners become more efficient, some users may switch from fans to air conditioning, increasing overall energy consumption.

We study this substitution rebound effect in an important setting for energy and climate policy: the U.S. freight transportation sector. The freight sector is large, representing approximately 10% of total U.S. energy consumption and between 30% to 35% of U.S. transportation energy consumption[6]. To address the sector's growing share of energy use and greenhouse gas emissions, in 2011 the U.S. Environmental Protection Agency (EPA) adopted heavy-duty vehicle fuel economy standards[7] for the 2014 through 2018 vehicle model years (phase 1). These standards were revised in 2016 to target model years 2018 through 2027 (phase 2), though implementation has been delayed by a series of challenges in the federal courts.

The standards target heavy duty trucks (class 7 and class 8 tractors) for efficient vehicle, engine and trailer technologies. The U.S. EPA predicts the phase II standards will improve new truck fuel efficiency 19% to 25% by 2027[7]. Because new trucks are incorporated over time as the fleet turns over, EPA estimates that by 2025 the average fuel intensity across the fleet will fall by approximately 5% to 6% relative to business as usual.

The effectiveness of these measures depends in large part on the magnitude of rebound effects[7]. Energy intensities differ by an order of magnitude across production technologies (modes) such as air, truck and rail. Improvements in the energy efficiency of one mode can change shippers' mode choices leading to substitution rebound effects that can be positive or negative. For instance if improved truck fuel efficiency causes some shippers to substitute from rail to truck, this shift would increase fuel consumption since, in general, truck shipments are more energy intensive. Alternatively, substitution from air to truck would reduce fuel consumption. These substitution effects are noteworthy compared to settings such as automobiles where rebound manifests mainly as an increase in driving[8–10].

We investigate mode substitution rebound effects in freight shipments using microdata on goods movement from the U.S. Commodity Flow Survey (CFS)[11] and estimate a series of multinomial logit models for shippers' mode choices. Using our parameter estimates, we simulate the 2016 fuel efficiency standards that lower truck energy intensity 5%. We hold the number and size of shipments constant to focus on mode substitution effects. Truck fuel economy regulations shift freight shipments from rail to truck, increasing truck output by 15 billion ton miles per year or approximately 1.3%. This shift reduces fuel savings from more efficient trucks from 653 million gallons per year to 489 million gallons, implying a rebound effect of approximately 25%, which is comparable to recent estimates for the *total* rebound effect in heavy-duty trucks[12–14]. When we account for reduced fuel consumption in other modes (from shipments that substitute to truck) total fuel savings are approximately 527 million gallons per year. This equates to an aggregate rebound effect from modal substitution across all freight shipments of approximately 19%. For some types of goods this effect is substantially larger, 40% to 50%. For other goods, the substitution rebound effect is *negative* because more efficient trucks cause some shipments that previously went by air to move instead by truck.

Our work informs energy policy in the U.S. domestic freight sector by providing insight into how fuel prices and energy policies affect shippers' substitution patterns across modes[15,16]. Our results also have implications for international trade, where we expect analogous effects and where energy consumption and emissions are increasingly important concerns[17]. Finally, similar substitution rebound effects can occur in other settings where producers choose between technologies with different energy intensities.

Freight transportation in the U.S.

Freight transportation is a critical input to production linking farmers, raw material, intermediate and final goods producers to consumers. Domestic freight and goods movement contributes approximately 4% to U.S. GDP[18]. Common transportation modes include air, truck, rail, barge, ship, pipeline and parcel/courier. Truck shipments represent approximately 46% of total ton miles. Rail, including shipments that combine truck and rail service, accounts for approximately 48% of ton miles. Inland water (barge) share, including shipments that combine water with truck and rail service, is approximately 4%. Finally, air and parcel/courier service account for about 0.2% and 1%, respectively[19]. In terms of shipment value, truck share of total shipment value is approximately 73%, compared to 5% for rail, 3% for air, 1.7% for barge and 14.2% for parcel/courier. Energy efficiency varies substantially by mode. Average fuel economy for a rail shipment is approximately 500 ton-miles per gallon of fuel compared to approximately 100 ton-miles per gallon for heavy-duty truck and 0.1 ton-miles per gallon for air freight.

Figure 1 provides summary statistics from the CFS to motivate our approach. The mean characteristics of shipments vary substantially by the type of good shipped. Figure 1a summarizes ton-mile weighted-average shipment characteristics for a number of different goods. The first three columns show shipment value in dollars per pound, distance in miles and weight in tons. The remaining columns show ton-mile weighted-average modal shares for major freight modes within the CFS. Mean shipment value per pound varies from approximately $0.01 per pound for coal to nearly $25 per pound for pharmaceuticals. Mean shipment distances vary from approximately 450 miles for fuel oil to nearly 1,500 miles for pharmaceuticals. Mean shipment weights vary from about 9 tons for pharmaceuticals to over 17,000 tons for coal and over 30,000 tons for metallic ores.

The modal shares shown in Figure 1a highlight important trends in how different types of freight shipments move within the United States. Higher value goods such as pharmaceuticals, mixed freight and machinery travel mainly by faster modes such as air and truck. Lower value goods tend to travel via slower more fuel efficient modes, such as rail and water, particularly when shipment distances are large. For example, rail and water modal shares are relatively high for metallic ores, grain, coal and basic chemicals. These trends are further highlighted in Figure 1b where we plot the mean shipment value per pound against shipment size in ton miles for different transportation modes. We see air and truck shipments tend to be smaller, higher value shipments. On the other hand, pipeline, rail and water shipments tend to be larger shipments of lower value goods.

These trends are consistent with the large literature on freight mode choice. For instance, while truck dominates short shipments of high-value goods, rail is competitive for longer shipments of these goods and dominates shorter shipments of low-value goods[20,21]. The value of goods being shipped drives inventory costs, *i.e.* the time costs associated with goods "in-transit" and not available for sale. Shippers' prefer faster modes that minimize these costs, all else equal. Larger shipments, in terms of either tons or miles, require more energy to transport. Shippers' prefer more fuel efficient modes that minimize the share of fuel costs reflected in rates, all else equal. However, more fuel efficient modes tend to be slower. Our empirical model below attempts to capture these trade-offs.

Finally, and importantly for our empirical strategy, average trends across goods hide important variation in shipment size, value and mode choice across shipments. For instance, Figure 1c plots mode shares for grain shipments by the deciles of shipment size in ton miles. We see smaller shipments are made almost exclusively by truck. However after the sixth decile, the share of shipments made by rail and barge grows. For the largest shipments, in the tenth decile, nearly all grain shipments are made by rail, with less than 10% of shipments made by truck. Other goods show similar trends, namely that within a particular good category, larger shipments tend to travel by different modes than smaller shipments. Similarly, if value per pound varies within a good, higher value shipments tend to travel on faster modes than lower value shipments. We exploit this variation to estimate the relationship between fuel costs and mode choice.

a

Commodity Group	Ton Mile Wgt. Avg Value ($/lb.)	Miles	Tons	Mode Share Air	Pipeline	Rail	Truck	Inland Water	Parcel/Courier
Basic Chemicals	$ 0.60	1,148	420	0.00	0.01	0.55	0.34	0.10	0.00
Coal	$ 0.01	1,165	17,160	0.00	0.00	0.95	0.02	0.04	0.00
Fertilizers	$ 0.25	1,088	221	0.00	0.01	0.62	0.34	0.03	0.00
Fuel	$ 0.41	680	4,709	0.00	0.24	0.37	0.38	0.01	0.00
Fuel Oil	$ 0.44	454	3,030	0.00	0.26	0.02	0.59	0.13	0.00
Grain	$ 0.14	1,156	4,703	0.00	0.00	0.81	0.10	0.09	0.00
Machinery	$ 6.44	1,270	17	0.01	0.00	0.03	0.92	0.00	0.03
Metallic Ores	$ 0.27	880	30,078	0.00	0.00	0.62	0.07	0.31	0.00
Mixed Freight	$ 2.31	766	14	0.01	0.00	0.04	0.91	0.02	0.02
Non-Metallic Mineral Products	$ 0.39	683	140	0.00	0.00	0.20	0.79	0.01	0.00
Pharmaceuticals	$ 24.91	1,471	9	0.02	0.00	0.00	0.88	0.00	0.10
Primary Base Metal	$ 0.98	955	52	0.00	0.00	0.29	0.71	0.00	0.00
Sand	$ 0.03	688	173	0.00	0.00	0.46	0.54	0.00	0.00
Vehicles	$ 4.52	1,250	30	0.01	0.00	0.18	0.78	0.00	0.03

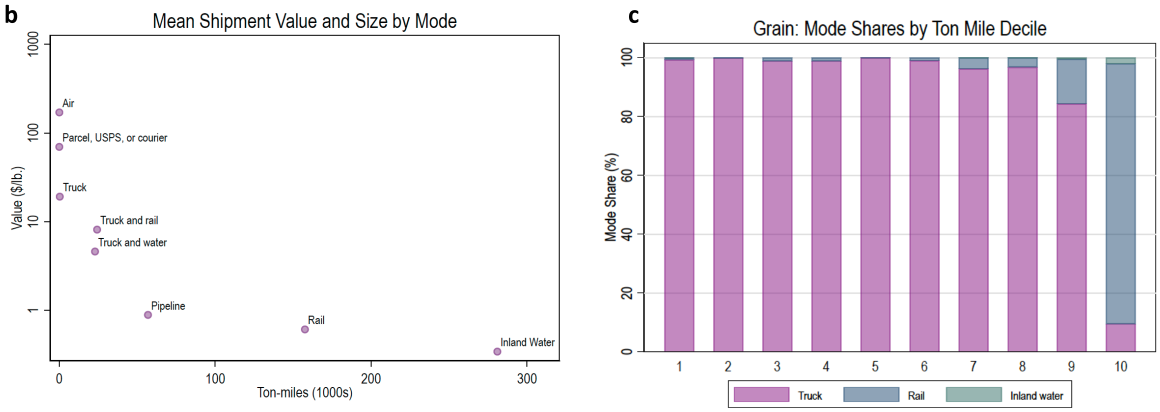


Figure 1: Characteristics of shipments contained in the Commodity Flow Survey. **a**, ton-mile weighted mean shipment value, distance, weight and transportation mode share for several representative goods. **b**, mean shipment value and size in ton-miles by mode. **c**, transportation mode shares for grain shipments by decile of shipment size in ton-miles.

Rebound and mode substitution

Here we introduce the concept of a mode substitution rebound effect. In the Supplementary information we derive our model for producer behavior in a manner analogous to earlier models of rebound in consumer settings[22]. Consider a firm that produces a single output y using $N+1$ inputs (freight modes) denoted $x = x_0, \ldots, x_N$. The firm's production function is $y = f(x)$ and the output price is p. The firm is a price taker in freight markets and faces rates $w = w_0, \ldots, w_N$ for each transportation mode. The firm's (compensated) factor demand function for each freight mode is $x_n(w, p) = u_n(w, y(w, p))$. Each mode x_n also has an energy intensity ($\frac{1}{fuel\ efficiency}$) of e_n. Assume each freight rate is an increasing monotonic function of energy intensity, *i.e.* $w_n = w(e_n)$. For an improvement in energy efficiency that lowers the energy intensity of x_0 to $\tilde{e}_0$ the change in energy consumption is:

$$\underbrace{x_0(\tilde{e}_0 - e_0)}_{Static\ Effect} + \underbrace{\tilde{e}_0 \frac{\partial u_0}{\partial y} \frac{\partial y}{\partial w_0}(\tilde{w}_0 - w_0) + \sum_{n=1}^{N} e_n \frac{\partial u_n}{\partial y} \frac{\partial y}{\partial w_0}(\tilde{w}_0 - w_0)}_{Expansion\ Effect} + \underbrace{\tilde{e}_0 \frac{\partial u_0}{\partial w_0}(\tilde{w}_0 - w_0) + \sum_{n=1}^{N} e_n \frac{\partial u_n}{\partial w_0}(\tilde{w}_0 - w_0)}_{Substitution\ Effect} \quad (1)$$

The static effect captures the change in energy consumption from an improvement in fuel efficiency of mode x_0, *e.g.* trucks, ignoring any rebound effect. The expansion effect is an intensive margin rebound effect due to changes in the quantity or size of freight shipments. The substitution effect is a rebound effect due to shifts in freight demand for truck $\frac{\partial u_0}{\partial w_0}(\tilde{w}_0 - w_0)$ and substitute modes $\frac{\partial u_n}{\partial w_0}(\tilde{w}_0 - w_0)$. Below, we estimate the static and substitution effects from an improvement in truck fuel efficiency and hold the expansion effect constant.

Effects fuel of costs on mode choices

We first estimate the relationship between fuel consumption and shippers' mode choices. Using our parameter estimates we then predict shippers' mode choices with and without fuel efficiency regulation. We illustrate our approach using results for several representative goods. Parameter estimates for these goods are presented in the Supplementary information. Figure 2 shows the effect of a 5% improvement in truck fuel-efficiency on mode choices for shipments of grain, coal, alcohol and precision instruments. The probabilities of selecting truck, rail, inland water or air for individual shipments are plotted as points. The lightly shaded points are for the initial level of fuel efficiency and the darkly shaded points reflect the improvement in truck fuel-efficiency. The dotted and solid lines are non-parametric fits to choice probabilities for the initial and more-efficient scenarios, respectively. Intuitively, we see the probability truck is selected increases with improved fuel-efficiency as indicated by the upward shifts in the points and fitted curves. This shift grows in magnitude for larger and longer shipments, but decreases for the largest shipments, *i.e.* those most suitable for rail. Conversely, the likelihood rail is selected decreases as indicated by the downward shift in the predicted probabilities. Note, there is little impact on barge choice probability, likely due to river access constraints.

Contrast these effects to those for coal. Figure 2b plots the mode choice probabilities for truck, rail and barge for the same truck fuel efficiency scenario. Here we see increasing truck efficiency has essentially no effect on mode choices. Truck is a poor substitute for rail service, given the relatively large shipment sizes and energy-intensive nature of coal transportation.

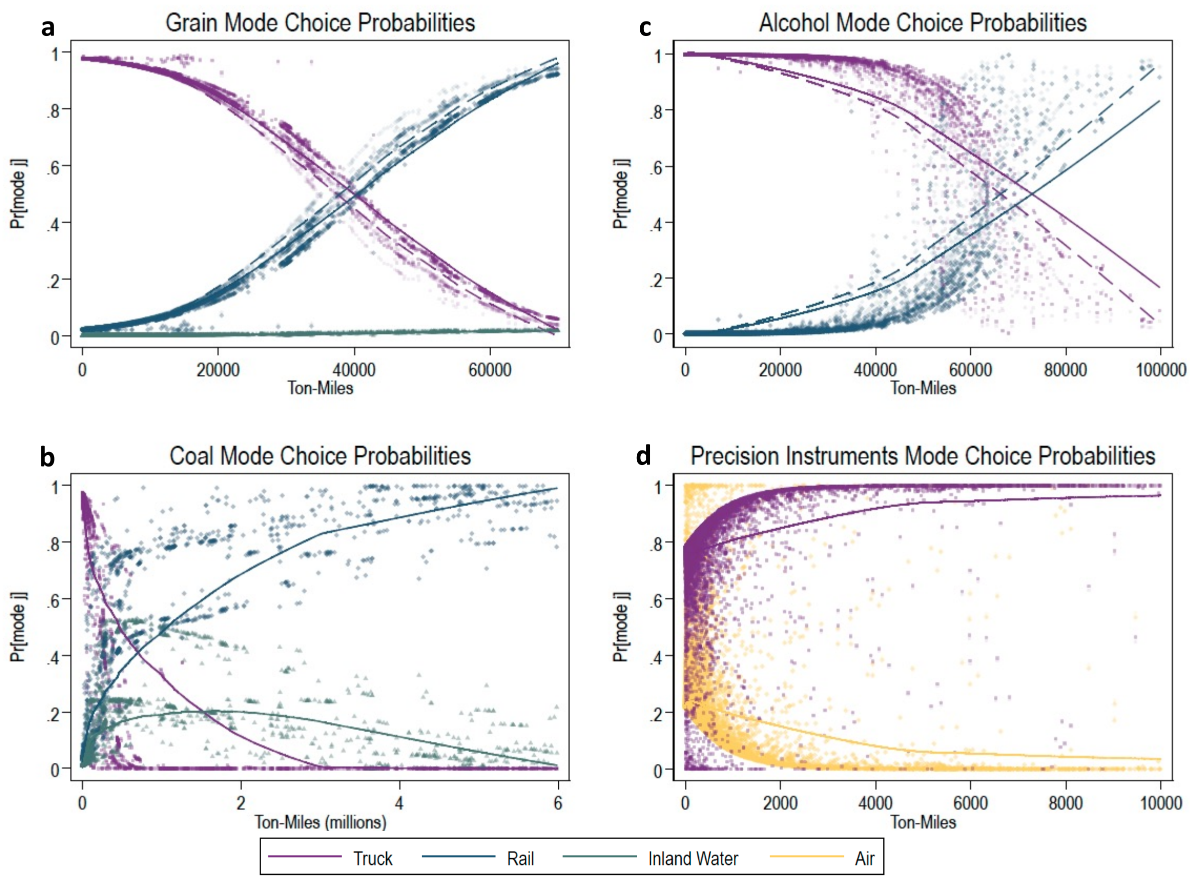


Figure 2: Truck, rail, barge and air mode probabilities with and without a 5% reduction in truck fuel intensity for four representative goods. Panels **a** and **b** show grain and coal shipments by truck, rail or inland water. Panel **c** shows alcohol shipments by truck or rail and panel **d** shows shipments of precision instruments by truck or air. Lightly shaded points are the logit model mode choice probabilities at the initial level of fuel efficiency. The darkly shaded points are predicted probabilities incorporating the reduction in truck fuel intensity. The dotted and solid lines represent non-parametric fits to estimates for the initial and more-efficient scenarios, respectively.

For alcohol and precision instruments, fuel expenditure matters for mode choice. For alcohol, truck and rail are good substitutes and a reduction in truck fuel intensity substantially shifts mode choice probabilities as indicated in Figure 2c. For precision instruments, truck efficiency improvements yield only small shifts in the truck versus air probabilities, Figure 2d. However, the large difference in energy intensity across modes still yields a modest reduction in overall fuel consumption as indicated in Figure 4, below.

To summarize the heterogenous effects across the different goods in the sample, Figure 3a plots the cross-price elasticities from changes in fuel cost between rail and truck shipments and Figure 3b plots elasticities for air and truck shipments. The full set of own and cross-price elasticity estimates for each good are presented in the Supplementary information. Manufactured products, paper and textiles are most responsive to changes in truck fuel costs when substituting truck for rail service with elasticities between 1.72 and 2.9. Coal, metallic ores and waste and scrap, with elasticities from approximately zero to 0.04, are relatively insensitive to changes in truck fuel costs. For goods shipped by air, live animals are most responsive when substituting truck for air service with an elasticity of approximately 1.6.

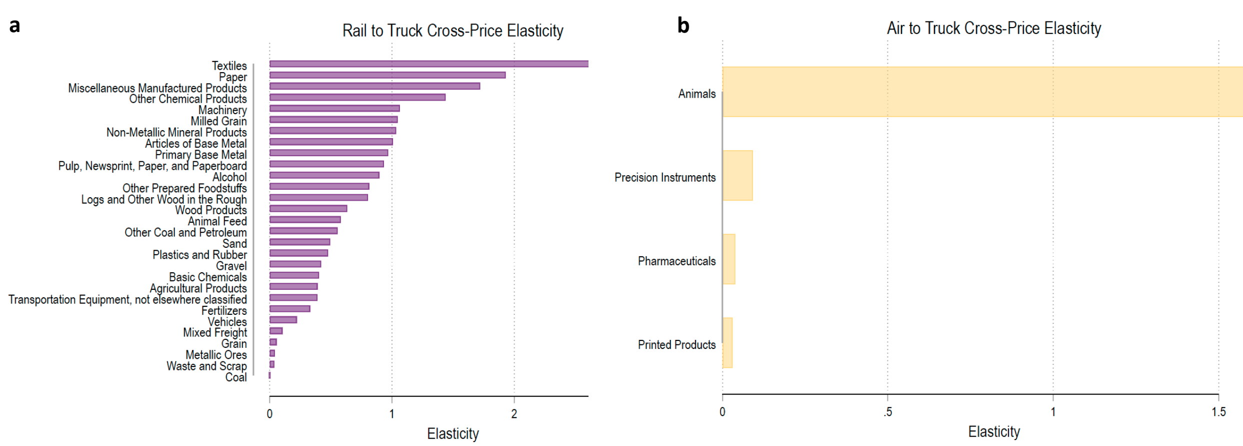


Figure 3: Estimated average cross-price elasticities between **a** rail and truck shipments and **b** air and truck shipments for different goods. Elasticities are calculated using the logit model parameter estimates for each good and each shipment's observed characteristics and then averaged over all shipments.

Fuel economy policy simulations

Results of our simulation exercise are shown in Table 1. The first column shows business as usual (BAU) estimates without truck fuel economy improvements. The middle column shows the static effect (without mode substitution rebound) of a 5% improvement in truck fuel efficiency. Fuel economy standards reduce truck fuel consumption 5% from 13,060 to 12,407 or approximately 653 million gallons per year. The *overall* effect is approximately 4.0% of transportation fuel consumption.

Results with mode substitution are in the third column. Truck fuel economy improvements shift freight from rail to truck, 14.7 billion ton miles or approximately 1.2% of business-as-usual rail freight output. There are smaller shifts from air and inland water to truck. We categorize these effects in two different ways. First, we calculate rebound based only on fuel consumption in the trucking sector, *i.e.* the first term in the substitution effect in Equation 1. This measure is most comparable to existing estimates of the heavy-duty vehicle rebound effect but only accounts for changes in fuel consumption due to substitution into trucking. Second, we calculate rebound in terms fuel consumption across all modes, *i.e.* both terms in the substitution effect in Equation 1. This measure accounts for all substitution-induced changes and best illustrates the overall effect on energy consumption.

Focusing on trucking alone, with mode substitution the decrease in truck fuel consumption is smaller, approximately 3% or 489 million gallons per year. This implies a rebound effect of approximately 25%. Recent estimates for the *total* heavy-duty truck rebound effect in the U.S. range from effectively zero[23] to between 20 and 30%[13]. Therefore, our results suggest modal substitution represents a substantial share of the total rebound effect.

Looking across modes, more efficient heavy-duty vehicles reduce fuel consumption for air, water and rail when these shipments substitute to truck. These shifts equate to an additional 38 million gallons per year in fuel savings, for a total reduction of 527 million gallons per year or approximately 3.3%. This implies a rebound effect, across the entire freight sector, of approximately 19% and highlights the importance of accounting for effects across all modes.

The aggregate effects discussed above also hide important heterogeneity across the types

Table 1: Simulated ton-miles, fuel use and emissions under 5% truck fuel economy regulation.

Fuel Prices, Fuel Use and Emissions	BAU	No Rebound (Static Effect)	With Substitution Rebound
Ton-miles			
Air (billion ton-miles)	1.57	1.57	1.56
Inland water (billion ton-miles)	126.90	126.90	126.77
Rail (billion ton-miles)	1,216.49	1,216.49	1,200.18
Truck (billion ton-miles)	1,110.11	1,110.11	1,124.76
Fuel			
Air (million gal.)	209.69	209.69	208.57
Inland water (million gal.)	211.50	211.50	211.28
Rail (million gal.)	2,703.30	2,703.30	2,667.07
Truck (million gal.)	13,060.06	12,407.06	12,570.88
Emissions			
Air (MMT)	2.01	2.01	2.00
Inland water (MMT)	2.15	2.15	2.15
Rail (MMT)	27.47	27.47	27.10
Truck (MMT)	132.69	126.06	127.72
Fuel (million gal.)	16,185	15,532	15,658
Emissions (MMT)	164.31	157.68	158.96
Percent change		4.0%	3.3%

of goods being shipped. Figure 4 plots estimates of the mode substitution-rebound effect by good. To provide a sense of magnitudes, the size of each bubble represents business-as-usual fuel consumption for that good. We see the substitution rebound effect varies substantially across goods. For alcohol, basic chemicals, fertilizers and pulp newsprint paper and paperboard, the substitution rebound effect is approximately 40% to 50%, *i.e* the actual emissions reductions are approximately half of what would be expected without modal substitution. For animal feed, grain, milled grain, other prepared foodstuffs, primary base metals, plastics and rubber and sand, the effect is approximately 30%. Other goods show smaller effects. The substitution effect is essentially zero for coal, machinery, mixed freight, printed products and waste and scrap. Air freight also responds to changes in truck fuel efficiency. As a result there are *negative* rebound effects for shipments of animals, pharmaceuticals and precision instruments due to substitution from air freight to truck. In other words, fuel savings are *larger* than would be predicted not accounting for mode switching.

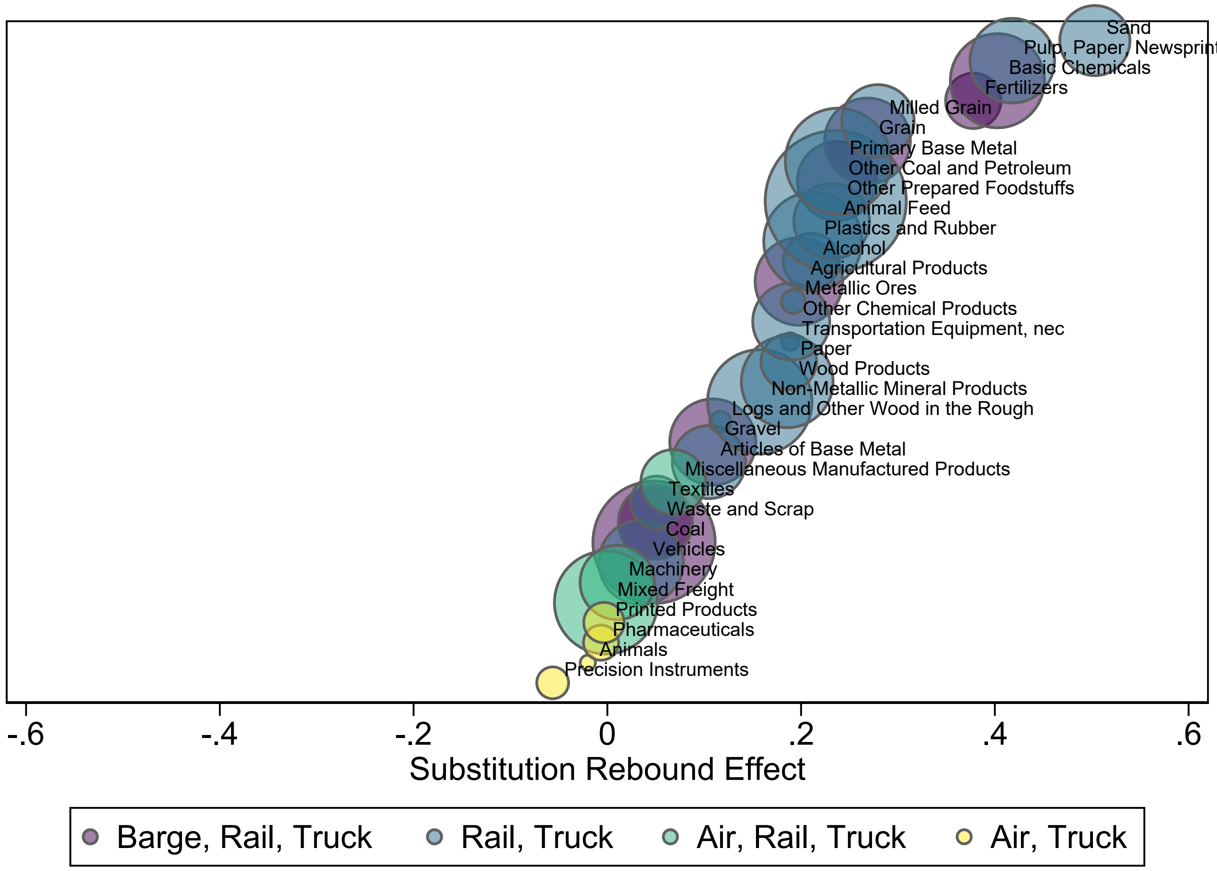
Discussion and conclusions

Freight transportation represents a large and increasingly important share of U.S. energy consumption and greenhouse gas emissions. Because energy intensities differ dramatically across freight modes, shippers' mode choice decisions have important implications for future energy and climate policies. We model the freight mode choices of U.S. shippers and find heavy duty truck fuel economy regulations cause some shipments that would have traveled by more efficient rail transport to instead travel by truck. This effect is large relative to estimates of the total heavy-duty vehicle rebound effect and results mainly from rail to truck substitution. This suggests a large portion of the overall heavy-duty truck rebound effect could be due to substitution effects. An analysis of truck fuel economy standards that ignores this mechanism can substantially overstate fuel and emissions savings.

Rebound effects that partially offset energy efficiency improvements are well known in passenger travel, buildings and energy consuming durable goods. Analogous to our mode choice example, substitution in production technology could make up a large part of responses to energy efficiency policy in these and other settings.

This work also highlights a relative benefit of climate policies that target complete sectors, rather than specific technologies, such as carbon taxation or cap-and-trade. There is no inefficient substitution bias introduced from policies that impact all technologies in the relevant choice set proportional to their environmental impact.

Figure 4: Rebound effect due to modal substitution Estimated mode substitution rebound effects with 5% truck fuel economy regulation. Rebound calculated as: $1 - \frac{fuel\ savings}{fuel\ savings\ with\ modes\ fixed}$. Negative values indicate fuel savings exceed predictions ignoring mode substitution. Bubble sizes reflect business as usual fuel consumption, without fuel efficiency standards, by good shipped.



Methods

Data

Shipment-level data on freight movements are from the U.S. Commodity Flow Survey Public Use Microdata (CFS PUM) file[11]. The CFS PUM contains administrative data on a sample of approximately 4.5 million U.S. shipments during 2012. The data include the type of good shipped reported at the Standard Classification of Transported Goods (SCTG) 2-digit level, shipment value, distance and weight. Also reported are shipment mode or modes (e.g. rail, barge, air, truck, etc. or multiple modes, *i.e.* truck and rail), origin and destination locations, whether the shipment was temperature-controlled, and sampling weights used to expand the sample to approximate the 2012 shipment population. We focus on the major modes for each good. We exclude pipeline shipments due to limited scope for substitution into or out of this mode and parcel/courier shipments due to their small ton-mile share.

We combine the shipment data with U.S. national monthly average prices for diesel and jet fuel[24,25]. Rail, truck and inland water modes all operate primarily on diesel and air shipments use jet fuel prices. For fuel efficiency, we use a mean fuel intensity for rail of 1/450 gallon per ton mile[26,27]. We use 1/85 gallon per ton mile for truck[17,7], 1/7.5 gallon per ton mile for air[17] and 1/600 gallon per ton mile for barge[28].

Mode choice model

To estimate parameters describing shippers' mode choices we follow classic models for freight mode choice[29–31,20,32], we assume shippers choose modes to minimize the sum of freight rate, inventory cost and a mode-specific fixed cost. Specifically, the cost of shipment i by mode n can be written as:

$$cost_{in} = \underbrace{\gamma_n e_n P_t \times tonmiles_i}_{\text{Rate}} + \underbrace{1/\sigma_n miles_i \times r \times value_i}_{\text{Inventory Cost}} + \underbrace{\delta_n}_{\text{Fixed Cost}} \tag{2}$$

where the first term captures freight rate, the second term represents inventory cost and the final term is a mode-specific fixed-cost δ_n. We assume freight rates depend on transportation companies' fuel expenditures and are marked up proportionally at rate γ_n. Fuel expenditure is the product of fuel price (P_t) and fuel consumption ($e_n \times tonmiles_i$), where e_n is the mode-specific fuel intensity and $tonmiles_i$ is the size of shipment i. For each mode, e_n is a constant. Inventory cost captures the time cost of transportation and depends on the shipment distance ($miles_i$), mode-specific speed ($\frac{1}{\sigma_n}$) and the value of time ($r \times value_i$), where $value_i$ is the *total* value of goods in the shipment and r is the discount rate. For goods that move by inland water, we allow mode-specific fixed cost to vary according to whether the shipment originates in the Mississippi River Basin via incremental fixed cost (δ_n^m). For goods that require temperature-controlled storage during transportation, we allow for incremental fixed cost (δ_n^{tc}).

We estimate a reduced form of Equation 2 by replacing the individual inventory cost parameters with coefficients to be estimated:

$$cost_{in} = \gamma_n e_n P_t \times tonmiles_i + \beta_{gn} miles_i \times value_i + \delta_{gn} + \epsilon_{in} \tag{3}$$

Since the rate term ($\gamma_n e_n P_t \times tonmiles_i$) is alternative specific but the time cost term is not, we estimate Equation 3 as an alternative specific logit model. We estimate Equation 3 separately for each good g to allow markups, mode speeds, values of time and fixed costs to vary by the type of good shipped. The mode choice parameters are identified by cross-sectional variation in shipment characteristics (ton-miles, miles, value, etc.) and (limited) time-series variation in fuel prices.

Because variation in shipment costs comes mainly from changes in shipment characteristics, the potential endongeneity problem is a bit more nuanced than the classic demand estimation concern, *i.e.* that cost shocks are correlated with unobserved mode-specific demand shocks. For instance, if a shock to truck shipment demand affects *diesel prices*, then our estimates of the rate (fuel expenditure) term would be biased towards zero. However in this case, our estimates are conservative in the sense that they under-estimate the effects of changes in fuel consumption on mode switching. It could also be the case unobserved shocks to shipment characteristics are correlated with shocks to demand for particular modes, *e.g* a number of unusually large or small shipments that for some reason must be made by truck. Here, the direction of bias is unknown. However, shocks of this type seem less likely. Unfortunately the nature of our data, *i.e.* shipments occurring within a single year makes traditional instrumental variables strategies challenging and our estimates must be interpreted in light of this potential bias. Additional information on our empirical approach and logit model parameter estimates for the representative goods are provided in the Supplementary information.

Simulation of truck fuel economy standards

To see the overall effect of EPA phase two fuel economy standards we simulate shippers mode choices with and without a 5% decrease in truck fuel intensity. We simulate three different cases. The first case is business-as-usual (BAU) without a truck efficiency improvement. The second imposes the 5% reduction in truck fuel intensity but assumes more fuel-efficient trucks do not affect shippers' mode choices. This difference between BAU and this scenario is a measure of the direct effect in Equation 1. The third imposes the 5% reduction in energy intensity and allows mode shares to adjust to changes in relative fuel efficiency. The difference between the second and third scenarios shows the aggregate effect of mode substitution rebound on energy consumption.

For each scenario, we calculate the latent value in (3) using the logit model parameter estimates for each good and add to this value a random draw from the extreme value error distribution. This gives choice probabilities for each mode. We assume shippers pick the most probable mode for each shipment and each error draw. We repeat this procedure taking new draws from the error distribution to yield 500 simulated mode choices for each shipment.

When shipments switch modes we adjust ton-miles in our fuel consumption calculations to reflect mean differences in travel distance across models. For instance, truck distances tend to be less between a given origin and destination due to more direct routing of truck shipments relative to rail. We calculate the ratio of rail, air and barge to truck distances between each origin-destination pair and apply mean values for the distance corrections. Fuel consumption is calculated using the mean fuel efficiencies for each mode listed above. Carbon emissions are calculated assuming 10.16 kg CO_2 per gallon of diesel fuel and 9.57 kg CO_2 per gallon of jet fuel. To calculate the aggregate values reported in Table 1 we first average across the 500 simulated mode choices for each shipment and then aggregate ton miles, fuel consumption and emissions for each mode.

Data availability

The Commodity Flow Survey Public Use Microdata are publicly available from the U.S. Census Bureau (https://www.census.gov/data/datasets/2012/econ/cfs/historical-datasets.html). Fuel price data are publicly available from the U.S. Energy Information Administration (https://www.eia.gov/dnav/pet/hist/LeafHandler.ashx?n=pet&s=emd_epd2d_pte_nus_dpg&f=m and https://www.eia.gov/dnav/pet/hist/eer_epjk_pf4_rgc_dpgD.htm).

Code availability

All code used to conduct the study is available at https://github.com/jehdukeegr/Freight-Mode-Rebound.

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Author contributions

J.B. and J.E.H conceptualized the study and acquired the funding. J.E.H. developed the software. J.B. and J.E.H conducted the formal analysis, wrote and edited the paper.

Competing interests

The authors declare no competing interests.

Supplementary information

Framework for production rebound effects

The mode substitution rebound effects studied here belong to a class of rebound effect related to agents' choices of production technology. To categorize the different mechanisms contributing to rebound in a production setting, consider a representative firm that produces a single output y using $N+1$ inputs denoted $x = x_0, \ldots, x_N$. The firm's production function is $y = f(x)$ and the output price is p. The firm is a price taker in the input market and faces factor prices $w = w_0, \ldots, w_N$. Each input x_n has an energy intensity per unit of consumption of e_n. While the producer does not directly pay the embodied energy consumption, assume the factor prices capture energy costs such that each factor price is an increasing monotonic function of energy intensity, $w_n = w(e_n)$. There is an investment in energy efficiency that lowers the energy intensity of x_0 to $\tilde{e}_0$ such that $\tilde{e}_0 < e_0$ and $\tilde{w}_0 < w_0$.

The effect of a price change can be decomposed into a substitution effect across the firm's production factors (technologies) and an expansion path effect affecting the scale of production[33–35]. To see this, define the firm's compensated factor demand function as $x(w,p) = u(w, y(w,p))$. Differentiating $u(w, y(w,p))$ yields the effect of a change in factor price w_0 on input w_n:

$$\left.\frac{\partial x_n}{\partial w_0}\right|_{w_{n\neq 0}} = \left.\frac{\partial u_n}{\partial w_0}\right|_{y, w_{n\neq 0}} + \left.\frac{\partial u_n}{\partial y}\right|_{\tilde{w}_0} \left.\frac{\partial y}{\partial w_0}\right|_{\tilde{w}_0, w_{n\neq 0}} \tag{4}$$

where $\frac{\partial u_n}{\partial w_0}$ is the substitution effect holding constant output and the other factor prices and $\frac{\partial u_n}{\partial y}\frac{\partial y}{\partial w_0}$ is the expansion path effect. For simplicity, Equation 4 shows only the cross-price effects. However, the own price effects can be derived in the same fashion. Equation 4 is the production analog to the Slutsky equation for price changes in consumer theory.

To understand the implications of (4) for energy efficiency rebound effects, note total energy consumption is just the sum of consumption across the different production technologies $\sum_{n=1}^{N} e_n u_n$. The energy efficiency investment lowers energy consumption for every unit of x_0 consumed. The factor price change $\tilde{w}_0 - w_0$, produces substitution and expansion effects across the firms inputs. Combining these effects yields:

$$x_0(\tilde{e}_0 - e_0) + \tilde{e}_0 \frac{\partial u_0}{\partial y} \frac{\partial y}{\partial w_0}(\tilde{w}_0 - w_0) + \sum_{n=1}^{N} e_n \frac{\partial u_n}{\partial y} \frac{\partial y}{\partial w_0}(\tilde{w}_0 - w_0) + \tilde{e}_0 \frac{\partial u_0}{\partial w_0}(\tilde{w}_0 - w_0) + \sum_{n=1}^{N} e_n \frac{\partial u_n}{\partial w_0}(\tilde{w}_0 - w_0) \tag{5}$$

This first term is the static energy efficiency effect. The second and third terms are the expansion effects for input w_0 and the other factors of production, respectively. In freight markets, the expansion effects captures changes in the intensive margin of freight demand. Our empirical application holds these effects constant. The fourth and fifth terms are the own and cross-price substitution effects. In the empirical application below we show the magnitude of these substitution effects can be large and can be positive or negative depending on the relative energy intensity of the substitute production technology.

A Freight data

We exploit substantially better data than has been used in the past to study freight mode choices. The Commodity Flow Survey Public Use Microdata file (CFS PUM) is the largest publicly available micro data set on U.S. freight shipments. The data come from a stratified sample of establishments originating shipments and stratified by geography, industry and establishment size. Regional location data for shipment origins and destinations are reported at the Combined Statistical Area (CSA) level, when available, or at the Metropolitan Statistical Area (MSA) level. The Census Bureau removes firm-level data and identifying information to protect shipper and transportation company confidentiality. These data show substantial variation in shipment size and value, both across goods and across shipments within a particular type of good. This heterogeneity, which has been largely absent in earlier studies using more aggregate data, reveals more realistic substitution patterns across modes. Further, the CFS PUM provides much more comprehensive coverage of geographic areas, goods and modes compared to data used previously and therefore paints a more accurate picture of recent U.S. freight patterns. Earlier studies using microdata typically focus on a small number of goods, modes or geographic areas. For instance, the CFS PUM is the only publicly available source for the highway mode.

Our empirical model focuses on the major modes used to ship each type of good. We treat the truck component of mixed modes, *i.e.* truck and rail, and truck and barge, as drayage and aggregate these shipments into the main modes, rail and barge. According to[36] "Shipments that included a truck drayage component are classified as Truck-Rail and Truck-Water in the CFS estimates." Because drayage distances are unobserved, we assume the truck share of miles is small relative to the rail or water component. Since mixed shipments represent small shares of total ton miles, 5% and 1% for truck-rail and truck-barge, respectively, this assumption is unlikely to substantially impact our results.

We combine the CFS shipment data with information on diesel and jet fuel prices[24,25]. Rail, truck and inland water modes all operate primarily on diesel and air shipments use jet fuel prices. Because diesel fuel used in locomotives is exempt from the federal fuel excise tax and from excise taxes in approximately 20 states, we subtract the federal and average state exemptions from retail prices for rail shipments. We collapse the monthly data to quarterly and match the relevant prices (diesel or jet) to individual shipments in the CFS PUM.

Table A1 summarizes shipment characteristics in the CFS PUM sample. The top panel expands the sample using the CFS PUM sampling weights, but is otherwise unweighted. The bottom panel reports summary statistics weighted by shipment size in ton-miles. While the unweighted sample illustrates important features of the CFS PUM, weighting by shipment-size is the more policy relevant metric since energy use and emissions are (roughly) proportional to shipment size in ton-miles. The maximum value of goods shipped is approximately \$520 million. Maximum shipment distance is approximately 6,700 miles and maximum shipment weight is approximately 140,000 tons. The two sets of summary statistics diverge due to the large number of small parcel and courier shipments in the CFS PUM sample. Therefore, mean shipment value is approximately \$1,400 in the unweighted sample but increases to \$415,000 when weighted. Similarly, mean shipment distance and weight are approximately 620 miles and 1.1 tons in the unweighted sample and 1,090 miles and 5,070 tons in the weighted sample.

The bottom of each panel shows modal shares in the weighted and unweighted samples. The "truck" mode combines shipments using private and for-hire trucks. Mixed modes, *e.g.* truck-rail and truck-inland water are classified as rail and barge shipments, *i.e.* truck is used to connect origins and destinations to the rail or barge service. Truck and parcel/courier represent 44% and 54% of shipments in the CFS PUM sample. However in terms of shipment size, parcel/courier is relatively less important than the other modes. Accounting for shipment size (lower panel), rail (48%), truck (46%) and water (4%) account for over 98% of freight output. Pipeline accounts for approximately 1% of shipments. However, modal substitution to pipeline is limited in the short-run due to fixed infrastructure. Air represents approximately 0.2% of freight output, while parcel/courier represents approximately 0.8%. We exclude pipeline and parcel/courier shipments from our analysis below because shipments using these modes have substantially different characteristics than those made on other modes and because pipeline and parcel/courier constitute a small share of total freight ton-miles. Finally, we exclude a handful of good categories that are dominated by a single mode, typically with greater than 99% share, such that there are insufficient observations to estimate parameters for competing modes. These include: meat, poultry and fish; tobacco products; monumental and building stone; electronics, other non-metallic minerals; and furniture.

B Empirical approach

We estimate Equation 3 using the CFS PUM data outlined above. Because there is relatively little variation in fuel prices during the sample year (2012), the parameters in (3) are identified by cross-sectional variation in shipment characteristics (ton-miles, miles, value, etc.) and (limited) time-series variation in fuel prices. Table A2 presents parameter estimates for the four representative goods: grain; coal; alcohol; and precision instruments. Parameter estimates for other goods show similar patterns.

For grain, alcohol and precision instruments estimates for the rate (fuel expenditure term) are negative and statistically significant indicating an increase in energy efficiency or decrease in fuel intensity increases the likelihood a given mode is chosen. For coal the estimated impact is small and insignificant, consistent with the notion coal moves mainly by rail and, to a lesser extent inland water, and truck is a relatively poor substitute for these modes. For grain shipments, increasing the inventory (time) cost, proxied by the produce of shipment distance and shipment value, increases the likelihood truck (a faster mode) is selected compared with rail or inland water. The effect is similar for precision instruments where air is more likely to be selected relative to truck as distance or shipment value increase. For coal, the estimated time cost parameter is negative for truck and barge indicating increased costs make these modes less likely compared to rail. Similarly for alcohol, increased time costs make truck less likely to be selected compared to rail. The relative advantage of rail is this setting may be due to the use of unit trains for transporting these goods. The Mississippi term estimates indicate inland water is more likely to be selected when grain or coal shipments originate in the basin. Finally, when alcohol shipments must be temperature controlled, *i.e.* beverages as opposed to fuel ethanol, truck is more likely to be selected compared to rail.

C Model predictions of aggregate mode shares

We assess the overall fit of our modeling by comparing predicted freight ton-miles with totals reported in the CFS. Table A3 presents the total ton-miles transported by mode for each good. Beside the CFS data we present the mean ton-miles by mode and good averaged across our simulations. In general, the predictions of the alternative specific logit model match the CFS PUM shares well. The model tends to slightly over-predict truck ton-miles and under-predicts rail ton-miles. Predicted total truck ton miles are within .9% of the CFS PUM total and rail ton miles are within 3.8%. The alternative specific logit systematically over-predicts barge ton-miles for a number of goods including basic chemicals, coal, fertilizers and grain. As a result, we overestimate barge share and underestimate fuel use in our baseline scenario. However, since we are mainly interested in how truck and rail shares change with improved truck fuel economy, and since barge is a poor substitute for most truck shipments, we do not see this as a major limitation of the alternative specific logit specification in this application.

D Supplementary tables

Table A1: Summary statistics and modal shares in weighted and unweighted samples.

	Mean	Std. Dev.	Min.	Max.
Unweighted				
Value	$ 1,440	$ 63,700	$ 1	$ 521,000,000
Miles	622.31	795	1.00	6,677
Tons	1.14	54	0.00	139,000
Shipment Share				
Air	0.02	0.12	0.00	1.00
Pipeline	0.00	0.01	0.00	1.00
Rail	0.00	0.04	0.00	1.00
Truck	0.44	0.50	0.00	1.00
Water	0.00	0.01	0.00	1.00
Parcel/Courier	0.54	0.50	0.00	1.00
Ton-Mile Weighted				
	Mean	**Std. Dev.**	**Min.**	**Max.**
Value	$ 415,000	$ 2,750,000	$ 1	$ 521,000,000
Miles	1,089.16	731	1.00	6,677
Tons	5,066.56	12,500	0.00	139,000
Ton-Mile Share				
Air	0.00	0.04	0.00	1.00
Pipeline	0.01	0.10	0.00	1.00
Rail	0.48	0.50	0.00	1.00
Truck	0.46	0.50	0.00	1.00
Water	0.04	0.20	0.00	1.00
Parcel/Courier	0.01	0.09	0.00	1.00

Table A2: Alternative specific logit model parameter estimates for grain, coal, alcohol and precision instruments.

Grain, Coal, Alcohol and Precision Instruments Mode Choice Results

	Grain	Coal		Alcohol	Precison Inst.
Rail	(Base Outcome)		**Rail/Truck**	(Base Outcome)	
Fuel Int. * Ton-Miles * Fuel P.	-3182.505	-0.358	Fuel Int. * Ton-Miles * Fuel P.	-3058.709	-3067.157
	(4.744)	(1.067)		(4.767)	(7.102)
Truck			**Truck**		
Miles * Shipment Value	0.010	-0.292	Miles * Shipment Value	-0.007	
	(0.000)	(0.001)		(0.000)	
Mississippi Basin	-1.010	1.027	Temperature Controlled	0.308	
	(0.004)	(0.009)		(0.012)	
Constant	4.337	3.398	Constant	7.986	
	(0.003)	(0.003)		(0.005)	
Inland Water			**Air**		
Miles * Shipment Value	-0.026	-0.007	Miles * Shipment Value		0.011
	(0.000)	(0.000)			(0.000)
Mississippi Basin	2.522	1.249	Constant		(1.283)
	(0.024)	(0.011)			(0.000)
Constant	-5.472	-0.951			
	(0.023)	(0.005)			
Observations	74451	31806		192658	81614
Pseudo R2	0.883	0.810		0.995	0.256

Notes: Alternative specific logit model estimates for grain and coal shipments. Shipment size measured in million ton-miles. Shipment value measure in million dollars. Stardard errors clustered at the route-level in parentheses.

Table A3: Observed (CFS PUM) ton miles by good and mode compared with mean simulated values using alternative specific logit parameter estimates.

	Truck		Rail		Water		Air	
Commodity Group	**CFS**	**Pred.**	**CFS**	**Pred.**	**CFS**	**Pred.**	**CFS**	**Pred.**
Agricultural Products	38.5	38.7	28.9	26.5	16.1	18.4	0.0	0.0
Alcohol	20.6	20.6	12.9	12.9	0.0	0.0	0.0	0.0
Animal Feed	33.3	33.5	19.9	19.8	0.0	0.0	0.0	0.0
Animals	1.3	1.3	0.0	0.0	0.0	0.0	0.0	0.0
Articles of Base Metal	33.8	33.9	6.1	5.9	0.0	0.0	0.0	0.0
Basic Chemicals	45.8	46.6	72.9	68.2	13.1	17.1	0.0	0.0
Coal	9.8	11.2	603.2	576.7	23.2	48.3	0.0	0.0
Fertilizers	17.8	18.1	32.0	31.5	1.5	1.7	0.0	0.0
Grain	17.5	17.9	136.8	131.7	15.3	20.0	0.0	0.0
Gravel	39.4	39.7	12.6	12.6	7.8	7.6	0.0	0.0
Logs and Other Wood in the Rough	3.2	3.2	0.3	0.3	0.0	0.0	0.0	0.0
Machinery	32.6	32.6	1.1	1.1	0.0	0.0	0.4	0.3
Metallic Ores	2.1	2.1	18.0	17.9	0.0	0.0	0.0	0.0
Milled Grain	34.3	34.5	15.1	14.8	0.0	0.0	0.0	0.0
Miscellaneous Manufactured Products	25.6	24.9	1.2	1.9	0.0	0.0	0.3	0.3
Mixed Freight	66.9	69.4	3.1	0.9	0.0	0.0	0.8	0.4
Non-Metallic Mineral Products	67.8	68.1	17.2	17.0	0.0	0.0	0.0	0.0
Other Chemical Products	36.3	36.5	8.2	8.0	0.0	0.0	0.0	0.0
Other Coal and Petroleum	47.6	47.8	26.8	24.9	9.3	10.9	0.0	0.0
Other Prepared Foodstuffs	126.9	127.3	68.0	67.5	0.0	0.0	0.0	0.0
Paper	21.1	21.2	3.9	3.8	0.0	0.0	0.0	0.0
Pharmaceuticals	6.6	6.6	0.0	0.0	0.0	0.0	0.1	0.1
Plastics and Rubber	54.4	54.7	43.5	43.2	0.0	0.0	0.0	0.0
Precision Instruments	3.7	3.8	0.0	0.0	0.0	0.0	0.4	0.3
Primary Base Metal	72.1	72.6	29.5	29.1	0.0	0.0	0.0	0.0
Printed Products	12.6	12.7	0.0	0.0	0.0	0.0	0.1	0.1
Pulp, Newsprint, Paper, and Paperboard	40.0	40.3	27.4	27.0	0.0	0.0	0.0	0.0
Sand	20.2	20.4	17.3	17.0	0.0	0.0	0.0	0.0
Textiles	21.3	21.3	0.8	0.7	0.0	0.0	0.0	0.0
Transportation Equipment, not elsewhere	2.1	2.1	1.5	1.4	0.1	0.1	0.0	0.0
Vehicles	49.1	49.3	11.5	11.3	0.0	0.0	0.0	0.0
Waste and Scrap	43.5	44.4	17.5	15.4	1.7	2.8	0.0	0.0
Wood Products	52.6	52.8	27.3	27.1	0.0	0.0	0.0	0.0

Notes: Commidity Flow Survey (CFS) ton miles by SCTG and mode (in millions of ton miles). Predicted ton-miles by SCTG and mode are average values across our simulated mode choices, Section 7, in millions of ton miles.

Table A4: Estimated own and cross-price elasticities for goods moving by barge, rail or truck.

	Agricultural Products				Basic Chemicals				Coal		
	Truck	Rail	Barge		Truck	Rail	Barge		Truck	Rail	Barge
Truck	-0.3087	0.3918	0.0849	Truck	-0.5961	0.4029	0.0165	Truck	0.0000	0.0000	0.0000
Rail	0.0512	-7.5574	10.7419	Rail	0.1101	-0.2476	0.6892	Rail	0.0000	-0.0024	0.0282
Barge	116.1375	215.7415	353.2747	Barge	183.0777	93.3057	672.6492	Barge	0.0000	0.0024	-0.0280

	Fertilizers				Grain				Gravel		
	Truck	Rail	Barge		Truck	Rail	Barge		Truck	Rail	Barge
Truck	-0.5784	0.3314	0.0000	Truck	-0.4266	0.0575	0.0039	Truck	-0.1373	0.4196	0.0206
Rail	0.1149	-0.0836	0.3336	Rail	0.0966	-4.4154	29.0532	Rail	0.0279	-4.2745	6.9892
Barge	183.7579	62.6101	2965.7030	Barge	0.0007	3.9681	-26.1886	Barge	0.0009	3.9597	-6.6151

	Other Coal and Petroleum				Transportation Equipment				Waste and Scrap		
	Truck	Rail	Barge		Truck	Rail	Barge		Truck	Rail	Barge
Truck	-0.2983	0.5557	0.0388	Truck	-0.2702	0.3883	0.1249	Truck	-0.0125	0.0358	0.0012
Rail	0.0467	-1.0258	2.1421	Rail	0.0432	-0.7465	6.8850	Rail	0.0018	-0.0271	0.1186
Barge	74.8693	235.6501	667.9596	Barge	0.0021	0.5004	-5.0803	Barge	0.0000	0.0875	-0.4763

Table A5: Estimated own and cross-price elasticities for goods moving by rail or truck.

	Alcohol			Animal Feed			Articles of Base Metal	
	Truck	Rail		Truck	Rail		Truck	Rail
Truck	-0.5590	0.8969	Truck	-0.3434	0.5822	Truck	-0.1771	1.0080
Rail	0.1011	-0.1623	Rail	0.0674	-0.1142	Rail	0.0313	-0.1780
	Logs and Wood in the Rough			Metallic Ores			Milled Grain	
	Truck	Rail		Truck	Rail		Truck	Rail
Truck	-0.0732	0.8031	Truck	-0.3531	0.0414	Truck	-0.4502	1.0482
Rail	0.0116	-0.1270	Rail	0.0682	-0.0080	Rail	0.0843	-0.1964
	Non-Metallic Mineral Products			Other Chemical Products			Other Prepared Foodstuffs	
	Truck	Rail		Truck	Rail		Truck	Rail
Truck	-0.2580	1.0334	Truck	-0.3167	1.4393	Truck	-0.4322	0.8137
Rail	0.0496	-0.1988	Rail	0.0612	-0.2783	Rail	0.0774	-0.1457
	Paper			Plastics and Rubber			Primary Base Metal	
	Truck	Rail		Truck	Rail		Truck	Rail
Truck	-0.3457	1.9298	Truck	-0.3749	0.4754	Truck	-0.3891	0.9697
Rail	0.0645	-0.3603	Rail	0.0695	-0.0881	Rail	0.0748	-0.1864
	Pulp, Paper and Newsprint			Sand			Textiles	
	Truck	Rail		Truck	Rail		Truck	Rail
Truck	-0.6261	0.9342	Truck	-0.4116	0.4930	Truck	-0.0998	2.8797
Rail	0.1221	-0.1822	Rail	0.0816	-0.0978	Rail	0.0009	-0.0246
	Vehicles			Wood Products				
	Truck	Rail		Truck	Rail			
Truck	-0.0512	0.2224	Truck	-0.3253	0.6328			
Rail	0.0101	-0.0439	Rail	0.0607	-0.1181			

Table A6: Estimated own and cross-price elasticities for goods moving by air or truck.

	Animals			Pharmaceuticals	
	Truck	Air		Truck	Air
Truck	-0.0524	1.5944	Truck	-0.0006	0.0388
Air	0.4436	-13.4936	Air	0.0094	-0.5867
	Precision Instruments			Printed Products	
	Truck	Air		Truck	Air
Truck	-0.0080	0.0922	Truck	-0.0002	0.0306
Air	0.0546	-0.6261	Air	0.0035	-0.5176

Table A7: Estimated own and cross-price elasticities for goods moving by air, rail or truck.

	Mixed Freight				Machinery		
	Truck	Rail	Air		Truck	Rail	Air
Truck	-0.0016	0.1039	0.0431	Truck	-0.0376	1.0654	0.0548
Rail	0.0002	-0.0156	0.0000	Rail	0.0068	-0.1967	0.0000
Air	0.0034	0.1216	-0.8438	Air	0.0078	0.0512	-0.9186

	Misc. Manufactured Products		
	Truck	Rail	Air
Truck	-0.1345	1.7215	0.1026
Rail	0.0215	-0.2777	0.0005
Air	0.0065	0.0043	-0.6549