Mode Choice, Energy, Emissions and the Rebound Effect in U.S. Freight Transportation

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Abstract

We exploit newly available microdata on goods movement in the U.S. to model shippers' freight mode choices. Because freight modes have vastly different fuel intensities, shippers' choices have large implications for fuel consumption and emissions. We find higher fuel prices yield substantial shifts from less to more fuel-efficient modes, particularly rail. We extend our model to analyze recently enacted fuel economy standards. Fuel economy standards can increase emissions and fuel consumption by shifting shipments to less fuel-efficient modes. Our results suggest mode-shifting makes up a large share of the total rebound effect in heavy-duty vehicles.

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1 Introduction

After several years of decline, recent estimates suggest U.S. carbon dioxide emissions are again on the rise. This reversal is due in large part to increases in energy consumption and emissions from transportation. Transportation has recently surpassed electricity generation as the largest source of U.S. carbon dioxide emissions (U.S. Energy Information Administration, 2018). While improvements in light-duty vehicle fuel economy have helped to offset increases in driving, freight-sector emissions have increased substantially over the past several years. As a result, freight now represents approximately a third of transportation sector energy consumption and emissions. Despite these trends, relatively little attention has been paid to understanding the factors that affect emissions from freight. This fact is particularly striking in contrast to the vast literature related to passenger vehicles.

The transportation technology, or mode, plays a central role in determining the emissions intensity of goods shipments. Energy intensities across modes such as air, truck and rail differ by an order of magnitude. Therefore, understanding how shippers choose which mode to use and how changes in fuel prices and shipment characteristics affect these choices has important implications for energy policy. In this paper, we exploit newly available microdata on goods movement in the U.S. to model shippers' freight mode choices during 2012.[1] The data contain detailed information on the type of good shipped, shipment characteristics and the mode used for each movement. We model cost-minimizing shippers who trade-off freight rates, that vary with fuel prices, against inventory costs, that reflect the average speeds of different freight modes. We estimate a series of discrete choice models for freight mode choice allowing rate, inventory and fixed cost parameters to vary across the type of good shipped.

Using our parameter estimates we simulate mode choices, fuel use and emissions under different fuel price scenarios. We find higher fuel prices yield substantial shifts from less to more fuel efficient modes, particularly rail. For instance, a 10% increase in fuel price increases rail ton miles by 1.7%, increases barge ton-miles by 4.0% and reduces truck ton miles by 2.9%. Combined, this translates to a 1.6% decrease in freight sector fuel consumption and emissions.

[1]These data are being made public on a trial basis and as such, are unfortunately only available for a single survey year.

In some goods categories, reductions can be as large as 3 to 3.5%. The largest effects are for intermediate-sized shipments of moderately-valued goods such as paper products, alcohol, fertilizers and chemicals. Because our approach focuses on short-run responses and because we hold shipments fixed, these estimates are likely a lower bound on actual emissions reductions due to modal substitution.

Shippers' mode choices can have important consequences for transportation-sector carbon policies. We illustrate this by considering hypothetical heavy duty vehicle fuel economy standards that approximate recent U.S. policies. Because shippers' mode choices implicitly depend on the fuel intensities of different modes via rates, policies to improve truck fuel economy could have the perverse effect of shifting freight from more efficient to less efficient modes (Winebrake et al., 2012). Intuitively, if truck fuel economy improves, marginal shippers who previously paid lower rail rates but higher inventory costs may now shift to truck. Because rail is four times more fuel efficient than truck, these shifts increase fuel consumption and emissions of those shipments. We call this effect the "cross-rebound" effect to recognize that this mechanism is a component of the total rebound effect coming from substitution across modes.

We adapt our modeling framework to quantify this effect by imposing mode-specific mean fuel intensities and estimating a mixed-logit model for mode choice. We first verify this approach yields predictions consistent with our base model. Then, we use the model to simulate shippers' mode choices under a fuel economy standard that lowers truck energy intensity by 5 percent. This level corresponds to EPA estimates for the improvement in truck fleet fuel efficiency in 2025 due to the recently enacted Tier II heavy duty vehicle fuel efficiency standards.

Truck fuel economy regulations result in modest shifts from rail to truck, approximately 1.3% of rail freight output (ton-miles). However, these shifts dramatically reduce fuel and emissions savings from fuel economy regulations. Ignoring modal substitution and applying a 5% reduction in truck fuel intensity (zero rebound) suggests fuel economy regulations lower total freight sector fuel consumption and emissions by approximately 4%. However, once we account for shipments that switch from truck to rail, the estimated reduction falls to only

3.3%, implying a cross-rebound effect of 18%. The effects vary substantially across the types of goods shipped. For goods such as paper products, alcohol, fertilizers and chemicals, the cross-rebound effect is 40 to 50%. For some goods, such as animals and precision instruments, the cross-rebound effect is *negative* because more efficient trucks entice some shipments that previously went by air to move instead by truck.

Our work contributes to three main literatures. First, we add to the large economics and engineering literatures modeling freight demand going back decades.[2] While this literature has established the main trade-offs faced by shippers in deciding how to move their goods, major industry changes over the past several decades have likely shifted these relationships. For example, computerization and improvements in information technology have reduced shipping costs, enabled realtime tracking, and improved service quality, particularly for trucking. Containerization has increased intermodal shipments that combine water, rail and truck modes. Major investments in infrastructure have made railroads more competitive with trucks on long-haul shipments of containerized freight. Here, we estimate parameters that reflect these changes and describe how shippers' choose modes today.

We also exploit substantially better data than has been used in the past to study freight mode choices. The 2012 U.S. Commodity Flow Survey Public Use Microdata file (CFS PUM) is the largest publicly available micro data set on U.S. freight shipments and was,

[2]This literature is generally divided into aggregate and disaggregate studies (Winston, 1985), where the former focus on estimating modal shares and the later on modeling individual or representative shipments. Examples of aggregate models include Friedlaender and Spady (1980) and Oum (1979), who model freight demand of cost-minimizing firms. Disaggregate data from surveys and waybills has led to the development of richer behavioral models that focus on shipment and shipper characteristics as well as the geography of freight transportation. Winston (1981) develops an early model using disaggregate data and estimates demand elasticities for rates, mean travel times and service quality for different commodity groups. Wilson, Wilson, and Koo (1988) model competition between rail and truck for grain shipments in the U.S. Upper Great Plains to investigate rail market power and pricing around the time of deregulation. Rich, Holmblad, and Hansen (2009) use a weighted discrete choice framework to estimate shippers' value of time for different modes and commodity groups. Norojono and Young (2003) use stated preference data to understand how factors related to service quality such as safety and reliability affect mode choice. Similarly, Wilson, Bisson, and Kobia (1986) use survey data to explore how shipment and shipper characteristics affect mode choice for general freight in Canada. Jiang, Johnson, and Calzada (1999) model for-hire and private freight shipping in France using a nested logit approach. Abdelwahab and Sargious (1992), Abdelwahab (1998), Holguin-Veras (2002) and McFadden, Winston, and Boersch-Supan (1985) model freight mode choice allowing shippers to simultaneously choose shipment size. Train and Wilson (2007) model shipments by rail and barge, where geography limits shippers' access to these modes. Arunotayanun and Polak (2011) and Greene and Hensher (2003) employ latent class and mixed-logit approaches to relax assumptions of the multinomial logit models typically used with disaggregate data and to allow for heterogeneity in shippers' preferences.

until recently, unavailable. 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 2012 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.[3]

Second, we contribute to the large literature on energy prices and carbon policy in the transportation sector. This literature has largely focused on passenger vehicles.[4] However, for the reasons noted above, understanding the role of freight transportation in emissions and energy consumption is increasingly important. While there is a literature exploring the environmental characteristics of freight in international trade, less is known about domestic goods movement.[5] The main focus of U.S. research to date has been on engineering estimates for emissions characteristics of different modes or future technologies. Two exceptions related to what we present here are Nealer, Matthews, and Hendrickson (2012) and Austin (2018). Nealer, Matthews, and Hendrickson (2012) use the 2002 CFS aggregate files to predict fuel and emissions reductions under different policy scenarios. However, their approach uses an input-output framework based on elasticities of substitution across modes for different goods. Austin (2018) studies the effects of fuel and per mile taxes on modal shares and freight-related externalities using historical elasticity estimates and aggregate data on shipments from the 2007 CFS. Here, we model the mode choice decisions of shippers and estimate mode choice parameters directly using detailed microdata from the 2012 CFS PUM, rather than relying on prior estimates.

[3] Earlier studies using microdata typically focus on a small number of goods, modes or geographic areas. For instance, the 2012 CFS PUM is the only publicly available source for the highway mode.

[4] For instance, Goulder, Jacobsen, and Van Benthem (2012) explore the effectiveness of incomplete regulation of automobile fuel economy. Anderson et al. (2011) explore the efficiency of different automobile fuel economy regulations. Jacobsen and Van Benthem (2015) investigate the role of vehicle scrappage in emissions leakage under vehicle fuel economy standards. Austin and Dinan (2005) and Anderson and Sallee (2016) compare the costs of reducing automobile fuel consumption under fuel economy standards and a gasoline tax. Klier and Linn (2013) and Busse, Knittel, and Zettelmeyer (2013) investigate the relationship between fuel prices and new vehicle fuel economy.

[5] For instance, Shapiro (2016) investigates the efficiency and distributional effects of a carbon tax on shipping in international trade. Cristea et al. (2013) estimate emissions due to freight transport in international trade and compare with manufacturing emissions.

Third, we add to the growing literature investigating the rebound or "backfire" effect whereby increases in efficiency lower operating costs of durable goods and increase intensity of use. These effects negate some of the benefits of energy efficiency in reducing overall energy consumption (Borenstein, 2015; Gillingham, Rapson, and Wagner, 2016). In freight markets, the rebound effect consists of changes in demand for freight services, *i.e.* the intensive margin, and changes in shippers' mode choices. Here, we focus on the effect of mode switching, *i.e.* the cross-rebound effect. We show improvements in energy efficiency of one portion of the freight sector, heavy-duty trucks, can lead to substitution away from more efficient modes, partially offsetting gains from energy efficiency. Comparing our results to recent estimates for the rebound effect in the trucking sector suggests mode switching makes up a large share of the total rebound effect.

Overall, our work highlights the important role of mode choice in freight sector energy use and emissions. The remainder of the paper proceeds as follows. Section 2 describes the U.S. freight transportation sector and Section 3 describes our data. Section 4 describes our empirical approach and presents our analysis of fuel prices, mode choice and emissions. Section 5 present our analysis of truck fuel economy standards and the cross-rebound effect. Section 6 presents an alternate identification strategy that exploits time-series variation in fuel prices, supporting our main results that use cross-sectional variation in shipment characteristics. Finally, Section 7 concludes.

2 Industry background

The U.S. freight sector is large and contributes substantially to U.S. carbon emissions. Domestic freight and goods movement contributes approximately 4% to U.S. GDP (Bureau of Transportation Statistics, 2018). Total transportation sector carbon emissions were 1,900 MMT in 2017, surpassing electricity sector emissions (U.S. Energy Information Administration, 2018). Freight's share of transportation carbon emissions is approximately 31%.[6] However unlike passenger vehicles, where fuel economy improvements have largely offset

[6] Authors' calculations using data from Oak Ridge National Laboratory (2018).

demand growth, freight emissions have grown by 13% since the Great Recession.[7]

Domestic freight is shipped by a number of different modes including air, truck, rail, barge, ship, pipeline and parcel/courier.[8] 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 (United States Census Bureau, 2018b). 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.

These shares reflect the substantially different rates, accessibility, speeds, and vehicle capacities across modes. Further, the modes also have vastly different fuel intensities. For instance, while rail can move one ton of freight approximately 450 miles on a gallon of fuel, trucks produce approximately 70 ton miles per gallon and air a little over 0.1 ton miles per gallon. Therefore, shippers' mode choices have large implications for emissions and fuel consumption.

The U.S. freight sector is composed primarily of independent companies who transport raw materials, intermediate and final goods, between producers and final-goods consumers. While some manufacturers, mining and agricultural firms move products short distances using privately-owned trucks, the vast majority of shipments use for-hire carriers.[9] Rates and the use of private contracts versus public tariffs vary by mode and the type of good shipped. In recent years, freight carriers have also instituted fuel surcharge programs whereby total shipping charges include an additional fee indexed to diesel prices creating an automatic mechanism for rates to move up and down with changes in fuel costs.[10]

Parts of the U.S. freight industry have undergone substantial changes over the last sev-

[7]Whereas emissions from passenger vehicles have grown by only 5%, based on authors' calculations using data from U.S. Energy Information Administration (2018).

[8]In the Commodity Flow Survey parcel/courier include shipments of letters or small packages weighing less than 100 lbs. including deliveries made by the U.S. Postal Service.

[9]Private trucks account for approximately 12% of total truck ton-miles (United States Census Bureau, 2018b). Because private and for hire fleets have similar fuel intensities our analysis below combines both trucking segments into a single mode.

[10]For example, see Union Pacific Railroad (2019) and YRC Freight (2019).

eral decades. Increased containerization has reduced costs and losses. It has also enhanced intermodal transportation whereby individual shipments travel by different modes.[11] In the trucking sector, widespread adoption of information and communication technologies have increased service quality and lowered costs through realtime tracking and just-in-time inventory practices. Rail abandonment and consolidation after deregulation in the 1980s eliminated service to some shippers. On the other hand, railroads have made major investments in intermodal terminals, upgraded tunnels and track to compete with the trucking sector on longer distance shipments (Association of American Railroads, 2018).

Finally, the U.S. has recently enacted regulations requiring substantial fuel economy improvements in the trucking sector. In 2011, the U.S. EPA released greenhouse gas and fuel economy standards for medium and heavy duty trucks produced during the 2014-2018 model years. In August 2016, EPA released phase II standards for trucks produced through the 2027 model years. The standards target vehicle, engine and trailer technologies for improving truck fuel efficiency. The U.S. EPA predicts the phase II standards will improve new truck tractor fuel efficiency 11% to 14% by 2021 and 19% to 25% by 2027. Standards related to trailers are expected to improve fuel efficiency by as much as 9% by 2027 (U.S. Environmental Projection Agency, 2016). Because new tractor-trailers are incorporated over time as the fleet turns over, EPA estimates that by 2025 the average fuel intensity across the tractor-trailer fleet will fall by approximately 5% to 6% relative to business as usual.[12] Because improvements in fuel efficiency may increase demand for trucking, the magnitude of the rebound effect is a major factor in determining the overall effectiveness of these policies (U.S. Environmental Projection Agency, 2016).

3 Data

We exploit detailed shipment-level data on freight movements from the U.S. Commodity Flow Survey Public Use Microdata (CFS PUM) file (United States Census Bureau, 2012). The

[11] For instance imports that arrive by sea may travel across the country by rail to lower fuel and labor costs but may be delivered to final destinations by truck.

[12] Our simulations below use 5% as the average effect of truck fuel efficiency standards.

CFS PUM contains administrative data on a sample of approximately 4.5 million shipments that occurred within the U.S. during 2012. Currently, the CFS PUM is only available for a single survey year, 2012. The data contain shipment characteristics including the type of good shipped at the Standard Classification of Transported Goods (SCTG) 2-digit level, shipment value, shipment distance, and shipment 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 at the state or regional level, the quarter during which the shipment occurred, whether the shipment was temperature-controlled, and sampling weights used to expand the sample to approximate the 2012 shipment population.[13] We observe 33 different SCTG commodity groups and several different modes. While prior studies using disaggregate data had much more information on shipment and shipper characteristics, we observe many more shipments for more types of goods than in earlier studies. Our analysis focuses on the major modes, air, truck, rail and inland water, for each commodity group. We treat mixed modes, *i.e.* truck and rail, and truck and barge, as drayage and aggregate these shipments into the main modes, rail and barge.[14]

Table 1 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.[15] 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

[13] 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.

[14] According to United States Census Bureau (2018c) "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 percent and 1 percent for truck-rail and truck-barge, respectively, this assumption is unlikely to substantially impact the results below.

[15] 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.

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.[16] 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 percent 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 SCTG categories that are dominated by a single mode, typically with greater than 99 percent share, such that there are insufficient observations to estimate parameters for competing modes.[17]

The mean characteristics of shipments vary substantially by the type of good shipped. Table 2 summarizes ton-mile weighted-average shipment characteristics for a number of different SCTG categories. 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 PUM. 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 Table 2 highlight important trends in how different types

[16] 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.

[17] These include: meat, poultry and fish; tobacco products; monumental and building stone; electronics, other non-metallic minerals; and furniture.

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 1 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.[18]

Importantly for our empirical strategy below, these trends hide important variation in shipment size, value and mode choice across shipments. For instance, Figure 2 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 commodity groups 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 commodity group, higher value shipments tend to travel on faster modes than lower value shipments.

Finally, to understand the role of fuel prices in mode choice, we collect U.S. national monthly average prices for diesel and jet fuel from the U.S. Energy Information Administration (2017b) and U.S. Energy Information Administration (2017a). Rail, truck and inland water modes all operate primarily on diesel. Air shipments use jet fuel. 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

[18]For instance, Oum (1979) finds that 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. These trends between shipment characteristics and modes have been highlighted by many other authors as well going back to Meyer et al. (1959), if not earlier.

prices (diesel or jet) to individual shipments in the CFS PUM.

4 Mode choices, fuel use and emissions

Because our shipment data are limited to 2012, and because there is relatively little fuel price variation during that year, our empirical model exploits cross-sectional variation in shipment value and size to estimate the relationships that predict shippers' mode choices. Following classic models for freight mode choice (Friedlaender and Spady, 1980, 1981; Levin, 1978; Meyer et al., 1959; Winston, 1981), we assume shippers choose modes to minimize the sum of freight rate, inventory cost and mode-specific fixed cost.[19] Specifically, the cost of shipment i by mode j can be written as:

$$cost_{ij} = \underbrace{\gamma_j \eta_j P_t \times tonmiles_i}_{\text{Rate}} + \underbrace{1/\sigma_j miles_i \times r \times value_i}_{\text{Inventory Cost}} + \underbrace{\delta_j}_{\text{Fixed Cost}} \tag{1}$$

where the first term captures freight rate, the second term represents inventory cost and the final term is mode-specific fixed-cost δ_j. We assume freight rates depend on transportation companies' fuel expenditures and are marked up proportionally at rate γ_j. Fuel expenditure is the product of fuel price (P_t) and fuel consumption ($\eta_j \times tonmiles_i$), where η_j is the mode-specific fuel intensity and $tonmiles_i$ is the size of shipment i. Inventory cost captures the time cost of goods in transit and depends on the shipment distance ($miles_i$), mode-specific speed ($\frac{1}{\sigma_j}$) 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_j^m). This parameter accounts for the fact some shipments have barge access via the Mississippi River system while others do not.[20] For goods that require temperature-controlled storage during transportation, we allow for

[19] We assume shippers' ultimate revenue does not vary by shipment mode such that cost minimization is consistent with profit maximization.

[20] Though rail access also varies by establishment, the geographic areas in the data are much too coarse to infer whether a particular shipment could be made by rail, except of course when we observe that mode directly.

incremental inventory cost (δ_j^{tc}).[21]

Our approach is explicitly short-run in that we assume transportation infrastructure is fixed. Further, we take shipment size as exogenous, *i.e.*, shippers first decide on the quantity of goods to ship and then pick the cost-minimizing mode. The total demand for freight is fixed. These assumptions reflect limitations of our data, whereby we only observe a single year's shipments and the actual characteristics of shipments made during that year and not the full set of options shippers face. That said, we do not restrict possible modes based on shipment size and mode-specific vehicle capacities. In other words, in both our model and data, a single large shipment could potentially travel in one barge, several rail cars or many truck trailers.

In practice, we estimate a reduced form of Equation 1 by replacing the individual unobserved rate and inventory cost parameters with coefficients to be estimated according to:

$$cost_{ij} = \alpha_{cj} P_t \times tonmiles_i + \beta_{cj} miles_i \times value_i + \delta_{cj} + \epsilon_{ij} \tag{2}$$

Because markups, fuel intensities, mode speeds, values of time and fixed costs vary by both the mode and the type of good shipped, we estimate Equation 2 separately for each SCTG c. We estimate Equation 2 as a multinomial logit. Specifically, the probability mode j is selected for shipment i is given by:

$$P(y_i = j|X, \alpha, \beta, \delta) = \frac{exp(\alpha_{cj} P_t \times tonmiles_i + \beta_{cj} miles_i \times value_i + \delta_{cj})}{\sum_{k=1}^{4} exp(\alpha_{ck} P_t \times tonmiles_i + \beta_{ck} miles_i \times value_i + \delta_{ck})} \tag{3}$$

While other specifications impose weaker assumptions than the multinomial logit, our choice is driven by the fact that characteristics for alternate modes that could be used to make a particular shipment are unobserved. 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 endongenity problem is a bit more nuanced than the classic demand estimation concern, *i.e.* that cost shocks are correlated with

[21]This captures factors such as the perishability of certain goods that are reflected in inventory cost.

unobserved mode-specific demand shocks. For instance, if a shock to truck shipment demand affects *diesel prices*, then our estimates of α_{cj} would be biased towards zero. However in this case, our estimates are conservative in the sense that they under-estimate the effects of policies that change fuel prices or energy intensity 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.

To investigate how well our model captures the behavior of shippers observed in the CFS PUM, we simulate 500 mode choices for each shipment by taking the value of the latent variable and bootstrapping the extreme value error term. We assume shippers choose the mode with the highest predicted probability. Table A1 in the supplementary appendix presents the total ton-miles transported by mode for each SCTG. Beside the CFS data we present the mean ton-miles by mode and SCTG averaged across our simulations. We see that the mean predicted values match the CFS totals very well. For trucks, the predicted ton-miles across SCTG's are all within 2% of the CFS totals, with most predictions matching the CFS totals much more closely. For rail, the predicted totals are all within 6%, though again most estimates match the CFS totals much more closely. We somewhat over-predict truck ton-miles and under-predict rail ton-miles, though the totals across all goods are within 0.6% to 0.8% of CFS totals. The model does less-well fitting water and air shipments. However, this is less of a concern since these modes make up a relatively small share of total ton-miles and hence fuel consumption and emissions. Overall, these results suggest our model provides a good fit to the aggregate patterns in the data.

Next, we explore how fuel prices affect mode choices on the margin. In Equation 2, α_{cj} captures how changes in fuel costs affect the probability mode j is selected. Therefore, we can use our estimates of α_{cj} to understand how changes in fuel prices, *e.g.* oil market volatility or carbon pricing, impact shippers' mode choices. Here we are relying on the fact fuel costs are proportional to the product of fuel price and ton-miles. Since there is little fuel price variation in 2012, α_{cj} is identified (mainly) by cross-sectional variation in ton-miles.

Therefore, the fuel price simulations implicitly assume changes in fuel price and shipment size have equivalent effects on mode choice. We relax this assumption in Section 6 where we estimate α_{cj} using cross-sectional variation in ton-miles plus time-series variation in fuel prices.

Because space limitations prevent us from presenting results for every SCTG, we illustrate our approach using results for several representative goods. Other SCTGs exhibit similar modal substitution patterns, though the specific ranges depend on characteristics of those goods. The parameter estimates for these representative goods are presented in Table A2 of the supplemental appendix. Here, we focus our discussion on the marginal effects of fuel price changes on mode choice probabilities.

Table 3 presents average marginal effects of a change in diesel fuel price for different bins of grain shipment size, on the left, and coal shipment size, on the right. The columns show the effects by mode. The first column shows the effect on truck mode choice probability. The second and third columns show effects for rail and inland water and so on. We begin by looking at grain shipments. For small shipments, 10,000 ton miles, an increase in fuel price is associated with a small decrease in the probability truck is used and a small increase in the probability rail is selected. Similarly for large shipments, 70,000 or 80,000 ton miles, an increase in fuel price leads to a small decrease in the probability truck is used and a small increase in the probability rail is selected. However, for intermediate-sized shipments, higher fuel prices are associated with large changes in mode choice probabilities. For shipments of 30,000 to 40,000 ton miles, a one dollar increase in diesel price is associated with a 22 to 24 percentage point decrease in the probability truck is used and a 21 to 24 percentage point increase in the probability the shipment moves by rail. There is also a small increase in the probability inland water is selected.

This suggests there is a range of grain shipment size where truck and rail are close substitutes. We see this visually in Figure 3 that plots the fitted mode choice probabilities for grain shipments by truck, rail and inland water.[22] The points above the truck curve and below the rail curve for small shipments correspond to relatively high value goods that tend to

[22]To simplify Figures 3, 4 and 5 we ignore diesel excise tax exemptions for rail and use a single diesel price for all modes.

travel by faster modes, all else equal, consistent with the overall patterns described previously. The gray markers show fitted mode choice probabilities for 2012 fuel prices. The colored markers show estimates assuming a 25 percent increase in fuel prices. For small shipments, the probability grain moves by truck is nearly one. For large shipments, the rail probability approaches one. However for intermediate-sized shipments, the fitted probabilities for truck and rail are roughly equal. Increasing fuel price increases the likelihood rail is selected and decreases the likelihood truck is selected, shifting both curves to the left.

Looking at coal shipments, the righthand side of Table 3 shows marginal effects of a fuel price increase for shipment sizes ranging from 60,000 to 200,000 ton miles. This range corresponds to small coal shipments where truck is competitive with rail and barge. For shipments ranging from 140,000 ton-miles to 180,000 ton miles, a one dollar increase in diesel price is associated with an approximately 20 to 21 percentage point decrease in the probability truck is used but a 13 to 14 percentage point increase in the probability the shipment moves by rail and a 6 to 7 percentage point increase in the probability it moves by barge. However for large coal shipments, rail and barge are the preferred modes and fuel price changes have more modest effects on mode choice probabilities. We see this in Figure 4, which plots the fitted mode choice probabilities for coal shipments at 2012 prices, again in gray, against probabilities with a 25% increase in fuel price. Truck share is essentially zero for shipments over several hundred thousand ton miles. The probability rail is selected grows from about 70% for shipments of several hundred thousand ton miles to over 80% for shipments of 6 million ton-miles. Barge shipments make up the difference and decline as shipment size increases. This feature is likely a consequence of geographic factors where the maximum distance of barge shipments is limited by navigable waterways in the eastern United States. While fuel price increases shift coal shipments to more efficient modes at smaller shipment sizes, for large shipments, fuel price increases lead to small shifts from barge to rail. Since these larger shipments are more energy intensive, overall we expect relatively modest reductions in fuel consumption and emissions from fuel price changes in coal transportation.

Next, we look at two relatively higher value commodity groups, alcohol and precision instruments. Truck is the dominant mode for shipments of both these goods. However, a large share of alcohol moves by rail. Air is a competitive mode for some shipments of precision instruments. Table 4 shows the marginal effects of fuel price changes for these modes over a range of shipment sizes. For alcohol shipments of around 60,000 ton miles the probabilities truck or rail are selected are approximately equal. In this range of shipment size, changes in fuel price have a very large impact on mode choice probabilities. For shipments of 60,000 to 80,000 ton-miles, a one dollar increase in diesel price is associated with a 32 to 51 percentage point increase in the probability rail is selected. We see this visually in Figure 5 that shows a large shift from truck to rail for intermediate-sized shipments when fuel prices increase. Shipments in this range are a mix of beverages, that are small in terms of tons but travel long distances, often 2000 miles, and fuel ethanol shipments that can be several hundred tons but travel shorter distances. As shipment sizes grow larger, rail dominates and fuel price changes have little effect on mode choice. These shipments are primarily fuel ethanol produced in the midwest and shipped by rail to East Coast and West Coast destinations. The large marginal effects for rail and truck, and the relatively large shipment sizes, suggest fuel price changes will lead to large shifts in fuel consumption and emissions.

In contrast, mode choices for shipments of precision instruments are relatively insensitive to changes in fuel price. We see this both in Table 4 and Figure 6, where fuel price increases yield small increases in the probability truck is selected across a range of shipment sizes. There is a large range of good values within this SCTG. This appears as range of predicted probabilities, i.e. the scatter in Figure 6 compared with, for instance, grain in Figure 3 that is much more homogenous in terms of value. This fact, combined with the large difference in average speed between truck and air, suggests many shipments are well suited to one mode and the alternative is a poor substitute. For instance, the mean value of precision instruments shipped by air is approximately $700 per pound versus $200 per pound for precision instruments shipped by truck. This is in contrast to a good like grain where the mean value of goods shipped by truck is $0.32 per pound versus $0.14 per pound for grain shipped by rail. We see further evidence that truck and rail are poor substitutes on the righthand side of Table 4. The largest marginal effects occur for shipments around 1,000 to 2,000 ton miles in size. Here, a one dollar increase in diesel price is associated with a 1 to

2 percentage point increase in the likelihood truck is selected over air. Overall, the small marginal effects and small shipment sizes suggest fuel price changes will have modest effects on fuel consumption and emissions.

To understand the potential for fuel and emissions reductions, we use our parameter estimates from the CFS PUM to simulate mode choices under several fuel price scenarios, again employing the bootstrapping procedure outlined above. Then, for each shipment we calculate fuel consumption and emissions from shipment size, in ton miles, and the fuel intensity of the predicted mode.[23] When shipments switch modes we adjust ton-miles to reflect mean differences across models.[24] We repeat this procedure for several fuel price scenarios. Table 5 summarizes total ton miles, fuel consumption and emissions across the different scenarios, averaged over the simulated mode choice experiments. Consistent with the marginal effects discussed previously, higher fuel prices increase the share of shipments made by rail and decrease truck share. This modal substitution yields substantial reductions in fuel use and emissions.

Under the business as usual scenario, using 2012 fuel prices, rail output is approximately 1.27 trillion ton miles while truck output is approximately 1.12 trillion ton miles. Total fuel consumption is approximately 16.4 billion gallons and total emissions are 166 million metric tons of carbon dioxide. A 10% increase in fuel price increases rail ton miles to approximately 1.29 trillion and lowers truck ton miles to approximately 1.10 trillion. This shift lowers fuel consumption and carbon emissions by approximately 1.6%. Similarly, larger fuel price increases of 25%, 50% and 100%, lower fuel consumption by 3.7, 6.9 and 12.0%, respectively. A doubling of fuel price increases rail's share of ton-miles from approximately half to nearly 60 percent.

[23]For rail we assume a fuel intensity of 1/450 gallon per ton mile consistent with Oak Ridge National Laboratory (2018) and Association of American Railroads (2019). There is more uncertainty about the real world energy intensity of freight movements by heavy duty truck, air and barge. We use 1/85 gallon per ton mile for truck (Cristea et al., 2013; U.S. Environmental Projection Agency, 2016), 1/7.5 gallon per ton mile for air consistent with Cristea et al. (2013) and 1/600 gallon per ton mile for barge (Kruse, Warner, and Olson, 2017).

[24]For instance, truck distances tend to be less between a given origin and destination, all else equal, due to more direct routing of truck shipments relative to rail. Though this effect is reflected in the mode choice parameter estimates (α_{cj}), the shipment characteristics must be adjusted for the fuel use and emissions calculations. 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.

The magnitude of fuel and emissions reductions vary across the types of goods shipped. Figure 4 shows the percentage reduction in carbon emissions by SCTG for a 10% increase in fuel price. Panel (a) plots the percentage reduction against shipment value in dollars per pound. Panel (b) plots the percentage reduction against shipment size in ton miles. The relationship between value and carbon reduction has an inverted u-shape. Reductions peak between 2.5 and 3.5 percent for pulp, newsprint, paper and paperboard; alcohol; basic chemicals; and milled grain, each with a mean value of approximately one dollar per pound.[25] Emissions decrease sharply for lower-valued goods and somewhat more flatly for higher-valued goods. Similarly, in panel (b), emissions reductions peak for goods with mean shipment sizes of several hundred-thousand ton-miles. Overall, this suggests moderately-valued goods traveling intermediate distances show the greatest potential for truck to rail switching and hence fuel use and emissions reductions.

5 Fuel economy standards and the rebound effect

The results above highlight an important mechanism in shippers' responses to policies such as fuel economy standards for heavy-duty vehicles. Recent estimates for the heavy-duty vehicle rebound effect in the U.S. range from effectively zero (Winebrake et al., 2015) to between 20 and 30 percent (Leard et al., 2015).[26] Estimates from other parts of the world suggest rebound effects of similar magnitudes. For instance Matos and Silva (2011) estimate the total direct rebound effect for road freight in Portugal to be approximately 24 percent. De Borger and Mulalic (2012) estimate effects between 10 and 17 percent in Denmark. Sorrell and Stapleton (2018) estimate larger effects, between 49 and 61 percent, for the UK. Since our cross-sectional approach lacks an intensive margin, we focus on the mode shifting component of the total effect. However, the results below suggest the cross-rebound effect

[25] Emissions for shipments of animals fall by approximately 12.5%, but are omitted to simplify these figures.

[26] Leard et al. (2015) estimate an elasticity of vehicle miles traveled (VMT) with respect to fuel cost of approximately -0.2. Combined with an elasticity of truck count with respect to fuel cost of approximately -0.10, this yields an overall VMT effect of approximately 30 percent. The authors also estimate the effect in terms of ton-miles of freight transported, which is more comparable to what we estimate here. In that case, the ton-mile elasticity is approximately -0.20 with a small statistically insignificant effect on truck counts. This suggests an overall effect in terms of ton-miles of approximately 20 percent.

represents a substantial share of the overall effect.

To illustrate the importance mode choice and the rebound effect, we analyze heavy-duty truck fuel economy standards that approximate recent U.S. policies. Our estimates above imply improvements in truck fuel economy will shift some freight movements from more fuel-efficient rail transportation to less fuel-efficient trucks. We adapt the approach in Section 4 to analyze the impact of truck fuel economy standards. This requires somewhat stronger assumptions. Because fuel economy standards change the fuel intensity of freight movements, we must first separate out the effect of fuel intensity from the rate term in Equation 2. Then, by varying truck fuel intensity, holding all other factors constant, we can predict mode choices, shares, fuel use and emissions. We rewrite Equation 2 as:

$$cost_{ij} = \gamma_j \eta_j P_t \times tonmiles_i + \beta_{cj} miles_i \times value_i + \delta_{cj} + \epsilon_{ij}. \tag{4}$$

Here, we use the same fuel intensities η_j as in the base model, discussed in footnote 23. Note that we now have alternative-specific data ($\eta_j P_t \times tonmiles_i$) on fuel expenditures across modes. However, shipment distances and values do not vary across modes. Therefore, we use a mixed-logit approach in estimating the parameters of Equation 4. We follow the same simulation approach described above, first estimating the parameters of Equation 4, then bootstrap the error to yield 500 simulated mode choices for each shipment.

Table A3 in the supplementary appendix compares the predicted modal shares using our mixed logit parameter estimates with the CFS PUM shares. As in Table A1, we present mean ton-miles across our simulations by SCTG. In general, the predictions match the CFS PUM shares fairly well. Predicted total truck ton miles are within .9% of the CFS PUM total and rail ton miles are within 3.8%. The mixed logit systematically over-predicts barge ton-miles for a number of SCTGs including basic chemicals, coal, fertilizers and grain. As a result, we overestimate barge share and underestimate fuel use and carbon emissions 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 mixed logit specification in this application. That said, it is because of this limitation that we prefer the multinomial logit approach for our main results above.

To see the effect of fuel economy regulation we impose a 5 percent reduction in truck fuel intensity and use our estimates to simulate shippers' mode choices. We recalculate the latent value with the lower fuel intensity parameter and pick the most probable mode for each shipment and each error draw. We then compute fuel consumption and emissions in two cases. The first imposes the 5 percent reduction in truck fuel intensity but uses the business as usual mode choice predictions, *i.e.* assumes more fuel efficient trucks do not affect shippers' mode choices. This is equivalent to assuming zero rebound since total shipments are fixed. The second imposes the 5 percent reduction in energy intensity and allows mode shares to adjust to changes in relative fuel efficiency. These results are shown in Table 6

Truck fuel economy regulation shifts freight shipments from rail to truck, approximately 16 billion ton miles or approximately 1.3% of business-as-usual rail freight output. This shift substantially reduces the effectiveness of truck fuel economy regulations. Without mode shifts, shown in the middle column of Table 6, truck fuel consumption would decrease by approximately 650 million gallons and total freight emissions would fall by 4%. However, modal substitution from rail to truck erodes these gains substantially such that fuel consumption and emissions fall by only 3.3%. This implies a "cross-rebound" effect of approximately a 18%. This effect takes into account shippers' re-optimization across modes (truck, rail, air and barge) due to improved truck fuel economy plus the differences in energy intensities across modes. Compared to the range of estimates for the total direct rebound effect reported above, approximately zero to 30 percent in the U.S., this suggests mode-shifting accounts for a large share of the overall effect.[27]

The effects are heterogenous across SCTGs depending on where truck and rail are better substitutes. Figure 8 plots estimates of the cross-rebound effect by SCTG. To provide a sense of magnitudes, the size of each bubble represents business-as-usual emissions for that SCTG. We see that the cross-rebound effect varies substantially across goods. For pulp, newsprint paper and paperboard; basic chemicals; fertilizers; and alcohol, the cross-rebound effect is approximately 50 percent, *i.e* the actual emissions reductions are approximately half of what

[27] The remainder coming from the intensive margin.

would be expected without modal substitution. For other prepared foodstuffs, grain, milled grain and sand the cross-rebound effect is approximately 30 percent. The effect is essentially zero for commodities such as waste and scrap, coal, mixed freight and printed products. Interestingly, air freight also responds to changes in truck fuel efficiency. As a result there are *negative* cross-rebound effects for shipments of animals and precision instruments achieve due to substitution from air freight to truck when truck fuel efficiency improves.

These results highlight the importance of considering shippers' mode choice behavior and the associated rebound effect in modeling the impacts of transportation sector energy and emissions policies. Similarly, policies that affect speeds of different modes via urban traffic congestion or infrastructure improvements are also likely to affect mode choices through inventory costs. Overall, modal substitution has important implications for understanding the direct and indirect impacts of transportation sector policies.

6 Validity of cross-sectional variation used to identify main results

Our parameter estimates above rely mainly on cross-sectional variation in shipment characteristics. While we argue both changes in shipment size and fuel price cause similar effects on shippers' incentives to use different modes, one may still be concerned fuel price changes lead to different substitution patterns than those coming from cross-sectional variation in shipment size. Further, longer run responses to fuel price changes may be different from those reported above. To explore the robustness of our main results to alternate identification, we exploit aggregate date from public tabulations of the 2002, 2007 and 2012 CFS surveys (United States Census Bureau, 2018a).

The public CFS tabulations present a trade-off. This period provides substantial variation in fuel prices, which range from \$1.55 per gallon in 2002 to \$3.77 per gallon in 2012. However, the public tabulations only report modal totals by origin and destination state. In other words, we observe total tons, ton miles and value by mode and SCTG between Iowa and

Illinois, for instance, but not individual shipments. A second limitation arises because the Census Bureau redacts a large number of observations in the public tabulations to protect shipper confidentiality. We suspect these missing observations are not randomly distributed, but instead disproportionally affect smaller or more concentrated freight markets. In sum, the approach presented here gains variation in fuel prices but introduces the strong possibility of aggregation and selection bias.

Despite these limitations, the tabulated data allow us to test our main estimation strategy. Specifically, we estimate a model for cost-minimizing shippers analogous to Equation 2 above. However because the data are aggregated, we model modal shares for SCTGs transported between different geographic regions (Levin, 1978). Specifically, we rewrite Equation 2 as:

$$cpt_{rjt} = \alpha'_j P_t \times \overline{miles}_{rjt} + \beta'_j \overline{miles}_{rjt} \times vpt_{rjt} + \delta'_j + \epsilon_{rjt} \tag{5}$$

where $\overline{miles}_{rjt}$ is the average shipment distance between origin and destination route r. Note that data aggregation requires a different interpretation of shippers' mode choice decisions. Here, we imagine shippers choose modes to minimize the *cost per ton* (cpt_{rjt}) of transporting a particular good along a given route r. This assumption is driven by the fact we only observe average shipment distances and total tons, ton miles and value. Conceptually, Equation 5 is the result of dividing Equation 2 by shipment tons and noting the data come from averages over a number of individual shipments.

We employ a similar procedure to that described above, estimating Equation 5 separately for each commodity group, then simulating 500 mode choices by bootstrapping the error. This approach yields estimates of the overall effects of fuel price increases in line with, though slightly larger than, those presented previously. Table 7 presents modal shares, total fuel use and emissions for business as usual and different fuel price scenarios. Note the fuel, emissions and ton miles totals are not directly comparable to those in Table 5 due to the missing observations discussed previously and the fact we pool observations across years. However, we see estimated fuel use and emissions reductions are comparable to those using the 2012 microdata and cross-sectional variation. A 10% increase in fuel price is associated with a 1.5% decrease in fuel use and emissions. Fuel price increases of 25, 50 and 100%

are associated with reductions of 3.7, 7.1 and 13.0%, respectively. While we are hesitant to put too much emphasis on specific magnitudes, the somewhat larger estimated effects in the panel are consistent with longer-run responses to fuel price changes. More importantly, the fact different data and identifying variation yield results similar to those reported above supports our preferred estimation strategy.

7 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. Yet, compared with other sectors such as passenger vehicles or electricity, relatively little is known about freight responses to energy policies. This is especially true in light of recent changes to freight modes and infrastructure that likely affect how shippers choose modes.

Here, we exploit newly available shipment-level data on millions of shipments that occurred in the U.S. during 2012. We estimate a series of discrete choice models describing how changes in rates, via fuel prices, and inventory costs affect mode choice. We first document 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, means many shipments are likely to shift to more fuel efficient modes when fuel prices increase. Using our parameter estimates, we predict modest fuel price changes yield substantial reductions in fuel consumption and emissions. For instance, across all the shipments we study, we find a 10% increase in fuel price is association with a 1.6% decrease in fuel consumption and emissions. In some goods categories, the emissions reductions can be two to three times larger. An alternate approach using more aggregate data but with more meaningful time-series variation in fuel prices, yields similar though somewhat larger estimated emissions reductions.

We use the recent example of heavy-duty vehicle fuel economy regulations to highlight the importance of modeling freight mode choice in transportation policies. In our example, policies that improve the fuel economy of trucks can cause some shipments that would have traveled by more efficient rail transport to instead travel by truck. We call this effect a "cross-rebound" effect. This effect is large relative to estimates of the total heavy-duty vehicle rebound effect. We show how an analysis of truck fuel economy standards that ignores this mechanism can substantially overstate fuel and emissions savings. Our model suggests policies that change the relative speeds of modes, for instance due to changes in traffic congestion, could lead to similar unanticipated consequences.

Overall, we demonstrate freight mode choice is an important factor in understanding responses to energy and climate policies. Our analysis highlights the benefits of using detailed micro-level data on a variety of goods to understand shippers' mode choices. The short-run analysis presented here provides valuable insight into these choices but likely represents a lower-bound on shippers' long-run responses to economic and policy changes in the U.S. freight sector.

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Figures

Figure 1: Relationships between modes and mean shipment characteristics.

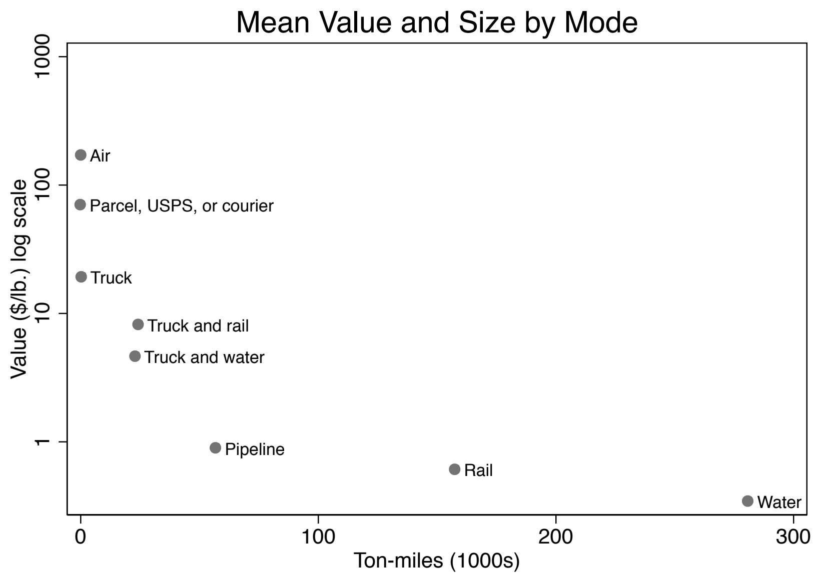


Figure 2: Truck, rail and barge mode shares by grain shipment size.

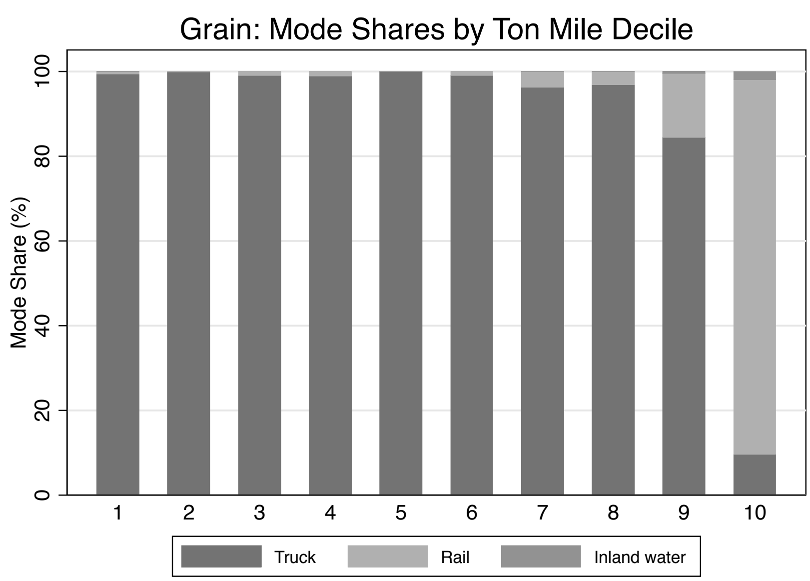


Figure 3: The effect of higher diesel prices on predicted truck, rail and barge choice probabilities for grain shipments.

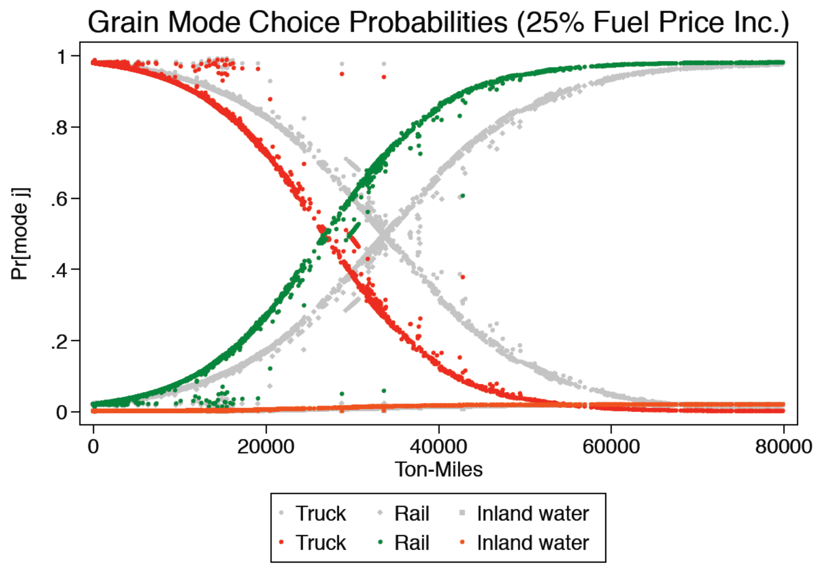


Figure 4: The effect of higher diesel prices on predicted truck, rail and barge choice probabilities for coal shipments.

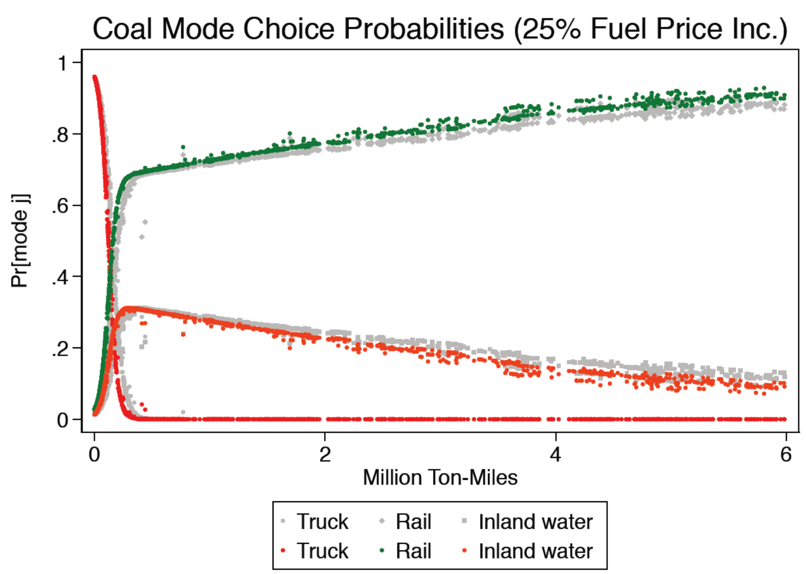


Figure 5: The effect of higher diesel prices on predicted truck and rail choice probabilities for alcohol shipments.

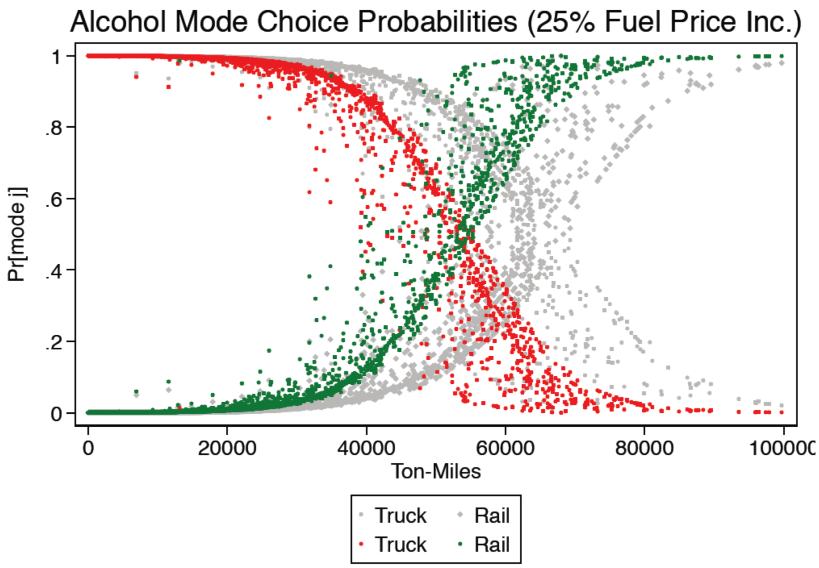


Figure 6: The effect of higher diesel prices on predicted truck and air choice probabilities for precision instrument shipments.

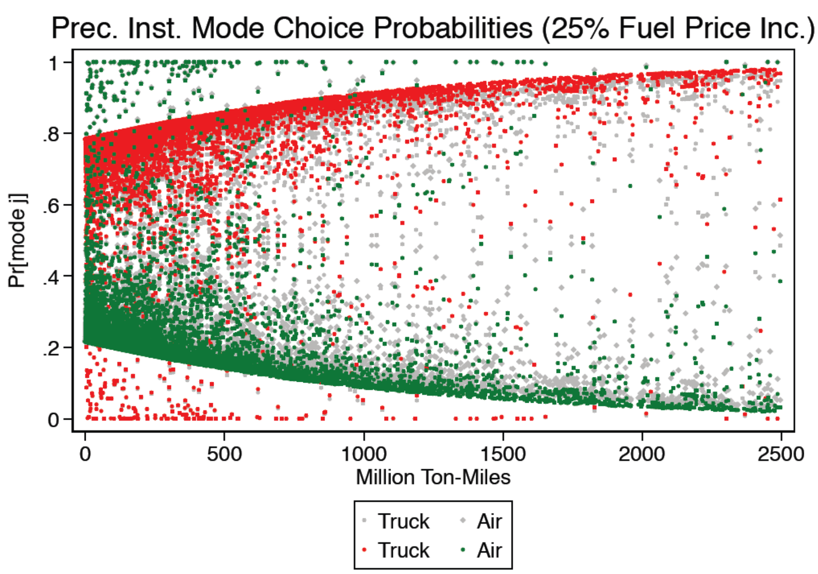
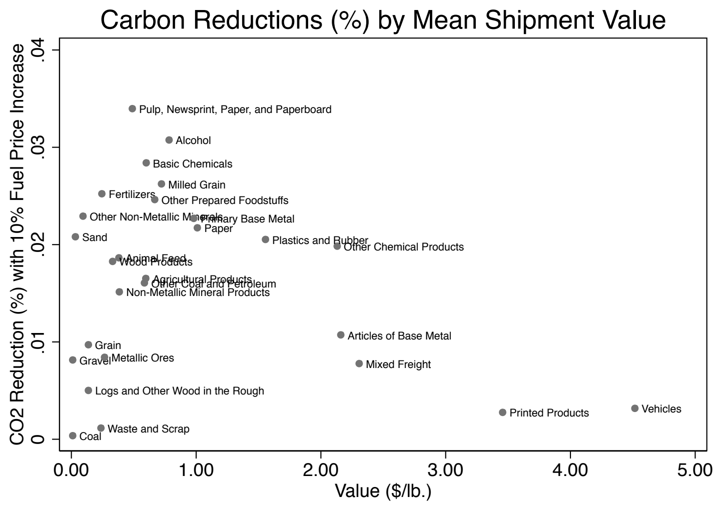


Figure 7: Heterogeneity in carbon reductions by mean good characteristics.

(a) Mean shipment value



(b) Mean shipment ton-miles

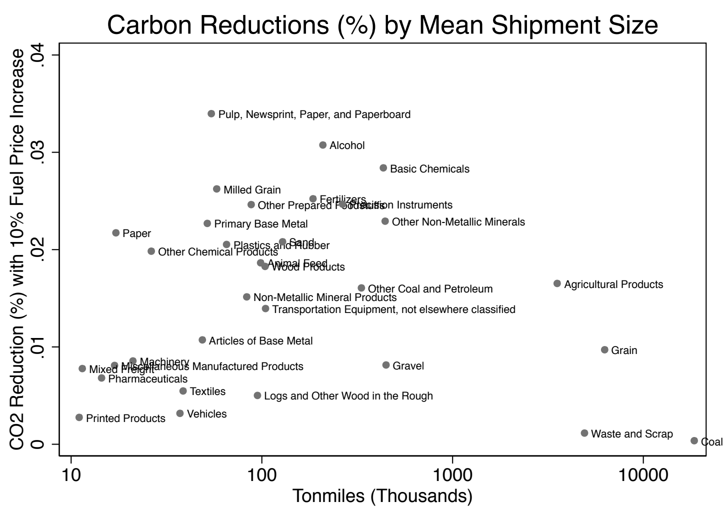
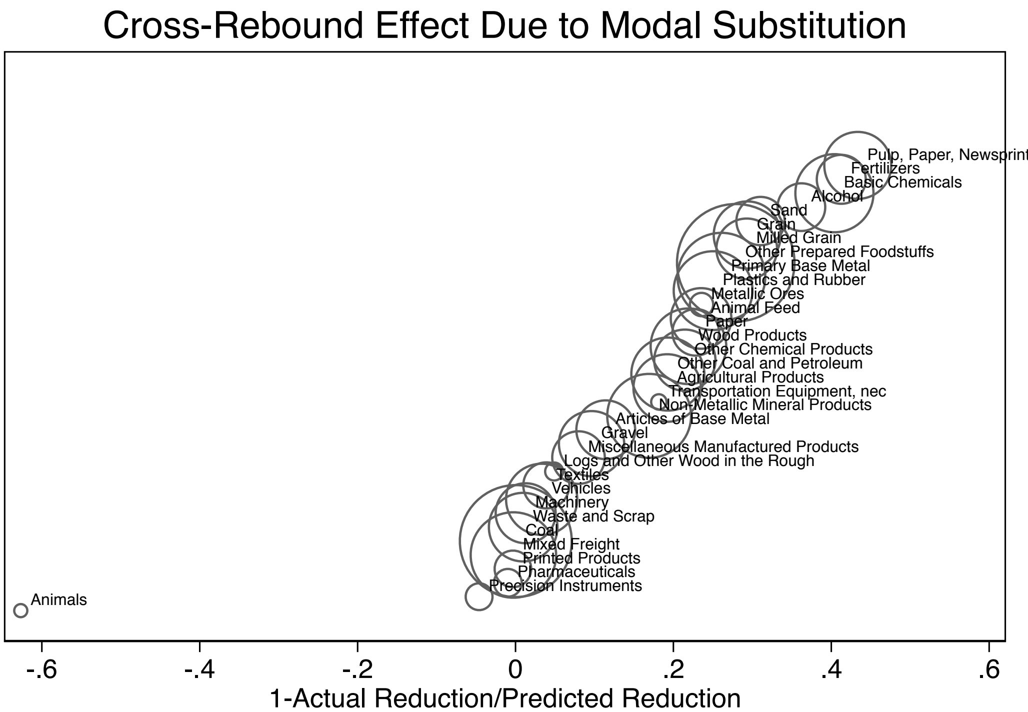


Figure 8: Rebound effect due to modal substitution ("cross-rebound") under truck fuel economy regulations. Bubble sizes reflect BAU emissions by SCTG.



8 Tables

Table 1: Summary statistics and modal shares in weighted and unweighted samples.

	Unweighted			
	Mean	Std. Dev.	Min.	Max.
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 2: Mean shipment value, weight, distance and mode shares for selected goods.

	Ton Mile Wgt. Avg			Mode Share					
Commodity Group	Value ($/lb.)	Miles	Tons	Air	Pipeline	Rail	Truck	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

Table 3: Marginal effects of a fuel price change on mode choices for grain and coal shipments.

Effect of Diesel Price on Mode Choice Probabilities

	Grain Shipments				Coal Shipments		
	Truck	Rail	Inland Water		Truck	Rail	Inland Water
10,000 Ton-Miles	-0.020	0.019	0.001	60,000 Ton-Miles	-0.041	0.029	0.013
	(0.008)	(0.008)	(0.000)		(0.046)	(0.033)	(0.015)
20,000 Ton-Miles	-0.096	0.093	0.003	80,000 Ton-Miles	-0.074	0.051	0.023
	(0.042)	(0.041)	(0.001)		(0.083)	(0.059)	(0.028)
30,000 Ton-Miles	-0.219	0.214	0.005	100,000 Ton-Miles	-0.116	0.080	0.036
	(0.053)	(0.053)	(0.002)		(0.120)	(0.084)	(0.042)
40,000 Ton-Miles	-0.2420	0.2380	0.0040	120,000 Ton-Miles	-0.160	0.110	0.050
	(0.046)	(0.043)	(0.003)		(0.132)	(0.091)	(0.050)
50,000 Ton-Miles	-0.144	0.142	0.0020	140,000 Ton-Miles	-0.196	0.134	0.062
	(0.095)	(0.093)	(0.002)		(0.098)	(0.067)	(0.047)
60,000 Ton-Miles	-0.060	0.059	0.001	160,000 Ton-Miles	-0.213	0.145	0.068
	(0.063)	(0.062)	(0.001)		(0.029)	(0.027)	(0.036)
70,000 Ton-Miles	-0.022	0.021	0.000	180,000 Ton-Miles	-0.208	0.140	0.067
	(0.029)	(0.029)	(0.000)		(0.089)	(0.068)	(0.040)
80,000 Ton-Miles	-0.007	0.007	0.000	200,000 Ton-Miles	-0.185	0.125	0.060
	(0.012)	(0.012)	(0.000)		(0.166)	(0.118)	(0.057)
Observations	24817	24817	24817		10602	10602	10602

Notes: Average marginal effects for a change in diesel price on mode choice probability evaluated at different shipments sizes (ton-miles). Marginal effect evaluated at the means of shipment value and miles. Stardard errors clustered at the route-level in parentheses.

Table 4: Marginal effects of a fuel price change on mode choices for alcohol and precision instrument shipments.

Effect of Diesel Price on Mode Choice Probabilities

	Alcohol			Precision Instruments	
	Truck	Rail		Truck	Air
30,000 Ton-Miles	-0.009	0.009	500 Ton-Miles	0.020	-0.020
	(0.003)	(0.003)		(0.004)	(0.004)
40,000 Ton-Miles	-0.037	0.037	1,000 Ton-Miles	0.023	-0.023
	(0.014)	(0.014)		(0.002)	(0.002)
50,000 Ton-Miles	-0.128	0.128	1,500 Ton-Miles	0.018	-0.018
	(0.054)	(0.054)		(0.004)	(0.004)
60,000 Ton-Miles	-0.332	0.332	2,000 Ton-Miles	0.013	-0.013
	(0.110)	(0.110)		(0.006)	(0.006)
70,000 Ton-Miles	-0.508	0.508	2,500 Ton-Miles	0.009	-0.009
	(0.031)	(0.031)		(0.005)	(0.005)
80,000 Ton-Miles	-0.405	0.405	3,000 Ton-Miles	0.005	-0.005
	(0.122)	(0.122)		(0.004)	(0.004)
90,000 Ton-Miles	-0.201	0.201	3,500 Ton-Miles	0.003	-0.003
	(0.116)	(0.116)		(0.003)	(0.003)
100,000 Ton-Miles	-0.079	0.079	4,000 Ton-Miles	0.002	-0.002
	(0.060)	(0.060)		(0.002)	(0.002)
	121138	121138	Observations	40807	40807

Notes: Average marginal effects for a change in diesel price on mode choice probability evaluated at different shipments sizes (ton-miles). Marginal effect evaluated at the means of shipment value and miles. Stardard errors clustered at the route-level in parentheses.

Table 5: Simulated fuel and emissions reductions from modal substitution for 2012 Public Use Microdata file.

Fuel Prices, Fuel Use and Emissions

	BAU	10%	25%	50%	100%
Air (billion ton-miles)	1.68	1.58	1.47	1.34	1.16
Inland water (billion ton-miles)	97.65	101.75	108.31	119.37	138.26
Rail (billion ton-miles)	1,265.09	1,292.23	1,329.13	1,381.85	1,466.52
Truck (billion ton-miles)	1,121.88	1,095.38	1,058.54	1,004.59	916.89
Fuel (million gal.)	16,397	16,138	15,783	15,267	14,431
Emissions (MMT)	166.46	163.84	160.24	155.01	146.53
Percent change		-1.6%	-3.7%	-6.9%	-12.0%

Table 6: Simulated ton-miles, fuel use and emissions under truck fuel economy regulation.

Fuel Prices, Fuel Use and Emissions	BAU	No Rebound	With Modal Sub.
Ton-miles			
Air (billion ton-miles)	1.58	1.58	1.57
Inland water (billion ton-miles)	126.56	126.56	126.43
Rail (billion ton-miles)	1,216.82	1,216.82	1,200.55
Truck (billion ton-miles)	1,110.11	1,110.11	1,124.74
Fuel			
Air (million gal.)	210.01	210.01	208.84
Inland water (million gal.)	210.93	210.93	210.71
Rail (million gal.)	2,704.04	2,704.04	2,667.89
Truck (million gal.)	13,060.15	12,407.14	12,570.59
Emissions			
Air (MMT)	2.01	2.01	2.00
Inland water (MMT)	2.14	2.14	2.14
Rail (MMT)	27.47	27.47	27.11
Truck (MMT)	132.69	126.06	127.72
Fuel (million gal.)	16,185	15,532	15,658
Emissions (MMT)	164.32	157.68	158.96
Percent change		4.0%	3.3%

Table 7: Simulated fuel and emissions reductions from modal substitution for the 2002, 2007 and 2012 public tabulations.

Fuel Prices, Fuel Use and Emissions	BAU	10%	25%	50%	100%
Air (billion ton-miles)	45.62	45.59	45.56	45.51	45.45
Inland water (billion ton-miles)	610.82	635.27	668.51	714.49	778.88
Rail (billion ton-miles)	3,431.56	3,489.38	3,573.58	3,711.50	3,962.24
Truck (billion ton-miles)	2,327.30	2,259.63	2,162.59	2,009.17	1,743.06
Fuel (million gal.)	42,106	41,476	40,572	39,144	36,670
Emissions (MMT)	424.21	417.81	408.63	394.12	368.99
Percent change		-1.5%	-3.7%	-7.1%	-13.0%

Supplementary appendix

A Abatement costs of freight mode substitution

To get a sense for the cost-effectiveness of freight mode substitution relative to our sources of carbon reduction, we construct marginal abatement cost curves by simulating mode choices and carbon emissions reductions for incremental carbon taxes up to \$100 per MT CO_2. We assume the tax is levied upstream and is fully passed through to transportation firms.[28] Appendix Figure A1 shows marginal abatement cost (MAC) curves for several representative SCTGs, panel (a), and the aggregate MAC curve, panel (b). Over this range of taxes, the marginal abatement cost curve is approximately linear, a tax of \$50/MT CO_2 yields approximately 3.3 MMT while a tax of \$100/MT CO_2 produces approximately 6.4 MMT of abatement. As before, the curves for individual SCTGs reveal interesting heterogeneity. The curves for coal and grain are quite steep owing to the fact the largest, and therefore most carbon intensive shipments of these goods already travel by rail. Similarly, the curve for precision instruments is steep as fuel price increases are insufficient to outweigh the high inventory costs these high-value goods would incur if switched from air to truck. A tax of \$50/MT CO_2 yields reductions less than 0.05 MMT in each case. Basic chemicals, prepared foodstuffs and primary base metals are moderately less steep. A tax of \$50/MT CO_2 yields abatement of approximately 0.25 to 0.50 MMT in each case.

Because our estimates focus on modal substitution, it is difficult to compare our results to prior studies that allow for more responses to carbon policy. Specifically, because we hold total shipments fixed, we ignore responses on the extensive margin. That said, comparisons with recent estimates of the heavy-duty vehicle rebound effect suggest the intensive margin response is small. Therefore, while it seems reasonable to interpret our estimates as a lower bound for emissions reductions from mode shifting in the U.S. freight sector, the mechanism we study here likely represents a substantial share of the overall response to higher fuel or

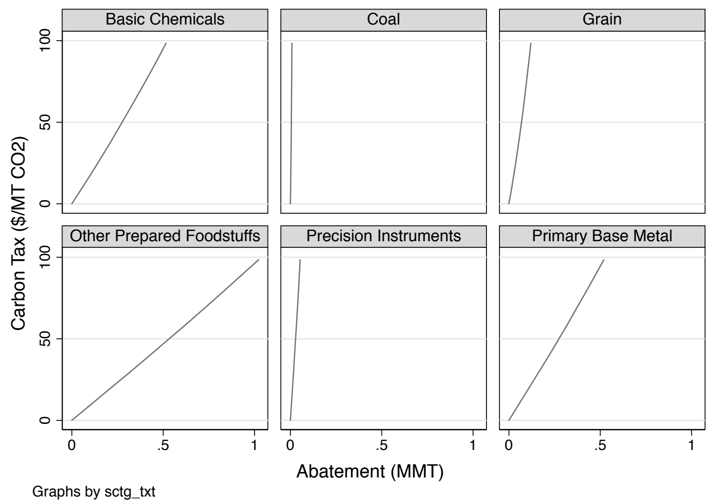
[28] Recent work by Marion and Muehlegger (2011) shows that while the pass-through rate of a diesel fuel tax depends on market conditions, on average the rate is approximately one. We use 10.16 kg CO_2 per gallon as the carbon intensity of diesel fuel.

carbon prices.

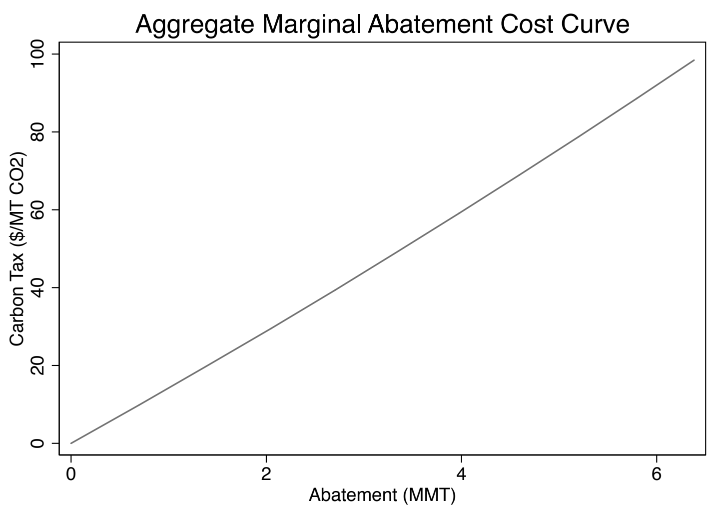
B Appendix figures

Figure A1: Marginal abatement costs of a CO_2 tax.

(a) Representative goods



(b) Aggregate



C Appendix tables

Table A1: Observed (CFS PUM) ton miles by SCTG and mode compared with mean predicted values, multinomial logit.

	Truck		Rail		Water		Air	
Commodity Group	CFS	Pred.	CFS	Pred.	CFS	Pred.	CFS	Pred.
Agricultural Products	38.5	38.6	28.9	27.8	16.1	17.2	0.0	0.0
Alcohol	20.6	20.6	12.9	12.8	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	46.4	72.9	72.1	13.1	13.4	0.0	0.0
Coal	9.8	9.9	603.2	601.7	23.2	24.6	0.0	0.0
Fertilizers	17.8	18.0	32.0	31.7	1.5	1.5	0.0	0.0
Grain	17.5	17.8	136.8	135.4	15.3	16.4	0.0	0.0
Gravel	39.4	39.7	12.6	12.2	7.8	7.9	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	32.7	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	25.7	1.2	1.2	0.0	0.0	0.3	0.2
Mixed Freight	66.9	67.1	3.1	3.1	0.0	0.0	0.8	0.6
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	26.4	9.3	9.5	0.0	0.0
Other Non-Metallic Minerals	15.0	15.1	10.9	10.8	5.4	5.4	0.0	0.0
Other Prepared Foodstuffs	126.9	127.4	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	1.5	0.1	0.1	0.0	0.0
Vehicles	49.1	49.2	11.5	11.4	0.0	0.0	0.0	0.0
Waste and Scrap	43.5	44.3	17.5	16.6	1.7	1.7	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 4, in millions of ton miles.

Table A2: Multinomial logit parameter estimates for grain, coal, alcohol and precision instruments using the CFS PUM sample.

Grain, Coal, Alcohol and Precision Instruments Mode Choice Results

	Grain	Coal		Alcohol	Precison Inst.
Truck			**Truck**		
Diesel Price * Ton-Miles	-31.976	-5.746	Diesel Price * Ton-Miles	-29.188	
	(6.489)	(2.977)		(2.547)	
Miles * Shipment Value	0.010	0.013	Miles * Shipment Value	-0.007	
	(0.002)	(0.022)		(0.003)	
Mississippi Basin	-1.044	1.142	Temperature Controlled	0.308	
	(0.588)	(1.033)		(0.355)	
Rail	(Base Outcome)		**Rail/Truck**	(Base Outcome)	
Inland Water			**Air**		
Diesel Price * Ton-Miles	0.042	-0.050	Diesel Price * Ton-Miles		-372.87
	(0.035)	(0.017)			(114.000)
Miles * Shipment Value	0.000	-0.001	Miles * Shipment Value		0.011
	(0.000)	(0.001)			(0.003)
Mississippi Basin	2.514	1.182			
	(0.860)	(1.135)			
Observations	24817	10602		96329	40807

Notes: Multinomial 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 SCTG and mode compared with mean predicted values, mixed logit.

	Truck		Rail		Water		Air	
Commodity Group	CFS	Pred.	CFS	Pred.	CFS	Pred.	CFS	Pred.
Agricultural Products	38.5	38.7	28.9	26.4	16.1	18.5	0.0	0.0
Alcohol	20.6	20.6	12.9	12.8	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	6.0	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	577.0	23.2	48.1	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	131.5	15.3	20.1	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	67.6	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	43.1	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	72.5	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	40.4	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	49.2	11.5	11.4	0.0	0.0	0.0	0.0
Waste and Scrap	43.5	44.4	17.5	15.7	1.7	2.6	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.