Distributional Consequences of Electrifying the Trucking Industry

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1 Research Plan

In the U.S., heavy-duty vehicles (HDVs) comprise just 10% of road vehicles but contribute 28% of greenhouse gas emissions and 45% of NO_x emissions (FHWA, 2016; EPA, 2018, 2020).[1] In California, HDVs are responsible for as high as 70% of NO_x emissions from road transport (CARB, 2019). While damages from greenhouse gases do not concentrate where they are emitted, NO_x emissions create localized damages through the formation of smog and PM 2.5. Policymakers have increasingly recognized the disproportionate burden of truck-emitted NO_x damages on disadvantaged communities because of their proximity to truck traffic (CARB, 2020). In 2020, the California Air Resources Board (CARB) adopted the Advanced Clean Truck Regulation, the first-ever rule for zero-emission HDVs, requiring manufacturers to meet increasing sales quotas for electric trucks starting in 2024.[2]

In this project, we quantify the extent of environmental inequality in truck-generated NO_x

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[1]Heavy-duty vehicles are defined as vehicles with a gross vehicle weight rating above 8,501 pounds. They are Class 2b and above vehicles. Most of those vehicles are commercial trucks. We use HDVs and trucks interchangeably in this paper.

[2]The sales quotas need to reach 55% for Class 2b – 3 trucks, 75% for Class 4 – 8 straight trucks, and 40% for truck tractors in 2035.

exposure and investigate how electrifying the trucking industry might mitigate or worsen this inequality. We start by establishing two facts about inequality in truck NO_x exposure: lower-income households are exposed to more truck NO_x emissions, and those emissions are disproportionately generated by shipments intended for higher-income regions. Thus, the inequality becomes two-fold; lower-income households both bear more costs from the pollution externality of truck shipping and benefit less from its economic value.

We then examine how adding electric trucks as a new shipping mode can change this picture of inequality in NO_x exposure. Will electric trucks be used differently between high- and low-value shipments? Will highway and urban routes be affected differently? If electric trucks are taken up disproportionately by shipments of high value that take urban routes, then policies pushing for electric trucks may inadvertently widen the inequality in trunk-generated NO_x exposure. Therefore, to address the distributional impacts of electrifying the trucking industry, it is crucial to predict what kinds of shipments are likely to take up electric trucks and where.

To do this, we estimate a model of shippers' transportation mode choices, and use the model to predict the electric truck take-up. In the model, the shippers trade off shipping costs with inventory costs, where shipping costs are affected by fuel cost and shipment weight, and inventory costs by the time spent on the road and shipment value. We follow the methodology in Bushnell and Hughes (2020) and supplement their data with the most recent freight shipment data from the U.S. Commodity Flow Survey Public Use Microdata. The attractiveness of electric trucks as a new transportation mode depends on the charging infrastructure and the battery technology and how they interact with shipment characteristics. If the battery range is low or charging infrastructure sparse, then urban trucks with low daily mileages and daytime-only duties and delivering consumer electronics will be more readily electrified than long-haul 18-wheeler trucks transporting fertilizers and hays. Furthermore, under some infrastructure and technology scenarios, taking up the electric truck mode may indicate a change in the shipping route, leading to spatial changes in NO_x emissions.[3]

With the estimated transportation mode choice model and the specified electric truck

[3]Modeling those important spatial features of charging and travel routes is consistent with Li (2019), who models the value of charging networks as increasing in not only the number of charging stations but also the location match quality with driving (here, shipping) needs.

mode, we can simulate the effect of charging infrastructure and battery technology on the spatial distribution of NO_x emissions prevented by electric trucks. We then ask whether the spatial distribution of prevented emissions will mitigate or worsen the NO_x exposure inequality, and decompose the change in inequality into two channels: the externality cost channel, where electric trucks change where pollution is emitted; or the economic benefit channel, where electric trucks change who are responsible for those emissions.

To inform policy making, we will first compute the efficient, the cost-effective, and the egalitarian benchmarks. Under the efficient distribution of electric truck take up, the marginal benefit of NO_x reduction in each region is equal to the marginal abatement cost, where the shipper welfare loss from the transportation mode choice model is part of the marginal abatement cost. Under the cost-effective benchmark, we set the national reduction at the efficient level, and compute the distribution of electric trucks that achieve that reduction with the least cost. Under the egalitarian distribution of electric truck take up, we achieve the efficient national reduction by equating the marginal benefit of NO_x reduction across regions. Having compared the three benchmarks, we will examine how close various types of policies can get us to each: a sales quota requirement as proposed by California, subsidies for charging infrastructure and battery technology, or both.

Timeline. We are in the process of establishing the current landscape of truck-generated NO_x exposure inequality (we report preliminary results below). In Summer 2021, we will estimate the transportation mode choice model and collect technical information necessary to specify the electric truck mode. We expect to present some illustrative results on the effect of charging infrastructure and battery technology on exposure inequality at the online conference on August 5-6, 2021. In Fall 2021, We will refine the distributional impact results and evaluate the relative importance of the externality cost channel and the economic value channel. In Spring 2021, we will simulate the three policy benchmarks and examine the performance of various policy instruments. We expect to present the final paper at the research conference on June 23-24, 2022.

Figure 1: Commodity Flow Survey (CFS) Areas



2 Data

Our first data set is the U.S. Commodity Flow Survey (CFS) Public Use Microdata files for 2012 and 2017. It contains quarterly freight shipment data collected by the U.S. Department of Transportation and the Department of Commerce. (Bushnell and Hughes, 2020) use the 2012 data to estimate a freight transportation mode model. The 2012 data contain 4.5 million shipment records, and the 2017 data contain 5.9 million. We observe the type of shipped commodity at the Standard Classification of Transported Goods level, shipment value, shipment weight, shipment origin and destination, shipping distance, the mode of transportation, the quarter of the year that the shipment is made, the shipper's industry classification, hazardous materials code, and indicator variables on exporting shipment and the usage of temperature control during transportation. The CFS designates the origins and destinations of each shipment record using a mixture of Combined Statistical Areas (CSA), Metropolitan Statistical Areas (MSA), and their balances within a state. Figure 1 shows the 133 CFS areas thus defined. Table 1 reports the summary statistics weighted by ton-miles. Trucks were responsible for 45% of the shipments in both 2012 and 2017.

The second data set we rely on is the Freight Analysis Framework Network and Regions

Table 1: Summary Statistics of Shipment Records in 2012 and 2017 Weighted by Ton-Miles

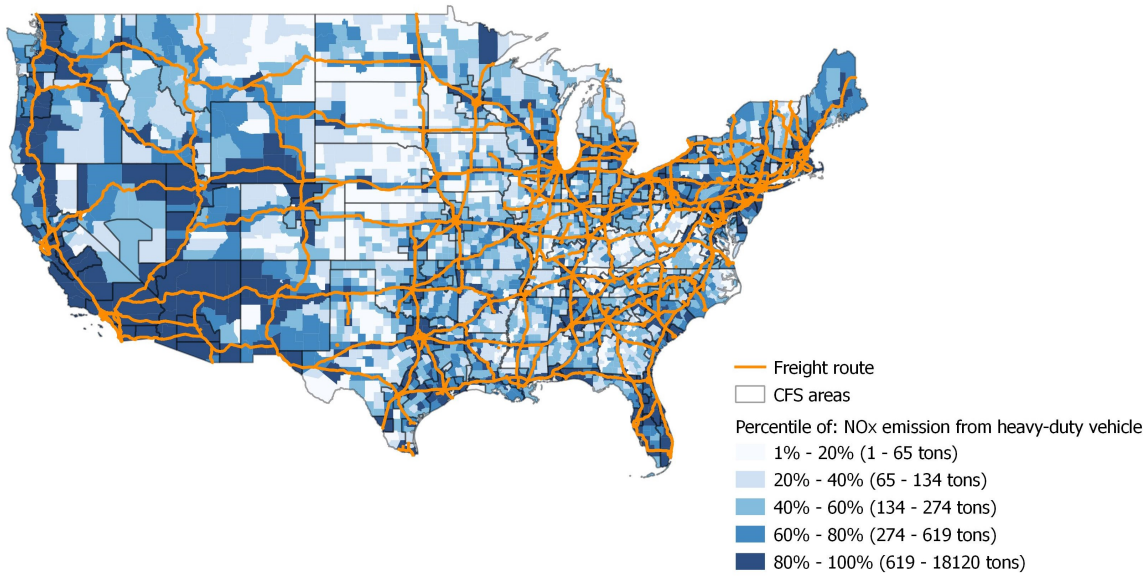
	Shipments in 2012				**Shipments in 2017**			
	Mean	Std.Dev.	Min	Max	Mean	Std.Dev	Min	Max
Value ($)	589,467	3,306,096	1	5.21e+08	345,893	2,040,447	0.94	3.22e+08
Weight (ton)	5,356	12,725	.00	138,514	3,928	9,916	.00	218,327
Distance (mile)	1,089	741	1	6,677	1,109	766	1	7,698
Temp control	.07	.26	0	1	.08	.27	0	1
Export	.09	.28	0	1	.09	.28	0	1
Air	.00	.04	0	1	.00	.06	0	1
Pipeline	.01	.10	0	1	.02	.13	0	1
Rail	.47	.50	0	1	.40	.49	0	1
Truck	.45	.50	0	1	.45	.50	0	1
Water	.06	.24	0	1	.09	.28	0	1
Parcel/Courier	.01	.09	0	1	.01	.10	0	1
Other Mode	.01	.08	0	1	.03	.18	0	1
N	4,534,071				5,962,572			

databases from the National Transportation Atlas Database. The former includes the shapefile of the U.S. highway network and intermodal connectors. Figure 2 plots the truck freight routes. The Regions database identifies the boundaries of MSAs and CSAs. We leverage those detailed GIS data to predict the current route taken by each shipping record and the counterfactual route that would be taken by electric trucks.

The third dataset records the county-level NO_x emission from the on-road vehicles in the U.S. This dataset is from the EPA National Emissions Inventory (NEI), which provides detailed estimates of various types of air emissions based primarily on the data reported by the local agencies and other data sources. The NEI is released every three years since 2008. The NEI on-road emission data sources contain NO_x emissions from on-road light-duty and heavy-duty vehicles that use gasoline, diesel, and other fuels. To compute these estimations of on-road emissions, the EPA uses the Model of Motor Vehicle Emission Simulator, except that California provides emissions to the EPA based on their state-specific model. In this paper, we focus on heavy-duty vehicle NO_x emissions data reported in the year 2017. Figure 2 shows substantial heterogeneity across countries in truck-generated NO_x emissions.

Finally, we collect MSA/CSA-level demographic data from the American Community Survey, including median household income, median age, population, and the racial compo-

Figure 2: Freight Routes and County-level Heavy-Duty Vehicle NO_x Emissions in 2017



sition.

We now present some preliminary findings on the extent of inequality in truck-generated NO_x exposure. We test whether lower-income households are exposed to more NO_x emissions, and whether those NO_x emissions are generated more by higher-income households. Table 2 tests the first hypothesis, by regressing log county-level emissions from the EPA NEI on demographic variables in that county, using 2017 data. The results show that while NO_x emissions from all road transport do not appear to be correlated with log median household income, the correlation is statistically negative when we restrict the NO_x emissions to those emitted by trucks. We find that 1% increase in the median household income is correlated with 0.37% decrease in truck-generated NO_x, holding fixed the racial composition, median age, and log population.

To test whether higher-income households are responsible for more truck NO_x, we turn to the CFS shipment data and examine the relationship between shipment-level NO_x emissions and *destination* median household income. We control for shipment value, median age, racial composition, and population of the destination, commodity group fixed effects, and quarter

Table 2: County-Level Truck NO_x and Demographics, 2017

	(1) Log(Total Vehicle NOx)	(2) Log(Truck NOx)
Log(Median Household Income)	−0.06	−0.37*
	(0.15)	(0.19)
Percentage of Black	−0.04	−0.16*
	(0.06)	(0.09)
Percentage of Asian	−2.55***	−3.35***
	(0.44)	(0.52)
Median Age	−0.00*	−0.01***
	(0.00)	(0.00)
Log(Population)	0.80***	1.09***
	(0.14)	(0.19)
Constant	−1.09***	−1.93***
	(0.23)	(0.33)
N	3138	3138
Adjusted R^2	0.833	0.703

Notes: An observation is a county in 2017. NO_x emissions in tons are from the EPA National Emissions Inventory. Robust standard errors are in parentheses. *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$.

fixed effects. We compute the NO_x emissions from each shipment record by multiplying shipment weight (ton), routed distance (mile), and an emission factor of 0.85g/ton-mile from Gladstein Neandross & Associates (2013). Table 3 Column (1) restricts the shipments to those that originate and end in the same CFS area and fails to find a statistically significant correlation between log shipment emissions and log destination median household income. However, once we restrict the shipments to those with different origin and destination CFS areas, we find that 1% increase in the destination median household income is associated with 0.09% increase in the shipment-level emissions. This means that for two shipments of the same commodity group, with the same value, and delivered in the same quarter to destinations with the same racial composition, median age, and population, the shipment intended for the higher-income destination generates more NO_x emissions.

We will work on establishing the status-quo distribution of truck NO_x emissions across

Table 3: Shipment-Level NO_x and Destination Demographics, 2017

	(1) Log(Within-CFS NOx)	(2) Log(Cross-CFS Shipment NOx)
Log(Destination Median Household Income)	0.03	0.09**
	(0.09)	(0.03)
Log(Shipment Value)	0.69***	0.55***
	(0.06)	(0.04)
Log(Destination Population)	0.68***	0.15
	(0.10)	(0.10)
Destination Median Age	−0.13***	−0.06***
	(0.05)	(0.01)
Destination Percentage of White	5.74***	0.73
	(1.79)	(1.02)
Destination Percentage of Black	4.39**	−1.16**
	(2.06)	(0.52)
Destination Percentage of Asian	3.73**	0.05
	(1.39)	(1.04)
Constant	−0.39	12.52***
	(2.46)	(1.89)
Commodity Group FE	X	X
Quarter FE	X	X
N	2124305	2056561
Adjusted R^2	0.421	0.327

Notes: An observation is a truck shipment record in the 2017 U.S. Commodity Flow Survey (CFS) Public Use Microdata file. We compute the NO_x emissions from each shipment record by multiplying shipment weight (ton), routed distance (mile), and an emission factor of 0.85g/ton-mile from Gladstein Neandross & Associates (2013). Standard errors clustered at the commodity group level are in parentheses. *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$.

demographics. For example, we can separate out NO_x emissions that fall entirely out of the destination CFS area to sharpen our results in Table 3, by inferring the routes taken by each CFS shipment using the National Transportation Atlas Database. We will then move on to investigating the distributional impacts of electrifying the trucking industry, by estimating a transportation mode choice model, specifying electric trucks as a new transportation mode, predicting the endogenous distribution of electric-truck take-up under various charging and battery technology scenarios, and identifying mechanisms and policies that can reduce inequality in truck NO_x exposure as well as bringing down the aggregate NO_x emissions.

3 Potential Contributions

First, we contribute to the environmental justice literature. Disadvantaged communities have been shown to live in regions with high concentrations of air pollution, close to highways (Currie and Walker, 2011; Herrnstadt et al., 2018), transportation hubs (Schlenker and Walker, 2016), industrial facilities (Currie et al., 2015) and power plants (Massetti et al., 2017). Banzhaf (2011), Mohai et al. (2009), Wolverton (2009), and Hausman and Stolper (2020) use empirical analysis to identify mechanisms that lead to environmental injustice, including disparities in willingness to pay and the cost of providing for environmental quality, direct discrimination, and information failure. We identify a novel policy lever, infrastructure and technology, that can affect the distribution of pollution damages across socio-demographic groups through electric truck take-up. Truck shipping also allows us separately two channels through which inequality is propagated: the externality-receiving end (lower-income households live in high emission areas) and the externality-generating end (higher-income households' shipping demand generate more emissions).

Second, we contribute to the growing literature on the roles of infrastructure and standards in facilitating the adoption of new transportation technologies. Zhou and Li (2018) find that more than half of the MSA's face critical mass constraints in the adoption of passenger electric vehicles. Li (2019) studies manufacturer investments in charging stations for passenger electric vehicles in the U.S. and finds that unifying three incompatible charging standards increases consumer surplus. Li et al. (2017) and Springel (2016) find that

subsidizing charging stations is more cost-effective than subsidizing vehicle purchases in increasing passenger electric vehicle take-up. To our best knowledge, our paper is the first to formally study, in the commercial trucking industry, the role of charging infrastructure and technology. Our framework is also applicable to the distributional impact of EV passenger vehicles.

Third, this paper adds to the literature on environmental performance and regulation of the automotive sector. Most papers in this strand focus on passenger vehicles. For example, Goldberg (1998),Knittel (2012),Reynaert (Forthcoming), and Reynaert and Sallee (Forthcoming) study passenger vehicle fuel economy regulations and greenhouse gas emissions, and Holland et al. (2016) and Ale-Chilet et al. (2021) examine excessive NO_x damages from the Dieselgate scandal and the alleged collusion among German automakers in suppressing the effectiveness of NO_x control technology, respectively. Few papers have formally examined the environmental performance of the trucking industry despite its disproportionate share of local and global pollutant emissions. Bushnell and Hughes (2020) model shippers' freight mode choices and use the estimated model to analyze the impact of heavy-duty vehicle fuel economy standards. Rittenhouse and Zaragoza-Watkins (2018) show that the same fuel economy standards caused a sales spike of high-emission trucks before the policy took effect and lead to environmental damages.

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