Distributional Consequences of Electrifying the Trucking Industry

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Abstract

Heavy-duty vehicles comprise one-tenth of road vehicles in the U.S. but contribute to half of local air pollution. An important motivation for electrifying trucks is to relieve the disproportionate burden of local air pollution on disadvantaged communities. We study the role of charging infrastructure in determining the distributional consequences of truck electrification. We start by building a micro-founded framework that quantifies environmental injustice based on the theoretical literature on income inequality. To apply this framework to truck electrification, we first estimate transport mode choices and spatial pollution models, and find that truck electrification saves $5 billion in annual local air pollution damages if charging stations are widely available. In this infrastructure scenario, tailpipe pollution reduction narrows inequality and improves welfare, although added power plant pollution dampens these effects. This infrastructure scenario also reduces the extent of inequality explained by race.

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1 Introduction

Electrification of the transportation sector holds great potential for reducing vehicle emissions. The emerging policy interest in electrifying heavy-duty vehicles emphasizes yet another benefit: improving environmental justice.[1] Heavy-duty vehicles comprise one-tenth of road vehicles but contribute to half of local air pollution (FHWA, 2016; EPA, 2020). Disadvantaged communities tend to live close to truck traffic and experience a disproportionate share of truck pollution. In 2020, the California Air Resources Board (CARB) pioneered zero-emission truck regulation by requiring manufacturers to meet increasing sales quotas for electric trucks starting in 2024. The District of Columbia and 14 states joined California by signing a memorandum of understanding in 2021.

Whether electric trucks can improve environmental justice depends crucially on the truck charging infrastructure. The charging infrastructure determines where shippers will find it technically feasible and economically attractive to switch shipments to electric trucks. These shipping choices lead to a spatial distribution of tailpipe pollution reductions. For example, if charging stations are limited and can only support trucks with low charging needs, heavy shipments (e.g., agricultural products) may still rely on diesel trucks that harm communities along the highway. How electric trucks use the charging infrastructure also determines which power plants generate additional electricity to support charging, leading to a spatial distribution of power plant pollution increases. For example, if coal plants are dispatched, then emissions will simply be displaced from tailpipes to smokestacks, reducing pollution for communities along highways but increasing pollution for those near power plants.

This paper aims to identify charging infrastructure designs that improve environmental justice under truck electrification. We first construct a micro-founded framework that connects pollution damages with the underlying income distribution. This allows us to use tools developed in the classical economic literature on income inequality to quantify the degree of environmental injustice. In particular, we argue that the Atkinson measure of inequality (Atkinson, 1970) based on pollution-adjusted income distributions is an attractive measure

[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 heavy-duty vehicles and trucks interchangeably in this proposal.

of environmental injustice. The Atkinson measure has an economically meaningful interpretation, can disentangle inequality and size effects, and can be decomposed into within-group and cross-group inequalities. To apply this theoretical framework to truck electrification, we predict which shipments will adopt electric trucks based on a transport mode choice model estimated from shipment-level data. The adoption decision is a function of charging infrastructure designs. Next, we convert this distribution of electrified shipments to the distribution of pollution changes in both tailpipe emissions and power plant emissions. Finally, we combine this spatial distribution of pollution changes with the underlying income distribution, and leverage our theoretical framework to quantify the distributional impacts of various charging infrastructure designs.

We define an unconstrained charging infrastructure scenario, where chargers are sufficient for all truck shipments to use electric trucks given the prevailing technical parameters. Our preliminary findings show that in this scenario, truck electrification reduces local air pollution damages by $5 billion. This reduction comes from a $26 billion reduction in tailpipe pollution damages and a $21 billion increase in power plant pollution damages.[2] These changes in the local air pollution damages vary substantially from county to county, ranging from a reduction of 10% to an increase of 10%, depending on where tailpipe emissions are reduced and where power plant emissions are increased. Applying our theoretical framework, we find that the tailpipe pollution reduction narrows inequality while the added power plant pollution widens it. Overall, truck electrification in the unconstrained infrastructure scenario reduces inequality, increases income size, and improves welfare within all sociodemographic groups defined by race, education, and age of the household head. It also slightly reduces the extent of pollution-adjusted inequality explained by race.

In ongoing work, we are analyzing additional charging infrastructure scenarios. These additional scenarios will feature a smaller number of chargers to be allocated and alternative electric truck technical parameters. With a tighter charger budget, not all truck shipments can be electrified, allowing us to study how various ways of allocating those chargers lead to preferential treatment of shipments and community groups. One possibility is to allocate

[2]Assuming a social cost carbon of $25, truck electrification reduces greenhouse gas emission damages by $7 billion, from a $22 billion reduction in tailpipe damages and $14 billion increase in power plant damages.

those chargers proportionally to highway truck flow. This approach is similar to those proposed in policy analysis such as Bradley et al. (2019), which site chargers based on a traffic flow model and checks if a sufficient number of chargers turn out to be in disadvantaged communities. Other possible ways of charger allocation include explicitly considering income in the allocation procedure. We also explore the potential for optimizing a given policy objective (e.g., inequality) by searching over charger locations and technical parameters.

Our main data is the 2017 U.S. Commodity Flow Survey (CFS) Public Use Microdata, with six million shipment observations. We also use transportation network databases, the National Emissions Inventory, and household-level sociodemographics data from the American Community Survey (ACS) Public Use Microdata. A quick look at the data reveals two facts about the baseline inequality in truck NO_x exposure in a world without electric trucks: lower-income households are exposed to more truck NO_x emissions, and those emissions are disproportionately generated by shipments intended for higher-income regions. We expect to access the more granular restricted-use CFS and ACS data in Fall 2022.

We use the CFS data to estimate a transport mode choice model in a conditional logit framework.[3] Shippers trade off variable shipping costs with inventory costs when choosing transport modes. The variable shipping cost depends on the distance, weight, and fuel price. The inventory cost depends on the value, distance, and speed. We estimate the model for each commodity group, and find substantial heterogeneity in how shippers trade off variable shipping costs and inventory costs across commodity groups.

The estimated transport mode choice model allows us to predict which shipments will adopt electric trucks given an infrastructure scenario. Compared with internal-combustion-engine (ICE) trucks, electric trucks typically feature lower variable shipping costs, and more so when they receive revenue from Low-Carbon Fuel Standard credits. However, electric trucks can incur higher inventory costs, as charging can take time. We find that in our unconstrained charging infrastructure scenario, where charging stations are widely available, most truck shipments will go electric conditional on electric trucks being made available to them. We are working on incorporating the upfront cost in predicting electric truck adoption.

[3]Bushnell and Hughes (2020) estimate a transport mode choice model using a multinomial logit framework with 2012 CFS data. Our conditional logit framework is suitable for analyzing the effect of adding a new transport mode.

We then compute the pollution implications of these shipments that will adopt the electric truck mode. Both tailpipe pollution and power plant pollution change under truck electrification. We use the EMFAC database developed by CARB to calculate the on-road emission factors of the existing ICE truck fleet as of 2017, and apply those emission factors to the electrified shipments to compute the tailpipe pollution they replace. To compute power plant pollution, we estimate a power plant emission model based on Holland et al. (2016b) that predicts how emissions at each power plant change as electricity load changes in response to truck charging. We then send both tailpipe pollution and power plant pollution to the AP3 air pollution model (see Holland et al., 2019) to compute the monetized damages of local air pollution for each of the 3109 counties in the contiguous U.S.

Those monetized pollution damages and the underlying income distribution are inputs to our theoretical framework that quantifies the distributional implications of truck electrification. We compute inequality as represented by the Atkinson measure, income size as represented by mean income μ, and the welfare index as represented by the equally-distributed-equivalent income Atkinson (1970) in our unconstrained charging infrastructure scenario. Within the range of the inequality aversion parameters we consider (from 0.25 to 1.5), we find that the tailpipe pollution effect narrows inequality and increases the income size, leading to higher welfare. The power plant pollution effect dampens those benefits. Overall, the unconstrained infrastructure scenario still reduces inequality, increases income size, and improves the welfare in aggregate as well as within sociodemographic groups.

This paper contributes to three strands of literature. First, we contribute to the environmental justice literature by providing a micro-founded framework to measure environmental injustice. Our framework connects the distribution of pollution exposure to the underlying income distribution. This reduces a two-dimensional inequality problem to a one-dimensional problem. To our best knowledge, Muller et al. (2018) and Jha et al. (2019) are the only papers that make this connection. While they use the Gini coefficient to measure inequality, we tap into the theoretical work on inequality that offers micro-founded inequality measures such as the Atkinson measure (Atkinson, 1970). That work also allows us to clarify the relationship between inequality, income size, and welfare, and to explore how inequality manifests within and across sociodemographic groups.

Second, we contribute to the growing literature on the roles and welfare effects of infrastructure and standards in facilitating the adoption of new transportation technologies. Zhou and Li (2018) find that more than half of the metropolitan statistical areas face critical mass constraints in the adoption of passenger electric vehicles. Li (2019) studies manufacturer investments in charging stations for passenger electric vehicles and finds that unifying the three charging standards would increase 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. We are the first to study the distributional effects of infrastructure for clean transportation technologies.[4] Infrastructure adds to the list of mechanisms underlying environmental injustice including disparities in willingness to pay and the cost of providing for environmental quality, direct discrimination, and information failure as identified in Banzhaf (2011), Mohai et al. (2009), Wolverton (2009), and Hausman and Stolper (2020).

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 (2021), and Reynaert and Sallee (2021) study passenger vehicle fuel economy regulations and greenhouse gas emissions, and Holland et al. (2016a) and Ale-Chilet et al. (2022) 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. Despite the trucks' disproportionate share of local and global pollutant emissions, only a handful of papers have examined their environmental performance. Bushnell and Hughes (2020) model shippers' transport mode choices and analyze the impact of heavy-duty vehicle fuel economy standards. Rittenhouse and Zaragoza-Watkins (2018) show that these fuel economy standards caused a sales spike of high-emission trucks before the policy took effect and led to environmental damages. Tong et al. (2021) use an integrated assessment model to assess the effects of electric trucks on electricity usage, emissions, health and climate.

We proceed as follows. Section 2 introduces our theoretical framework for quantifying

[4]Holland et al. (2019) study how the environmental benefits of passenger electric vehicles correlate with sociodemographic variables without explicitly considering the role of charging infrastructure.

inequality from pollution exposure. In Section 3, we describe our data and provide evidence on the disparities across sociodemographic groups in receiving and generating truck-related pollution. Section 4 presents our transport mode choice model. Section 5 simulates the electric truck take-up in our unconstrained charging infrastructure scenario. In Section 6, we report the pollution effect of truck electrification. Section 7 computes the inequality, size, and welfare effects of truck electrification. We conclude in Section 8.

2 Model

In this section, we first conceptualize how an environmental policy affects a household's equivalent income. The use of equivalent income allows us to apply a vast array of income inequality measures developed in the literature. We then focus on the Atkinson measure and summarize three advantages of using this measure in informing policy discussions about environmental justice. Finally, we apply this framework to truck electrification, by demonstrating how it affects environmental justice and providing a road map for empirical analysis.

2.1 Equivalent Income

A household $i \in I$ has an indirect utility function $v(y_i, c_i)$, where y_i is the income and c_i is the pollution. An environmental policy changes the income by Δy_i and the pollution by Δc_i. For example, government subsidies for electric vehicles (EV) provide tax credits for EV owners and reduce local pollution. We assume for simplicity that the policy does not affect the prices of goods that enter the direct utility function.

Define the household's equivalent variation, EV_i, as the lump-sum change to the pre-policy income at the pre-policy pollution, that would induce the same utility as does the environmental policy:

$$v(y_i + EV_i, c_i) = V(y_i + \Delta y_i, c_i + \Delta c_i). \tag{1}$$

The equivalent variation EV_i summarizes the effect of the environmental policy on household i. It can also be interpreted as the willingness to accept not having the policy. We call $y_i + EV_i$ the equivalent income.

The use of equivalent variations reduces two-dimensional policy effects into a single-dimensional monetized effect. This allows us to use a vast array of single-dimensional inequality measures from the theoretical literature (e.g., Atkinson, 1970; Yitzhaki, 1983; Chakravarty, 1988). Although two-dimensional measures of inequality exist (e.g., Atkinson and Bourguignon, 1982; Maasoumi, 1986; Tsui, 1995), they do not provide guidance for the choices of parameters in empirical work (Bosmans et al., 2015). In contrast, environmental valuation methods (such as hedonic price models) have empirically estimated the monetized benefits of pollution reduction in many contexts (e.g., Chay and Greenstone, 2005). These estimates and methods inform the part of the equivalent variation EV_i that comes from pollution change Δc_i.

2.2 Measuring Environmental Justice with the Atkinson Measure

We use the Atkinson measure of inequality (Atkinson, 1970) in our analysis. A common approach in empirical studies of income inequality is to adopt summary statistics of inequality such as the Gini coefficient or the coefficient of variation. Such measures do not explicitly express the value judgment underlying it (e.g., see Newbery, 1970).[5] The Atkinson measure allows for a micro-founded investigation of the meaning and extent of environmental justice.

In Atkinson (1970), income distributions are ranked based on their social welfare $W = \int_{\mathcal{Y}} u(y)dF(y)$, where $u(y)$ is an increasing and concave function of individual equivalent income y, and F is the distribution of equivalent incomes. To construct an inequality measure, Atkinson (1970) introduces the notion of the equally-distributed equivalent (EDE) income y_e, with $W = u(y_e)$. In other words, when assigned to each individual, the EDE income would give the same level of social welfare as the given income distribution. The EDE income generates a complete ordering of income distributions in terms of welfare: $y_{e,2} \geq y_{e,1}$ is equivalent to $W_2 \geq W_1$. Due to the concavity of u, y_e is lower than the mean income $\mu = \int_{\mathcal{Y}} ydF(y)$, and its proportional shortfall from μ measures the relative welfare loss due

[5]For example, Newbery (1970) points out that the ranking of income distributions in terms of the Gini coefficient cannot be supported by any additively separable social welfare function. Muller et al. (2018) and Jha et al. (2019) use the Gini coefficient to measure inequality based on equivalent income.

to inequality. Accordingly, the inequality index is given by

$$\alpha = 1 - y_e/\mu \in [0, 1], \tag{2}$$

The extreme cases with $\alpha = 0$ and $\alpha = 1$ mean complete equality and complete inequality, respectively. Invariance with respect to proportional shifts in the income distribution requires that this measure take the following parametric form:

$$\alpha_\epsilon = 1 - \left[\frac{1}{n}\sum_{i=1}^{n}\left(\frac{y_i}{\mu_n}\right)^{1-\epsilon}\right]^{1/(1-\epsilon)}, \tag{3}$$

where n is the number of individuals and μ_n is the mean income. The parameter $\epsilon > 0$ captures the aversion to inequality: the higher ϵ, the more weight is attached to income at the bottom of the distribution relative to those at the top.[6]

The micro-founded Atkinson measure provides three advantages that enable meaningful policy discussions about environmental justice. First, the Atkinson measure has a uniquely intuitive interpretation. An Atkinson measure of 0.6, for example, implies that if equivalent incomes were equally distributed, only 40 percent of the present total equivalent income would be needed to achieve the same level of social welfare.

Second, the Atkinson measure clarifies how welfare reflects the trade-off between income size (i.e., mean income) μ and income inequality α (Ebert, 1987). Equation (2) shows that given an income size, an increase in inequality leads to a decrease in welfare. However, an increase in inequality will not harm welfare if mean income increases enough. Alternatively, if policymakers interpret environmental justice as inequality reduction, then policies that reduce inequality could still reduce welfare if they substantially reduce mean income.

Third, we can decompose the extent of inequality within and across sociodemographic groups using the Atkinson measure.[7] This group decomposition of inequality helps policymakers identify where environmental injustice comes from and target policies accordingly.

[6]For $\epsilon = 1$, the inequality measure is defined as $\alpha_1 = 1 - \frac{1}{\mu}\prod_{i=1}^{n} y_i^{1/n}$.

[7]The Gini coefficient is not decomposable in the sense of subgroup consistency, where subgroup consistency requires that the overall inequality can be written as an increasing function of each of the within-group inequality (Cowell, 2000). Without this property, it is possible that inequality in every subgroup rises and yet overall inequality reduces.

For each sociodemographic group $g \in \{1, \cdots, G\}$, the income vector is $\mathbf{y}_g$ with size n_g and $n = \sum_{g=1}^{G} n_g$, μ_g is the mean income within the group, y_{eg} is group g's EDE income, and $\alpha_{\epsilon,g}$ is group g's Atkinson measure. Cowell and Jenkins (1995) propose the following decomposition of inequality:

$$\alpha_\epsilon = \alpha_\epsilon^W + \alpha_\epsilon^B - \alpha_\epsilon^W \alpha_\epsilon^B, \tag{4}$$

where $\alpha_\epsilon^W = \sum_{g=1}^{G} s_g \alpha_{\epsilon,g}$ is the weighted average of within-group inequality across groups weighted by the income share $s_g = (n_g \mu_g)(n\mu_n)^{-1}$ for group g. The between-group inequality α_ϵ^B is the inequality that would be found in the whole population if everyone were given their group's EDE income. With the weighted average within-group inequality α_ϵ^W and the between-group inequality α_ϵ^B, we can measure the extent of inequality explained by the demographic variable used to define groups using $R_B = \alpha_\epsilon^B / \alpha_\epsilon$ or $R_W = 1 - \alpha_\epsilon^W / \alpha_\epsilon$.

2.3 Illustrative Application to Truck Electrification

Our framework can be broadly applied to measure environmental injustice under any policy based on equivalent incomes. This subsection provides a conceptual example of applying our framework to truck electrification. The rest of our paper applies our framework empirically.

Table 1 presents the inequality, size, and welfare effects of electrifying a hypothetical shipment. The first row represents the no-electrification scenario. We endow the origin A of this shipment with a baseline income of \$100, the on-route location B with \$150, and the destination C with \$200. We calculate that the Atkinson measure of inequality is 0.077, the mean income is \$150, and the welfare as measured by the EDE income is \$138. This implies that giving each location \$138 would reach the same welfare as does the current income distribution $(100, 150, 200)$.

Electrifying the shipment changes each location's equivalent income in two ways. First, it can reduce the cost of shipping. This economic benefit can be added directly to the baseline income at the origin and the destination, depending on how the economic saving gets split between shippers and consumers. Second, electrification changes the distribution of pollution across the three locations. Assuming that the route does not change, the electrified shipment reduces tailpipe pollution across the three locations. The increase in the power

Table 1: Illustrating the Inequality, Size and Welfare Effects of Truck Electrification

	Equivalent Income			Income	Income	Welfare
	Origin A	On-Route B	Destination C	Inequality	Size	Index
No electrification	100	150	200	0.077	150	138
Electrification						
Scenario 1	120	150	250	0.089	173	158
Scenario 2	120	150	210	0.051	160	152
Scenario 3	90	160	200	0.106	150	134
Scenario 4	120	150	130	0.009	133	132

Notes: Income size is represented by the mean income. Welfare index equals the product of income size and income equality, where income equality equals one minus income inequality. Computed using a relative inequality aversion of $\epsilon = 2$.

plant pollution, however, may only affect selected locations.

In Scenario 1, the equivalent variations that summarize economic and pollution effects lead to an income distribution of ($120, $150, $250). This is possible if A experiences net pollution reduction, B's tailpipe pollution reduction and power plant pollution increase cancel out, and C benefits from the lower price of the shipment. Both A and C are better off while B stays put. As a result, the income size increases to $173. However, the inequality widens because the richer location C benefits more than the poorer location A; the Atkinson measure increases to 0.089 from 0.077. The net welfare still increases, as the size effect dominates the inequality effect.

Scenario 2 also features electrification gains to A and C, but the richer location C benefits less than the poorer location A. This substantially reduces the inequality measure from 0.077 in the no-electrification scenario to 0.051. In fact, Scenario 2 dominates the no-electrification scenario in every measure: lower inequality, larger income size, and higher welfare.

Scenarios 3 and 4 show the remaining possible directions of change. Compared to the no-electrification scenario, Scenario 3 widens inequality and lowers welfare, and Scenario 4 narrows inequality and lowers welfare. These scenarios are possible if, for example, the power plant pollution increases large enough (e.g., with a dirty electricity grid).

The ultimate goal of this paper is to identify charging infrastructure designs that lead to scenarios like Scenario 2 in Table 1. We now introduce the data that enables us to bring the theoretical framework to empirical application.

3 Data

3.1 Data Sources

Our main data set is the 2017 U.S. Commodity Flow Survey (CFS) Public Use Microdata. It contains freight shipment data collected by the U.S. Department of Transportation and the Department of Commerce. The data contain 5.9 million observations. 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 origin and destination 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.

Figure 1: Commodity Flow Survey (CFS) Areas



Notes: 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.

Table 2 reports the summary statistics of shipment observations weighted by ton-miles. An average shipment, weighted by ton-miles, has a value of $474,937, weighs 4,615 tons, and travels 1,100 miles. Trucks are responsible for 44% of the shipping ton-miles, followed by

Table 2: Summary Statistics of Shipments in 2017 Weighted by Ton-Miles

	Mean	Std.Dev.	Min.	Max.
Value ($)	474,937	2,801,592	1	3,499,500,000
Weight (tons)	4,615	11,373	0	218,327
Distance (miles)	1,100	755	1	7,698
Temperature-controlled	0.08	0.26	0.00	1.00
Export shipping	0.09	0.28	0.00	1.00
Air	0.00	0.05	0.00	1.00
Pipeline	0.01	0.12	0.00	1.00
Rail	0.43	0.50	0.00	1.00
Truck	0.44	0.50	0.00	1.00
Water	0.09	0.29	0.00	1.00
Parcel/Courier	0.01	0.09	0.00	1.00
Other	0.01	0.08	0.00	1.00

Notes: Base on the 2017 U.S. Commodity Flow Survey (CFS) Public Use Microdata.

rail (43%) and water (9%).

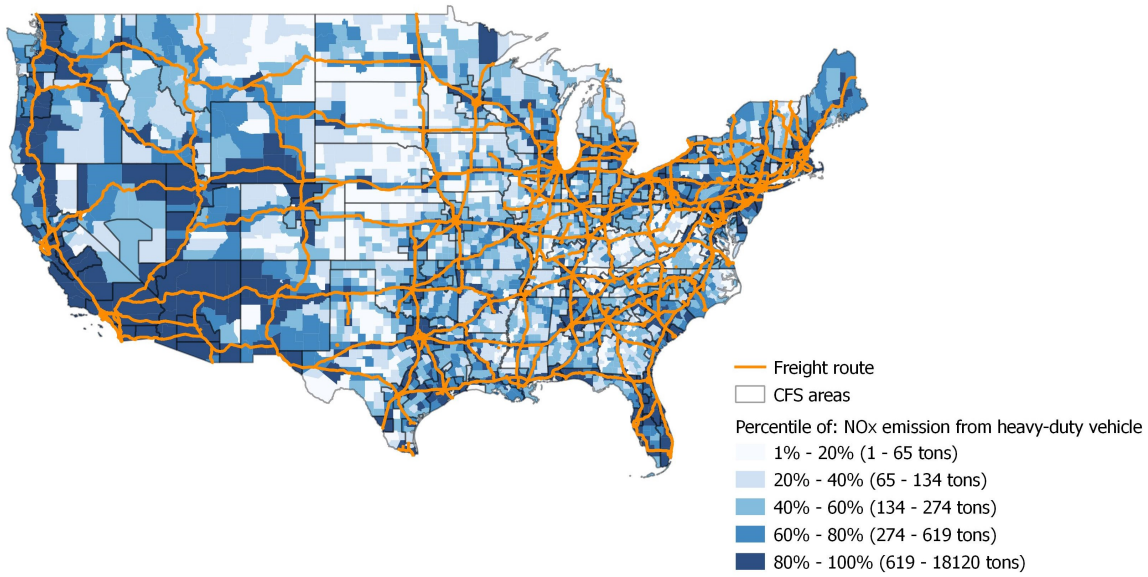
Our analysis requires the routes that shipments take as well as the counterfactual routes they would take under alternative transport modes. We infer those routes by combining shipment origin and destination information with several transport network databases from the Bureau of Transportation Statistics. These databases include Freight Analysis Framework Network and Regions, Navigable Waterway Lines and Water Ports, Airports and Intermodal Freight Facilities Air-to-Truck, and North American Rail Nodes and Lines.

Figure 2 plots the truck freight routes from the Freight Analysis Framework Network database. The routes include state primary and secondary roads, National Highway System and National Network. Figure 3 shows waterways and railways. We plot the airports closest to each CFS point (or the population-weighted centroid of a CFS area) and assume that air routes are direct links between CFS points.

We gather sociodemographic information from the American Community Survey (ACS) as provided by the Minnesota Population Center's Integrated Public Use Microdata Series (IPUMS). The 2017 survey samples 1.24 million households in the U.S. The data provide information such as income, education, race, age of each member of the sampled household and the Public Use Microdata Area (PUMA) in which the household is located.[8] Household

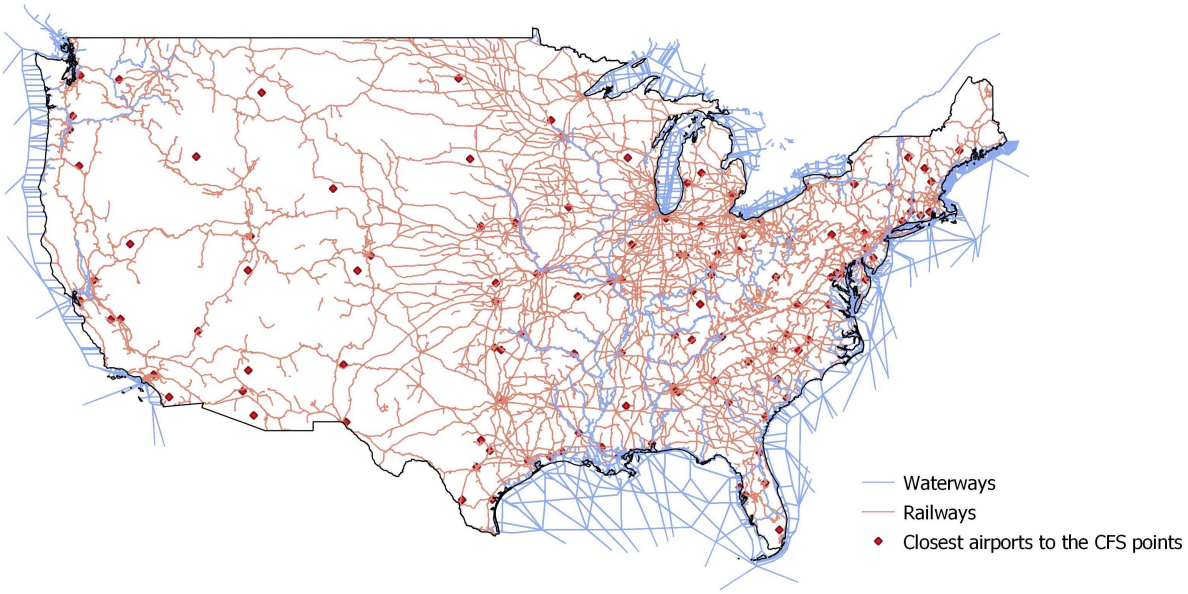
[8]A PUMA may be smaller or larger than a county. If multiple counties are located in the same PUMA, we apply the PUMA-level statistics to those counties.

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



Notes: The CFS areas designate the origins and destinations of shipment records in the Commodity Flow Survey (CFS) Public Use Microdata. The truck freight routes are from the Freight Analysis Framework Network and Regions databases. County-level NO_x emissions from the on-road vehicles are from the EPA National Emissions Inventory.

Figure 3: Waterway and Railway Routes and Closest Airport to the CFS Points



Notes: The CFS points are the population-weighted center points of CFS areas.

sampling weights allow us to calculate nationally-representative statistics.

Finally, the EPA National Emissions Inventory (NEI) provides county-level estimates of air emissions from heavy-duty vehicles. Those estimates are based primarily on the data reported by the local agencies and other data sources. Figure 2 shows substantial heterogeneity across counties in truck-generated NO_x emissions in 2017. We use these EPA estimates only in the next subsection to provide evidence for unequal distribution of truck pollution across sociodemographic groups. In later sections, we calculate truck emissions from the CFS shipments in our sample based on inferred shipping routes and truck emission factors.

We expect to access the restricted-use versions of the CFS and ACS data starting in Fall 2022. The restricted-use CFS dataset identifies a shipment with its origin address and destination zip codes. The restricted-use ACS dataset identifies the address of each sampled household. Those more geographically granular data will allow us to estimate more precise models.

3.2 Suggestive Evidence of Environmental Injustice from Truck Pollution

We now present suggestive evidence of environmental injustice from truck pollution in a world without electric trucks. We use NO_x as a representative example. We test whether lower-income households are exposed to more truck NO_x emissions, and whether those NO_x emissions are generated more by shipments intended for higher-income destinations.

Table 3 tests the first hypothesis, by regressing log county-level NO_x emissions per household on log household income while controlling for various fixed effects. Column (1) uses the log total vehicle NO_x emissions (i.e, from passenger cars as well as trucks) per household as the outcome variable. Column (2) uses only truck emissions and shows that a 1% increase in the log household income is associated with a 0.08% reduction in log truck NO_x emissions. This effect is slightly larger (in magnitude) than the effect on total vehicle NO_x emissions, although the difference is not statistically significant. Columns (3)-(5) add fixed effects and the negative correlations between household income and truck NO_x emissions persist. For example, Column (5) shows that for households that are located in the same state and have

a household head with the same race and educational attainment, those with lower income are still exposed to higher truck NO_x emissions.

Table 3: Log Vehicle NO_x Emissions Per Household and Log Household Income, 2017

	(1) Total	(2) Truck	(3) Truck	(4) Truck	(5) Truck
Log(Household Income)	−0.073***	−0.079***	−0.034**	−0.040***	−0.028***
	(0.014)	(0.014)	(0.010)	(0.009)	(0.007)
State FE			X	X	X
Race FE				X	X
Education FE					X
N	1.182e+08	1.182e+08	1.182e+08	1.182e+08	1.182e+08
Adjusted R^2	0.013	0.013	0.426	0.435	0.438

Notes: NO_x emissions in tons are from the EPA National Emissions Inventory. Column (1) uses total vehicle NO_x emissions and all other columns use truck NO_x emissions. Races include Asian, Black, White, Other (including American Indians and Alaska Native), and Mixed. Education attainment includes below high school, some high school education, and some college education or above. Standard errors clustered at the state level are in parentheses. *: $p < 0.05$, **: $p < 0.01$, ***: $p < 0.001$.

Table 4 repeats the regression in Column (1) of Table 3 by the race of the household head. The results show that households with a white household head experience the strongest negative correlations between household income and truck NO_x emissions, followed by mixed race and black. The correlations are still negative for Asians and other races (including American Indians), although they are not statistically significant.

Table 4: Race-Specific Relationship between Log Truck NO_x Emissions Per Household and Log Household Income, 2017

	(1) Asian	(2) Black	(3) White	(4) Other	(5) Mixed
Log(Household Income)	−0.035	−0.055***	−0.095***	−0.035	−0.083***
	(0.021)	(0.012)	(0.014)	(0.028)	(0.014)
N	5747797	14418842	90452437	5155268	2471608
Adjusted R^2	0.003	0.007	0.018	0.002	0.014

Notes: Truck NO_x emissions in tons are from the EPA National Emissions Inventory. Standard errors clustered at the state level are in parentheses. *: $p < 0.05$, **: $p < 0.01$, ***: $p < 0.001$.

To test our second hypothesis of whether higher-income regions are responsible for generating 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, racial composition (percentages of each race) and population of the destination CFS (weighted by county population), commodity group fixed effects, and quarter 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 5 Column (1) restricts the shipments to those that originate and end in the same CFS area, where we fail 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 a 1% increase in the destination median household income is associated with a 0.11% increase in the shipment-level NO_x emissions. This means that for two truck shipments of the same commodity group, with the same value, and delivered in the same quarter to destinations with the same racial composition and population, shipments intended for higher-income destinations generate more NO_x emissions.

Table 5: Shipment-Level NO_x and Destination Demographics, 2017

	(1) Within-CFS	(2) Cross-CFS
Log(Destination Median Household Income)	0.120	0.109**
	(0.112)	(0.035)
Log(Shipment Value)	0.683***	0.550***
	(0.064)	(0.043)
Log(Destination Population)	0.613***	0.121
	(0.097)	(0.097)
Race Composition	X	X
Commodity Group FE	X	X
Quarter FE	X	X
N	2124305	2056561
Adjusted R^2	0.406	0.324

Notes: An observation is a truck shipment record in the 2017 U.S. Commodity Flow Survey (CFS) Public Use Microdata. 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. *: $p < 0.05$, **: $p < 0.01$, ***: $p < 0.001$.

To sum up, we find that lower-income households are exposed to more truck NO_x emissions and that more of those NO_x emissions are generated by shipments intended for higher-income destinations. We take these findings as only suggestive evidence for environmental injustice from truck shipping for two reasons. First, to the extent that lower-income households have a higher marginal utility of income, even the same pollution exposure will damage their welfare more than it damages the welfare of higher-income households. The seemingly small negative correlations between truck emission and household income in Table 3 may therefore translate into large welfare disparities between poor and wealthy households. Second, emissions need to be combined with an atmospheric model to become ambient concentrations, which in turn need to be combined with an economic valuation model to become monetized pollution damages. The monetized pollution enters the measure of inequality in our framework in Section 2. We now turn to our formal analysis of the distributional consequences of truck shipping and electrification that addresses these concerns.

4 Estimating Transport Mode Choices

We estimate a conditional logit transport mode choice model using 2017 CFS PUM data. In contrast to multinomial logit models, conditional logit models have coefficients that do not depend on alternatives. This makes it feasible to simulate the effect of adding a new alternative.

Each shipment i chooses the transport mode j to minimize the unobserved latent value C_{ij}. The latent value has a deterministic component that depends on the variable shipping cost, the inventory cost, and the mode-specific fixed shipping cost:

$$C_{ij} = \alpha_1 \times \underbrace{mile_{ij} \times ton_i \times p_j}_{\text{Variable shipping cost}} + \alpha_2 \times \underbrace{mile_{ij} \times value_i / speed_j}_{\text{Inventory cost}} + \underbrace{\delta_j}_{\text{Fixed shipping cost}} + \epsilon_{ij} \qquad (5)$$

where $mile_{ij}$ is the routed distance of shipment i transported in mode j, ton_j is the weight of shipment i, p_j is the fuel price per ton-mile of transporting in mode j, $value_i$ is the value of shipment i, $speed_j$ is the speed of mode j, and ϵ_{ij} is the idiosyncratic cost shock assumed to be i.i.d. and follow the Type-I extreme value distribution. The inventory cost measures the

time cost of having the shipment on the road. The fixed shipping cost δ_j is mode-specific and can represent the average cost of packaging shipments for transportation in a given mode.

CFS provides the routed distance $mile_{ij}$ only for the chosen mode. To infer the routes under alternative modes, we use transportation network data from the Bureau of Transportation Statistics to calculate the route length between each pair of CFS points along highway, waterway, railway, and airway[9] We find the closest water ports,[10] airports and rail stations along highway routes to CFS centroids and calculate the corresponding shortest distance under each transport mode.

The fuel price p_j and the shipping speed $speed_j$ are not in the 2017 CFS PUM data. For the fuel price, we use the average 2017 freight revenue per ton-mile from the Bureau of Transportation Statistics,[11] at \$1.2515 per ton-mile by air, \$0.0402 per ton-mile by rail, \$0.1882 per ton-mile by truck, and \$0.0274 per ton-mile by water. For the shipping speed, we consult several resources[12] and set 560 miles per hour by air, 38 miles per hour by rail, 55 miles per hour (the U.S. highway speed limit) by truck, and 8 miles per hour by water.

We estimate Equation (5) separately for each commodity group c. We include dummy variables of whether the shipment originates in the Mississippi River Basin and whether the shipment requires temperature control (as in Bushnell and Hughes (2020)) for selected commodity groups. Table 6 reports the mode choice model results by commodity group. All commodity groups have negative shipping cost coefficients, and almost all commodity groups have negative inventory cost coefficients. There is a lot of heterogeneity in the shipping cost and inventory cost coefficients across commodity groups, suggesting the importance of using commodity-group-specific transport mode choice models in simulating market responses to truck electrification.

For example, we find that the transport mode choices of basic chemicals are more sensitive to the shipping cost and less sensitive to the inventory cost than those of cereal grains. This implies that if the electric truck mode would induce the same shipping cost reduction (due to

[9] we assume that airlines take the direct route.

[10] We keep water ports only within 25 miles of the CFS points.

[11] Available at `https://www.bts.gov/content/average-freight-revenue-ton-mile`.

[12] Available at `https://www.flightdeckfriend.com/ask-a-pilot/how-fast-do-commercial-aeroplanes-fly` (air), `https://railroads.dot.gov/elibrary/higher-speed-freight-truck-market-analysis` (rail), and `https://www.up.com/customers/track-record/tr082719-water-pros-cons.htm` (water).

Table 6: Transport Mode Choice Model Estimation Results

Commodity Group	Shipping Cost (Thousand $)	Std.Err	Inventory Cost (Million $-hr)	Std.Err	1(Miss.)	1(Temp. Control)
Animals and Fish	-0.146	0.091	0.027	0.028	Y	
Cereal Grains	-0.758***	0.030	-0.677***	0.038		
Agricultural Products	-0.501***	0.051	-0.182***	0.021	Y	Y
Animal Feed	-0.844***	0.023	-0.206***	0.079	Y	Y
Meat and Seafood	-0.489***	0.075	0.061***	0.016	Y	Y
Milled Grain Products	-1.04***	0.033	-0.616***	0.066		
Fats and Oils	-0.703***	0.019	-0.538***	0.067	Y	Y
Alcohol	-1.08***	0.049	-0.202***	0.026	Y	
Tobacco	-4.86***	1.210	-0.803**	0.312		
Non-Metallic Minerals	-0.643***	0.045	-1.66***	0.137		
Metallic Ores	-0.528***	0.082	0.004***	0.001	Y	
Fuel Oils	-0.686***	0.045	-0.155***	0.016		
Coal and Petroleum Products	-1.23***	0.066	-0.310***	0.017	Y	Y
Basic Chemicals	-0.910***	0.023	-0.132***	0.022	Y	Y
Pharmaceutical Products	-0.236***	0.085	-0.001**	0.001	Y	Y
Fertilizers	-1.01***	0.042	-0.347***	0.026		
Chemical Products	-0.815***	0.036	-0.138***	0.019	Y	Y
Plastics and Rubber	-0.846***	0.068	-0.242***	0.048	Y	Y
Logs and Wood	-0.354***	0.102	0.087	0.059		
Wood Products	-0.743***	0.016	-0.490***	0.025	Y	Y
Pulp and Paper	-0.576***	0.019	-0.360***	0.045	Y	Y
Paperboard Articles	-1.20***	0.064	-0.267***	0.042	Y	Y
Printed Products	-0.759***	0.155	-0.664*	0.381	Y	Y
Textiles and Leather	-1.24***	0.087	-0.233***	0.063		
Non-Metallic Mineral Products	-0.479	0.384	0.041	0.042	Y	Y
Base Metal	-0.926***	0.022	-0.200***	0.031	Y	Y
Articles of Base Metal	-0.729***	0.049	-0.164***	0.034	Y	Y
Machinery	-0.395***	0.078	0.020***	0.006	Y	Y
Electrical Equipment	-0.371***	0.103	-0.165***	0.042	Y	Y
Motorized Vehicles	-1.31***	0.120	-0.004	0.004	Y	Y
Transportation Equipment	-0.451***	0.072	-0.123***	0.024	Y	Y
Precision Instruments	-0.287**	0.122	-0.083**	0.034	Y	Y
Furniture	-0.499***	0.112	0.055**	0.026	Y	Y
Miscellaneous	-0.613***	0.115	-0.012	0.023	Y	Y
Waste and Scrap	-0.449***	0.018	-0.267***	0.031	Y	Y
Mixed Freight	-0.567***	0.092	0.051***	0.018	Y	Y

Notes: Based on 2017 Commodity Flow Survey (CFS) Public Use Microdata (PUM). 1(Miss.) indicates whether a shipment originates in the Mississippi River Basin, and 1(Temp.Control) indicates whether a shipment requires temperature control. Observations with commodity group suppressed in CFS PUM are not included. The following commodity groups are omitted because their estimation does not converge: monumental or building stone, natural sands, gravel and crushed stone, coal, and gasoline-aviation-fuel-ethanol. Standard errors are clustered on the shipment level. *: $p < 0.05$, **: $p < 0.01$, ***: $p < 0.001$.

the lower per-mile cost of electricity) for both commodities, then shippers of basic chemicals would be more inclined to adopt electric trucks than those of cereal grains. This also implies that if the charging infrastructure would feature slower charging, thereby increasing the shipping time of those shipments, then shippers of basic chemicals would be less bothered by this drawback of electric trucks than those of basic chemicals. Existing studies have ignored shipper preferences by imposing exogenous electric truck adoption rates (e.g., a complete transition of the national truck fleet to electric trucks). Our results show that it is crucial to take into account commodity-specific shipper preferences in predicting how the charging infrastructure will induce the adoption of electric trucks.

5 Simulating Electric Truck Take-Up

With the estimated transport mode choice model, we can simulate the probability that each shipment would take up the electric truck mode under various infrastructure scenarios. We first describe how we construct the infrastructure scenarios. We then parameterize the electric truck mode for the shipments in our data as a function of the infrastructure scenarios. Finally, we present results on the take-up rates of electric trucks.

5.1 Infrastructure Scenarios

An infrastructure scenario specifies the battery capacity, battery efficiency, charger power, and charging locations. We construct an unconstrained charging infrastructure scenario, where electric trucks can technically support all truck shipments given current technical parameters in California Air Resources Board (2021). We will define additional scenarios based on this benchmark scenario, by selectively siting chargers under a budget constraint or improving the technical parameters.

The battery capacity specifies how much electricity a fully-charged electric truck carries. The battery efficiency specifies the amount of electricity needed to travel one mile. Both the battery capacity and efficiency depend on the size of the truck. Consistent with the California Air Resources Board (CARB), we group trucks into three sizes: Class 2-3 (gross vehicle weight ranging from 6,001 lbs to 14,000 lbs), Class 4-6 (from 14,001 lbs to 26,000 lbs),

and Class 7-8 (26,001 lbs and above).[13] Based on California Air Resources Board (2021), we choose for our unconstrained charging infrastructure scenario a battery capacity of 80 kWh for Class 2-3, 200 kWh for Class 4-6, and 1000 kWh for Class 7-8, and a battery efficiency of 0.6 kWh/mi, 1.2 kWh/mi, and 2.1 kWh/mi, respectively. The ratio of the battery capacity over the battery efficiency is the battery range. The battery range in our unconstrained charging infrastructure scenario is 133 miles, 167 miles, and 476 miles, respectively. Additional scenarios feature larger battery capacity or higher battery efficiency.

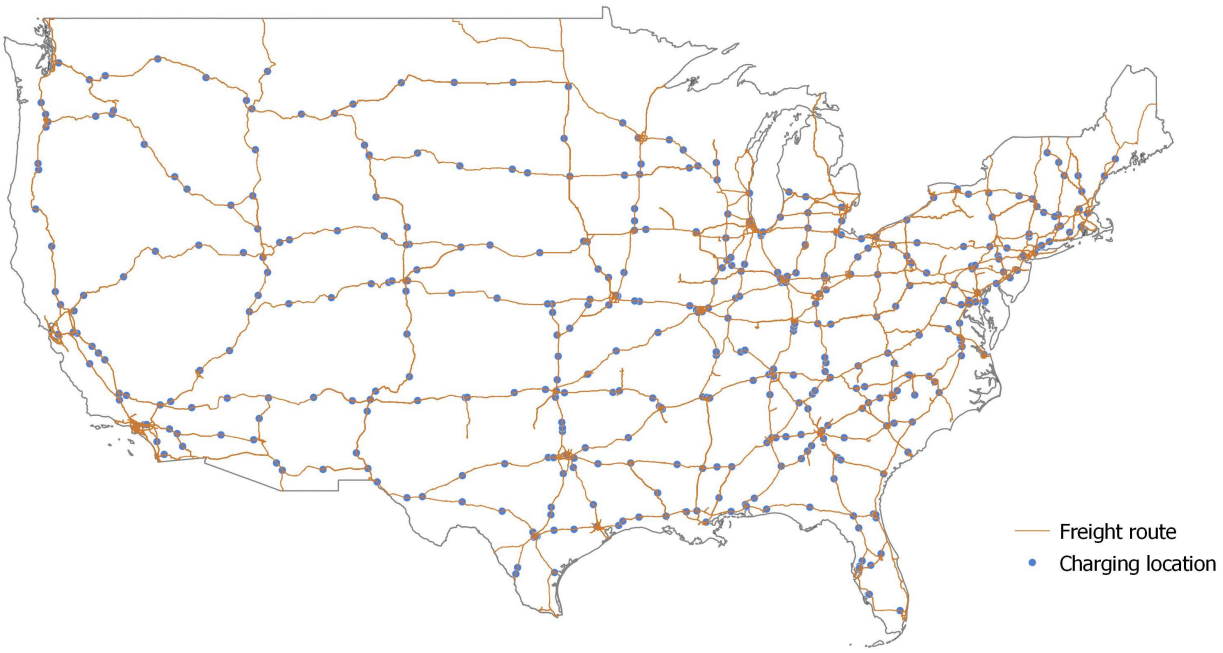
The charger power describes the amount of electricity charged per unit of time. Based on California Air Resources Board (2021), we choose for our unconstrained charging infrastructure scenario a charger power of 150 kW. The ratio of the battery capacity over the charger power is the time to fully charge the battery. The charging time in our unconstrained charging infrastructure scenario is 0.53 hours for Class 2-3, 1.33 hours for Class 4-6, and 6.67 hours for Class 7-8. Additional scenarios feature larger charger power.

To site chargers in our unconstrained charging infrastructure scenario, we make it *feasible* for every truck shipment in our data to go electric on their current highway routes.[14] Which of those feasible truck shipments will *choose* to go electric depends on the transport mode choice model we have estimated in Section 4. We first site chargers at all shipment origins as defined by the population-weighted center of each Commodity Flow Survey (CFS) area. These origin chargers allow for overnight charging before the shipment departs (Bradley et al., 2019). We then site chargers at highway intersections and highway corridors to allow for opportunity charging, consistent with Tong et al. (2021). To determine the charging locations along a highway corridor, or a segment defined by consecutive highway intersections or origins, we gather all the shipments that travel along that corridor, find the shipment with the minimum battery range, and site chargers to meet that minimum battery range. We arrive at 129 charging locations at CFS points, 89 at highway intersections, and 429 along highway corridors. Each location can have multiple chargers, depending on the electricity

[13]Our shipment data do not specify truck sizes. To infer the truck size carrying each shipment, we use 2002 Vehicle Inventory and Use Survey (VIUS) data to estimate a multinomial choice model that predicts the truck size based on the commodity group, the origin state, the shipment weight, and the distance of a typical trip. We then use this model to predict the truck size in our shipment data.

[14]The federal limit on the gross vehicle weight is 80,000lbs. Our unconstrained charging infrastructure scenario makes electric trucks feasible for all truck shipments below that limit.

Figure 4: Charging Locations in the Unconstrained Charging Infrastructure Scenario



Notes: Those charging locations make it feasible for every truck shipment below 80,000 lbs (the federal weight limit) in the 2017 Commodity Flow Survey (CFS) data to go electric on their current highway routes. We choose a battery range of 133 miles for Class 2-3 trucks, 167 miles for Class 4-6 trucks, and 476 miles for Class 7-8 trucks based on the current technology parameters in California Air Resources Board (2021).

demand of trucks passing those locations that need charging.[15] Figure 4 shows those charging locations in our unconstrained charging infrastructure scenario.

Additional scenarios allocate a smaller total number of chargers than in our unconstrained charging infrastructure scenario. Thus, only some of truck shipments can be electrified in those scenarios, allowing us to study how various ways of allocating those chargers lead to differential treatment of shipments and sociodemographic groups. In ongoing work, we are developing four constrained siting scenarios. First, we will proportionally allocate chargers based on highway truck flow. To the extent that disadvantaged communities are located close to highways, allocating by highway traffic could achieve preferential treatment of disadvantaged communities. This approach is similar to those proposed in policy analysis such

[15]We have calculated that the number of chargers needed in California would be 141,660 to achieve our unconstrained charging infrastructure scenario with a redundancy factor of three (i.e. assuming that the number of chargers at a charging location should be three times the electricity need divided by 24 hours and the per-charger power to allow for slacks, or that a charger is utilized 8 hours per day on average). Our number is roughly consistent with the 157,000 chargers found by California Energy Commission (2021) to be needed in California.

as Bradley et al. (2019), which site chargers based on a traffic flow model and checks if a sufficient number of chargers turn out to be in disadvantaged communities.

Second, we will allocate chargers by explicitly considering the role of income. For example, we can rank all the shipments' origin CFS points or routes from the lowest to the highest median household income. Then, we allocate the chargers for the corresponding shipments in order and stop assigning chargers when the number of chargers reaches the budget. In doing so, we prioritize electrifying the trucks that originate in or pass by low-income communities.

Third, we will site chargers only in states that have signed the Memorandum of Understanding on electric truck regulation. [16] This scenario reflects the likely policy scenario without federal intervention and can shed light on political economy concerns regarding truck electrification. For example, suppose a significant portion of trucks that affect disadvantaged communities in a state delivers to a neighboring state that does not install chargers. The origin state may find it beneficial to subsidize the neighboring state on charger installation. The neighboring state may thus choose to free-ride on other states' electric truck initiatives.

Fourth, we will explore the potential of optimizing a given policy objective (e.g., inequality) by choosing charger locations using an approximate knapsack algorithm. Li (2019) uses the exact knapsack algorithm to site EV chargers. The exact knapsack algorithm does not apply in our setting because the number of chargers in one location affects the marginal value of chargers in another.

For the rest of this paper, we report results under the unconstrained charging infrastructure scenario, in which electric trucks are a feasible option for all truck shipments. In ongoing work, we construct additional scenarios featuring improved values of the technical parameters and selective siting of chargers under a budget constraint.

5.2 Electric Truck Mode Parameterization

With the specifications of battery capacity, battery efficiency, charger power, and charging locations, we now parameterize the electric truck mode for each truck shipment in the 2017

[16] These states are California, Colorado, Connecticut, Hawaii, Maine, Maryland, Massachusetts, New Jersey, New York, North Carolina, Oregon, Pennsylvania, Rhode Island, Vermont, and Washington, as well as the District of Columbia.

CFS PUM data. The shipping cost of a truck shipment i of truck size s if it adopts the electric truck mode is:

$$\underbrace{mile_i \times batteryEff_s \times elecP_s}_{\text{Electricity expenditure}} - \underbrace{mile_i \times carbonFactor_s \times creditP}_{\text{Low-Carbon Fuel Standard credit revenue}}, \tag{6}$$

where $mile_i$ is the routed distance of this shipment (mi), $batteryEff_s$ is the battery efficiency of truck size s (kWh/mi), $elecP_s$ is the electricity price of truck size s (\$/kWh), $carbonFactor_s$ is the CO_2 emission factor of the replaced internal-combustion-engine (ICE) truck (g/mi), $creditP$ is the Low-Carbon Fuel Standard (LCFS) credit price (\$/ton). Based on California Air Resources Board (2021) we choose an electricity price of \$0.15/kWh for Class 2-3, \$0.14/kWh for Class 4-6, and \$0.13/kWh for Class 7-8, and an LCFS credit price of \$200 per ton. We use the EMFAC database,[17] developed by CARB as official emissions inventories of on-road mobile sources in California, to calculate the on-road CO_2 emission factors of the existing ICE truck fleet as of 2017. The CO_2 emission factor is 541 g/mi for Class 2-3, 1340 g/mi for Class 4-6, and 1708 g/mi for Class 7-8.

The inventory cost of a truck shipment i of truck size s if electrified is:

$$value_i \times [\underbrace{mile_i/speed}_{\text{Driving time}} + \underbrace{\max(mile_i - range_s, 0) \times batteryEff_s/chargerPower}_{\text{Charging time}}], \tag{7}$$

where $value_i$ is the value of the shipment (\$), $speed$ is the truck speed (55 mi/hr), $range_s$ is the battery range of truck size s (mi), and $chargerPower$ is the charger power (kW). The charging time component of the inventory cost reflects the presumption that the electric truck would fully charge overnight at its origin before it departs, which would not take up shipping time. Only the opportunity charging away from the origin could slow down the shipment; the opportunity charging need is the difference between the routed distance and the range if the former is longer and zero otherwise.

Table 7 reports the shipping and inventory costs by truck size and type in the unconstrained infrastructure scenario. On one hand, electrification reduces the shipping cost across truck sizes. This reflects the higher efficiency of electric motors relative to ICEs. The LCFS

[17] Available at `https://arb.ca.gov/emfac/emissions-inventory`.

Table 7: Shipping and Inventory Costs by Truck Size and Type in the Unconstrained Infrastructure Scenario

Truck Size	Type	Variable	Mean	Sd	p10	p50	p90
Class 2-3	ICE	Shipping Cost ($)	32.7	76.5	0.8	3.6	105.0
		Inventory Cost ($-hr)	4733.8	111284.8	1.1	63.9	3252.3
	Electric	Shipping Cost ($)	18.8	43.9	0.5	2.1	60.3
		Shipping Cost w/LCFS	-6.1	14.3	-19.6	-0.7	-0.1
		Inventory Cost ($-hr)	5565.2	133577.8	1.1	64.6	3599.7
Class 4-6	ICE	Shipping Cost ($)	88.2	166.4	2.6	16.4	277.0
		Inventory Cost ($-hr)	46092.7	1267430.0	95.5	1624.4	74483.1
	Electric	Shipping Cost ($)	40.6	76.7	1.2	7.6	127.7
		Shipping Cost w/LCFS	-30.8	58.1	-96.8	-5.7	-0.9
		Inventory Cost ($-hr)	61154.7	1775741.0	96.0	1661.7	94316.8
Class 7-8	ICE	Shipping Cost ($)	79.3	167.4	2.2	14.7	231.8
		Inventory Cost ($-hr)	88525.8	1936389.0	44.7	2131.1	154992.3
	Electric	Shipping Cost ($)	48.6	102.5	1.4	9.0	142.0
		Shipping Cost w/LCFS	-18.4	38.9	-53.9	-3.4	-0.5
		Inventory Cost ($-hr)	118626.0	3044726.0	44.7	2133.8	173113.8

Notes: Each observation is a truck shipment below 80,000 lbs in the 2017 Community Flow Survey Public Use Microdata. ICE stands for internal combustion engine. LCFS stands for Low-Carbon Fuel Standard.

credit revenue reduces the shipping cost even more, and most shipments have negative shipping costs at a credit price of $200. On the other hand, electrification increases the inventory cost because of possible delays due to charging. Our transport mode choice model will predict which shipments will take up electrification when faced with the tradeoff between the inventory cost and the shipping cost under electrification.

Equations (6) and (7) assume that the shipment does not change the route and that there is no congestion at charging locations. These assumptions are valid in the unconstrained infrastructure scenario. In constrained scenarios, however, we will need to allow for the possibility of rerouting and congestion. Little's Law from queueing theory calculates the expected wait time at any charging location given shipment arrivals and charging time. Geospatial packages in R produce a list of paths ordered by physical distance, which, combined with the expected wait and charging time at charging locations, solves the rerouting

problem. Our ongoing work will also take into account the hours of service regulation for truck drivers.

5.3 Take-Up of Electric Trucks

We simulate how many truck shipments would adopt the electric truck mode given an infrastructure scenario. We compare the weighted sum of the variable shipping cost and the inventory cost (weighted by our transport mode choice model estimates of α_1 and α_2 for each commodity group) for each shipment between the ICE truck mode and the electric truck mode. Assuming that the fixed shipping cost δ_j and the idiosyncratic shock ϵ_{ij} do not vary across the ICE truck mode and the electric truck mode, shippers will choose the truck mode with the lower weighted sum.

Our results show in our unconstrained charging infrastructure scenario, 96.3% of truck shipments would adopt electric trucks, conditional on electric trucks being made available to them. If we break it down by truck size, 98.5% of shipments currently transported on Class 2-3 trucks, 93.7% on Class 4-6 trucks, and 70.2% on Class 7-8 trucks would go electric. These high take-up rates are not surprising, given that our unconstrained charging infrastructure scenario is constructed to have no charging infrastructure constraint. We also quantify the marginal cost savings per electrified shipment, by computing the savings in the sum of the shipping cost and the re-scaled inventory cost (by $\hat{\alpha}_2/\hat{\alpha}_1$ specific to each commodity group). We find that the marginal cost saving of an average electrified shipment is 39.2 dollars for Class 2-3, 120.9 dollars for Class 4-6, and 119.8 dollars for Class 7-8.

In ongoing work, we are incorporating upfront costs in determining the take-up of electric trucks.[18] The transport mode choice model informs us of only the marginal cost savings after the shippers have obtained the electric trucks in the first place. California Air Resources Board (2021) provides representative upfront costs of ICE and electric trucks as well as lifetime mileage and depreciation by truck size. Accordingly, we will conduct a net present value analysis for each truck shipment for which the electric truck mode saves the marginal

[18]The changes in the upfront costs and marginal costs of shipping accrue to firms. Absent a model that maps firm profits to household income, we do not include these economic savings in our calculation of inequality measures.

cost. We can then obtain the set of truck shipments that shippers would still electrify even if they bear the full upfront cost of truck replacement. We will later consider the possibility that air, rail, and water shipments might also adopt electric trucks.

6 Computing Pollution Effects

In this section, we describe how we calculate the changes in tailpipe pollution and power plant pollution under truck electrification. We then report those changes for our unconstrained charging infrastructure scenario.

6.1 Tailpipe Pollution

If a shipment adopts an electric truck, it avoids the tailpipe pollution from the internal combustion engine (ICE) truck along the route. To compute the reduction in the tailpipe pollution, we first calculate the on-road emission factors of the ICE truck fleet in California using the EMFAC database developed by the California Air Resources Board. We assume that those emission factors are representative of the national ICE truck fleet. Table 8 reports those emission factors by truck size as of 2020, weighted by vehicle miles traveled across fuel types (diesel and gasoline). Larger trucks have larger emission factors for all the local air pollutants except VOC. This is because the share of diesel engines increases sharply with truck size, and diesel has a lower VOC emission factor than gasoline.

Table 8: On-Road Emission Factors of Existing Internal Combustion Engines Truck Fleet in California in 2020, g/mi

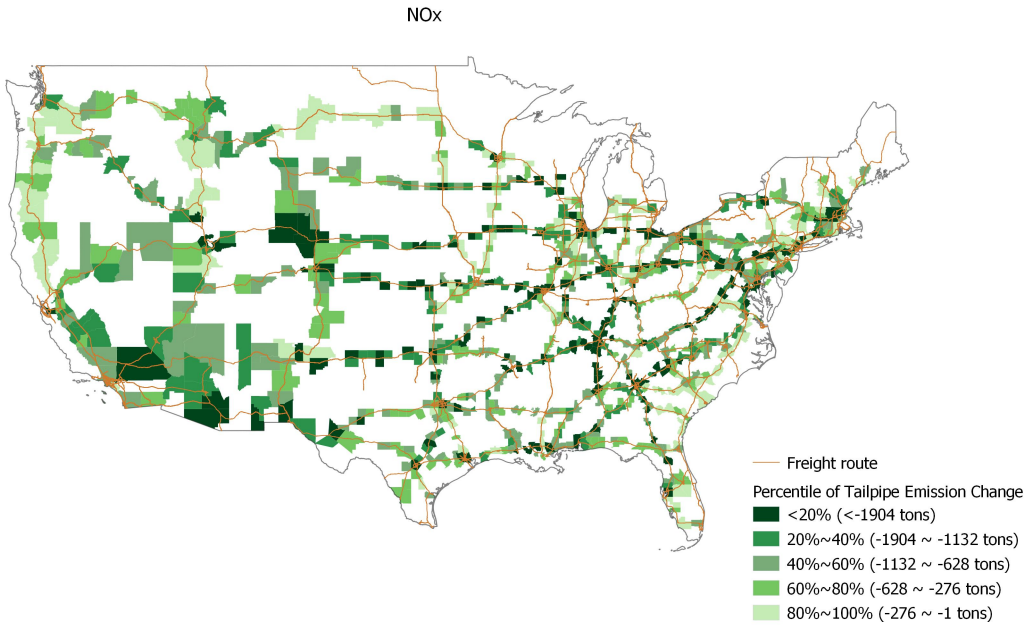
Truck Size	NO_x	$PM_{2.5}$	SO_2	VOC	NH_3
Class 2-3	.568	.017	.005	.296	.044
Class 4-6	2.755	.072	.013	.248	.140
Class 7-8	3.831	.089	.016	.112	.190

Notes: Calculated based on the EMFAC database developed by the California Air Resources Board, weighted by vehicle miles traveled across fuel types (diesel and gasoline).

The tailpipe pollution reduction of pollutant p from an electrified shipment i of truck size s is $mile_i \times emissionFactor_{ps}$. We then allocate this tailpipe pollution reduction to each county

according to the distance it travels in that county. Figure 5 shows the county-level changes in the tailpipe NO_x pollution in percentiles in our unconstrained charging infrastructure scenario. Darker shades indicate counties for which truck electrification reduces more tailpipe NO_x pollution in absolute terms. The ranking of counties in their tailpipe pollution reduction is similar for other pollutants. In relative terms, the median reduction as a percentage of baseline local air pollution (from the National Emissions Inventory data) is 19% for NO_x, 2% for $PM_{2.5}$, 5% for SO_2, 8% for VOC, and 9% for NH_3.

Figure 5: Percentiles of Absolute Change in Tailpipe NO_x Emissions in the Unconstrained Charging Infrastructure Scenario, 2017



Notes: Route-level emission reduction is allocated to each county by the distance traveled in that county. Darker shades indicate counties for which truck electrification reduces more tailpipe NO_x emission in absolute terms.

6.2 Power Plant Pollution

Electric trucks require charging, which adds to the electricity load on the electric grid. The added load changes the dispatch pattern of power plants and their emissions. We predict the

changes in power plant emissions under truck electrification in two steps. First, we estimate power-plant-specific air pollution models that are functions of the electricity load from each North American Electric Reliability Corporation (NERC) region in the same interconnection as the power plant, in the style of Holland et al. (2016a). Power plant k's emission on date t is:

$$e_{kt} = \sum_{n \in I(k)} \beta_{kn} load_{nt} + \mu_{m(t)} + \epsilon_{kt}, \tag{8}$$

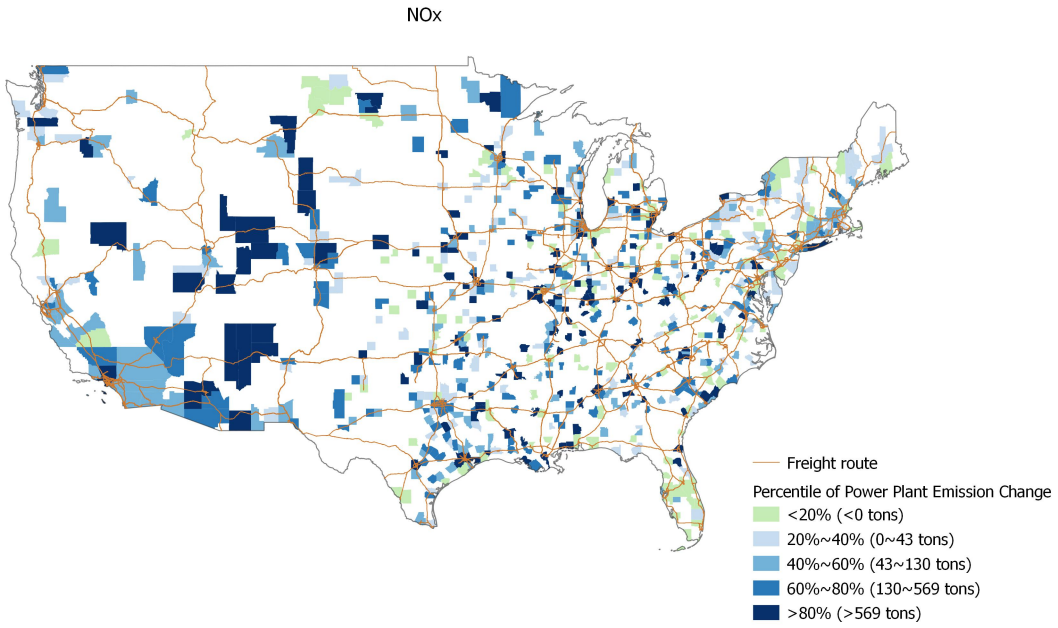
where $I(k)$ is the set of NERC regions in the same interconnection as power plant k, $load_{nt}$ is the electricity load in NERC region n, $\mu_{m(t)}$ is the month fixed effect, and ϵ_{kt} is an i.i.d. idiosyncratic error. The coefficient of interest is β_{kn} that measures the change in plant k's emission from increased electricity load in NERC region n. As Holland et al. (2016a), we consider 9 NERC regions (CA, ERCOT, FRCC, MISO, NPCC, RFC, SERC, SPP, non-CA WECC) and 3 interconnections (East, West, Texas).

To estimate Equation (8) for each power plant, we use daily 2020 electricity load data from FERC Form 714 "Annual Electric Balancing Authority Area and Planning Area Report". The daily power plant SO_2 and NO_x emissions are from EPA Air Market Programs Data. We infer the daily power plant $PM_{2.5}$ emissions by multiplying the plant's load with that plant's average $PM_{2.5}$ emission factor from EPA National Emissions Inventory.

Second, we calculate where each electrified shipment would charge and the amount of electricity charged. We sum up the electricity charging need at each NERC region. We find that to support the charging need of shipments in the 2017 Commodity Flow Survey that would take up electric trucks in our unconstrained charging infrastructure scenario, the added electricity load ranges from 22.5 TWh in FRCC (Florida) and 34.3 TWh in NPCC (Northeastern) to 183 TWh in non-CA WECC (Western) and 184 TWh in SERC (Southeastern). Plugging those NERC loads in each power plant's emission model in Equation (8), we obtain the change in the local air pollution at each power plant. We then sum up those power plant emission changes to the county level.

Figure 6 shows such changes in NO_x emissions in our unconstrained charging infrastructure scenario. Darker blue shades represent counties with larger absolute increases in power plant NO_x emissions. Some counties experience power plant NO_x reductions. This is possible

Figure 6: Percentiles of Absolute Change in Power Plant NO_x Emissions in the Unconstrained Charging Infrastructure Scenario, 2017



Notes: County-level emission change from power plants is predicted using power-plant-specific air pollution models that are functions of the electricity load from each North American Electric Reliability Corporation (NERC) region in the same interconnection as the power plant, in the style of Holland et al. (2016a).

if electric truck charging causes transmission constraints that divert electricity generation from one county's power plant to another county's plant. In relative terms, the median increase as a percentage of Baseline local air pollution is 1.6% for NO_x, 1.0% for $PM_{2.5}$, and 1.4% for SO_2. These changes appear smaller than the changes in tailpipe pollution. However, power plant pollution changes and tailpipe pollution changes can occur in different counties; many power plants are not located along freight routes.

6.3 Monetized Pollution Damages

Having obtained the county-level changes in tailpipe pollution and power plant pollution, we use the AP3 air pollution model (see Holland et al., 2019) to compute their monetized damages. The AP3 model converts county-level local air pollution including NO_x, $PM_{2.5}$,

SO_2, VOC, and NH_3 to monetized damages through air transport models, dose-response functions, and economic valuations of mortality risks.

Table 9 summarizes the changes in the tailpipe pollution damages and power plant pollution damages in our unconstrained charging infrastructure scenario. The results show in this scenario, truck electrification reduces local air pollution damages by $5 billion. This reduction comes from a $26 billion reduction in tailpipe pollution damages and a $21 billion increase in power plant pollution damages. For global pollutants, we find that truck electrification in the unconstrained charging infrastructure scenario reduces the global CO_2 damages by $7 billion, or a $21 billion reduction from truck tailpipes and a $14 billion increase from power plants, assuming a social cost of carbon of $25 per ton.

Table 9 shows that an average county gains $1.54 million in avoided local air pollution damages from truck electrification. However, not all counties benefit: the median county saves a modest amount of $40 thousand dollars, and 10% of the counties incur at least $2.97 million additional pollution damages per county. What this heterogeneity in county-level pollution effects implies for inequality is a question we now turn to.

Table 9: Local Air Pollution Effect of Truck Electrification in the Unconstrained Charging Infrastructure Scenario, 2017

Pollution Damages	U.S. (billion $)	Average County (million $)	Sd (million $)	p10	p50 (million $)	p90
Tailpipe Effect	-25.9	-8.34	32.04	-15.28	-1.41	-0.13
Power Plant Effect	21.1	6.80	21.71	0.12	1.78	13.91
Net Effect	-4.8	-1.54	23.86	-4.69	-0.04	2.97

Notes: Each observation is a county. Dollars are in 2017 values.

7 Inequality, Income Size, and Welfare

In this section, we compute the Atkinson measure of inequality (α_ϵ), income size (mean income μ), and the welfare index (the Equally-Distributed Equivalent or EDE income y_e) in our unconstrained charging infrastructure scenario. Our income data from American Community Survey (ACS) is at the household level. Our pollution damages are county-level and allocated to the household level by the household weight given in the ACS. We follow

the literature and choose 0.25, 0.75, and 1.5 for the inequality aversion parameter.[19]

7.1 Main Results

Table 10 reports our main result. The inequality measure for the distribution of household income reported in the ACS ranges between 0.0889 to 0.4518, depending on the inequality aversion parameter. An inequality measure of 0.2465, associated with the inequality aversion parameter 0.75, indicates that had income were equally distributed, only 75% of the total income would be needed to achieve the same welfare as the status quo. In the "No Electric Trucks" column, we report the inequality, income size, and welfare index of the income distribution adjusted for the baseline local air pollution damages from the EPA National Emissions Inventory. Adjusting for baseline pollution damages widens inequality as measured by the Atkinson measure, consistent with Muller et al. (2018) with the Gini coefficient approach. Because those baseline pollution damages reduce the mean income as well, they reduce overall welfare.

In the "Electric Trucks" column of Table 10, the "Adj. income w/ tailpipe" sub-column in shows the effects of truck electrification if we only consider the reduction in the tailpipe pollution from the baseline pollution. Compared with the baseline-pollution-adjusted income distribution, the tailpipe pollution reduction in our unconstrained charging infrastructure scenario narrows inequality and increases the income size, leading to a higher EDE income by $188–1,934 per household.

Most of those gains from tailpipe pollution reduction, however, are eroded by the power plant pollution changes. The last sub-column of Table 10 shows that once we also consider the power plant pollution changes under truck electrification, inequality mostly reverts to the levels under the baseline-pollution-adjusted income distribution. The mean income is almost as low. Taking inequality and income size together, we find that truck electrification in our unconstrained charging infrastructure scenario still increases welfare, by $57–865 in EDE income per household.

[19]The U.S. Census Bureau uses values of 0.25, 0.5 and 0.75 (DeNavas-Walt et al., 2013). The study for the OECD by Sawyer (1976) uses values of 0.5 and 1.5. LIS, a cross-national data center in Luxembourg, uses values of 0.5 and 1 for 40 countries (see http://www.lisdatacenter.org/dataaccess/ key-figures/download-key-figures/).

Table 10: Inequality, Size, and Welfare Effects of Truck Electrification in the Unconstrained Charging Infrastructure Scenario, 2017

			No Electric Trucks	Electric Trucks	
	Inequality aversion	Unadjusted income	Adj. inc. w/ baseline pollution	Adj. inc. w/ tailpipe	Adj. inc. w/ tailpipe & plant
Inequality	0.25	0.0889	0.1054	0.1049	0.1053
	0.75	0.2465	0.3009	0.2986	0.3002
	1.5	0.4518	0.6012	0.5782	0.5980
Income Size ($)		88,142	81,079	81,241	81,129
Welfare Index ($)	0.25	80,304	72,532	72,720	72,589
	0.75	66,415	56,679	56,987	56,773
	1.5	48,324	32,336	34,270	33,201

Notes: We use the Atkinson measure of inequality. The income size is the mean income per household. The welfare index is the Equally-Distributed Equivalent income. Baseline pollution comes from the EPA National Emissions Inventory. Adjusted income with tailpipe is the income distribution adjusted for the baseline pollution and changes in tailpipe pollution. Adjusted income with tailpipe and plant is the income distribution adjusted for baseline pollution and changes in both tailpipe and power plant pollution. The pollutants include NO_x, $PM_{2.5}$, SO_2, VOC, and NH_3, and their damages are monetized using the AP3 air pollution model. Dollars are in 2017 values.

7.2 Within-Group Results

We report the income inequality, size, and welfare effects within certain sociodemographic groups in Table 11, using a central value of 0.75 for the inequality aversion parameter. Results using other values exhibit similar patterns. Across household heads' races, education, ages and regions, the common result is that truck electrification in the unconstrained infrastructure scenario reduces inequality, increases income size, and improves welfare.

In the racial grouping, households with a white household head experience the smallest percentage reduction in inequality (0.17%), behind Asian and Black (0.24%), mixed (0.29%), and others (0.55%). In terms of welfare, the black group experiences the largest percentage increase in welfare (0.49%), while the white group experiences the smallest increase (0.11%).

To relate those within-race results to our suggestive evidence of environmental injustice in Section 3, recall that Table 4 has shown that log household income and log truck NO_x emissions (as reported by EPA) are the most negatively correlated for whites. Here, we find (though not reported in Table 11) that whites experience the second smallest reduction in inequality when only the tailpipe pollution effect is considered. This result, together with

Table 11: Within-Group Effects of Truck Electrification in the Unconstrained Charging Infrastructure Scenario, 2017

	Inequality Change	Size Change	Welfare Change
Asian	-0.24%	0.07%	0.18%
Black	-0.24%	0.18%	0.49%
White	-0.17%	0.05%	0.11%
Others	-0.55%	0.13%	0.34%
Mixed	-0.29%	0.08%	0.20%
Below high school	-0.51%	0.12%	0.35%
High school	-0.36%	0.07%	0.20%
College and above	-0.16%	0.05%	0.11%
Youth (<25 yrs)	-0.38%	0.09%	0.23%
Adult	-0.21%	0.06%	0.46%
Senior (>64 yrs)	-0.30%	0.07%	0.21%
Northeast	-0.44%	0.12%	0.33%
South	-0.27%	0.07%	0.18%
West	-0.14%	0.04%	0.10%
Midwest	-0.14%	0.02%	0.08%

Notes: We report the results with a central value of 0.75 for the inequality aversion parameter. The percentage change is between the distribution of income adjusted for baseline pollution from EPA National Emissions Inventory and the distribution of income additionally adjusted for the tailpipe and power plant pollution effects.

the small other effects reported in Table 11, suggests that the unconstrained infrastructure scenario may not be effective in improving environmental justice where it may be most needed.

For the remaining groupings, we find that households whose heads have not attended high school experience the largest percentage increase in welfare (0.35%) and the largest percentage decrease in inequality (-0.51%), while those whose heads have received college education experience the smallest increase in welfare (0.11%) and smallest decrease in inequality (-0.18%). Households with adult household heads have the largest increase in welfare (0.46%), while households with youth heads have the largest decrease in inequality (-0.38%). In terms of regions, the Northeast experiences the largest increase in welfare (0.33%) and the largest decrease in inequality (-0.44%).

7.3 Inequality Decomposition

In the previous subsection, we have analyzed the inequality and welfare effects of truck electrification *within* sociodemographic groups. We now investigate how truck electrification changes income inequality *across* sociodemographic groups.

Table 12: Extent of Inequality Explained by Selected Sociodemographics in the Unconstrained Charging Infrastructure Scenario, 2017

	No Electric Trucks	Electric Trucks
Race		
R_W	2.62%	2.60%
R_B	3.70%	3.67%
Education		
R_W	12.16%	12.16%
R_B	16.53%	16.52%
Age		
R_W	3.87%	3.87%
R_B	5.44%	5.44%
Region		
R_W	0.62%	0.62%
R_B	0.88%	0.89%

Notes: The two measures of cross-group inequality, R_W and R_B, are from Cowell and Jenkins (1995). We report the results with a central value of 0.75 for the inequality aversion parameter. The "No Electric Trucks" column corresponds to the distribution of income adjusted for baseline pollution from EPA National Emissions Inventory. The "Electric Trucks" column additionally considers the tailpipe and power plant pollution effects. Race includes Asian, black, white, others, and mixed. Education includes below high school, high school, and college and above. Age includes youth (below 25 yrs), adult, and senior (above 64 yrs). Region includes Northeast, South, West, and Midwest.

Table 12 reports two measures of the extent of inequality explained by selected sociodemographic variables without and with electric trucks in the unconstrained charging infrastructure scenario. We again use a central value of 0.75 for the inequality aversion parameter, and the results using other parameter values are similar. We have three findings. First, only a minority of the pollution-adjusted inequality, with or without electric trucks, is explained by the sociodemographic variables. The majority of inequality is to be found within sociodemographic groups, as reported in Table 11. Second, among the sociodemographic variables

we examine, education best explains the pollution-adjusted inequality with or without electric trucks. Third, truck electrification in the unconstrained charging infrastructure scenario has a negligible effect on the amount of inequality explained by the other sociodemographic variables, but it slightly reduces the amount of inequality explained by race.

To sum up, the unconstrained infrastructure scenario reduces inequality, increases income size, and improves the welfare in aggregate and within sociodemographic groups. This is consistent with Scenario 2 in Table 1 in Section 2. The unconstrained infrastructure scenario also slightly reduces the pollution-adjusted inequality across races, a result that we obtain thanks to the decomposability of the Atkinson measure.

8 Conclusion

In this paper, we study the role of charging infrastructure in determining the distributional consequences of truck electrification. We start by building a micro-founded framework that connects the distribution of pollution damages to the underlying income distribution through equivalent variations. This connection mobilizes the tools and measures developed in the theoretical literature on income inequality. In particular, we propose the use of the Atkinson measure (Atkinson, 1970) in quantifying environmental justice because of its intuitive interpretation, ability to capture the tradeoff between inequality and income size, and decomposability along sociodemographic dimensions.

To apply our framework to truck electrification, we first estimate a transport mode choice model based on the 2017 Commodity Flow Survey (CFS) Public-Use Microdata to understand how shippers of various commodity groups trade off variable shipping costs with inventory costs. We then construct a charging infrastructure scenario where charging stations are widely available with technical parameters typically found in policy and engineering reports. In this unconstrained charging infrastructure scenario, the transport mode choice model predicts an adoption pattern of electric trucks, were they available in 2017, that would lead to $5 billion savings in local air pollution damages. These aggregate savings come from a $26 billion reduction in tailpipe pollution damages and a $21 billion increase in power plant pollution damage.

Using our theoretical framework to combine these findings with household-level sociodemographics data from the American Community Survey (ACS) Public-Use Microdata, we find that the unconstrained infrastructure scenario of truck electrification reduces inequality, increases income size, and improves welfare within all sociodemographic groups defined by race, education, and age of the household head. It also slightly reduces the extent of pollution-adjusted inequality explained by race.

Our ongoing work includes the following. First, we construct additional scenarios that will feature various ways of preferentially targeting disadvantaged communities in building out charging infrastructure and alternative technical parameters. Second, for each additional scenario, we introduce fine details to more accurately predict electric truck adoption, including rerouting, congestion, and hours-of-service regulation. Third, we expect to access the restricted-use CFS and ACS data in Fall 2022, which enable substantially more granular and precise characterization of the environmental justice effects of truck electrification.

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