Distributional Consequences of Electrifying the Trucking Industry: The Role of Charging Infrastructure and Technology

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Abstract

Heavy-duty vehicles comprise one-tenth of road vehicles in the U.S. but contribute almost half of NO_x emissions. An important motivation for electrifying the trucking industry is to relieve the disproportionate burden of NO_x exposure on disadvantaged communities. The spatial pattern of NO_x reduction depends crucially on which shipments and routes will use electric trucks. This paper investigates the role of charging infrastructure and technology in mediating the effect of truck electrification on environmental justice. We first construct a micro-founded framework that connects shipping-related pollution damages and economic surplus with the underlying income distribution, thereby using tools developed in the classical literature on income inequality to quantify the equity-efficiency tradeoff of shipping. To apply our framework to truck electrification, we simulate the distribution of shipments and routes that would take up electric trucks based on a transport mode choice model estimated from shipment-level data in 2012 and 2017. We identify infrastructure and technology scenarios under which the resulting distributions improve both equity and efficiency relative to no electrification.

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1 Introduction

In the U.S., heavy-duty vehicles comprise just one-tenth of road vehicles but contribute 45% of NO_x emissions (FHWA, 2016; EPA, 2018).[1] In California, this percentage is as high as 70% (CARB, 2019). NO_x emissions create localized damages through the formation of harmful smog and particulate matters. Policymakers have increasingly recognized the disproportionate exposure to truck NO_x by disadvantaged communities because of their proximity to truck traffic (CARB, 2020). In 2020, the California Air Resources Board pioneered zero-emission truck rules by adopting the Advanced Clean Truck Regulation, requiring manufacturers to meet increasing sales quotas for electric trucks starting in 2024.[2]

How will truck electrification change environmental injustice related to truck NO_x exposure? The spatial distribution of avoided NO_x emissions depends on which shipments will use electric trucks and the routes they will take. This dependence is a function of not only shipment characteristics, but also the charging technology and infrastructure. For example, with a short battery range, only urban delivery trucks may be electrified, reducing pollution disproportionately for urban consumers. A limited number of charging stations placed along highways may only benefit trucks with a long enough range, which may exclude trucks with heavy shipments such as agricultural products. Even if charging stations are disproportionately available in disadvantaged communities, long-haul shipments that would require charging throughout their routes may not benefit from them.

In this project, we investigate the role of charging technology and infrastructure in mediating the effect of truck electrification on environmental justice. We start with a conceptual framework to quantify the distributional impacts of shipping. We use equivalent variations to convert electrification-induced changes in pollution externality and economic surplus to changes in equivalent income. This allows us to connect environmental inequality with the underlying income inequality, thereby leveraging the micro-founded tools of quantifying income inequality developed in the seminal work by Atkinson (1970). In our framework, equal exposure to pollution does not necessarily imply equity; the same amount of pollution damage would hurt low-income households more than high-income households because the utility function is concave. We use stylized examples to illustrate how shipping electrification can improve both equity and efficiency.

To bring this theoretical framework to our truck electrification context, we estimate a transport mode

[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 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.

choice model based on shipment-level data, and use the model to simulate the distribution of shipments and routes that will be transported by electric trucks under various charging technology and infrastructure scenarios. Our theoretical framework then allows us to examine the equity-efficiency tradeoffs across those scenarios. We decompose the effects of technology and infrastructure on environmental justice into two effects: (1) the externality effect, where electric trucks reduce pollution damages from affected shipments and routes; and (2) the economic effect, where the availability of electric trucks as a transport mode changes the economic surplus in the shipment origins and destinations.

Our main data is the U.S. Commodity Flow Survey (CFS) Public Use Microdata in 2012 and 2017, with over ten million quarterly shipment-level observations. 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. When combined with our theoretical framework, these findings imply substantial inequality under the current shipping pattern and a large potential for improving both equity and efficiency.

We use the data to estimate a multinomial transport mode choice model. Shippers trade off shipping costs with inventory costs. Shipping costs are affected by the fuel cost and the shipment weight, and inventory costs by the time spent on the road and the shipment value. Our transport mode choice model is based on Bushnell and Hughes (2020), who estimate their model with only the 2012 CFS data.

To simulate the distribution of shipments that will be electrified based on the estimated transport mode choice model, we need to parameterize the electric truck mode for each shipment. To do so, we construct technology and infrastructure scenarios based on engineering studies and policy documents, including variations in the locations of charging stations, specifications of charging stations, and specifications of the battery technology. These scenarios determine which shipments *can* be electrified under technology constraints, and *will* be electrified due to economic attractiveness.

Finally, by combining our theoretical framework with the resulting distribution of pollution damages and economic surplus from truck electrification, we answer the following policy questions. Given a technology scenario, how can the government allocate a fixed number of charging stations while being conscientious about equity and efficiency? How do equity and efficiency depend on the number of charging stations, taking into consideration the cost of charging stations? Which technology scenario yields the best "bang for the buck", in terms of efficiency and equity, for government investment in charging stations? For the California Advanced Clean Truck Regulation specifically, we can examine the extent to which its mandated shares of electric trucks could be achieved under various technology and infrastructure scenarios, and explore

the efficiency and equity consequences.

Our work is related to three strands of literature. First, we contribute to the environmental justice literature by constructing and empirically implementing a micro-founded framework that connects environmental injustice to the underlying income inequality. To our best knowledge, Muller et al. (2018) is the only other paper that makes this connection. While they use the Gini coefficient to measure inequality, we tap into the rich theoretical work on inequality by using the micro-founded Lorenz curve approach and the Atkinson measure from Atkinson (1970). Our framework can be readily applied to studying environmental injustice induced by other modes of shipping (such as air, rail, and water), and is useful for thinking about environmental injustice in general.

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 welfare effects of charging infrastructure and technology in the commercial trucking industry. Infrastructure and technology add to the list of mechanisms underlying environmental injustice, which includes 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 (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. 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. In Section 3, we describe our data. Section 4 presents our mode choice model and the estimates. All other work is ongoing. Our analysis does not consider general equilibrium effects, where the introduction of electric trucks may change the overall shipping demand, supply and prices. Neither do we consider the changes in the emissions from the electricity sector that supplies electricity to electric trucks; NO_x emissions from the U.S. electricity sector are much lower than those from road transport.

2 Model

In this section, we build a simple micro-founded model to conceptualize how electrifying the trucking industry can affect environmental justice. This model guides our empirical analysis.

2.1 Setup

Consider three locations, A, B, and C. Each location has a representative resident. A shipment is produced in Location A, passes Location B, and is sold in Location C. Let $V(I, c, p)$ denote the common (indirect) utility function of the residents, where I is the income, c is the pollution concentration, and p is the exogenous price of the shipment. We assume that the utility function is increasing and concave in income, and decreasing and concave in pollution. Let the pre-shipping income profile be $\boldsymbol{I} = (I_A, I_B, I_C)$.

After shipping, Location A enjoys the shipping profit $\pi \geq 0$ on top of the original income. This profit comes at the cost of pollution increase in the amount of $e_A > 0$. Define A's equivalent variation, EV_A, as the lump-sum change to the pre-shipping income that would induce the same utility after shipping:

$$V(I_A + EV_A, c, \infty) = V(I_A + \pi_A, c_A + e_A, p). \tag{1}$$

The shipment price in Location A also changes from infinity (representing unavailability of the shipped good) to a finite price $p > 0$. To make sure that Location A does not consume the shipment, we assume that the shipment price exceeds A's willingness to pay for the shipment. Thus, EV_A is induced by only the shipping profit π_A and the increased pollution e_A.

Location B neither produces nor consumes, but suffers from increased pollution in the amount of $e_B > 0$.

B's equivalent variation, EV_B, is implicitly defined as follows:

$$V(I_B + EV_B, c, \infty) = V(I_B, c_B + e_B, p), \tag{2}$$

where we also assume that the shipment price exceeds the willingness to pay.

Location C consumes the good and/or uses the good as an intermediate input for production for profit $\pi_C \geq 0$, as well as suffers from the increased pollution in the amount of $e_C > 0$. C's equivalent variation EV_C satisfies:

$$V(I_C + EV_C, c, \infty) = V(I_C + \pi_C, c_C + e_C, p), \tag{3}$$

where EV_C captures the effects of using the shipment towards production and consumption as well as the increased pollution.

The equivalent variation profile, $\boldsymbol{EV} = (EV_A, EV_B, EV_C)$, summarizes the welfare effects of shipping through equivalent income changes. The equivalent variations can also be interpreted as the willingness to accept in lieu of shipping. In our illustration of the Lorenz curve approach below, we make the following assumption:

Assumption 1. $EV_A \geq 0, EV_B < 0, EV_C \geq 0$.

The first two constraints are reasonable if A and C fully take into account their local pollution damages when making the shipping transaction. The last constraint is because B suffers pollution.

The use of equivalent variations allows us to apply techniques from the classical theoretical literature on income inequality. Using equivalent income to tie pollution exposure to the underlying income inequality enables a micro-founded investigation of the meaning and extent of environmental justice. To our best knowledge, Muller et al. (2018) is the only other paper on environmental justice that combines pollution damages with income. While they use the Gini coefficient to measure inequality, we will use the Lorenz curve approach and the Atkinson measure from the seminal work of Atkinson (1970).

2.2 Inequality Measures

In this subsection, we illustrate the use of the Lorenz curve and the Atkinson measure to quantify when shipping mitigates or worsens inequality compared with no shipping. The next subsection will examine how electrification adds to this picture.

We have two income distributions at hand: (1) the before-shipping income distribution, $\boldsymbol{I} = (I_A, I_B, I_C)$; and (2) the after-shipping income distribution, $\boldsymbol{I'} = (I_A+EV_A, I_B+EV_B, I_C+EV_C)$, both with equal weights across locations. The Lorenz curve approach of quantifying inequality requires minimal assumptions, but it induces only a partial ordering of income distributions. The Atkinson measure is a cardinal measure that yields a complete ordering and an intuitive interpretation, at the cost of making functional form assumptions.

To start, we impose the following regularity conditions on the utility function that apply to both inequality measures, as in Atkinson (1970):

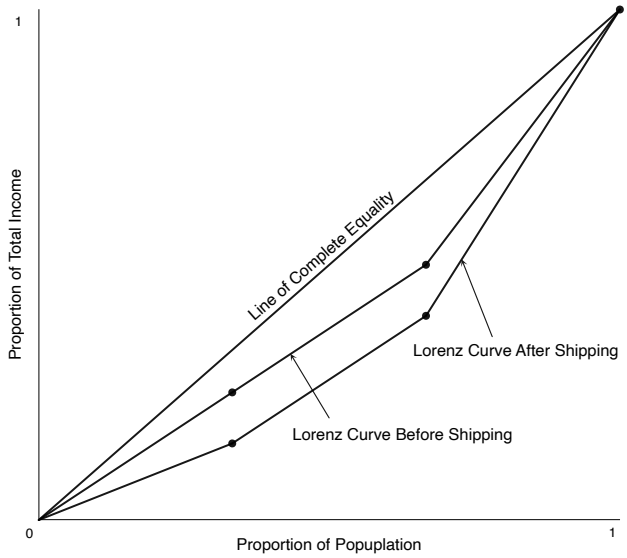
Assumption 2. The social welfare function is symmetric and additively separable in individual utilities, $W = \int_0^{\bar{I}} V(I)\mathrm{d}F(I)$, where $V(I)$ is an increasing and concave individual utility function and $F(I)$ is the income distribution.

For two income distributions with the same mean, Atkinson (1970) shows that the income distribution with the Lorenz curve lying everywhere above the other yields a higher social welfare W under Assumption 2, regardless of the specification of $V(I)$ beyond monotonicity and concavity. From the Lorenz curve perspective, using the Gini coefficient is problematic because the same Gini coefficient can correspond to infinitely many Lorenz curves (Schutz, 1951). To illustrate the Lorenz curve approach, imagine a special case under Assumption 1, with $EA = 0$, $EV_B = -EV_C < 0$. In this case, shipping makes Location A indifferent (because pollution damages exactly offset the producer surplus), and hurts Location B as much as it benefits Location C. Figure 1 plots the Lorenz curves for $\boldsymbol{I} = (25, 25, 50)$ and $\boldsymbol{I'} = (25, 20, 55)$ in this three-person economy. The 45-degree line indicates complete equality. The Lorenz curve after shipping is everywhere below that before shipping, indicating that in this case shipping widens inequality and reduces social welfare.

To apply the Lorenz curve approach more generally, we compare any pair of same-mean income distributions $\boldsymbol{I}$ and $\boldsymbol{I'}$ satisfying Assumption 1 with Destination C enjoying the highest income both before and after shipping. We consider three cases:

Case 1. $I_A \leq I_B, I'_A \leq I'_B$, so that the ascending income orders for plotting the Lorenz curves before and after shipping are both alphabetical. The Lorenz curve at Location A is higher after shipping, because $\frac{I_A}{\sum I} \leq \frac{I_A+EV_A}{\sum I'}$ as $EV_A \geq 0$ from Assumption 1 and $\sum I = \sum I'$ from the same-mean assumption. However, the Lorenz curve at Location B is lower after shipping, because $\frac{I_A+I_B}{\sum I} \geq \frac{I_A+EV_A+I_B+EV_B}{\sum I'}$ as $EV_A + EV_B = \sum EV - EV_C = 0 - EV_C \leq 0$ from the same set of assumptions. Therefore, the Lorenz curves intersect, and we cannot rank the income distributions in this case.

Figure 1: Lorenz Curves Before and After Shipping



Notes: The before-shipping income distribution is $\boldsymbol{I} = (25, 25, 50)$, and the after-shipping distribution is $\boldsymbol{I'} = (25, 20, 55)$, both with equal weights across the three locations. The 45-degree line represents complete equality.

Case 2. $I_A \leq I_B, I'_A \geq I'_B$, so that Locations A and B switch their income order after shipping. As before, the Lorenz curve at the middle income is lower after shipping. Therefore, if the Lorenz curve at the bottom income is also lower after shipping, then shipping widens inequality. This happens when $I_A \geq I_B + EV_B$, where Location B suffers so much pollution damage that it is even poorer than the pre-shipping A. This is the special case depicted in Figure 1.

Case 3. $I_A > I_B$, so that Location B has the lowest income before shipping. Under the assumption that $EV_A \geq 0$ and $EV_B < 0$, this implies that $I_A + EV_A > I_B + EV_B$, so that the income order does not change before and after shipping. As before, the Lorenz curve at the middle income is lower after shipping. The Lorenz curve at B, the lowest-income location, is also lower after shipping, because $\frac{I_B}{\sum I} > \frac{I_B + EV_B}{\sum I'}$. Therefore, shipping worsens inequality in this case.

We sum up our results from the Lorenz curve approach in the following proposition. Note that the proposition does not rely on the functional form of utility (other than monotonicity and concavity).

Proposition 1. In the three-person economy, if the destination has the highest equivalent income before and after shipping, then under Assumptions 1-2, shipping widens inequality and reduces social welfare whenever

$I_A > I'_B$ for the same-mean income distributions.

While the Lorenz curve approach is conclusive only when the curves do not cross, the Atkinson measure proposed in Atkinson (1970) induces a complete ordering of income distributions by assuming a functional form for the utility. Let I_{EDE} denote the equally distributed equivalent income defined implicitly by $V(I_{EDE})\int_0^{\bar{I}} \mathrm{d}F(I) = \int_0^{\bar{I}} V(I)\mathrm{d}F(I)$. Let μ denote the mean of the income distribution. To construct the Atkinson measure, Atkinson (1970) starts with the following assumption:

Assumption 3. The equally distributed measure, $\alpha \equiv 1 - I_{EDE}/\mu$, is invariant with respect to proportional shifts in the income distribution.

Atkinson (1970) argues that this constant (relative) inequality-aversion assumption is reasonable; that if one income distribution is a scaled-up version of the other, then they should be viewed as characterized by the same degree of inequality. Atkinson (1970) goes on to show that Assumptions 2-3 imply that $V(I)$ has the following form:

$$V(I) = \begin{cases} \beta + \gamma \frac{I^{1-\epsilon}}{1-\epsilon}, & \epsilon \neq 1 \\ \ln I, & \epsilon = 1, \end{cases} \tag{4}$$

where $\gamma > 0$ and β are constants, and $\epsilon \geq 0$ is the degree of relative inequality-aversion. A larger ϵ attaches more weight to transfers at the lower end and less to those at the top. In contrast, the Gini coefficient has a constant degree of relative inequality-aversion, so that for typical distributions, it always attaches more weight to transfers in the center of the distribution. Atkinson (1970) argues that this implication of the Gini coefficient may not be socially desirable. When $V(I)$ has the functional form in Equation (4), the equally distributed measure for a discrete income distribution $P(\cdot)$ becomes:

$$\alpha = 1 - [\sum_i (\frac{I_i}{\mu})^{1-\epsilon} P(I_i)]^{1/(1-\epsilon)}, \tag{5}$$

which is known as the Atkinson measure.

Adapted to our model, the Atkinson measures for the income distributions before and after shipping are:

$$\alpha = 1 - \frac{3^{-\epsilon/(1-\epsilon)}}{\sum I}[I_A^{1-\epsilon} + I_B^{1-\epsilon} + I_C^{1-\epsilon}]^{1/(1-\epsilon)} \tag{6}$$

$$\alpha' = 1 - \frac{3^{-\epsilon/(1-\epsilon)}}{\sum I + \sum EV}[(I_A + EV_A)^{1-\epsilon} + (I_B + EV_B)^{1-\epsilon} + (I_C + EV_C)^{1-\epsilon}]^{1/(1-\epsilon)} \tag{7}$$

These measures enable us to compare any income distributions before and after shipping, without the restrictions on the incomes and equivalent variations including Assumption 1, same-mean income distributions, and the shipping destination enjoying the highest income. For example, if $\boldsymbol{I} = (30, 20, 50)$ and $\boldsymbol{EV} = (10, -5, 3)$, then with $\epsilon = 0.5$ (slight relative inequality-averse), the Atkinson measure is 0.034 before shipping and 0.057 after shipping. With $\epsilon = 2$, the Atkinson measures increase across the board to reflect more inequality-aversion, with 0.129 before shipping and 0.246 after shipping. Shipping widens inequality in both cases.

In addition to inducing a complete ranking of income distributions, the Atkinson measure has two attractive features. First, it is intuitively interpretable. In the example above, when $\epsilon = 2$ after shipping, the Atkinson measure of 0.246 implies that if incomes were equally distributed across three locations, we should need only $1 - 0.246 = 75.4\%$ of the present total income to achieve the same level of social welfare. Second, because the Atkinson measure is associated with the utility function specified in Equation (4) and the social welfare function specified in Assumption 2, we can quantify the efficiency-equity tradeoff. In the example above, with $\epsilon = 2$, shipping worsens both inequality and the social welfare compared with no shipping. In fact, the equivalent variation for Destination C (and Origin A, respectively) would have to reach 36 (27) unilaterally for shipping to induce a higher social welfare, but then the Atkinson measure would increase from 0.246 to 0.382 (0.302). On the contrary, the equivalent variation for Destination B only needs to increase from -5 to -3.2 to ensure that shipping increases both social welfare and equity relative to no shipping. We now examine how shipping electrification adds to this picture.

2.3 Effects of Shipping Electrification

The introduction of shipping electrification can have three effects: (1) the externality effect, where shipments that will be shipped by electric trucks reduce pollution; (2) the economic effect, where shipments that will be shipped by electric trucks change the economic surplus of shipping origins and destinations; (3) the general equilibrium effect, where shipping electrification can change the overall shipping demand, supply, and prices. This paper considers the externality and the economic effects.

To capture the externality and the economic effects, we proceed in three steps. First, we construct electrification technology and infrastructure scenarios. These scenarios determine which shipments *can* be electrified under technology constraints, and *will* be electrified due to economic attractiveness. In this first step, we take the scenarios as given and assume that the social planner has no role other than choose where to install charging stations given a fixed quota. Our scenarios have the following components:

- Locations of charging stations, such as at highway intersections (Tong et al., 2021), proportionately by traffic volume, and disproportionately in low-income communities;
- Specifications of charging stations, such as the charging speed;
- Specifications of in-truck battery technology, such as the range and the maximum allowable load (as batteries are heavy and displace the shipment weight).

Engineering studies and policy documents can inform the parameterization of these components. Then, under each technology and infrastructure scenario, we can evaluate the feasibility and economics of electrifying each shipment. For example, shipments heavier than the maximum allowable load cannot be electrified. If the shortest-distance route has charging stations spaced farther than the battery range, we will use the road network to identify possible rerouting to make electrification feasible. For those shipments that are feasible to electrify with or without rerouting, we derive the associated fuel cost savings and inventory cost change (as shipping may be slowed by charging) for the electric truck mode.

Second, we predict which shipments will be electrified through a transport mode choice model. We estimate a transport mode choice model based on quarterly shipment data in 2012 and 2017, which we will describe in Section 3. The data do not have electric trucks as a transportation mode. The model is a multinomial choice model adapted from Bushnell and Hughes (2020), which predicts the likelihood of a shipment choosing a particular transport mode (rail, truck, air, water) based on fuel cost and inventory cost as well as fixed effects. We will describe the model and some estimation results in Section 4. With the estimated model, we add the electric truck mode to the mode choice set and simulate the probability of each shipment to be electrified in each technology and infrastructure scenario.

To capture the externality effect of shipping electrification, we will compute the avoided NO_x emissions from electrified shipments. The AP3 model that converts the spatial distribution of avoided NO_x emissions to that of avoided monetized damages will be helpful. We will add these avoided pollution damages as equivalent variations to the pre-shipping income.

For the economic effect of shipping electrification, note that the inclusive value from the transport mode choice model, when normalized to a monetary scale, represents the negative of the economic cost of shipping each shipment. Therefore, the change in the inclusive value as we introduce the electric truck mode, minus any associated capital cost change, measures the economic savings from electrification that will be shared between the destination and the origin. Assuming various ratios of splitting those economic savings between origins and destinations, we can add them as equivalent variations to their pre-shipping income.

Third, we compute the Atkinson measures (equity) and the social welfare (efficiency) of the equivalent income distributions before and after the introduction of shipping electrification under each technology and infrastructure scenario. Each scenario, including the no-electric truck scenario, will be characterized by a point in the efficiency-equity space. These points will allow us to identify scenarios that dominate others in equity and/or efficiency.

To illustrate, we go back to our simple model and show how electrification can change efficiency and equity. Suppose we have two shipments, one from Location A to B to arrive at C, and the other from A to B to arrive at C', where Location C' has higher income than C. Table 1 lays out the income distributions in each scenario and reports the corresponding Atkinson measure and social welfare. We derive the income distributions such that each shipment increases the origin surplus and the destination surplus by 4, and incurs a pollution damage of 2 to each location. The population is even distributed between the four locations. The Atkinson measure and the social welfare are computed with a degree of relative inequality-aversion of 2. The results show that compared with no shipping, shipping without electrification worsens both equity and efficiency. Equity is compromised because rich locations become richer, and poor locations become poorer from pollution; efficiency is compromised because the same pollution damages create far more utility loss at Location B due to concavity of the utility function. Therefore, a situation with apparent equity in pollution damages does not necessarily imply equity or efficiency in equivalent income distributions. Electrifying either route will improve equity and efficiency, not only over the case of shipping without electrification, but also over no shipping. However, electrifying the A-B-C route is even better than electrifying the A-B-C' route for both equity and efficiency. In our empirical work, we cannot compare before and after shipping, because the before-shipping income distribution is not observed. We can, however, compare shipping with and without electrification.

Our analysis can inform the following policy questions that pertain to government investment in charging infrastructure: (1) Given a technology scenario, how can the government spatially allocate a fixed number of charging stations while being conscientious about equity and efficiency? (2) Which technology scenario, combined with the corresponding conscientious allocation of a fixed number of charging stations, yields the highest equity and efficiency? (3) Holding fixed the technology scenario, how do equity and efficiency depend on the number of charging stations, taking into consideration the cost of charging stations? (4) Which technology and infrastructure scenario yields the best "bang for the buck", in terms of efficiency and equity, for government investment in charging stations? We can also examine the extent to which target shares of electric trucks in the California Advanced Clean Truck Regulation could be achieved with which

Table 1: Illustration of the Equity-Efficiency Effects of Shipping Electrification

	Equivalent Incomes				Atkinson Measure	Social Welfare
	A	B	C	C'		
Before Shipping	15	15	30	40	0.165	-0.192
Shipping w/o electrification	19	11	32	42	0.225	-0.199
Shipping w/ electrification						
A-B-C electrified	23	15	34	42	0.141	-0.163
A-B-C' electrified	23	15	32	44	0.145	-0.164

Notes: One shipment uses the route A-B-C and the other A-B-C'. Each shipment increases both the producer surplus and the buyer surplus by 4 and the pollution damages at each location by 2. Population is even distributed between the four locations. The degree of relative inequality-aversion of 2.

technology scenario and government infrastructure investment, with what efficiency and equity consequences.

3 Data

Our first data set is the U.S. Commodity Flow Survey (CFS) Public Use Microdata for 2012 and 2017. It contains quarterly freight shipment data collected by the U.S. Department of Transportation and the Department of Commerce. 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 2 shows the 133 CFS areas thus defined. The top two panels in Table 2 report the summary statistics of shipment observations weighted by ton-miles. Trucks are responsible for 44% of the shipments.

The second data set we rely on is the Freight Analysis Framework Network and Regions databases from the National Transportation Atlas Database. The former includes the shapefile of the U.S. highway network and intermodal connectors. Figure 3 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.

Figure 2: Commodity Flow Survey (CFS) Areas

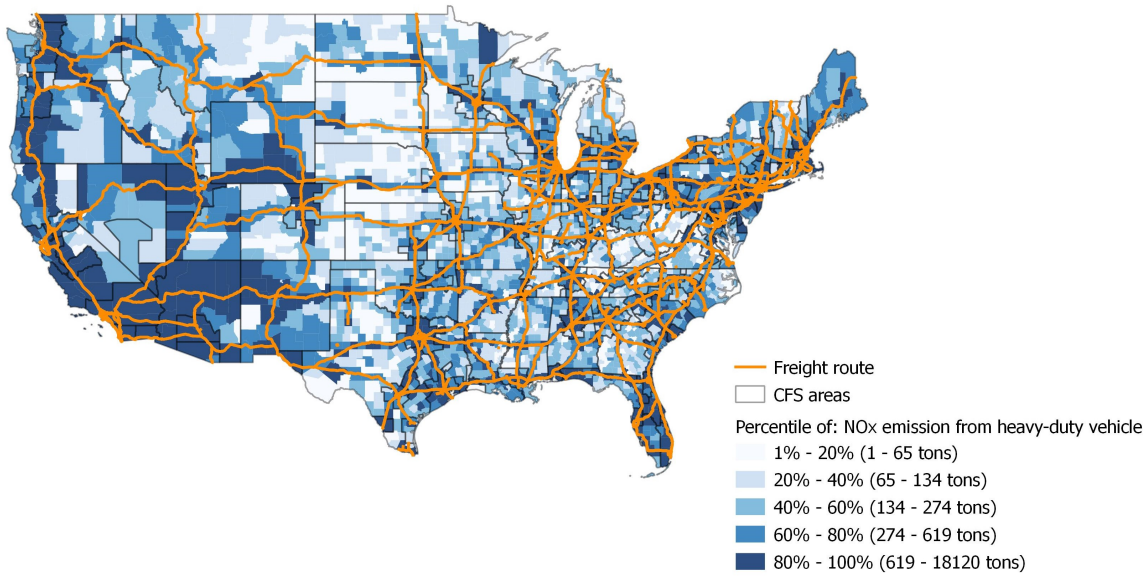


Notes: The CFS designates the origins and destinations of each shipment record using a mixture of Combined Statistical Areas (CSA), Metropolitan Statistical Areas (MSA), and their balances within a state.

Table 2: Summary Statistics Weighted by Ton-Miles

	Mean	Std.Dev.	Min.	Max.
Value ($)	474,937	2,801,592	1	3,499,500,000
Weight (tons)	4,615	11,373	0	218,327
Distance (miles)	1,100	755	1	7,698
Temperature-controlled (%)	0.08	0.26	0.00	1.00
Export shipping (%)	0.09	0.28	0.00	1.00
	Shipment Share			
Air	0.00	0.05	0.00	1.00
Pipeline	0.01	0.12	0.00	1.00
Rail	0.43	0.50	0.00	1.00
Truck	0.44	0.50	0.00	1.00
Water	0.09	0.29	0.00	1.00
Parcel/Courier	0.01	0.09	0.00	1.00
Other	0.01	0.08	0.00	1.00
	Median Household Income ($)			
Destination	195,429	378,402	15,832	2,139,450
Origin	152,064	330,350	15,832	2,139,450
On-route	113,481	101,537	15,832	2,139,450
N	10,499,832			

Figure 3: 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.

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. Figure 3 shows substantial heterogeneity across counties in truck-generated NO_x emissions in 2017.

Finally, we collect MSA/CSA-level demographic data from the American Community Survey, including median household income, median age, population, and the racial composition. The bottom panel in Table 2 shows that when weighted by ton-miles, the median household income is higher at destinations than origins on average. Locations where shipments pass by have the lowest median household income on average. Those differences are statistically significant at a 95% confidence level.

We now present some findings that suggest the extent of inequality in truck-generated NO_x exposure, in a world without electric trucks. 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 3 tests the first hypothesis, by regressing log county-level emissions from the EPA NEI on demographic variables in that county, using the 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.

Table 3: 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. *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$.

To test our second hypothesis of 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 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 4 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.

Table 4: 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. *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$.

These findings, when combined with our theoretical framework, yield two implications. First, the current shipping pattern may have induced substantial inequality. Because the utility function is concave, even the same amount of pollution damage would hurt low-income households more than high-income households. Our finding that low-income households actually face *more* pollution further widens this inequality. Second, there can be a large potential to change the current shipping pattern in a way that improves both equity

and efficiency. Our finding that shipments bound for higher-income areas generate more pollution, combined with the low marginal utility of income in those high-income areas, implies that passing on the cost of electrification onto those destinations may hurt those high-income areas less than it benefits low-income areas. We now turn to our formal analysis of the distributional impacts of truck electrification, the first step of which is estimating a transport mode choice model.

4 Estimating Transport Mode Choices

We estimate a multinomial logit transportation mode choice model using 2012 and 2017 CFS PUM data. Each shipper chooses the transportation mode to minimize the sum of variable shipping cost, inventory cost, and fixed shipping cost. The variable shipping cost is mostly from fuel consumption, assumed to be proportional to the shipment size. The inventory cost depends on the product of shipping distance and value of goods. The total cost of shipment i of commodity group c by mode j in quarter q of year t is:

$$cost_{ij} = \underbrace{\alpha_{cj} \times p_{qt} s_i}_{\text{Variable shipping cost}} + \underbrace{\beta_{cj} \times d_i v_i}_{\text{Inventory cost}} + \underbrace{Fixed\ Effects}_{\text{Fixed shipping cost}} + \epsilon_{ij} \tag{8}$$

where p_{qt} is the quarterly fuel price, s_i is the shipment size measured in ton-miles, d_i is the transportation distance, v_i is the shipment value measured in dollars, and ϵ_{ij} is the idiosyncratic cost shock assumed to be i.i.d. and follow the Type-I extreme value distribution. We estimate those parameters by matching the predicted probability of shipment i choosing mode j with the empirical frequencies as closely as possible. We estimate this equation for each cargo type c. Following Bushnell and Hughes (2020), we capture the fixed cost of the shipment by controlling for dummy variables of whether the shipment originates in the Mississippi River Basin, and whether the shipment require temperature control.

Table 5 shows the estimated parameter results for selected commodity groups. For now, we estimate the model separately for 2012 and 2017. Our parameter estimates using the 2012 data are similar to Bushnell and Hughes (2020). We find that low fuel costs and high inventory costs make trucks more attractive than rail for transporting grain. The same forces make water more attractive than rail for transporting coal. For alcohol, high inventory costs favor rail transport over trucks, but the need for temperature control has the reverse effect. These results suggest that electric trucks as a new transport mode could experience very heterogeneous adoption patterns across commodity groups, depending on how the charging technology and

Table 5: Transport Mode Choice Model Estimation Results

	(1) Grain2012	(2) Grain2017	(3) Coal2012	(4) Coal2017	(5) Alcohol2012	(6) Alcohol2017
Rail						
			(Base Outcome)			
Truck						
Diesel Price*Shipment Size	-30.86***	-53.36***	-6.389	-321.9	-29.08***	-45.87***
	(6.346)	(7.244)	(3.385)	(186.0)	(2.567)	(6.379)
Distance*Shipment Value	0.010***	0.0376	0.0160	2.583	-0.008**	-0.0164**
	(0.002)	(0.0276)	(0.025)	(5.979)	(0.003)	(0.005)
Mississippi Basin	-0.727	0.0870	1.129	8.279*		
	(0.563)	(0.459)	(1.026)	(3.475)		
Temperature Control					0.322	0.870*
					(0.351)	(0.382)
Constant	4.273***	4.099***	3.460***	3.937***	7.962***	8.015***
	(0.347)	(0.281)	(0.649)	(0.611)	(0.224)	(0.172)
Water						
Diesel Price*Shipment Size	0.057	0.621	-0.052***	-0.064**		
	(0.122)	(0.468)	(0.016)	(0.020)		
Distance*Shipment Value	-0.0002	-0.008	0.0003	0.005**		
	(0.002)	(0.007)	(0.0008)	(0.001)		
Mississippi Basin	-0.200	1.072	0.993	0.451		
	(0.722)	(0.764)	(1.042)	(0.795)		
Constant	-3.736***	-2.807***	-0.702	-1.462		
	(0.562)	(0.485)	(0.768)	(0.958)		
Air						
Diesel Price*Shipment Size		-6.745				
		(3.723)				
Distance*Shipment Value		0.036				
		(0.0235)				
Mississippi Basin		20.51***				
		(0.960)				
Constant		-26.57***				
		(0.237)				
N	24856	32635	10801	7852	96329	145936

Note: Shipment size is measured in million ton-miles. Shipment value is measured in million nominal dollars.
Standard errors in parentheses clustered at the route-level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

infrastructure scenarios change the fuel and inventory costs.

References

Ale-Chilet, J., Chen, C., Li, J., and Reynaert, M. (2021). Colluding against environmental regulation. Working paper.

Atkinson, A. B. (1970). On the measurement of inequality. *Journal of Economic Theory*, 2(3):244–263.

Banzhaf, H. S. (2011). Regulatory impact analyses of environmental justice effects. *Journal of Land Use and Environmental Law*, 27(1):1–30.

Bushnell, J. B. and Hughes, J. E. (2020). Mode choice, energy, emissions and the rebound effect in us freight transportation.

CARB (2019). California air resources board staff current assessment of the technical feasibility of lower nox standards.

CARB (2020). California takes bold step to reduce truck pollution. https://ww2.arb.ca.gov/news/california-takes-bold-step-reduce-truck-pollution.

EPA (2018). National emissions inventory. www.epa.gov/air-emissions-inventories/2014-national-emissions-inventory-nei-data.

FHWA (2016). Highway statistics 2014. www.fhwa.dot.gov/policyinformation/statistics/2014.

Gladstein Neandross & Associates (2013). Technical Appendix – Modeling Assumptions for Freight Pathway Components. Technical report.

Goldberg, P. K. (1998). The Effects of the Corporate Average Fuel Efficiency Standards in the US. *The Journal of Industrial Economics*, 46(1):1–33.

Hausman, C. and Stolper, S. (2020). Inequality, information failures, and air pollution.

Holland, S. P., Mansur, E. T., Muller, N. Z., and Yates, A. J. (2016). Damages and expected deaths due to excess NOx emissions from 2009 to 2015 Volkswagen diesel vehicles. *Environmental Science and Technology*, 50(3):1111–1117.

Knittel, C. R. (2012). Automobiles on steroids : Product attribute trade-offs and technological progress in the automobile sector. *American Economic Review*, 101:3368–3399.

Li, J. (2019). Compatibility and investment in the U.S. electric vehicle market.

Li, S., Tong, L., Xing, J., and Zhou, Y. (2017). The market for electric vehicles: Indirect network effects and policy design. *Journal of the Association of Environmental and Resource Economists*, 4(1):89–133.

Mohai, P., Lantz, P. M., Morenoff, J., House, J. S., and Mero, R. P. (2009). Racial and socioeconomic disparities in residential proximity to polluting industrial facilities: Evidence from the americans changing lives study. *American Journal of Public Health*, 99(S3):S649–S656.

Muller, N. Z., Matthews, P. H., and Wiltshire-Gordon, V. (2018). The distribution of income is worse than you think: Including pollution impacts into measures of income inequality. *PLoS ONE*, 13(3):1–15.

Reynaert, M. (Forthcoming). Abatement Strategies and the Cost of Environmental Regulation: Emission Standards on the European Car Market. *Review of Economic Studies*.

Reynaert, M. and Sallee, J. (Forthcoming). Who Benefits When Firms Game Corrective Policies? *American Economic Journal: Economic Policy*.

Rittenhouse, K. and Zaragoza-Watkins, M. (2018). Anticipation and environmental regulation. *Journal of Environmental Economics and Management*, 89:255–277.

Schutz, R. R. (1951). On the Measurement of Income Inequality. *American Economic Review*, 41(1):107–122.

Springel, K. (2016). Network externality and subsidy structure in two-sided markets: Evidence from electric vehicle incentives.

Tong, F., Jenn, A., Wolfson, D., Scown, C. D., and Auffhammer, M. (2021). Health and Climate Impacts from Long-Haul Truck Electrification. *Environmental Science and Technology*.

Wolverton, A. (2009). Effects of socio-economic and input-related factors on polluting plants location decisions. *The B.E. Journal of Economic Analysis and Policy*, 9(1).

Zhou, Y. and Li, S. (2018). Technology adoption and critical mass: The case of the us electric vehicle market. *The Journal of Industrial Economics*, 66(2):423–480.