Pollution from Freight Trucks in the Contiguous United States: Public Health Damages and Implications for Environmental Justice

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Abstract
PM$_{2.5}$ produced by freight trucking has significant adverse impacts on human health. Here we explore the spatial distribution of freight trucking emissions and demonstrate that public health impacts due to freight trucking disproportionately affect certain racial and ethnic groups. Based on the US federal government data, we build an emissions inventory to quantify heterogeneity of trucking emissions and find that ~10% of NO$_x$ and ~12% of CO$_2$ emissions from all sources in the US come from freight trucks. The costs to human health and the environment due to NO$_x$, PM$_{2.5}$, SO$_2$, and CO$_2$ from freight trucking in the US are estimated respectively to be $11$B, $5.5$B, $100$M, and $30$B (social cost of carbon of $51$ per ton). We demonstrate that more freight pollution occurs in counties and census tracts with a higher proportion of Black and Hispanic residents. Counties with a higher proportion of Black and Hispanic residents are also more likely to be net importers of pollution damages from other counties.

Main Text
Introduction
Medium and heavy-duty vehicles (MHDVs) account for ~21% of transport sector’s energy use (1) and ~24% of total transportation greenhouse gas (GHG) emissions (2). Transportation is the largest source of greenhouse gas emissions in the United States, accounting 29% of total emissions in 2019. They are also a major source of pollutants such as fine particulate matter (PM$_{2.5}$), oxides of nitrogen (NO$_x$), and GHGs, especially carbon dioxide (CO$_2$). While reducing emissions from freight trucking is desirable, and mitigation costs are lower for road transport than for other modes (3), the tight coupling between economic growth and road freight makes it difficult to achieve reductions (4). In 2017, the most recent year for which Commodity Flow Survey (CFS) data are available, freight trucks carried ~72% ($10.4$ trillion) of total domestic freight by value (5). Absent major policy interventions, as other transportation modes become cleaner, and the volume of freight truck VMT grows, the proportion of emissions from freight trucking will likely increase in the coming decades.

Air pollutant emissions have steadily declined in the US over the decades due to federal emissions control regulation such as the Clean Air Act (CAA) (7), and the switch to ultralow sulfur fuel diesel (ULSD) (8). Yet, it is estimated that exposure to PM$_{2.5}$ continues to cause between ~85,000 and 200,000 (9–11) premature deaths each year in the US. While current policies prioritize emissions reduction, they provide little guidance on addressing environmental justice when implementing air pollution reductions or on how to address distributional impacts (12). Even though absolute PM$_{2.5}$ concentrations have declined by ~70% since early 1980s (13), racial-ethnic and socio-economic disparities (14–18) continue to exist (11, 13). A recent paper by Tessum et al. (11) found higher than average PM$_{2.5}$ exposures across minority groups in comparison to the white population from different sources. The authors report overall disparity in exposure through population-weighted ambient concentrations, however, no study has explored the impacts of air pollution on racial and ethnic minorities from the freight trucking sector using a bottom-up emissions inventory. Our analysis fills this gap.
The design of effective abatement policies to curtail air pollution from freight trucking requires granular and high-quality information on emissions from trucks. The most comprehensive publicly available emissions inventory in the US is produced by the Environmental Protection Agency (EPA) and is called the National Emissions Inventory (NEI) (19). This is a national compilation of emissions by the US EPA from different local agencies and is released approximately every 3 years (the most recent version is for 2017). For on-road mobile sources such as trucks, the EPA uses emissions reported by local agencies (20). As such, estimates can vary at the local level depending on the method used to aggregate emissions in different counties. Many counties do not report their information: just over 50% of the counties submitted information to EPA for compilation in NEI 2017 (20). For counties that do not submit data, EPA estimates county emissions based on historical information the EPA has for the county. As a result, there are methodological differences and potential inconsistencies in how the NEI estimates emissions for each county. Developing our own emissions inventory allows us to follow a methodologically consistent approach. The advantages of developing an emissions inventory from the “bottom-up” are well documented (21–23). For instance, the US EPA distributes emissions based on road lengths and population and not on road activity. Consequently, this leads to the under-estimation of emissions on rural interstate highways that are sparsely populated but are heavily traversed by freight trucks. Building a bottom-up emissions inventory allows us to avoid that.

Through this study, we make three contributions to the literature. First, we conduct a bottom-up assessment, which is spatially resolved and based on the most recently available national freight data, the Freight Analysis Framework Version 4 (FAF4) (24), of freight trucking emissions for the contiguous US. In doing so, we report environmental, climate, and public health air pollution monetized damages due to freight trucking at the county level for the contiguous states. Second, we quantify the extent of air pollution health damages that are being exported from or imported to individual counties due to freight trucking activity. At any given location, emissions from distances as great as 800 km can cause air pollution related health damages (25). Therefore, a large fraction of the human health burden within a county or census tract of freight trucking emissions may be due to emissions that have occurred elsewhere. We develop our estimates using publicly available data from the US federal government (FAF4 data) which we combine with the reduced complexity model (RCM) Estimating Air Pollution Social Impact Using Regression (EASIUR) (26, 27) and the source-receptor Air Pollution Social Cost Accounting (APSCA) model (25). By doing so, we explore the spatial heterogeneity in air pollution damages at the county level based on source-receptor relationships. We focus on air pollution damages attributable to outdoor PM$_{2.5}$ exposure because it is responsible for ~90% of all air pollution related health damages (28). Third, we perform the analysis at the resolution of individual counties and census tracts to evaluate air pollution related health damages and distributional effects. We observe distributional impacts of air pollution across racial and ethnic groups both at the county and at the census tract resolution. Figure 1 illustrates the method we use to compute trucking emissions, air pollution, and climate change damages.

Materials and Methods
Study Area and Scope
Our study includes freight shipments in the 48 contiguous US states (excluding Alaska, Hawaii, Puerto Rico, and other US territories). The reference year used in the study is 2017, as that is the most recent year for which the national emissions inventory (NEI) is available (19). This allows us to compare our emissions results with the NEI. The approach we use to extract freight trucking emissions from the NEI is discussed in Supplementary Note 1.

Data
We use the Federal Highway Administration’s (FHWA’s) FAF4 data (24), which estimates freight flows through 132 domestic zones in the US. Although a more recent version of the Freight Analysis Framework Version 5 (FAF5) is available, it has yet to be updated with information on county level freight shipments. Thus, we use the FAF4 data throughout the analysis except for our analysis of modal shift to class-I railroads where we use Commodity Flow Survey (CFS) data. FAF4 data includes a shape file of FAF4 zones providing detailed information on the road network (~446,000 miles; see Figure 1(A) and relevant freight attributes such as the annual average daily traffic volumes on road segments, road lengths and route type. The distribution of trucking VMT by road type is included in Supplementary Information Table S2. To explore the environmental justice implications of air pollution related damages, we use data from the US Census Bureau (37).

Estimating freight trucking VMT
Road length: The FAF4 road network data consist of road links (RLs) and average daily long distance and local truck traffic counts for different freight vehicles in 2012. These included long-haul trucks, short-haul freight trucks and non-freight vehicles (buses). For determining vehicle categories, we assume that all long-haul highway trips are conducted by heavy duty tractor-trailer diesel trucks (class 8b or above) whereas all non-long haul highway freight trips are conducted by single unit trucks (class 6 trucks). We estimate the route road length (in miles) for each road link by taking the difference between the starting and ending mile posts reported in the data for each road link. We dropped 94 out of 670,045 road links for which the result was a negative road length, which we assumed to be erroneous. Links with negative lengths account for ~0.01% of the total and dropping them should have a negligible effect on the results.

Annual average truck counts: Since freight trucking is mostly diesel powered, we assume based on Bickford et al.(23) that 98% of all trucks in our freight data are diesel trucks. Furthermore, the reported average daily truck counts include non-cargo freight vehicles such as commuter and transit buses. In 2012, there were 765,000 bus registrations out of ~58 million truck registrations (excluding sport utility vehicles, vans, and other light vehicles) (38, 39). Thus, to exclusively reflect diesel cargo freight trucks in our truck counts and remove the effect of buses and other non-cargo vehicles, we adjust the daily average truck count on each road link by subtracting 1% of total vehicle counts on each link. We express annual MHDV daily truck traffic on each road link as:

\[ MHDV_{l,daily} = FAFAADTT_{l,daily} \times DF \times TF \]
Where,
\( MHDV_{t,daily} \) is the daily average MHDV count on a road link \( i \) (expressed as volume per day per section of the road)
\( FAFADTT_{daily} \) is the FAF4 annual average daily truck traffic for long-distance and non-long distance freight trucks on road link \( i \) (expressed as volume per day per section of the road)
\( DF \) is the diesel fraction to adjust vehicle counts to include only diesel freight trucks and its value is assumed to be 0.98 from literature (23)
\( TF \) is the truck fraction to remove the effect of commuter and transit buses from the annual average daily truck traffic counts. Its value is assumed to be ~0.99 based on vehicle registration data.

**Annual Freight Trucking Vehicle Miles Traveled:** We estimate the daily medium and heavy-duty vehicle miles traveled (MHDVMT) for each road link by multiplying \( MHDV_{t,daily} \) by the length of the road segment. We annualize the VMT on each road link by multiplying by 365. However, the MHDVMT obtained is for the year 2012, and the base year of our analysis is 2017. Using annual VMT data (40) provided by the US Department of Transportation (DOT), we estimate compounded annual growth rate (CAGR) increase in MHDVMT between 2012 and 2017. The MHDVMT in 2017 for each road link is then estimated as:

**Equation 3.2**

\[
MHDVMT_i = MHDV_{t,daily} \times RL_i \times Year_{days} \times GF_{VMT}
\]

Where,
\( MHDVMT_i \) is the annualized VMT for medium and heavy-duty vehicles in 2017 for each road link \( i \)
\( MHDV_{t,daily} \) is the daily average medium and heavy-duty vehicle count on a road link \( i \) (expressed as volume per day per section of the road)
\( RL \) is length of the road segment (in miles) for each road link \( i \)
\( Year_{days} \) is 365, the number of days in a year
\( GF_{VMT} = (1 + CAGR_{VMT})^{2017-2012} \) is the growth in MHDVMT between 2012 and 2017. \( CAGR_{VMT} \) is estimated to be 2% each year based on authors’ calculations from freight trucks’ VMT data (40) provided by the US DOT.

**Estimating spatially resolved emissions arising from freight trucking**

We estimate spatially resolved emissions at the county level for PM\(_{2.5}\), SO\(_2\), NO\(_x\), and CO\(_2\) in each county by multiplying MHDVMT by the lifetime VMT weighted emission factors (in g/mile) from the Greenhouse Gases, Regulated Emissions, and Energy Use in Transportation (GREET) model (41) for all the road segments contained in the county. For PM\(_{2.5}\) emissions, we include tire and break wear emissions in addition to primary PM\(_{2.5}\) emissions. Absent better data, we use a constant emission factor regardless of whether the road is in an urban or rural area, even though emission factors for each type may be different. To examine the implications of doing this, we perform a sensitivity analysis with emission factors included in Tong et al. (42). The results are included in **Supplementary Note 3**. We sum the air pollutant and GHG emission estimates from
road links within a county to estimate county level total for 2017. The emissions at the county level are estimated as:

**Equation 3.3**

\[ E_{k,p} = \sum_{i \in k} MHDVMT_i \times EF_p \]

Where,

- \( E_{k,p} \) is the total MHDV emissions (in tons) for pollutant \( p \) (PM\(_{2.5}\), SO\(_2\), NO\(_x\), CO\(_2\)) in each county \( k \),
- \( MHDVMT_i \) is the VMT on road segment \( i \) for MHDVs
- \( EF_p \) is the emission factor (in g/mile) for pollutant \( p \) for the freight truck category under consideration
- \( K \) is the set of all road segments \( i \) contained within county \( k \). The sum is performed over all the road segments \( i \) that are contained within the county \( k \)

**Estimating public health and climate damages due to freight trucking**

Using state-of-the-art CTMs to estimate the concentration of air pollutants that results from emissions is very computationally intensive. In order to reduce the computational burden for policy analysis, air quality researchers have developed reduced complexity integrated air quality models (RCMs) to estimate monetized air pollution damages. RCMs divide the entire US into a grid of cells and include a set of look up tables of marginal social costs (MSC; in US $ per ton of pollutant emitted) for emissions associated with each grid cell. For our analysis, we assume that trucking emissions are marginal so that the public health damages due to CAPs are a simple product of total emissions and MSC for a given pollutant species, location, and height. While the MSC for CAPs is sensitive to location and height, the MSC for CO\(_2\) does not depend on these factors, and we estimate damages from CO\(_2\) emissions by multiplying emissions by a social cost of carbon (which we assume to be $51 per ton CO\(_2\); 2020 US $) (29, 30).

We use an RCM called EASIUR (26, 27) to estimate marginal damages due to primary PM\(_{2.5}\), SO\(_2\), and NO\(_x\) for 148 x 112 cells with each grid cell 36 km x 36 km in size. Since we are interested in on-road freight transport emissions, we use the annual MSC associated with all area sources with a zero-stack height. We ignore seasonal variation. Next, we conduct an overlay analysis and find how much of each county’s area lies within the bounds of each grid cell. We repeat this exercise for each grid cell in the contiguous US and distribute the marginal social costs through a weighting factor based on the area of county contained in each grid cell. Finally, we calculate the marginal damages as a product of the MSC in each county multiplied by the emissions of a particular pollutant species at a given location. EASIUR provides MSC assuming a value of statistical life (VSL) of $8.6M (2010 US $). **Supplementary Note 4.2** explains how we have updated the MSCs to 2017 dollars using income adjustment and population adjustment while accounting for inflation. For CO\(_2\), we assume a social cost of carbon (SCC) of $51 per ton of CO\(_2\) (29, 30).

Mathematically, this can be expressed as:

**Equation 3.4**
\[ MD_p = \sum_k MSC_{k,p} \times E_{k,p} \]

Where, 

\( MD_p \) is the marginal damage in 2017 dollars for the US for pollutant \( p \) (PM\(_{2.5}\), SO\(_2\), and NO\(_x\)).  

\( MSC_{k,p} \) is the marginal social cost in county \( k \) for pollutant \( p \) (expressed in US $ per ton of pollutant emitted)  

\( E_{k,p} \) is the emissions for county \( k \) for pollutant \( p \) (expressed in tons) 

EASIUR provides an estimate of all the damages that occur everywhere from the emissions that originate within county, regardless of where those damages occur. To understand where damages occur, we employ source-receptor (S-R) relationships from the APSCA model to spatially disaggregate social cost of pollutants (25). As a boundary check, we also calculate air pollution damage estimates from freight trucking at the source counties using another RCM called the Air Pollution Emission Experiments and Policy Version 3 (AP3) (43). We find reasonable consistency between the results of each model. The results of the comparison of the public health damages from freight trucking are included in Supplementary Note 4.2.

**Impact of freight trucking pollution across demographic groups**

While the monetized environmental and climate change impacts are felt across different geographical sub-units, here, we focus on the distributional effects of freight trucking emissions on different ethnic and racial subgroups. This is important because the literature shows that, historically, adverse air pollution-related health impacts have been inequitable (14–18). To evaluate differences in the impacts of pollution from freight trucking on different racial groups, we use county level population data from US Census Bureau’s 2010 decennial census (37). Based on county as the unit of spatial aggregation, we focus on seven self-identified racial and ethnic subgroups, selected so that they are mutually exclusive: (1) Black or African American alone (variable code P003003), (2) Hispanic or Latino origin by race (variable code P005010), (3) American Indian and Alaskan Native alone (variable code P003004), (4) Asian alone (variable code P003005), (5) Native Hawaiian and Other Pacific Islander alone (variable code P003006), (6) some other race alone (variable code P003007), and (7) two or more races (variable code P003008). We model emissions for pollutant \( p \) (PM\(_{2.5}\), SO\(_2\), and NO\(_x\)) in county \( c \) as a function of the demographic and other attributes of the census tract where the emissions occur and an unobserved error term (\( \epsilon_{p,c} \)). \( \beta \) is the modeled coefficient for each corresponding independent variable \( X \) for county \( c \). The model specification is:

**Equation 3.5**

\[
Y_{p,c}(X) = \beta_0 + \beta_{area} \log(X_{c,area}) + \beta_{black}X_{c,black} + \beta_{amerind}X_{c,amerind} + \beta_{haw}X_{c,haw} \\
+ \beta_{asian}X_{c,asian} + \beta_{hisp}X_{c,hisp} + \beta_{twomore}X_{c,twomore} \\
+ \beta_{totpop} \log(X_{c,totpop}) + \beta_{medinc} \log(X_{c,medinc}) + \epsilon_{p,c}
\]
Where,

\( Y_{p,c} \) is the log of freight trucking emissions for pollutant \( p \) (PM\(_{2.5}\), SO\(_2\), and NO\(_x\)) in county \( c \)

\( X_{c}^{area} \) is the area of the county \( c \)

\( X_{c}^{black} \) is the proportion of the total population in county \( c \) that is black

\( X_{c}^{amerind} \) is the proportion of the total population in county \( c \) that is American Indian and Alaska native

\( X_{c}^{haw} \) is the proportion of the total population in county \( c \) that is Hawaiian and other Pacific Islanders

\( X_{c}^{asian} \) is the proportion of the total population that is Asian in county \( c \)

\( X_{c}^{hisp} \) is the proportion of the total population in county \( c \) identifying as Hispanic or Latino

\( X_{c}^{twomore} \) is the proportion of the total population identifying in county \( c \) as having two or more races

\( X_{c}^{totpop} \) is the total population in county \( c \)

\( X_{c}^{medinc} \) is the median income of the household in county \( c \)

We then perform the same analysis at the census tract level. To calculate the emissions that occur within each census tract, we download census tract shapefiles from the U.S. Census Bureau (44). Using the shapefile of the FAF4 road network, we estimate the centroid of each road segment. We then use the “rgeos” package in the R programming environment to identify which census tract each road segment centroid is located in. We repeat the calculations described in Equation 3.3 but sum the emissions that occur along each road segment over all the road segments that fall within a census tract (instead of summing over all the road segments that fall within a county).

Finally, the effect of trucking emissions on minority populations in the census tract is evaluated using linear regression. We model emissions for pollutant \( p \) (PM\(_{2.5}\), SO\(_2\), and NO\(_x\)) in census tract \( t \) as a function of the demographic and other attributes of the census tract where the emissions occur and an unobserved error term \( \epsilon_{p,t} \). \( \beta \) is the modeled coefficient for each corresponding independent variable \( X \) for census tract \( t \). The model specification is:

Equation 3.6
\[ Y_{p,t}(X) = \beta_0 + \beta_{\text{area}} \log(X_{t,\text{area}}) + \beta_{\text{black}} X_{t,\text{black}} + \beta_{\text{amerind}} X_{t,\text{amerind}} + \beta_{\text{haw}} X_{t,\text{haw}} \\
+ \beta_{\text{asian}} X_{t,\text{asian}} + \beta_{\text{hisp}} X_{t,\text{hisp}} + \beta_{\text{twomore}} X_{t,\text{twomore}} \\
+ \beta_{\text{totpop}} \log(X_{t,\text{totpop}}) + \beta_{\text{medinc}} \log(X_{t,\text{medinc}}) + \epsilon_{p,t} \]

Where,

\( Y_{p,t} \) is the log of freight trucking emissions for pollutant \( p \) (PM\(_{2.5}\), SO\(_2\), and NO\(_x\)) in census tract \( t \)

\( X_{t,\text{area}} \) is the area of the census tract \( t \)

\( X_{t,\text{black}} \) is the proportion of the total population in the census tract \( t \) that is black

\( X_{t,\text{amerind}} \) is the proportion of the total population in the census tract \( t \) that is American Indian and Alaska native

\( X_{t,\text{haw}} \) is the proportion of the total population in the census tract \( t \) that is Hawaiian and other Pacific Islanders

\( X_{t,\text{asian}} \) is the proportion of the total population that is Asian in census tract \( t \)

\( X_{t,\text{hisp}} \) is the proportion of the total population in census tract \( t \) identifying as Hispanic or Latino

\( X_{t,\text{twomore}} \) is the proportion of the total population identifying in census tract \( t \) as having two or more races

\( X_{t,\text{totpop}} \) is the total population in census tract \( t \)

\( X_{t,\text{medinc}} \) is the median income of the house hold in census tract \( t \)

To assess the factors that may affect whether the county where the census tract is located is a net importer or exporter, we run a logit model specification at the county and the census tract level. It is expressed as:

**Equation 3.7**

\[
\logit\left(p_{p,t}(x)\right) = \log\left(\frac{p(x)}{1 - p(x)}\right) = \eta_{p,t}(x) \\
\eta_{p,t}(x) = \beta_0 + \beta_{\text{area}} \log(X_{t,\text{area}}) + \beta_{\text{black}} X_{t,\text{black}} + \beta_{\text{amerind}} X_{t,\text{amerind}} + \beta_{\text{haw}} X_{t,\text{haw}} \\
+ \beta_{\text{asian}} X_{t,\text{asian}} + \beta_{\text{hisp}} X_{t,\text{hisp}} + \beta_{\text{twomore}} X_{t,\text{twomore}} \\
+ \beta_{\text{totpop}} \log(X_{t,\text{totpop}}) + \beta_{\text{medinc}} \log(X_{t,\text{medinc}}) + \epsilon_{p,t} 
\]
\( p(x) \) is the probability of the county where the census tract \( t \) is located of being a net importer for pollutant \( p \) (PM\(_{2.5}\), SO\(_2\), and NO\(_x\))

\( X_t^{\text{area}} \) is the area of the census tract \( t \)

\( X_t^{\text{black}} \) is the proportion of the total population in the census tract \( t \) that is black

\( X_t^{\text{amerind}} \) is the proportion of the total population in the census tract \( t \) that is American Indian and Alaska native

\( X_t^{\text{haw}} \) is the proportion of the total population in the census tract \( t \) that is Hawaiian and other Pacific Islanders

\( X_t^{\text{asian}} \) is the proportion of the total population that is Asian in census tract \( t \)

\( X_t^{\text{hisp}} \) is the proportion of the total population in census tract \( t \) identifying as Hispanic or Latino

\( X_t^{\text{twomore}} \) is the proportion of the total population identifying in census tract \( t \) as having two or more races

\( X_t^{\text{totpop}} \) is the total population in census tract \( t \)

\( X_t^{\text{medinc}} \) is the median income of the household in census tract \( t \)

Results

Freight Trucking Emissions in the US

Table 1 shows freight trucking emissions for the year 2017. We compare these estimates with economy-wide estimates of emissions from the US EPA’s 2017 NEI. Despite the methodological differences in our method and those used in compiling NEI 2017, the comparison serves as a sanity check. We observe that NO\(_x\) and CO\(_2\) emissions from diesel freight trucks are \(~10\%\) and \(~12\%\) of the total US emissions. The estimated emissions diverge from values estimated by 2017 NEI between 11% and 47% for different pollutants and the directionality of the difference is not preserved across pollutant type. The largest differences arise for PM\(_{2.5}\), where our FAF4-based estimate is smaller by 46% and CO\(_2\) where our FAF4-based estimate is larger by 47%.

Health and Environmental Impacts of Freight Trucking

The emissions burden is highest in the counties that include the road network in the FAF4 network (see Figure 2(A)). Figure 2(B-D) shows county level spatial distribution of PM\(_{2.5}\), NO\(_x\), and SO\(_2\) emissions from MHDV trucking. Based on where the freight trucking activity occurs, we observe that NO\(_x\) trucking emissions are high in counties in the northeast, southern, and western parts of the US. PM\(_{2.5}\) and NO\(_x\) emissions from freight trucking are the lowest in Delaware, Vermont, and the District of Columbia.
Spatially Resolved Public Health Impacts of Freight Trucking

We estimate the total annual public health damage resulting from diesel trucks for PM$_{2.5}$, SO$_2$, and NO$_x$, to be $5.5B, $100M, $11B, respectively, and the societal damage from CO$_2$ emissions to $30B, assuming a social cost of carbon of $51 per ton (2020 US $) (29, 30). These costs have been expressed in 2017 US dollars. While the numbers for PM$_{2.5}$, SO$_2$, and NO$_x$, are estimates of the human health damage that occurs everywhere from emissions that originate in each county, here we also separate that estimate into damage that occurs within each county from the emissions within that county, and damage that occurs within the county due to emissions that are “imported” from other counties. Likewise, we split the estimate of damages that originate in a county into damages that are felt within the same county and damages that are “exported” to other counties. This allows us to estimate the total damage that occurs within each county and whether the county is a net importer or exporter of air pollution damages. We perform this disaggregation using APSCA. APSCA provides receptor resolved air pollution damages at the county level. Figure 3(A-C) show public health PM$_{2.5}$, SO$_2$, and NO$_x$, damages resolved at the source counties due to freight trucking in the US for 2017. This is the total damage from emissions that originate in a particular county and includes the damage caused by source county emissions activity within the county itself. If we exclude the air pollution damage that the source county causes within itself, we observe that the counties located in the states of Texas ($3.4B), Pennsylvania ($1.5B), Indiana ($1.1B), New Jersey ($1B), and New York ($800M) contribute ~49% of all exported air pollution related damages occurring in the US.

Figure 3(D-F) show public health PM$_{2.5}$, SO$_2$, and NOx damages resolved at the receptor counties due to freight trucking in the US for 2017. This is the total damage a county receives from emissions occurring in other counties, including from the emissions that occur within the county. Cumulatively, the counties located in the states of Texas ($2.7B), New York ($1.4B), Pennsylvania ($1.1B), New Jersey ($930M), and Illinois ($850M) receive ~44% of all imported annual air pollution damage due to freight trucking in the contiguous US. Figure 4 provides map of counties that are net exporters and net importers of freight trucking air pollution related human health damages in the contiguous US. We do a sensitivity check using another RCM called AP3 and check the results by assessing public health damages from freight trucking emissions included in NEI, 2017. The results of these comparisons are included in Supplementary Note 4.2.

Environmental Justice Implications

While it is difficult to accurately determine air pollutant exposure concentrations without running a Chemical Transport Model (CTM), the results included below provide a first order estimate of the relationship between air pollution emissions and the proportion of the population each county and census tract that belongs to a minority group. We observe that freight trucking emissions of PM$_{2.5}$, SO$_2$, and NO$_x$ are significantly higher in counties with higher Black and Hispanic populations (Table 2). This effect is also preserved at the census tract level (Table 3). If the Black population in the county increases by 1 percentage point, the emissions in that county are 1.8 (1.1 to 2.9) percentage points higher. Similarly, if the Hispanic population in the county increases by
1 percentage point, then the emissions in that county are 20 (14 to 28) percentage points higher. Additionally, as a check, we run the analysis at the county and census tract level on data available from NEI, 2017. For the county level, we see that our findings are consistent with the results derived by running the analysis on the NEI 2017 (Supplementary Information Table S9 and Table S10). A detailed description of the distribution of the dependent and independent variables including additional diagnostic testing is enclosed in Supplementary Note 6. We also run model specifications on both FAF4 and NEI 2017 emissions inventory to gauge whether a county is likely to be an exporter or importer based on the total air pollution damage that the county imports or exports. We observe that census tracts with a higher proportion of Black, American Indian, and two or more races have higher odds of being an importer of air pollution damage due to freight trucks (see Supplementary Information Table S11 and Table S12).)

Discussion

Our results suggest that freight trucking contributes significantly to NO\textsubscript{x} and CO\textsubscript{2} emissions in the contiguous US. A potential medium-term solution is to shift a fraction of the freight from trucks to railroads to reduce GHG emissions substantially (see Supplementary Note 5).

We find that more freight trucking emissions occur in census tracts containing larger proportions of Black and Hispanic populations. While such disproportionate air pollution impacts have been noted in general terms in the research literature, our work documents this effect arising specifically from trucking sector in our work. This disproportionate effect is the result of years of racially malign infrastructure citing policy (31, 32). Our findings indicate that areas with higher proportions of minority populations have higher likelihood of being an importer of air pollution damages. Therefore, local governments should consider conducting more research in areas with high trucking emissions to identify ways to reduce some of the air pollution effects felt by vulnerable population groups. This work also has implications for local governments trying to formulate future emissions reduction policies, especially when air pollution arises from geographical areas that are not within their administrative control. Finally, policymakers at all levels must consider exploring opportunities under the Bipartisan Infrastructure Law (33) to clean up legacy pollution by investing in projects that redress environmental harm and advance environmental justice in a meaningful way. Given keen interest in the U.S. government to rebuild the national infrastructure in a way that advances environmental justice (34–36).

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Figures and Tables

**Data**
- Annual average truck volume; length of road segments (FAF4 Data)
- Lifetime mileage weighted emission factors (GREET Model)
- Marginal social costs for PM$_{2.5}$, SO$_2$, NO$_x$ (EASIUR Model)
- Census tract demographic information (US Census Bureau Data)

**Analysis**
1) Freight trucking emissions for each road
2) Compute monetized air pollution social costs from freight trucking by pollutant type
3) Distribute monetized air pollution social costs from freight trucking using APSCA
4) Estimate air pollutant emissions at the census tract level

**Outputs**
- Freight trucking emissions at the county level
- Air pollution related human health damages in source county
- Air pollution related human health damages in receptor county
- Distributional effects across ethnic and racial groups

**Figure 1.** Step process detailing our modeling approach.
Figure 2. (A) FAF4 road network in the contiguous US. These routes comprise ~446,000 miles of roads. The dataset includes interstate highways, national highway system (NHS) roads, rural and urban principal arterials along with intermodal connectors. (B-D) County level spatial distribution of PM$_{2.5}$, NO$_x$, and SO$_2$ emissions from MHDV trucking. The spatial distribution of CO$_2$ emissions is similar to other air pollutants shown in the figure.
Figure 3. (A-C) Public health damages from PM$_{2.5}$, SO$_2$, and NO$_x$ due to freight trucking aggregated at the source counties. The source county damage shows total air pollution damage that occurs across all other counties due to the freight trucking activity originating from the source county. It includes the air pollution damage that occurs from the county within itself. (D-F) Public health damages from PM$_{2.5}$, SO$_2$, and NO$_x$ due to freight trucking aggregated at the receptor counties. The receptor damage at a county includes total air pollution damage due to freight trucking activity occurring in other counties. It includes the damage that occurs within the receptor county due to freight trucking activity within the receptor county.
Figure 4. Map showing counties that are net exporters and importers of freight trucking air pollution related public health damages. We expressed the damages as a ratio by dividing the net exported and imported damage in each county. Damages are expressed in 2017 US $. 
Table 1. Freight trucking emissions comparison between FAF4 and NEI for 2017. NOx and CO2 constitute a non-trivial share of US emissions. The difference in estimates column provides the percentage difference of FAF4, 2017 diesel truck emission estimates from NEI, 2017 diesel truck emission values. The estimates in the last two columns provide percentage contribution of freight trucking emissions to total US emissions from FAF4 and NEI data. These are obtained by dividing the FAF4 and NEI freight trucking emissions by emissions from all sources in NEI, 2017.

| Pollutant/GHG | FAF4 freight trucking emissions (tons) | NEI freight trucking emissions (tons) | % Difference | Total NEI emissions (tons) | % US emissions from freight trucking (FAF4) | % US emissions from freight trucking (NEI 2017) |
|---------------|----------------------------------------|--------------------------------------|--------------|---------------------------|---------------------------------------------|---------------------------------------------|
| PM$_{2.5}$    | 28K                                    | 50K                                  | -46%         | 5.2M                      | 0.53%                                       | 1.0%                                        |
| SO$_2$        | 4.6K                                   | 3.7K                                 | 24%          | 2.5M                      | 0.18%                                       | 0.10%                                       |
| NO$_x$        | 1.1M                                   | 1.3M                                 | -11%         | 11M                       | 10%                                         | 12%                                         |
| CO$_2$        | 640M                                   | 430M                                 | 47%          | 5.3B                      | 12%                                         | 8.2%                                        |
Table 2. Effect of freight trucking PM$_{2.5}$, SO$_2$, and NO$_x$ emissions on racial and ethnic subgroups at the county level. The dependent variable is the log of PM$_{2.5}$, SO$_2$, and NO$_x$ emissions emitted by freight trucks in counties. For predictor variables that are log values, the relationship can be estimated as $\%\Delta Y_p = %\beta \times \Delta X_c$. For predictors that are not log values, the relationship is estimated as $%\Delta Y_p = 100 \times (e^{\beta} - 1)$. These numbers are statistically significant and the numbers in the parenthesis provide standard errors.

### Dependent variable:

$log(PM_{2.5})$  $log(SO_2)$  $log(NO_x)$

|                  | (1)  | (2)  | (3)  |
|------------------|------|------|------|
| $log(X_c^{area})$| 0.330*** | 0.333*** | 0.353*** |
|                  | (0.026) | (0.027) | (0.031) |
| $X_c^{black}$    | 1.055*** | 1.058*** | 1.079*** |
|                  | (0.157) | (0.161) | (0.185) |
| $X_c^{amerind}$  | -0.194 | -0.208 | -0.260 |
|                  | (0.339) | (0.348) | (0.400) |
| $X_c^{haw}$      | -31.359 | -31.073 | -29.578 |
|                  | (19.515) | (20.004) | (22.997) |
| $X_c^{asian}$    | -5.163*** | -5.322*** | -6.126*** |
|                  | (1.295) | (1.327) | (1.526) |
| $X_c^{twomore}$  | -4.062* | -3.998* | -3.623 |
|                  | (2.241) | (2.297) | (2.641) |
| $X_c^{hisp}$     | 3.054*** | 3.067*** | 3.133*** |
|                  | (0.169) | (0.173) | (0.199) |
| $log(X_c^{medinc})$ | 0.763*** | 0.780*** | 0.872*** |
|                  | (0.105) | (0.107) | (0.124) |
| $log(X_c^{totpop})$ | 0.640*** | 0.643*** | 0.662*** |
|                  | (0.018) | (0.018) | (0.021) |
| Constant         | -21.056*** | -23.160*** | -19.419*** |
|                  | (1.214) | (1.244) | (1.430) |

|                  | (1)  | (2)  | (3)  |
|------------------|------|------|------|
| Observations     | 3,106 | 3,106 | 3,106 |
| $R^2$            | 0.499 | 0.489 | 0.437 |
| Adjusted $R^2$   | 0.498 | 0.488 | 0.435 |
| Residual Std. Error (df = 3096) | 1.124 | 1.153 | 1.325 |
| F Statistic (df = 9; 3096) | 342.960*** | 329.736*** | 266.639*** |

*Note: $^*p<0.05$  $^{**}p<0.01$  $^{***}p<0.001$*
Table 3. Effect of freight trucking PM$_{2.5}$, SO$_2$, and NO$_x$ emissions on racial and ethnic subgroups at the census tract level. The dependent variable is the log of PM$_{2.5}$, SO$_2$, and NO$_x$ emissions emitted by freight trucks in census tracts. For predictor variables that are log values, the relationship can be estimated as $\%\Delta Y_p = \%\beta \times \Delta X_t$. For predictors that are not log values, the relationship is estimated as $\%\Delta Y_p = 100 \times (e^{\beta} - 1)$. These numbers are statistically significant and the numbers in the parenthesis provide standard errors.

| Dependent variable: | log(PM$_{2.5}$) | log(SO$_2$) | log(NO$_x$) |
|---------------------|-----------------|-------------|-------------|
| $\log(X^\text{area})$ | 0.472*** | 0.477*** | 0.511*** |
|                     | (0.005) | (0.005) | (0.005) |
| $X^\text{black}$ | 0.826*** | 0.831*** | 0.865*** |
|                     | (0.044) | (0.045) | (0.048) |
| $X^\text{amerind}$ | -0.626*** | -0.643*** | -0.741*** |
|                     | (0.177) | (0.179) | (0.192) |
| $X^\text{haw}$ | -2.145 | -2.273 | -3.063 |
|                     | (2.419) | (2.444) | (2.632) |
| $X^\text{asian}$ | -0.656*** | -0.627*** | -0.471*** |
|                     | (0.124) | (0.125) | (0.135) |
| $X^\text{twomore}$ | -8.904*** | -8.892*** | -8.868*** |
|                     | (0.607) | (0.613) | (0.660) |
| $X^\text{hisp}$ | 0.752*** | 0.766*** | 0.842*** |
|                     | (0.047) | (0.047) | (0.051) |
| $\log(X^\text{medinc})$ | -0.022 | -0.025 | -0.049** |
|                     | (0.021) | (0.021) | (0.023) |
| $\log(X^\text{totpop})$ | 0.251*** | 0.251*** | 0.251*** |
|                     | (0.018) | (0.018) | (0.019) |
| Constant | -12.214*** | -14.132*** | -9.314*** |
|                     | (0.264) | (0.267) | (0.288) |

Observations 57,766 57,766 57,766  
R$^2$ 0.229 0.229 0.223  
Adjusted R$^2$ 0.229 0.229 0.223  
Residual Std. Error (df = 3096) 1.925 1.945 2.095  
F Statistic (df = 9; 3096) 1,911.068*** 1,905.408*** 1,846.974***  
Note: *p**p***p<0.01
Supplementary Information for

Pollution from Freight Trucks in the Contiguous United States: Public Health Damages and Implications for Environmental Justice

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Supplementary Text

1. Extracting Freight Trucking Emissions from the National Emissions Inventory (NEI), 2017

In the present study, we focus on short haul and long-haul heavy-duty trucks (class 7 or above) because they account for ~81% of freight transportation’s total medium and heavy-duty petroleum consumption by mode in the US (see Table 1.17) (1). In our study, we assume that a dominant share of US freight tonnage is carried by diesel fueled freight trucks. We compare our emission results to the emissions from NEI, 2017 (2).

In order to estimate percentage of freight trucking’s contribution to air pollutant and greenhouse gas (GHG) emissions, we consider emissions from all sources included in the NEI: point, non-point, on-road, non-road, and wildfire events. We only account for emissions in the contiguous US states and exclude Alaska, Hawaii, Puerto Rico, Virgin Islands, American Samoa, Guam, and other non-contiguous territories. Next, we merge the NEI with the source classification codes (SCCs) (3) that the US EPA uses to classify different activities that contribute to emissions. SCC provide “a unique source category-specific process or function that emits air pollutants” (3). Within the on-road sources, there are 16 vehicle categories included in the “SCC level three description” where the fuel used is indicated as diesel fuel. These are, (1) passenger truck, (2) light commercial truck, (3) single unit short-haul truck, (4) single unit long-haul truck, (5) refuse truck, (6) combination short-haul truck, (7) combination long-haul truck, (8) truck (9), tank cars and trucks, (10) automobiles/truck assembly operations, (11) automobiles and light trucks, (12) tank truck cleaning, (13) intercity bus, (14) transit bus, (15) school bus, and (16) motor home. Out of these, we only include four truck categories (i.e. (3) single unit short-haul truck, (4) single unit long-haul truck, (6) combination short-haul truck, (7) combination long-haul truck) that are relevant for heavy-duty freight trucking. We include these five truck categories that are relevant for medium and heavy-duty freight trucking and exclude the others such as passenger truck, tank cars and trucks, automobiles/truck assembly operations, automobiles and light trucks, and tank truck cleaning. The excluded truck categories belong either to the passenger vehicle fleet or are involved in other local operations and don’t engage in freight trucking on the road network. Table S1 provides emissions for pollutants and GHG from NEI, 2017.

Table S1. Freight trucking emissions obtained from NEI, 2017 data (2).

| Pollutant | NEI total emissions, 2017 | NEI trucking emissions, 2017 | % of total US emissions |
|-----------|--------------------------|-----------------------------|-------------------------|
| PM$_{2.5}$ | 5.2M                     | 50K                         | 1.0%                    |
| SO$_2$    | 2.5M                     | 3.7K                        | 0.10%                   |
| NO$_x$    | 11M                      | 1.3M                        | 12%                     |
| CO$_2$    | 5.3B                     | 430M                        | 8.2%                    |

2. Freight Analysis Framework 4 (FAF4) Road Network

FAF4 data consists of ~450k miles of roads consisting of interstate highways, urban and rural principal arterials (4). It builds on the CFS data (5), which is a publicly available dataset and provides information on national freight flows in the US. FAF4 information is
more comprehensive in coverage than the CFS data because it includes industries and shipments that are not included in CFS while providing shipment information at the county level (6). Although a more recent version of the Freight Analysis Framework Version 5 (FAF5) is available, it has yet to be updated with information on county level freight shipments. Table S2 provides percentage distribution of vehicle miles travelled (VMT) by single unit and combination trucks on roads in the FAF4 dataset.

Table S2. VMT by single unit and combination trucks by type of road in the FAF4 dataset. A major share of combination truck VMT is traversed on the interstate highways whereas the VMT is more distributed for single unit trucks.

| Road Type                        | % Combination truck VMT | % Single unit truck VMT |
|----------------------------------|-------------------------|-------------------------|
| 1: Interstates                   | 80%                     | 32%                     |
| 2: Other Freeways and Expressways| 4%                      | 13%                     |
| 3: Other Principal Arterial      | 13%                     | 38%                     |
| 4: Minor Arterial                | 3%                      | 13%                     |
| 5: Major Collector               | 1%                      | 4%                      |
| 6: Minor Collector               | 0%                      | 0%                      |

3. Emission Factors for Single Unit and Combination Trucks

We use emission factors for single unit and combination trucks from the Greenhouse gases, Regulated Emissions, and Energy use in Technologies (GREET) model (7). Table S3 reproduces the emission factors for PM$_{2.5}$, SO$_2$, NO$_x$, and CO$_2$ used for single unit (class-6 trucks) and combination trucks (class 8 or above) in the study.

Table S3. Lifetime mileage weighted emission factors (in g/mile) for single unit and combination trailer freight diesel trucks. These values have been taken from the GREET model (7). The PM$_{2.5}$ emission factor accounts for tire and brake wear emissions.

| Pollutant/ GHG | Emission factor for combination trailer truck (in g/mile) | Emission factor for single unit truck (in g/mile) |
|----------------|----------------------------------------------------------|-----------------------------------------------|
| PM$_{2.5}$     | 0.086                                                    | 0.0467                                        |
| SO$_2$         | 0.0149                                                   | 0.0070                                        |
| NO$_x$         | 4.585                                                    | 0.9383                                        |
| CO$_2$         | 1588                                                     | 1414                                          |

As a sensitivity check, we also compare our long-haul trucking results by running the analysis using emission factors from Table S8 in Tong et al.(8). Using an average fuel economy of 6.3 miles per diesel gallon equivalent (9) for long-haul freight trucking, we convert the emission factors to g/mile. Next, we weight the emission factors using lifetime miles for a combination tractor (Table 2-28)(10) to estimate lifetime mileage weighted emission factors. Tong et al.’s (8) method is different than ours in that they estimate tail pipe emissions profiles using empirical data, literature, and GREET model (7). The authors use a mass-balance approach and harmonize emissions from literature for different air pollutants and greenhouse gases. Table S4 compares emissions for long-
haul freight trucking using modified emission factors from Tong et al.(8) and our emissions based on emission factors from the GREET model (7).

Table S4. Comparison of long-haul freight trucking emissions (in tons) using lifetime mileage weighted emission factors reported in Tong et al. (8) and GREET model (7).

| Pollutant/ GHG | Long-haul trucking emissions (in tons) using Tong et al. emission factors | Long-haul trucking emissions (in tons) using GREET emission factors |
|----------------|--------------------------------------------------------------------------|---------------------------------------------------------------------|
| PM$_{2.5}$     | 5.5K                                                                     | 17K                                                                 |
| SO$_2$         | 80                                                                       | 3K                                                                  |
| NO$_x$         | 108K                                                                     | 920K                                                                |
| CO$_2$         | 32M                                                                      | 31M                                                                 |

4. Reduced-Complexity Chemical Transport Models (CTMs)
Social costs arising from exposure to fine particulate matter (PM$_{2.5}$) on human health are critical for designing effective air pollution control policies. However, the tools available to link changes in PM$_{2.5}$ emissions and subsequent impacts on public health effects are limited. Usually, such situations require deploying and running a state-of-the-science CTM, however, the process can be computationally expensive and time consuming. To overcome these limitations and facilitate a quick estimation of social costs on human health due to air pollution, researchers have developed reduced-complexity models (RCMs) that provide tabulated marginal social costs for different pollutant species. In this study, we employ RCMs to estimate air pollution related public health damages from freight trucking. The subsequent section will discuss the models employed.

4.1. Estimating Air Pollution Social Impacts Using Regression (EASIUR)
In this study, we estimate the impacts of freight trucking pollution on human health at the county level using an RCM called EASIUR (11, 12). The model provides estimates of marginal social costs for four species— (1) primary fine particulate matter (PM$_{2.5}$) species (elemental carbon), and three secondary inorganic species, namely, sulfur dioxide (SO$_2$), oxides of (NO$_x$), and ammonia (NH$_3$). These inorganic species are responsible for secondary formation of PM$_{2.5}$. These estimates of marginal social costs were derived by running regressions on the results of a CTM. The EASIUR model maps the contiguous United States in 148 x 112 grid cells where each grid cell is 36 km x 36 km and is available for four seasons and for three emission elevations: ground level and two stack heights (150 m and 300 m) for point sources. For the scope of this analysis, we ignore any seasonal variation in marginal social costs arising from freight trucking pollution and only consider annual impacts of freight trucking on public health at the ground level. Additionally, the model also comes along with Air Pollution Social Cost Accounting (APSCA) model (available here: https://barney.ce.cmu.edu/~jinhyok/apsca/) that allows for estimating source-receptor (S-R) relationships for marginal changes in emissions for different pollutant species at a fine spatial resolution (12).
4.2. Comparison of freight trucking air pollution related public health social costs from different models

As a check, we compare our freight trucking public health damage results by running the analysis on two emissions inventories: (1) FAF4 and (2) NEI, 2017. Additionally, we compare the results using another model called the Air Pollution Emission Experiments and Policy Version 3 (AP3) *(13) on both the emission inventories. This is an updated version of the Air Pollution Emission Experiments and Policy Version 2 (AP2) model that employs (S-R) matrices to map ambient concentrations to respective counties. The contributions are reflected as an individual element in the S-R matrix. The model is available for four heights: (1) ground-level, (2) point sources located less than 250 m in height, (3) point sources located between 250 m to 500 m in height, and (4) point sources greater than 500 m in height. We use only the ground-level sources to assess the annual impacts of freight trucking on public health.

To estimate freight trucking public health damages, first, we require the EASIUR marginal damages for 2017. To do this, we use the approach suggested by Heo et al. (11) in the supplementary information. The EASIUR marginal damage estimates can be adjusted for a VSL (V) for 2017 using the following adjustment factor ($F_{2017}$):

$$F_{2017} = \frac{VSL_{2017}}{VSL_{2010}}$$

Where,
- $F_{2017}$ is the adjustment factor by which the EASIUR marginal damages are adjusted
- $VSL_{2017}$ is the VSL value for the year 2017
- $VSL_{2010}$ is the VSL value for the year 2010 and it’s value is $8.6M$

Next, we need to estimate $VSL_{2017}$. At the time the EASIUR model was released, it used a VSL value of $8.6M$ while relying on population year and income year 2005. We update the population year to 2017 for estimating public health damages by modifying the EASIUR python script. Additionally, we also need to consider income growth and inflation. We do this by using income growth adjustment factors that come along with the EASIUR model. First, we calculate the updated VSL for the income year 2017 using the following equation:

$$VSL_{2017} = VSL_{2010} \times \left(\frac{I_{2017}}{I_{2010}}\right) \times \left(\frac{CPI_{2017}}{CPI_{2010}}\right)$$

$$VSL_{2017} = 8.6M \times \left(\frac{1.174}{1.010}\right) \times \left(\frac{245}{218}\right)$$

*The marginal social costs for pollutant species for the updated AP3 model was obtained from the authors of Tschofen et al. (21)*
\[ VSL_{2017} = \$10.3M \]

Where,
- \( VSL_{2017} \) is the VSL value for the year 2017
- \( VSL_{2010} \) is the VSL value for the year 2010
- \( I_{2017} \) is the income growth adjustment factor in the EASIUR model and its value is 1.174
- \( I_{2010} \) is the income growth adjustment factor in the EASIUR model and its value is 1.010
- \( CPI_{2017} \) is the consumer price index (CPI) for the year 2017 and is obtained from the U.S. Bureau of Labor Statistics (BLS) (14)
- \( CPI_{2010} \) is the CPI for the year 2010 and is obtained from the U.S. (BLS) (14)

This calculation gives us a \( VSL_{2017} \) of \$10.3M in 2017. As a check, the VSL report by the US Department of Transportation (DOT) in 2017 was \$10.2M (15). So, the method is broadly consistent.

### 4.2.1. Public health damage results based on the FAF4 emissions inventory

Table S5 provides absolute values of air pollution related public health damages from freight trucking in 2017 US $ based on the FAF4 emissions inventory.

**Table S5.** Premature mortality and public health damages (in 2017 US $) due to freight trucking for EASIUR and AP3 model. These results are based on the bottom up FAF4 emissions inventory compiled by the authors and the VSL value used is \$10.3M in 2017 US $.

| Model | PM\(_{2.5}\) Premature mortality | SO\(_2\) Premature mortality | NO\(_x\) Premature mortality | Trucking damages (in US $) | Trucking damages (in US $) | Trucking damages (in US $) |
|-------|---------------------------------|-----------------------------|-----------------------------|---------------------------|---------------------------|---------------------------|
| EASIUR | 527                             | 11                          | 1,076                       | 5.4B                      | 110M                      | 11B                       |
| AP3    | 552                             | 19                          | 2,381                       | 5.7B                      | 370M                      | 25B                       |

For the FAF4 emission inventory, we also compare county level results across EASIUR and AP3. The social costs are broadly consistent with a slight deviation from the y-x line for SO\(_2\) and NO\(_x\) damages (see Fig. S1). This is because of other associated uncertainties and in general, the cost estimates for secondary pollutants are found to be more variable and the correspondence in terms of Pearson’s correlation for secondary pollutants marginal damages, especially for NO\(_x\) and SO\(_2\) damages across both models is lower (16).
Fig. S1 Comparison of freight trucking air pollution related public health social costs (in log10 tons) from EASIUR and AP3. These damages are based on the FAF4 emissions inventory. We observe that social costs from both the models roughly lie on the y=x line.

4.2.2. Public health damage results based on the NEI emissions inventory

Table S6 provides absolute values of air pollution related public health damages from freight trucking in 2017 US $ based on the NEI 2017 emissions inventory. As in the case of previous comparison, here, we compare county level results across EASIUR and AP3 for the NEI 2017 emissions inventory. The social costs are broadly consistent with a slight deviation from the y-x line for SO$_2$ and NO$_x$ damages (see Fig. S2).

Table S6. Premature mortality and public health damages (in 2017 US $) due to freight trucking for EASIUR and AP3 model. These results are based on the NEI emissions inventory compiled by the authors and the VSL value used is $10.3M in 2017 US $.

| Model | PM$_{2.5}$ | SO$_2$ | NO$_x$ |
|-------|------------|-------|--------|
|       |            |       |        |

7
|                | Premature mortality | Trucking damages (in US $) | Premature mortality | Trucking damages (in US $) | Premature mortality | Trucking damages (in US $) |
|----------------|---------------------|----------------------------|---------------------|----------------------------|---------------------|----------------------------|
| EASIUR         | 1,160               | 12B                        | 10                  | 100M                       | 1,552               | 16B                        |
| AP3            | 1,270               | 13B                        | 37                  | 384M                       | 3,684               | 38B                        |

Fig. S2. Comparison of freight trucking air pollution related public health social costs (in log10 tons) from EASIUR and AP3. These damages are based on the NEI emissions inventory. We observe that social costs from both the models roughly lie on the y=x line.

5. **Shifting tonnage from freight trucks to railroads**

Shifting freight tonnage from diesel freight trucks to class-1 railroads holds significant potential for GHG mitigation. We produce a zeroth order estimate of the change in emissions from shifting freight to railroads from trucks. Our estimate is limited by several
assumptions. First, we only account for modal shifts for class-1 freight rail and ignore other categories such as class-2 and class-3 railroads. This is because “class-1 railroads account for around 68% of freight rail mileage, 88% of employees and 94% of revenue” (17). Second, we use an approximation for adjusting freight rail emission factors. Usually, the US EPA reports locomotive emission factors in g/gal instead of g/ton-mile. While it is desirable to have emission factors for rail in g/ton-mile of freight hauled, it has its own limitations. Depending on the terrain where the railroad is operating, the useful work done to haul a ton-mile of freight varies (18). We adjust emission rates expressed in g/gal to reflect equivalent g/ton-mile emission factor by dividing the emission factor in g/gal by the average freight rail fuel efficiency. We discuss the approach adopted to estimate emission factors for different pollutants and GHG in the subsequent section.

We assume that all freight trucking beyond 300 miles is conducted by long-haul heavy-duty tractor-trailer diesel trucks and assume that each truck carries on average 20 tons of freight. We assume that all trips greater than 300 miles might be shifted to rail and use data from CFS 2017. CFS provides information on 5,978,523 shipments and each shipment record has shipment size (in ton-miles) along with a weighting factor. Multiplying the shipment size with the assigned weighting factor allows us to estimate total ton-miles shipped each year for trips (19). This can be expressed as:

**Equation 3.5**

\[
\text{Ton} - \text{miles}_l = \sum_{s=1}^{n} \text{Weighting Factor}_l \times \left( \frac{\text{Shipment Weight}_l}{2000} \right) \times \text{Shipment Distance Routed}_l
\]

Where,
- \(\text{Ton} - \text{miles}_l\) are ton-miles of shipment \(l\)
- \(\text{Weighting Factor}_l\) is the weighting factor of shipment \(l\)
- \(\text{Shipment Weight}_l\) is the weight of the shipment \(l\). We divide this by 2000 since the shipment weight is in pounds
- \(\text{Shipment Distance Routed}_l\) is the routed distance between the origin and destination of the shipment \(l\)

**5.1. Emission factors for Class-1 railroad**

**PM\textsubscript{2.5} emission factor:** For locomotives, particulate matter (PM) emissions are expressed as PM\textsubscript{10} (i.e., particles that are up to 10 microns in diameter) or PM\textsubscript{2.5} (i.e., particles that are up to 2.5 microns in diameter). According to the US EPA guidance, we assume that for class-1 rail, PM\textsubscript{2.5} emissions are nearly 97% of all PM\textsubscript{10} emissions (18). From Table 4 in 2017 US rail national emissions inventory (NEI), we find that the weighted PM\textsubscript{10} emission factor after accounting for locomotives fleet mix in 2017 is 3.944 g/gal. Thus, the PM\textsubscript{2.5} emission factor is 3.82568 g/gal.

**NOx emission factor:** The NOx emission factor is 134.770 g/gal and is the same as used in the 2017 US rail NEI inventory.
SO₂ and CO₂ emission factor: These dependent on the amount of sulfur and carbon present in the diesel fuel and the engine efficiency. For SO₂ and CO₂, we use the following equation from the US EPA guidance document (18) to estimate emission factor.

Equation 1

\[ SO_2 \left( \frac{g}{gal} \right) = (fuel\ density) \times (conversion\ factor) \times \left( \frac{64\ g\ SO_2}{32\ g\ S} \right) \times (S\ content\ of\ fuel) \]

We assume that the fuel used is ultra-low sulfur diesel (ULSD) with sulfur content of 15 ppm and the density of the diesel fuel is 3,200 g/gal. Further, the fraction of fuel sulfur converted to SO₂ is assumed to be 97.8 % (18). Using these numbers, the SO₂ emission factor comes out to be

\[ SO_2 \left( \frac{g}{gal} \right) = (3,200) \times (0.978) \times (2) \times (15 \times 10^{-6}) = 0.093888 \text{ g/gal} \]

Similarly, we estimate the CO₂ emission factor using the following equation:

Equation 2

\[ CO_2 \left( \frac{g}{gal} \right) = (fuel\ density) \times \left( \frac{44\ g\ CO_2}{12\ g\ C} \right) \times (C\ content\ of\ fuel) \]

The density of the diesel fuel is assumed to be 3,200 g/gal and the carbon content of the fuel is 87 % on a mass basis.(18) Therefore, the CO₂ emission factor is

\[ CO_2 \left( \frac{g}{gal} \right) = (3,200) \times (3.67) \times (0.87) = 10,217 \text{ g/gal} \]

According to the Association of American Railroads (AAR), in 2019, class-1 rail roads had a freight rail fuel efficiency of 472 ton-miles per gallon (see Fig. S3) (20).
Fig. S3. Freight rail fuel efficiency of freight railroads from 1980-2019. The figure has been taken from AAR report (20).

We divide the g/gal emission rates by 472 ton-miles/gal provides a rough measure of g/ton-mile of emission rates for class-1 rail. Table S7 provides the emission factors for railroad expressed in g/ton-mile.

Table S7. Emission factors for class-1 railroad expressed in g/ton-mile for 2017.

| Pollutant/ GHG | EF rail (in g/ton-mile) |
|----------------|------------------------|
| PM$_{2.5}$     | 0.1575                 |
| SO$_2$         | 0.0049                 |
| NO$_x$         | 0.0001                 |
| CO$_2$         | 10.6427                |

Next, we estimate total emissions for PM$_{2.5}$, SO$_2$, NO$_x$, and CO$_2$ for freight trucks and rail and the percentage change that would result from switching 5% to 50% of ton-miles from freight trucks to class-1 railroads. Fig. S4 shows percentage change in emissions by shifting part of the freight tonnage to rail. We find that this strategy may be effective in reducing SO$_2$ and CO$_2$ emissions considerably. The relationship between the ton-miles shifted to rail and emissions reduction is linear. If we move 5% and 50% of the total ton-miles in the CFS that are hauled by freight trucks to Class-1 rail, we observe a reduction of SO$_2$ emissions (4% to 43% reduction) and CO$_2$ emissions (4% to 43% reduction). However, the shift in ton-miles does not reduce PM$_{2.5}$ appreciably. While we do not calculate how the distribution of emissions would change spatially if freight were shifted to rail, but it is possible that such a shift might also have adverse distributional outcomes if the rail operations continue to remain diesel powered and pass-through high population density areas.
Fig. S4. % change in PM$_{2.5}$, SO$_2$, NO$_x$, and CO$_2$ emissions if a percentage of the total freight ton-miles are shifted from diesel freight trucks to Class-1 railroads.

6. Distributional effects of freight trucking air pollution at the county level
We use the FAF4 emissions inventory and run a demographic analysis to evaluate the environmental justice implications of freight trucking related air pollution at the county level. Next, we apportion the freight trucking emissions in respective census tracts and repeat the analysis. Here, we discuss the approach for county level regression specification. We run three linear regression specifications for PM$_{2.5}$, SO$_2$, and NO$_x$ emissions from freight trucking at the county level.

6.1. Satisfying linear regression assumptions
In order to use linear least squared regression, we need to satisfy the Gauss-Markov assumptions. These are:

1. **Linearity in parameters**: In this case, we have to be able to write a model such that $y_i = X_i \beta_i$ for $y_i$ and $X_i$ but the variables themselves can have non-linear transformations. Our model specifications satisfy this requirement and the only non-linear transformation we apply is the log transform to all dependent variables and some independent variables.

2. **Random sampling**: This condition allows us to take the results of our sample regression specification and be able to apply it to the true population regression. To the best of our ability and knowledge, we have attempted to satisfy this condition while collating data and avoided introducing any bias in the data.

3. **Zero conditional mean of errors**: This is popularly known as the omitted variable bias. This means that anything that is not in the model specification but potentially related with the independent and dependent variable could bias our estimates. In our modeling, we take great care in ensuring that we satisfy this requirement by including census relevant variables that could influence freight trucking emissions.

4. **No perfect collinearity**: In our analysis, we ensure that we exclude variables that are linear functions of each other because it results in poor specification of the regression model.
6.2. Distribution of dependent variables in FAF4 data
We hypothesize that the errors in our regression relationship function \( y_i = \beta_0 + \beta_i x_i + \epsilon_i \) are normally distributed such that \( \epsilon_i \sim N(0, \sigma^2) \). Next, we look at plot the quantiles of our dependent variables against quantiles of normal distribution. The plot of the quantiles of two distributions against each other is called a quantile-quantile plot (Q-Q plot). The advantage of using a Q-Q plot is that it allows us to simulate as many draws from the normal distribution as possible to satisfactorily represent the distribution. Fig. S5 shows Q-Q plots for dependent variables. We see that the log-transformed variables are much closer to the normal distribution.
Fig. S5. Q-Q plot of untransformed dependent variables (PM$_{2.5}$, SO$_2$, and NO$_x$ emissions). The untransformed variables are non-linear (a,c,e; left panel) whereas the log transformed dependent variables, i.e., log(PM$_{2.5}$), log(SO$_2$), and log (NO$_x$) emissions (b,d,f; right panel) are distributed normally.

6.3. Distribution of independent variables in FAF4 data

Table S8 provides a summary of dependent and independent variables that we use in our analysis. We calculate proportions of different racial and ethnic sub-groups at the county level from the total population provided in the census data. Additionally, we log transform the area of the county, median county level household income, and the total population of the county.

Table S8. Description of variables used in the regression analysis at the county level. We also conduct the analysis using the same variables at the census tract level.

| Variables | Description |
|-----------|-------------|
| $Y_{p,c}(\mathbf{X})$ | log of freight trucking emissions for pollutant $p \in$ (PM$_{2.5}$, SO$_2$, and NO$_x$) in county $c$ |
| $X_{area}$ | area of the county $c$ |
| $X_{black}$ | proportion of the total population in the county $c$ that is black |
| $X_{amerind}$ | proportion of the total population in the county $c$ that is American Indian and Alaska native |
| $X_{haw}$ | proportion of the total population in the county $c$ that is Hawaiian and other Pacific Islanders |
| $X_{asian}$ | proportion of the total population in the county $c$ that is Asian |
| $X_{hisp}$ | proportion of the total population in the county $c$ identifying as Hispanic or Latino |
| $X_{twomore}$ | proportion of the total population in the county $c$ that identifies as having two or more races |
| $X_{totpop}$ | total population in county $c$ |
| $X_{medinc}$ | median household income in county $c$ |

Fig. S6 shows the histograms of county relevant independent variables included in the specification.
Fig. S6. Distribution of independent variables that are included in the model specification. We use Freedman-Diaconis rule to determine bin widths for the histograms. The above distributions are based on the FAF4 emissions inventory that was compiled by the authors of the study.

6.4. Studentized Regression Residual Plots

Another method to evaluate conditional distribution of dependent variables is to look at the distribution of the regression residuals. If our regression relationship is such that \( y_i = \beta_0 + \beta_1 x_i + \epsilon_i \) and the errors are normally distributed \( \epsilon_i \sim N(0, \sigma^2) \), then the residuals must also be normally distributed. Thus, if we assume that our errors come from a normal distribution, then we can compare the studentized residuals to a standard normal distribution. We notice that the distribution of residuals looks reasonable for the three model specifications (see Fig. S7).
Fig. S7. Regression residual plots for the three model specifications.

6.5. Distributional impacts of freight trucking pollution at the county and census tract level

In this section, we compare distributional impacts of freight trucking at the county level by running regression specifications on freight trucking emissions from the NEI 2017 emissions inventory. The NEI 2017 inventory is publicly available from the US EPA website (2). Table S9 and Table 10 show the results of running the specifications at the county and census tract level for PM$_{2.5}$, SO$_2$, and NO$_x$ emissions. For the census tract results, we down scale the county level emission estimates from NEI 2017 to the census tract by population weighting approach. We observe disproportional effects of trucking air pollution on minority populations in the NEI 2017 emission inventory at the county level. As observed in the case of FAF4 emissions inventory, counties with higher proportions of black and Hispanic populations are subjected to higher absolute emissions from freight trucking.

Table S9. Comparison of demographic effects of PM$_{2.5}$, SO$_2$, and NO$_x$ freight trucking emissions at the county level. These results are based on logged emissions from freight trucking in the NEI 2017 emissions inventory. The numbers in the parenthesis provide standard errors.

| Regression Results |
|--------------------|
| Dependent variable: |
|                  | log(PM2.5) | log(SO2) | log(NOx) |
|------------------|------------|----------|----------|
|                  | (1)        | (2)      | (3)      |
| log(County Area) | 0.319***   | 0.326*** | 0.364*** |
|                  | (0.015)    | (0.016)  | (0.016)  |
| Black            | 0.627***   | 0.841*** | 0.567*** |
|                  | (0.087)    | (0.097)  | (0.094)  |
| American Indian  | -0.266     | -0.508** | -0.301   |
|                  | (0.196)    | (0.219)  | (0.211)  |
| Hawaiian         | -1.706     | -2.075   | -0.571   |
|                  | (10.857)   | (12.116) | (11.674) |
| Asian            | -3.686***  | -4.979***| -3.368***|
|                  | (0.720)    | (0.804)  | (0.774)  |
| Two or more races| 2.517**    | 1.871    | 2.587*   |
|                  | (1.256)    | (1.401)  | (1.350)  |
| Hispanic         | 0.239**    | 0.763*** | 0.519*** |
|                  | (0.094)    | (0.105)  | (0.101)  |
| log(Median Household Income) | 0.232*** | 0.372*** | 0.288*** |
|                  | (0.058)    | (0.065)  | (0.062)  |
| log(Total Population) | 0.714*** | 0.729*** | 0.690*** |
|                  | (0.010)    | (0.011)  | (0.011)  |
| Constant         | -14.677*** | -19.217*** | -12.803*** |
|                  | (0.675)    | (0.754)  | (0.726)  |
| Observations     | 3,106      | 3,106    | 3,106    |
| R²               | 0.750      | 0.722    | 0.718    |
| Adjusted R²      | 0.749      | 0.721    | 0.718    |
| Residual Std. Error (df = 3096) | 0.625 | 0.698 | 0.672 |
| F Statistic (df = 9; 3096) | **1,030.285*** | **891.765*** | **878.023*** |

**Note:** *p**p***p<0.01

Table S10. Comparison of demographic effects of PM$_{2.5}$, SO$_2$, and NO$_x$ freight trucking emissions at the census tract level. These results are based on logged emissions from freight trucking in the NEI 2017 emissions inventory.

Regression Results
**Dependent variable:**

|                  | log(PM2.5) | log(SO2) | log(NOx) |
|------------------|------------|----------|----------|
| (1)              | (2)        | (3)      |
| log(Tract Area)  | 0.135***   | 0.142*** | 0.159*** |
|                  | (0.001)    | (0.001)  | (0.001)  |
| Black            | -0.183***  | -0.150***| -0.250***|
|                  | (0.011)    | (0.012)  | (0.012)  |
| American Indian  | 0.362***   | 0.124**  | 0.299*** |
|                  | (0.048)    | (0.052)  | (0.050)  |
| Hawaiian         | -0.783     | 1.072    | 3.281*** |
|                  | (0.625)    | (0.680)  | (0.660)  |
| Asian            | -1.228***  | -1.205***| -0.910***|
|                  | (0.029)    | (0.032)  | (0.031)  |
| Two or more races| -2.134***  | -2.260***| -0.595***|
|                  | (0.155)    | (0.168)  | (0.163)  |
| Hispanic         | -0.534***  | -0.306***| -0.231***|
|                  | (0.012)    | (0.013)  | (0.013)  |
| log(Median Household Income) | -0.403*** | -0.379***| -0.385***|
|                  | (0.005)    | (0.006)  | (0.006)  |
| log(Total Population) | 0.964***   | 0.982*** | 0.948*** |
|                  | (0.005)    | (0.005)  | (0.005)  |
| Constant         | -6.189***  | -9.397***| -3.533***|
|                  | (0.067)    | (0.073)  | (0.071)  |

Observations | 70,887 | 70,887 | 70,887 |
R^2           | 0.565  | 0.527  | 0.543  |
Adjusted R^2  | 0.565  | 0.527  | 0.543  |
Residual Std. Error (df = 71398) | 0.549  | 0.597  | 0.580  |
F Statistic (df = 9; 71398) | 10,243.520*** | 8,772.670*** | 9,342.184*** |

*p**p***p<0.01

We also assess whether a county is more likely to be an importer or not. To evaluate this, we conduct a logistic regression at the county and census tract level. **Table S11** and **Table S12** shows the results of logistic regressions on both FAF4 and NEI 2017 emission inventories at the county and census tract level.
Table S11. Logistic regression results of a county being an importer. These results are based on the NEI 2017 and FAF4 emission inventories. The numbers in the parenthesis provide standard errors. Increasing the predictor by 1-unit results in multiplying the odds of having the outcome by $e^\beta$.

|                      | FAF4 Importer | NEI 2017 Importer |
|----------------------|---------------|-------------------|
| log(County Area)     | -0.136***     | 1.329***          |
|                      | (0.050)       | (0.081)           |
| Black                | 0.337         | 5.864***          |
|                      | (0.292)       | (0.472)           |
| American Indian      | -1.897**      | -2.034**          |
|                      | (0.746)       | (0.823)           |
| Hawaiian             | -20.923       | -76.244*          |
|                      | (37.650)      | (45.967)          |
| Asian                | 0.378         | -23.947***        |
|                      | (2.721)       | (5.773)           |
| Two or more races    | 20.720***     | 18.593***         |
|                      | (4.523)       | (5.259)           |
| Hispanic             | -2.011***     | 2.942***          |
|                      | (0.341)       | (0.524)           |
| log(Median Household Income) | -0.708*** | -3.904***         |
|                      | (0.197)       | (0.272)           |
| log(Total Population) | 0.357***     | -0.376***         |
|                      | (0.035)       | (0.044)           |
| Constant             | 6.751***      | 16.551***         |
|                      | (2.294)       | (2.999)           |
| Observations         | 3,107         | 3,076             |
Log Likelihood  
-2,007.219  
-1,476.191  

Akaike Inf. Crit.  
4,034.437  
2,972.381  

Note:  
*p**p***p<0.01  

Table S12. Logistic regression results of the county being an importer where the census tract is located. These results are based on the NEI 2017 and FAF4 emission inventories. The numbers in the parenthesis provide standard errors. Increasing the predictor by 1-unit results in multiplying the odds of having the outcome by $e^\beta$.

| FAF4 Importer | NEI 2017 Importer |
|---------------|-------------------|
| $\beta$      | $\beta$          |
| log(Tract Area) | -0.203***        | 0.428*** |
|               | (0.005)           | (0.006)  |
| Black         | 1.330***          | -0.467*** |
|               | (0.061)           | (0.055)  |
| American Indian | 0.992***        | 2.602*** |
|               | (0.194)           | (0.346)  |
| Hawaiian      | -2.004            | 32.284*** |
|               | (2.974)           | (3.152)  |
| Asian         | 0.869***          | -4.370*** |
|               | (0.182)           | (0.309)  |
| Two or more races | 5.159*** | -5.671*** |
|               | (0.752)           | (0.815)  |
| Hispanic      | -0.512***         | 1.061*** |
|               | (0.054)           | (0.055)  |
| log(Median Household Income) | 0.621*** | -1.527*** |
|               | (0.026)           | (0.029)  |
| log(Total Population) | 0.003 | -0.035 |
|               | (0.021)           | (0.022)  |
|                |         |         |
|----------------|---------|---------|
| Constant       | -2.764*** | 8.793*** |
|                | (0.324)  | (0.342) |
|                | -0.203*** | 0.428*** |
| Observations   | 57,766   | 70,887  |
| Log Likelihood | -32,295.980 | -31,243.720 |
| Akaike Inf. Crit. | 64,611.960 | 62,507.450 |

Note: *p**p***p<0.01

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