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Marginal emission factors for public transit: Effects of urban scale and density

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ABSTRACT

The objective of this study is to determine the relationship between fundamental urban scale characteristics (population, area, density) and marginal emission factors (MEF) for public transit. Emissions intensity of travel is typically examined using average emission factors (AEF), but MEF (how emissions change with travel volume) are more important for understanding the effects of interventions. MEF and AEF are estimated and compared for transit systems across the U.S. using panel data from 376 urban areas over 27 years. Results show that both MEF and AEF vary substantially across cities and decrease with urban population, area, density, and transit system extent – but AEF are around 50% more sensitive to urban scale. The distinction between MEF and AEF is especially important for bus transit in smaller, less dense cities. Marginal analysis shows that mode shift from private vehicles to transit should be encouraged, even where average emissions from transit are higher.

1. Introduction

Greenhouse gas (GHG) emissions from the transport sector in North America, unlike other sectors, are still increasing, despite steady improvements in motor vehicle efficiency (Environment and Climate Change Canada, 2018; U.S. Environmental Protection Agency, 2017). Passenger motor vehicle travel dominates transportation-related GHG emissions, and travel mode is a primary determinant of the emissions intensity of travel. Hence, interventions that facilitate mode shift toward lower intensity modes of travel are core mitigation strategies for sustainable transportation (Cambridge Systematics, 2009).

The emissions intensities of different modes of travel are typically evaluated and compared based on average emission factors (AEF). But the more important metric for understanding the environmental effects of mode choices and mode shift strategies is marginal emission factors (MEF) – i.e., how emissions change with a change in utilization of a given travel mode. The distinction between average and marginal emission factors is recognized in the energy sector where the emissions intensity of different power production technologies are compared based on marginal factors (Soimakallio et al., 2011). However, marginal emissions have been neglected in the transportation sector.

To explain the difference between AEF and MEF, consider a bus transit system currently serving 20,000 passenger-trips and generating 5,000 kg CO_2 per day. The AEF per passenger-trip for the system is simply the quotient 250 g CO_2. The MEF for the system is the increase in total emissions with a marginal change in ridership: i.e., how much more total emissions would be generated by 20,001 passenger-trips per day than by 20,000. The MEF depends on how bus operations change with ridership, and is most likely not 250 g CO_2. The MEF is determined by the additional vehicle-miles driven, as well as any increase in emissions per vehicle-mile due to higher

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passenger loads. If bus operations increase proportionately to ridership (maintaining equivalent passenger loads), the MEF would be similar to the AEF. If, however, bus operations increase less than proportionately (increasing passenger loads with ridership), then the MEF would be less than the AEF.

Given that MEF are expected to differ from AEF, the question becomes which is the most appropriate measure for a certain situation. The AEF represents the overall emissions efficiency of a service or system, while the MEF represents the impacts of changing utilization of that service or system. If we are interested in the environmental impacts of interventions on a system that affect utilization, then it is the MEF that should be used. In particular, it is MEF, not AEF, which represents the emissions impact of changing ridership and mode shifts to or away from public transit. Hence, public information campaigns about the environmental impacts of travel choices should be reporting MEF, not AEF. Similarly, the impacts of mode shift strategies in climate action plans should be calculated using MEF, not AEF. On the other hand, if we are interested in evaluating whether a service should exist at all, the AEF may be the relevant measure. Also, the MEF applies at the margin, and so estimating the impact of large changes in utilization could require integration of an MEF function.

A recently proposed framework compares MEF and AEF for passenger travel modes based on two key parameters: the elasticity of vehicle travel to passenger travel volumes and the elasticity of vehicle emission rates to vehicle occupancy (Bigazzi, 2019). Using national data from the U.S. Federal Highway Administration and other sources, it was shown that MEF for passenger travel can vary substantially from AEF, and that the size of the difference varies among modes. For example, the estimated MEF/AEF ratio nationally was 0.9 for private vehicle travel and 0.5 for public transit. Hence, the distinction between average and marginal perspectives is particularly important when evaluating the sustainability of travel by public transit.

Beyond systematic differences among modes, it is also important to understand how MEF vary with system attributes and context. This understanding is needed to refine transportation sustainability measures and intermodal comparisons, and to analyze the effectiveness of mode shift and other mitigation strategies in different settings. For public transit, both AEF and MEF likely vary substantially among systems in different cities, because city size, population and employment density, and urban form (among other factors) influence transit service and operational efficiency. High urban density (measured in various ways) supports more efficient travel in general, and more efficient transit in particular (T. A. Clark, 2013; Guerra & Cervero, 2011; Lee & Lee, 2014). What is not yet known is how MEF vary among transit systems in different types of cities. The difference between MEF and AEF depends on the relationship between vehicle and passenger travel, which is expected to vary by context.

The objective of this paper is to determine the relationship between fundamental urban scale characteristics (population, area, density) and marginal emission factors for public transit systems. In particular, are the effects of scale and density on the emissions intensity of travel by public transit different between average and marginal perspectives? To answer this question, AEF and MEF are estimated and compared for transit systems across the U.S. by regression analysis using Federal Transit Administration panel data aggregated to 376 urban areas over 27 years.

2. Method

2.1. Marginal emission factor calculation

If E is the total mass of GHG emissions from a passenger transportation system over a given period of time, then the average emission factor (AEF) for that system with respect to passenger travel is $AEF = \frac{E}{PMT}$, where PMT is the passenger miles traveled in the system over the same time period. The marginal emission factor (MEF) for the system can be calculated $MEF = AEF\left(\varepsilon_{\mathrm{V}}^{\mathrm{P}} + \varepsilon_{e}^{o} - \varepsilon_{\mathrm{V}}^{\mathrm{P}}\varepsilon_{e}^{o}\right)$ where $\varepsilon_{\mathrm{V}}^{\mathrm{P}} = \frac{\mathrm{PMT}}{\mathrm{VMT}}\frac{d\mathrm{VMT}}{d\mathrm{PMT}}$ is the elasticity of vehicle miles traveled (VMT) to PMT and $\varepsilon_{e}^{o} = \frac{o}{e}\frac{de}{do}$ is the elasticity of vehicle emission rate e (mass per distance) to vehicle occupancy o (passengers per vehicle), as described in Bigazzi (2019).

The elasticity $\varepsilon_{\mathrm{V}}^{\mathrm{P}}$ is expected to range from 0 to 1, and is the primary variable investigated in this paper (as described in the next subsection). Based on past literature, the elasticity ε_{e}^{o} is expected to be in the range of 0–0.3 for buses and 0.0–0.1 for passenger rail (Alam and Hatzopoulou, 2014; Andersson and Lukaszewicz, 2006; N. Clark et al., 2007; Frey et al., 2007; Yu et al., 2016; Zhang et al., 2014). Consistent with Bigazzi (2019), assumed values of ε_{e}^{o} for the analysis in this paper are 0.16 for buses, 0.05 for passenger rail, and 0.10 for other transit modes (demand response, shared ride, and other).

2.2. Modeling transit elasticity by city

Elasticity of vehicle travel to passenger travel $\varepsilon_{\mathrm{V}}^{\mathrm{P}}$ is estimated for transit systems across the U.S. using a log-linear two-way fixed effects panel data regression model with the form $\ln\left(\mathrm{VMT}_{i,t}\right) = \beta\ln\left(\mathrm{PMT}_{i,t}\right) + \gamma\ln\left(\mathrm{PMT}_{i,t}\right)X_{i,t} + \alpha_i + \tau_t + \epsilon_{i,t}$, where β and γ are estimated parameters, $X_{i,t}$ is an interaction variable, α_i are city fixed effects, τ_t are year fixed effects, and $\epsilon_{i,t}$ is a random error term for observations from city i in year t. The estimated model parameters are used to calculate elasticity as $\varepsilon_{\mathrm{V}}^{\mathrm{P}} = \beta + \gamma X$.

Inclusion of city and time fixed effects are tested with Breusch-Pagan Lagrange Multiplier Tests. Random effects are tested using a Hausman Test, and serial correlation of model residuals is tested using a Breusch-Godfrey Test. All hypothesis testing uses a $p < 0.05$ threshold. Models are estimated using R statistical software (R Core Team, 2016) with the package 'plm' (Croissant and Millo, 2008).

2.3. Data

The elasticity regression models are estimated using the National Transit Database (NTD) from the U.S. Federal Transit

Administration (FTA), downloaded in October 2019 (Federal Transit Administration, n.d.). This publicly-available dataset contains required and optional annual reporting data from more than 600 transit systems across the U.S. in reporting years 1991 through 2017. The NTD defines 22 modes of transit, which are aggregated to 5 main transit modes for this analysis:

- **Bus**: Bus, Bus Rapid Transit, Commuter Bus, Trolleybus,
- **Rail**: Alaska Railroad, Cable Car, Commuter Rail, Heavy Rail, Hybrid Rail, Light Rail, Monorail/Automated Guideway, Other Rail, Streetcar Rail,
- **Demand response**: Demand Response, Demand Response Taxi,
- **Shared ride**: Vanpool, Jitney, Publico, and
- **Other**: Aerial Tramway, Ferryboat, Inclined Plane, Other Transit.

The data are also aggregated to urban areas based on Primary Urbanized Area (UZA) designation in the NTD. Urbanized Areas are defined by the U.S. Census as an area with at least 50,000 total people with contiguous density of at least 1,000 persons per square mile, and including one or more incorporated cities or towns.

The primary NTD-reported variables used in the analysis are Passenger Miles Travelled (PMT) and Vehicle Revenue Miles (VRM), defined as the in-service operating travel distance of transit vehicles (cars for rail modes) in each system. VRM serves as the measure of VMT, which excludes deadhead miles. Three urban scale and density variables are tested as covariates of elasticity (i.e., interaction variables in the model): population, area (in square miles), and population density (in persons per square mile). Population and area for each UZA-year are given in the NTD. UZA density is computed as a ratio of the given population to area. Transit system route extent is also tested as a covariate using the NTD variable Directional Route Miles (DRM). DRM is only given in the NTD for Bus, Rail, and Other transit modes (not Demand response or Shared ride). The four elasticity covariates (population, area, density, and extent) are tested individually in separate models due to their intrinsic interdependence (and observed correlation).

Observations in the NTD consist of reported totals for a given UZA-mode-year combination. The dataset is first filtered by removing observations without reported PMT or VRM. Those variables (PMT and VRM) are only required by the FTA for "full reporters", an FTA designation for transit agencies that operate more than 30 vehicles or operate fixed guideway services. Observations with reported VRM or PMT under 1000 are also removed (24 observations). Finally, the dataset is limited to UZA with at least 5 years of data to support the panel data regression approach (eliminating 24 UZA). After filtering, the dataset for regression analysis contains data from 376 unique UZA over 27 years (unbalanced with 8,336 unique UZA-year combinations, and 18,460 UZA-mode-year combinations).

Panel data models are estimated at three scales to examine different aspects of the relationship between transit elasticity ε_V^P and urban scale. First, general transit *system* elasticity is estimated using aggregate data from all transit modes by UZA, with urban scale interaction variables. Second, general transit *mode* elasticity is estimated using data from each mode and UZA, with urban scale variables also interacted with modal dummy variables. Third, city-specific transit elasticity is estimated using only bus transit data, with UZA (dummy) variables as the interaction variables. From the results of the third modelling approach, relationships between elasticity and urban scale are examined using the city-specific ε_V^P estimates. The third approach uses only bus transit data because it is the dominant transit mode that covers most UZA in the NTD.

2.4. *Emission estimates*

GHG emissions in mass CO_2e (carbon dioxide equivalent) for each transit system are based on rates from the Transportation Energy Data Book (TEDB), with average energy intensity of vehicle travel by transportation mode (in btu per VMT) reported in Table 2.14 of the TEDB (Davis et al., 2016) – see Table 1 below. GHG emissions per unit energy intensity is assumed to be 0.07 g CO_2e per btu, based on the TEDB and U.S. Environmental Protection Agency guidance (U.S. Environmental Protection Agency, 2015).

Total transit system operating CO_2e emissions per year are calculated as the product of the reported annual VRM and the emissions intensity given in Table 1. AEF for each system is then the total CO_2e emissions divided by the reported annual PMT. Private vehicle emission rates are included in the analysis as a comparison reference for transit. AEF for private vehicles is calculated as 235 g CO_2e/PMT, assuming an average occupancy of 1.7. MEF for private vehicles is then based on the MEF/AEF ratio reported in Bigazzi (2019).

The approach of applying fixed energy and emission intensity values (per VMT) is a limitation in the analysis, necessitated by the scope of covering all urban areas across the U.S., for which more detailed historical emissions data are not available. If such data were

Table 1
Average energy and emission intensity of vehicle travel by mode.

Mode	Energy intensity* (btu/VMT)	Emissions intensity** (g CO_2e/VMT)
Bus transit	35,419	2,479
Rail transit	63,512	4,446
Demand response	20,047	1,403
Shared ride (assumed as passenger truck)	6,555	459
Other transit (assumed as rail)	63,512	4,446
Private vehicle (average of car and passenger truck)	5,697	399

* From the TEDB (Davis et al., 2016).
** Assuming 0.07 g CO2e per btu.

available, MEF could be estimated directly using a panel data regression of $E\tilde{}PMT$. That modelling approach for this dataset would be misleading because E estimates here are essentially scaled VRM data, and so MEF results would account for ε_V^P but not ε_e^o.

3. Results

A summary of the analysis data derived from the NTD is given in Table 2. The values summarized in the table are based on the last reported year for each city/system. Many of the variables have positive skew, with mean values exceeding the third quartile value, particularly PMT and VRM. Most UZA have bus and demand response transit services, whereas the other transit services exist in <20% of UZA, usually in larger cities.

3.1. Multimodal transit system models

Multimodal transit system models use data aggregated across all transit modes within each city (8,336 unique UZA-year observations in an unbalanced 376-UZA by 27-year panel). Five models are estimated: one with no interaction variable for reference, and then four with each of the scale interaction variables of population, area, density, and transit system extent (DRM). Significant city and time fixed effects are confirmed with Breusch-Pagan Lagrange Multiplier tests, and random effects are rejected based on a Hausman Test. Breusch-Godfrey tests indicate serial correlation in the error term, and so robust standard errors are estimated using the Driscoll and Kraay covariance matrix estimator in the ‘plm’ package in R (Croissant and Millo, 2008).

Model estimation results are summarized in Table 3. All four scale variables have a significant positive relationship with the elasticity of transit system vehicle travel (VRM) to ridership (PMT), ε_V^P. In other words, VRM changes more with PMT in larger and denser cities, and in larger transit systems (by DRM). The elasticity values are around 0.4 and change little over the interquartile range (IQR) of the interaction variables, but range up to almost 0.5 in the 95th percentile cities by area and density (and up to 0.8 in the very largest cities by population and area). Elasticity varies most with density over the interquartile and the 5th-95th percentile ranges, but varies more with area over the full variable ranges. The effects of scale on elasticity across cities have positive skew due to the asymmetry (skew) of the scale variables themselves.

3.2. Transit mode models

The transit mode models use data aggregated by mode and city (18,460 unique UZA-mode-year observations in an unbalanced 870

Table 2
Summary of annual transit system data used in analysis.

Variable		N	1st quartile	Median	Mean	3rd quartile
UZA population		376	89,932	185,239	666,313	421,294
UZA area (mi^2)		376	49	94	237	237
UZA density (persons/mi^2)		376	1,598	1,967	2,212	2,555
Directional revenue miles (DRM)	Bus	365	140	290	688	583
	Rail	46	21	88	273	257
Passenger miles traveled (x1000 PMT)	Bus	365	2,414	6,499	54,596	19,850
	Rail	46	10,433	49,317	710,069	270,703
	Demand response	361	206	570	2,773	1,988
	Shared ride	77	1,531	4,906	16,791	14,388
	Other	21	92	485	23,405	16,570
Vehicle revenue miles (x1000 VRM)	Bus	365	580	1,296	5,620	3,116
	Rail	46	728	2,733	25,277	12,065
	Demand response	361	210	524	2,345	1,538
	Shared ride	77	285	880	3,026	3,321
	Other	21	14	29	180	179
Average passenger load (PMT/VRM)	Bus	365	3.7	5.3	5.7	7.1
	Rail	46	12.9	18.5	19.0	24.9
	Demand response	361	0.9	1.1	1.2	1.3
	Shared ride	77	4.5	5.4	5.6	6.5
	Other	21	11.2	26.0	49.9	72.9
Average emission factor, AEF (gCO_2e/PMT)	UZA	376	370	528	757	760
	Bus	365	347	467	628	665
	Rail	46	179	240	423	344
	Demand response	361	1,051	1,320	1,474	1,512
	Shared ride	77	70	86	93	103
	Other	21	61	171	388	395
Total emissions (tonnes CO_2e)	by UZA	376	1,844	3,958	30,781	10,671
	Bus	365	1,437	3,213	13,933	7,723
	Rail	46	3,235	12,153	112,380	53,642
	Demand response	361	295	735	3,290	2,157
	Shared ride	77	131	404	1,389	1,524
	Other	21	60	130	799	794

Table 3
Multimodal transit system elasticity and urban scale.

Interaction variable	PMT parameter* (β)	Interaction parameter* (γ)	Adjusted R^2	Elasticity (ε_V^P) over IQR** of interaction variable	Elasticity (ε_V^P) over 5th-95th percentile range of interaction variable
None	0.398	NA	0.406	NA	NA
Population (100,000)	0.371	0.00240	0.420	(0.374; 0.384)	(0.373; 0.442)
Urban area (100 mi^2)	0.360	0.0130	0.421	(0.367; 0.394)	(0.364; 0.485)
Density (1000 persons/mi^2)	0.273	0.0527	0.418	(0.358; 0.409)	(0.340; 0.480)
Directional revenue miles (100 mi)	0.390	0.000323	0.413	(0.390; 0.392)	(0.390; 0.400)

* All significant at $p < 0.05$.
** IQR: interquartile range, 25th to 75th percentile.

UZA-mode by 27-year panel). Bus, as the most common mode, is used as the reference level for *t*-tests comparing modal parameters. Separate models are again estimated for each of the four scale variables. The scale variables are interacted with modal dummy variables, yielding separate β and γ parameters for each mode in each model.

Elasticity estimates from these models are summarized in Fig. 1, showing elasticity for each mode over the 5th-95th percentile range of the interacting scale variable. Similar to the multimodal models, all scale variables have significant positive effects on transit elasticity. Adjusted R^2 values are 0.68 for the three urban scale models (population, area, and density), and 0.56 for the route extent (DRM) model – a marked improvement in goodness of fit over the non-mode-specific models in the previous subsection, signifying the unique elasticity of different transit modes.

The largest effects of urban scale variables on elasticity are for bus and other transit; rail elasticity varies the least with urban scale. Substantial differences in elasticity between transit modes persist over the range of urban scales; bus elasticity in the 95th percentile largest cities is still lower than rail elasticity in the 5th percentile cities (with rail). The elasticity ranges in Fig. 1 are affected by substantial positive skew in the scale variables; elasticity in the smallest 5% of cities is similar to the low end of the ranges shown in Fig. 1, while elasticity in the largest 5% of cities ranges over 0.90 for most mode/scale interactions (even for bus interacted with population and area – but not density, which only reaches 0.69).

A reference model with no scale variables yields elasticity estimates of 0.384 for bus, 0.833 for rail, 0.763 for demand response, 0.858 for shared ride, and 0.431 for other transit. In that model, rail, demand response, and shared ride estimates are all significantly different from bus, but other transit is not. Similarly, in the interaction models, the effects of population and density scale variables on rail, demand response, and shared ride elasticities are all significantly different from (smaller than) their effects on bus elasticity, but the effects on other transit elasticity is not significantly different. The effect of route extent on rail elasticity is also not significantly different from the effect on bus elasticity.

To translate the elasticity differences into effects on MEF, Table 4 gives average and marginal emission factors for each mode,

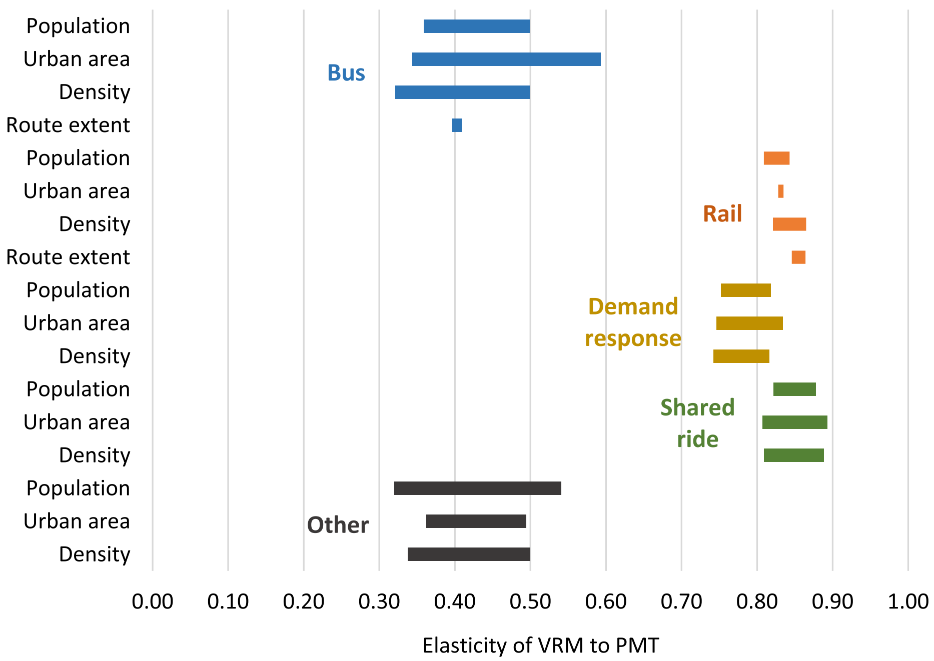

Fig. 1. Transit elasticity by mode, with scale variables over the 5th-95th percentile range.

derived from the elasticity estimates with varying urban density. AEF are PMT-weighted means for each mode, and so vary from the unweighted means given in Table 2. The most substantial difference between MEF and AEF is for bus transit, which falls from the second-highest intensity mode by average factors (after demand response) to below rail transit and private vehicles by marginal factors (at median density). Marginal emissions intensity for bus transit is also more sensitive to urban density than emissions factors for other modes. For example, the bus MEF over the given density range encompasses the full range of rail MEF over the same density values.

3.3. *City-specific models*

The third set of models are used to estimate unique elasticity values for each city's bus system, by using UZA dummy variables as the interaction variables. The model is estimated on the unbalanced panel data set of 365 UZA with bus transit over 27 years (N = 8,041). Adjusted R^2 for the model is 0.696. Resulting city-specific bus elasticity estimates are trimmed at the 5th and 95th percentiles (−0.149 and 0.898). Estimated elasticity, AEF, and MEF for each city are summarized in Table 5 (based on the last reported year of operation). Mean AEF across cities in Table 5 is higher than the PMT-weighted AEF for bus in Table 4 because most bus PMT occurs in larger cities with more efficient transit systems.

Relationships between MEF and AEF estimates by city and urban scale variables are summarized in Table 6 as correlation coefficients and elasticity values. MEF and AEF both significantly decrease with all 4 scale variables, signifying that transit is indeed more efficient (per PMT) in larger and denser cities and larger transit systems. The MEF/AEF ratio increases with all four scale variables, but only varies significantly with density and route extent, indicating that in denser cities and larger transit systems there is a smaller relative difference between MEF and AEF. Moreover, AEF is more sensitive to urban scale than MEF, as indicated by the magnitudes of correlations and elasticities approximately 50% higher.

City-specific AEF and MEF for bus transit are illustrated in Fig. 2, segmented into UZA population tertiles (separated at 117,000 and 314,000 persons). The figure is trimmed for legibility, excluding outliers above 1450 g CO_2e/PMT. Emission factors vary widely across cities within each population level, due to the many other factors influencing transit ridership and efficiency. Comparing across population levels, while both types of emission factors are lower in larger cities, MEF do not vary as much with population as AEF vary. As a result, the differences between the MEF and AEF distributions increase in smaller cities. Median AEF are two times higher than median MEF in the largest cities, but three times higher in the smallest cities. The high population cut-off is relatively low, given the strong positive skew of the UZA population distribution (314,000 persons/mi^2 is approximately the population of the Lansing, Michigan UZA, for example). The largest tertile (1/3rd) of cities serves 93% of bus transit PMT and 87% of bus VRM in the dataset, while the smallest tertile serves just 3% and 5% of each, respectively. Segmentations on area or density yield similar results, due to the association among scale variables.

4. Discussion

Regarding the main objective of this paper, the results show that marginal emission factors for all transit modes are lower in larger cities (by area and population), denser cities, and larger transit systems (by route extent). Marginal emission factors for transit are consistently lower than average emission factors across city scales. Marginal emission factors also vary less with scale and density, resulting in smaller differences from average emission factors in larger, denser cities (with higher MEF/AEF ratios closer to one). By shifting from the average to the marginal perspective, (1) transit appears more efficient overall, and (2) transit efficiency is still higher in larger and denser cities, but (3) transit efficiency increases *less* with urban scale.

Although elasticity of vehicle to passenger travel (and thus MEF/AEF ratios) varies with urban scale for all transit modes, the effects of scale are generally smaller than the systematic differences between modes. Comparing bus and rail transit, MEF/AEF ratios are much lower for bus transit, and more sensitive to scale. Demand response and shared ride transit are similar to rail in terms of MEF/AEF ratios around 0.8, but also more sensitive to urban scale. The marginal perspective is especially important to consider for bus transit in smaller, less dense cities (which tend to have lower ridership): bus transit can have high average emissions in those cities, but marginal emissions are still lower than that of private auto.

The observed relationships between the elasticity ε_V^P (and MEF/AEF ratios) and urban scale are likely related to the amount of unused transit capacity in a city. Increasing PMT is more likely to increase VRM in larger, denser cities with less unused capacity.

Table 4
Emission factors by mode with varying urban density.

Mode	AEF	MEF/AEF ratio			MEF		
		At median density	Over density range*		At median density	Over density range*	
Bus	255	0.472	(0.430;	0.579)	121	(110;	148)
Rail	158	0.841	(0.830;	0.872)	133	(131;	138)
Demand response	1187	0.787	(0.768;	0.834)	933	(911;	990)
Shared ride	83	0.849	(0.828;	0.899)	70	(69;	74)
Other transit	34	0.446	(0.404;	0.550)	15	(14;	19)
Private vehicles**	235	0.895	(0.853;	0.937)	210	(200;	220)

* 5th-95th percentile.
** From (Bigazzi, 2019).

Table 5
Elasticity and emission factor estimates for bus systems by city.

Variable	5th percentile	25th percentile	Median	Mean	75th percentile	95th percentile
Elasticity (ε_V^P)	−0.149	0.139	0.340	0.337	0.537	0.898
MEF/AEF ratio	0.035	0.277	0.446	0.443	0.611	0.915
AEF	126	350	467	594	667	3,857
MEF	7	125	199	256	313	2,428

Table 6
Relationships between city-specific bus emission factors and urban scale variables.

Scale variable	MEF/AEF ratio		MEF		AEF	
	Correlation	Elasticity	Correlation	Elasticity	Correlation	Elasticity
Population	0.053	0.057	−0.125*	−0.151***	−0.183***	−0.208***
Area	0.045	0.044	−0.149**	−0.136**	−0.217***	−0.180***
Density	0.142**	0.207*	−0.149**	−0.361**	−0.247***	−0.569***
Route extent	0.055	0.067*	−0.139*	−0.170***	−0.202***	−0.236***

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

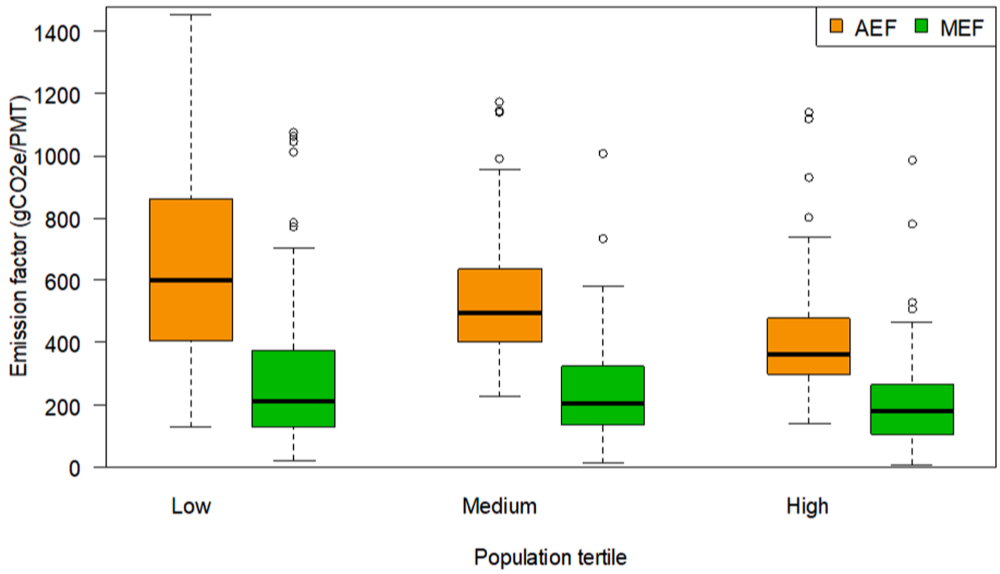

Fig. 2. City-specific bus transit emission factors.

Conversely, smaller cities with more excess capacity are more likely to serve additional travel with existing VRM. Other potential causes of the observed relationships include funding (if larger cities have greater opportunities to increase VRM as ridership grows but smaller cities have more budget-constrained transit operations), scope of service (if larger cities have to increase VRM by a larger amount to achieve a similar improvement in service quality), socio-demographics (e.g., proportions and spatial distributions of transit-dependent populations), and possibly other factors. The MEF are derived from observed concomitant changes in ridership and transit operations, and so the analysis cannot distinguish how causal directionality may generate different MEF: i.e., ridership-responsive transit services versus ridership changes in response to changes in transit services. More detailed investigation of VRM-PMT relationships at the city scale would help illuminate the causal mechanisms.

The scope of this study was limited to examining the aggregate, systemic relationships between urban scale variables and transit emission factors; many other facets of transit systems and their context also influence emissions but were not investigated, including vehicle types and ages, fuels, terrain, climate, congestion, and more (Alam and Hatzopoulou, 2014; Cooper et al., 2013; Wei and Frey, 2020). Because of this limitation, the specific emission factor values should be used with caution; rather, the core findings relate to the systematic differences between MEF and AEF, and their relationships with urban scale. Caution should also be used to apply emission factors at the scale of estimation (in this case, entire transit systems); within a transit system, MEF would vary at the line or stop level. Several other system attributes were considered but excluded from the analysis due to endogeneity in the regression models (because they are calculated from VRM), including aggregate frequency (VRM/DRM), passenger load (PMT/VRM), and rail fraction of VRM.

Some cities are transitioning to electric buses, which will reduce lifecycle emissions per VMT. Electric buses would thus reduce a system's AEF, but may have little impact on the MEF/AEF ratio. The relationship between PMT and VRM (ε_V^P) would likely not change with electric buses, but the effect of passenger loads on emission rates (ε_e^o) could be slightly lower if electric bus energy consumption is less effected by stops and dwell time, for example. If so, this would magnify differences between MEF and AEF by reducing the MEF/AEF ratio. Because vehicle emission rates were assumed the same for all cities, systematic variation in vehicle-related efficiency among cities was not included in the analysis. For example, if predominantly larger cities can afford newer, higher-efficiency or electric buses, that would further lower both AEF and MEF for those cities, increasing the transit efficiency advantage of larger cities by both AEF and MEF measures.

For transit services operating on shared right-of-way, traffic congestion can reduce transit vehicle efficiency per VMT and so increase AEF. As congestion is associated with larger cities, neglecting city-specific congestion levels may overestimate the relationship between AEF and city size. The effect of congestion on the MEF/AEF ratio is unknown. More congested road networks may influence the relationship between ridership and service level (modifying ε_V^P) by reducing the utility of driving as an alternative mode. Congestion may also directly influence the effect of passenger loads on emission rates for bus transit (modifying ε_e^o). Each of these changes is difficult to predict, and should be examined in future work, perhaps using urban-scale congestion measures that distinguish arterial and freeway congestion levels. More complete marginal effects of mode shift from driving to transit could then be estimated, including the marginal impacts of reduced congestion.

Another limitation of this study is the data set; the NTD used in the analysis does not contain all U.S. transit data – only data from "full reporters" (all urban agencies operating more than 30 vehicles or operating fixed guideway services, in addition to voluntary full reporters). The set of full reporters does include most urban transit systems, however, and this limitation is unlikely to materially affect the findings. Missing data on rural systems would not be included in the analysis, and urban systems with <1,000 VRM were excluded, representing a small portion of U.S. transit travel.

The NTD data are also expected to contain reporting errors by the transit agencies (clerical or inherited from the raw data), and it is unknown the extent to which these errors may be systematic and could thus affect the results. The key NTD data fields used for this analysis are PMT and VRM. Each could contain clerical errors, but they are most likely random and so unlikely to materially affect the findings. VRM is readily, reliably, and directly measurable from transit operations, and so unlikely to have substantial systematic errors. PMT is more challenging to measure, and typically inferred from automatic passenger counters (APC) on vehicle doors which are not highly reliable. Some transit systems may have vehicles without APC, while others may have more precise methods of measuring PMT such as fare card data (particularly for rail transit). With appropriate data processing, there is no expected bias direction for the PMT data, but it is reasonable to assume that larger cities have more precise PMT estimates, and so less PMT error. Ultimately, this suggests that ε_V^P estimates, and by extension MEF/AEF ratios, are more uncertain for smaller cities, although there is no expected direction of bias. Some of the wider spread in emission factors in smaller cities seen in Fig. 2, for example, may be partly due to PMT data errors. The possibility of data errors is a limitation, necessitated by the difficulty of obtaining more reliable transit data with such a large spatial and temporal coverage. In future work, more detailed analysis for individual urban systems should be compared to validate the findings of this broad-scope analysis.

This study examined the elasticity of vehicle to passenger travel ε_V^P in detail, but not the other key variable for MEF/AEF ratios: ε_e^o, the elasticity of vehicle emission rates to passenger occupancy. This limitation would affect the findings if ε_e^o varies systematically with urban scale – which is not expected, but should be examined in future work. The analysis also only included emissions of GHG, not local pollutants such as diesel particulates, for which ε_e^o could be higher, increasing the MEF/AEF ratios.

It is interesting to consider the findings in context of the recent downturn in transit ridership resulting from the COVID-19 pandemic and related travel and activity restrictions. If a similar analysis were conducted at a future date with several more years of NTD data, the COVID-19 effect would be captured by a time fixed effect, and so not substantially influence the results. However, in the more distant future, there could be a structural change in the relationship between transit VRM and PMT, if travel behavior changes fundamentally as a consequence of the pandemic. Reduced transit demand would increase AEF due to lower passenger loads, assuming transit services are reduced less to maintain minimum service standards. For MEF effects beyond that, we could find that transit systems have to provide more VRM capacity per rider to accommodate social distancing (increasing MEF/AEF), or that remaining transit riders are less sensitive to service quality due to the increasing importance of disease transmission in travel decisions (decreasing MEF/AEF).

The findings in this paper support the idea that public transit, especially bus transit, appears more efficient and sustainable when compared to other modes on a marginal (versus average) basis. AEF can over-represent the emissions impacts of changing ridership by a factor of 2 or more. The importance of considering marginal emissions is magnified in small, low-density cities, where the differences between MEF and AEF are larger. High urban density supports transit efficiency from both marginal and average perspectives, and differences between the two decrease with urban scale. Finally, public transit is a more sustainable choice than private auto travel and mode shift should be encouraged, even in small cities where average emissions from travel by bus may be higher than for travel in private vehicles.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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