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Comparison of marginal and average emission factors for passenger transportation modes

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HIGHLIGHTS

- Average and marginal emission factors per passenger kilometer traveled are compared.
- Marginal energy and emission factors are substantially lower than average factors.
- Differences between marginal and average intensity vary by mode and service.
- Environmental benefits of public transit are greater considering marginal intensity.
- Average factors discount the benefits of shifting travel away from private vehicles.

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ABSTRACT

Comparisons of the energy and emission intensity of transportation modes are standard features of sustainable transportation research, policy, and advocacy. These comparisons are typically based on average energy and emission factors per passenger trip or per passenger-kilometer traveled. However, as acknowledged in the energy production sector, comparing average emission factors can misinform policy and other decisions because it fails to represent the *marginal* impact of changing demand. The objective of this paper is to quantify the difference between average and marginal energy and emission factors for passenger transportation modes. Transportation system operations data are used to estimate energy and emission factors per passenger-kilometer traveled for U.S. urban and intercity travel. Marginal emission factors range from 30% (intercity rail) to 90% (private vehicles) of average factors. For urban travel, private vehicles and public transit have similar average emission factors, but marginal factors are 50% lower for transit. The average emission factor for intercity rail is 10% lower than air travel and 30% lower than private vehicles, but the marginal factor is 60% and 80% lower, respectively. Using average energy and emission factors to represent the impacts of travel by different modes is biased against public transit and discounts the benefits of shifting travel away from private passenger vehicles.

1. Introduction

(Motorized transportation consumes a vast amount of energy, generates a large portion of global greenhouse gas emissions, and substantially degrades air quality, leading to significant negative effects on the world climate, human health, ecosystems, and more [1,2]. Diverse mitigation efforts around the world aim to reduce energy consumption and pollution emissions from transportation systems, often through improvement of vehicle and fuel technology and by encouraging "mode shift" to more efficient modes of transportation [3,4]. Comparisons of the energy and emission intensity of transportation modes are standard features of sustainable transportation policy [5], advocacy [6], and research [7,8]. These comparisons are typically based on average emission factors per passenger-trip or per passenger-kilometer-traveled (PKT) [9,10].

Research in the energy production sector has shown that comparing technologies and fuels by average emission factors can misinform policy and other decisions because it fails to represent the marginal impact of changing consumption [11]. Hawkes [12] points out that "a change in demand does not act upon all elements of the electricity system proportionally and as such a system-average emissions factor (AEF) could be misleading." Alternatively, marginal emission factors (MEF) represent the impacts of changing consumption with respect to current conditions. For electricity production, MEF vary by context but are typically higher than AEF [13]. Hence, the environmental impacts of policies that influence electricity consumption are underestimated when based on AEF.

Methods used to estimate short-run and long-run MEF for the energy

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Nomenclature

AEF	average emission factor (mass per PKT)
e	average distance-based vehicle emission rate (mass per VKT)
E	total mass emissions of a pollutant of interest from a transportation system
ε_e^o	elasticity of average vehicle emission rate (e) to vehicle occupancy (o)
ε_V^P	elasticity of vehicle travel to passenger travel quantities
MEF	marginal emission factor (mass per PKT)
o	average vehicle occupancy (persons per vehicle)
PKT	passenger-kilometers traveled
VKT	vehicle-kilometers traveled

sector include regression [13], energy system models [12], graphical methods [14], and fuzzy logic [15]. The methodological differences can substantially impact emission estimates and life cycle assessments [16]. Research in the energy sector has applied MEF to study load management [17], environmental pricing [18], and community energy management [19]. MEF for power generation have also been applied to study the environmental impacts of demand-related policies in power-consuming sectors, such as industrial motor replacement [20].

Regarding the transportation sector, MEF for electric power generation have been used to estimate the environmental impacts of shifting vehicle fuel technology from petroleum to electricity [21,22]. However, marginal energy and emission factors for transportation systems themselves have not been established. Analyses of "travel demand management" strategies and other policies that influence travel by mode instead utilize average energy and emission factors. Similar to energy systems, if AEF and MEF for transportation systems are substantially different, then reliance on AEF would misinform policy decisions. In addition, application of AEF would mislead forecasts of energy demand from the transportation sector resulting from changing transportation technology, infrastructure, and policy.

Transportation mode is a defining characteristic of passenger travel, and central to transportation system planning, design, and management. Given the importance of mitigating the energy demands and environmental impacts of transportation systems, and the focus on mode shift as a mitigation strategy, it is essential to understand not just the average but the marginal energy and emission intensity of different transportation modes. Past research has only quantified and compared average energy and emission intensity of transportation modes. This paper aims to bring a new perspective to analysis of transportation systems by introducing marginal energy and emission factors for different modes of transportation.

The objective of this paper is to quantify the difference between marginal and average energy and emission factors per passenger-kilometer traveled for transportation system operations, and to investigate differences among transportation modes. It is hypothesized that MEF are lower than AEF for transportation systems due to changes in vehicle occupancy that accompany changes in travel demand, particularly for schedule-based public transit services with available passenger capacity. A mathematical framework is developed to calculate MEF from passenger and vehicle travel volumes. Aggregate data from U.S. transportation systems are then applied in regression analysis to estimate MEF for urban and intercity passenger transportation modes.

2. Method

2.1. Framework

Let E be the total mass emissions of a certain pollutant of interest from operations of a passenger transportation system over a given period. If VKT (vehicle kilometers traveled) is the vehicle travel quantity in the system over the same period, then $e = \frac{E}{\mathrm{VKT}}$ is the average distance-based vehicle emission rate (in mass per VKT) in the system. Let PKT (passenger kilometers traveled) be the passenger travel quantity in the same system; the average vehicle occupancy is $o = \frac{\mathrm{PKT}}{\mathrm{VKT}}$.

The AEF per PKT for the system is $AEF = \frac{E}{\mathrm{PKT}} = \frac{e}{o}$ and the MEF is the differential $MEF = \frac{dE}{d\mathrm{PKT}}$. Substituting $E = e{\cdot}\mathrm{VKT}$ and differentiating (see Supplementary Information),

$$MEF = \frac{e}{o}\left(\frac{\mathrm{PKT}}{\mathrm{VKT}}\frac{d\mathrm{VKT}}{d\mathrm{PKT}} + \frac{o}{e}\frac{de}{do}\left(1 - \frac{\mathrm{PKT}}{\mathrm{VKT}}\frac{d\mathrm{VKT}}{d\mathrm{PKT}}\right)\right) \tag{1}$$

Defining the elasticity of vehicle travel to passenger travel quantities as

$$\varepsilon_V^P = \frac{\mathrm{PKT}}{\mathrm{VKT}}\frac{d\mathrm{VKT}}{d\mathrm{PKT}} \tag{2}$$

and the elasticity of average vehicle emission rate to vehicle occupancy as

$$\varepsilon_e^o = \frac{o}{e}\frac{de}{do}, \tag{3}$$

MEF in Eq. (1) simplifies to:

$$MEF = AEF(\varepsilon_V^P + \varepsilon_e^o - \varepsilon_e^o \varepsilon_V^P) \tag{4}$$

From Eq. (4), the relationship between marginal and average emission factors for a transportation system depends on the relationships between passenger and vehicle travel quantities (ε_V^P) and between vehicle occupancy and emission rates (ε_e^o) in the system of interest. Both elasticities ε_V^P and ε_e^o are expected to be between 0 and 1, leading to an MEF between 0 and AEF. A high value of ε_V^P (around 1) indicates that vehicle occupancy is stable, and changes in PKT are accompanied by proportional changes in VKT. Conversely, low ε_V^P (around zero) indicates that VKT is stable with respect to PKT, and changes in PKT are accommodated by changes in vehicle occupancy. A high value of ε_e^o (around 1) indicates that vehicle emission rates per VKT increase proportionally with vehicle occupancy, while a low value of ε_e^o (around zero) indicates that emission rates are independent of passenger load. This study focuses on estimation of ε_V^P from aggregate transportation system data. Representative values for ε_e^o and AEF are drawn from the literature to compare MEF across transportation modes.

2.2. Elasticity of vehicle travel to passenger travel

Similar to previous investigation of MEF in the electricity production sector [18], in this study ε_V^P is estimated using log-linear regression models with the general function form

$$\ln(\mathrm{VKT}) = \alpha_0 + \alpha_1\ln(\mathrm{PKT}) + \beta_j X_j + \gamma_j \ln(\mathrm{PKT})X_j + \epsilon \tag{5}$$

where α_0, α_1, β_j, and γ_j are estimated parameters, X_j is a set of interaction variables, and ϵ is a set of error terms appropriate to the model form (i.e., fixed effects for panel models or autoregressive terms for time-series models). The estimated parameters are used to calculate elasticity as $\varepsilon_V^P = \alpha_1 + \gamma_j X_j$, which includes the interaction effect of X_j on elasticity.

Several aggregate travel datasets from the U.S. are used to estimate ε_V^P for different transportation modes. Panel data are used if available, and longitudinal or cross-sectional data otherwise. Private vehicle travel data are taken from the 1995, 2001, and 2009 National Household Travel Surveys (NHTS) conducted by the U.S. Department of Transportation U.S. Department of Transportation, Federal Highway Administration [23]. A household-based cross-sectional regression model is estimated separately for each survey year (with samples of 35,000–120,000 households in each year), and a metropolitan-level panel data regression model is estimated by aggregating households (using expansion weights given in the NHTS data) by metropolitan area in each survey year.

Annual public transit travel data from 1991 through 2015 are taken from the National Transit Database maintained by the U.S. Department of Transportation, Federal Transit Administration [24]. The transit data are used in panel data regression models for multi-modal transit systems and for individual transit services by mode (bus, rail, demand response, and vanpool). National annual intercity rail (Amtrak) and commercial air travel data are taken from the U.S. Bureau of Transportation Statistics [25]. Time series (longitudinal) regression models are estimated for annual intercity rail travel (1960–2015) and for annual (1960–2015) and monthly (2000–2017) air travel.

Household cross-sectional models are estimated by weighted least squares using sampling weights given in the NHTS data. Longitudinal data models are estimated by generalized least squares with first-order autoregressive and moving average terms. Panel data models are estimated with two-way fixed effects and robust standard errors. Population, population density, and "urban" dummy variables are tested as interaction effects in the cross-sectional and panel data models. Details of the datasets, model specifications, and error structures are provided in the Supplementary Information, along with parameter estimation and diagnostic testing results. The main body of the paper gives summary results for evaluating ε_V^P.

2.3. Elasticity of emission rates to vehicle occupancy

Representative values of ε_e^o for different transportation modes are drawn from the literature. For private passenger vehicles, ε_e^o is expected to be in the range of 0.01–0.08. Previous studies reported fuel consumption increases at 0.5–2.7% per 100 lb for passenger cars [26–28], which suggests ε_e^o of 0.01–0.08 assuming a baseline passenger load of 150–300 lbs. These studies also reported elasticity of fuel consumption to total vehicle weight of 0.21–0.83, which translates to ε_e^o of 0.01–0.08 using reference vehicle weights of 3000–4000 lbs and the same baseline passenger loads.

For buses, ε_e^o is expected to be in the range of 0.03–0.30, higher than for passenger cars because passenger mass comprises a higher fraction of total loaded vehicle mass. Elasticity of fuel consumption to passenger load has been reported as 0.15 (± 0.12) for buses in Beijing [29] and 0.2 for Euro IV buses in Europe [30]. Fuel consumption has been reported to increase by 7–30% for full versus empty buses, depending on operating speed, road grade, and other factors [31,32]. The effects of load on bus emissions also depend on pollutant and operating speed [33,34].

For passenger rail, previous analysis concluded that energy consumption varied little with load factor, with a 3–5% difference in energy consumption of fully loaded versus empty trains [35]. Other research suggested potential energy savings of 0.1–0.5 kWh/100 km per 100 kg train weight [27], which translates to an elasticity of energy to passenger load of 0–0.10 assuming baseline passenger loads of 10–30 tonnes and energy consumption of 5–10 kWh/km [35]. For airplanes, a 5% increase in load factor has been reported to increase fuel burn by 0.80% for long-haul flights and by 2.54% for short-haul flights Baughcum and Tritz [36], implying ε_e^o of 0.16–0.51.

In summary, this study uses the following central estimates (and ranges) of ε_e^o: 0.04 (0.01; 0.08) for private passenger vehicles, 0.16 (0.03; 0.30) for buses, 0.05 (0.00; 0.10) for passenger rail, and 0.33 (0.16; 0.51) for air travel. For other transit modes (demand response, vanpool, and multi-modal systems), ε_e^o is assumed to be 0.10 (0.01; 0.20), approximately midway between the bus and rail values.

2.4. Average energy and emission factors

Average energy intensity for U.S. travel modes is based on the Transportation Energy Data Book (TEDB) [37] which reports energy intensity in btu/passenger-mile in Table 2.14 and Fig. 2.7 of the TEDB. Energy intensity is converted to greenhouse gas (GHG) emission factors using 0.07 g CO_2-equivalent (CO_2e) per btu. The CO_2e conversion is for both electricity and petroleum fuels, which have similar values of CO_2e/btu based on 10,339 btu/kWh electricity and 125,000 btu/gallon petroleum fuel from Appendix A of the TEDB, and 750 g CO_2e per kWh and 8900 g CO_2e per gallon fuel from U.S. Environmental Protection Agency guidance [38].

3. Results

Estimates of the elasticity of vehicle travel to passenger travel (ε_V^P) for the studied transportation systems are given in Table 1. Detailed information on the model specifications and statistical results is given in the Supplementary Information. Interaction effects are summarized below and described in the Supplementary Information but not included in Table 1. Private passenger vehicle and vanpool elasticities are the highest at around 0.9, followed by demand response and rail transit (0.8), air travel (0.6–0.7), bus transit and multi-modal transit systems (0.5), and intercity rail (0.3). The width of the 95% confidence intervals for most of the elasticity estimates is around 0.1 or less, except for intercity rail for which the elasticity estimate is less precise.

The private vehicle elasticities of VKT to PKT in Table 1 are similar in all three survey years and when estimated at the household and

Table 1
Estimated elasticity of vehicle travel to passenger travel.

Travel mode	Data[a] & aggregation	Model form	Elasticity estimate, ε_V^P (95% confidence interval)
Private vehicles	NHTS: Surveyed households in 1995 (N = 34,764), 2001 (N = 58,603), and 2009 (N = 123,184)	Cross-sectional	1995: 0.88 (0.87; 0.88) 2001: 0.87 (0.87; 0.88) 2009: 0.89 (0.88; 0.89)
Private vehicles	NHTS: 50 metropolitan areas in 1995, 2001, and 2009 (unbalanced, N = 116)	Panel	0.90 (0.85; 0.94)
Transit systems (multi-modal)	NTD: Annual totals for 701 transit systems, 1991–2015 (unbalanced, N = 11,555)	Panel	0.45 (0.41; 0.49)
Transit services	NTD: Annual totals for 2,235 transit services, 1991–2015 (unbalanced, N = 27,912)	Panel	Bus: 0.51 (0.47; 0.55) Rail: 0.76 (0.74; 0.78) Demand response: 0.82 (0.80; 0.85) Vanpool: 0.88 (0.82; 0.94)
Intercity rail	BTS: National annual totals, 1960–2015 (N = 32)[b]	Longitudinal	0.27 (-0.04; 0.57)
Air	BTS: National annual totals, 1960–2015 (N = 32)[b]	Longitudinal	0.69 (0.62; 0.75)
Air	BTS: National monthly totals, 2000–2017 (N = 210)	Longitudinal	0.58 (0.55; 0.60)

[a] Data source abbreviations: BTS (Bureau of Transportation Statistics, U.S. Department of Transportation), NHTS (National Household Travel Survey, Federal Highway Administration, U.S. Department of Transportation), NTD (National Transit Database, Federal Transit Administration, U.S. Department of Transportation).
[b] Every fifth year 1960–1990, then annually 1990–2015.

metropolitan area levels. Interaction with an "urban" dummy variable is significant (at $p < 0.05$) in the household-based 2001 model; interaction with a continuous variable for population density is significant in the 2001 and 2009 models. In all three cases the magnitude of the interaction effect on elasticity is small, with elasticity changes of less than 0.01 between urban and non-urban and over the observed range of population density. The elasticity in the metropolitan area model is slightly higher than the household-based model, which is consistent with the small positive "urban" interaction effect.

Regarding the public transit modes in Table 1, estimated rail transit elasticity (0.76) is higher than bus transit elasticity (0.51). A similar modal model using more disaggregate transit services (see Supplementary Information) reveals variability in elasticity among rail services (from 0.30 for streetcars to 0.81 for commuter rail) and among bus services (from 0.49 for commuter bus to 0.95 for bus rapid transit). Multi-modal transit system elasticity in Table 1 (0.45) is lower than that of the individual transit services, and closest to bus transit, which is the most common transit service type and the largest source of total transit PKT.

Public transit system elasticity interaction with both population and population density is positive and significant (at $p < 0.05$). Unlike for private vehicle elasticity, the magnitudes of the interaction effects on public transit elasticity are substantial: the elasticity estimate for multi-modal transit systems ranges from 0.32 to 0.76 over the observed range of population density. For modal transit service elasticity, population and population density have positive interaction effects on bus, vanpool, and demand response transit, but negative interaction effects on rail transit. The bus transit elasticity estimate ranges from 0.39 to 0.76 over the observed range of population density, while rail transit elasticity ranges from 0.88 to 0.66. In the largest and densest cities the estimated elasticity of bus transit exceeds that of rail transit, although the central estimate is lower; estimated bus and rail transit elasticities align at 0.70 in a city with metropolitan population density of 2270 persons per square-km, similar to San Jose, California.

Table 2 summaries both elasticities (ε_V^P and ε_e^o), AEF, and the resulting MEF by mode. Marginal to average emission factor ratios for each mode are also shown in Fig. 1, including uncertainty bars representing the ranges of values given in Table 2. Marginal emission factors for all modes are lower than their respective average emission factors, even using the high-end estimates. Consistent with the elasticity results in Table 1, the MEF/AEF ratios are highest (0.8 or more) for private vehicle travel, demand response transit, and vanpool. Air travel has the highest ε_e^o, which brings the MEF/AEF ratio up to 0.77, equal to rail transit. Estimated MEF/AEF ratios for all other modes are below 0.6.

Fig. 2 shows marginal and average GHG emission factors from the last two columns in Table 2. Demand response transit is omitted from the figure because emission intensity is higher by a factor of 5. A re-ordering of emission intensity by mode is evident when comparing marginal versus average factors in Fig. 2. The modes with lower elasticity of vehicle to personal travel (bus transit, intercity rail, and multi-modal transit systems) are more efficient from a marginal than average perspective. Public transit AEF is similar to private vehicle travel (3% lower), but the MEF is 46% lower. The MEF for intercity rail is less than half that of any other mode: 64% lower than air travel and 78% lower than private vehicles, whereas the AEF are 8% and 33% lower, respectively.

For a more disaggregate and direct comparison with published AEF, Fig. 3 gives marginal and average energy factors for light rail systems in 21 U.S. cities. The AEF are taken directly from Fig. 2.7 of the TEDB [37]. The MEF are based on ε_V^P estimates from a panel model of light rail transit systems by city, with results given in the Supplementary Information, Table S 5. Light rail ε_V^P estimates range from 0.24 to 1.32 (mean 0.79, standard deviation 0.26), reflecting a wide array of system performance. Elasticity values greater than 1 indicate three cities in which ridership (in PKT) has not kept pace with expansion of light rail services (in VKT): Salt Lake City (1.32), Houston (1.26), and Minneapolis (1.01).

A comparison of the AEF and MEF in Fig. 3 reveals meaningful differences in light rail energy intensities from the average versus marginal perspectives. Systems in which VKT has grown at pace or even faster than PKT are less efficient from a marginal perspective (e.g., Salt Lake City, Houston), whereas others in which PKT has grown faster than VKT are more efficient (e.g., Pittsburgh, San Francisco, Hampton). As a salient example from the middle of the AEF distribution, light rail AEF is 20% higher in San Francisco than Houston, but MEF is 56% lower.

4. Discussion

The results provide the first known quantification of marginal energy and emission factors for transportation systems, and show that marginal intensities are lower than average intensities for all studied passenger transportation modes. Thus, policies that increase or decrease passenger travel will have smaller energy and environmental impacts than suggested by average energy and emission factors. In addition, the difference between marginal and average intensity varies greatly among transportation modes and services. For passenger travel in US cities, private vehicles and public transit have similar AEF, but transit MEF is around half that of private vehicles. For US intercity travel, the differences in energy and emission factors between rail and air modes is eight times greater from a marginal than an average perspective. These differences by mode are substantial, and the current use of average factors misrepresents the energy and environmental impacts of travel mode shifts. Energy and environmental analyses of transportation systems such as the Transportation Energy Data Book [37] should include marginal intensity in mode and city comparisons (as illustrated in Fig. 3).

Table 2
Elasticities, AEF, and MEF by travel mode.*

Travel mode	Elasticity of VKT to PKT, ε_V^P		Elasticity of emission rates to vehicle occupancy, ε_e^o		MEF/AEF ratio		Energy intensity (btu/PKT)		GHG emission intensity (gCO2e/PKT)	
	estimate	(range)	estimate	(range)	estimate	(range)	AEF	MEF	AEF	MEF
Private vehicles	0.90	(0.85; 0.94)	0.04	(0.01; 0.08)	0.90	(0.85; 0.94)	2051	1844	144	129
Transit systems	0.45	(0.41; 0.49)	0.10	(0.01; 0.20)	0.51	(0.42; 0.59)	1988	1004	139	70
Bus transit	0.51	(0.47; 0.55)	0.16	(0.03; 0.33)	0.59	(0.49; 0.69)	2361	1389	165	97
Rail transit	0.76	(0.74; 0.78)	0.05	(0.00; 0.10)	0.77	(0.74; 0.80)	1553	1199	109	84
Demand response transit	0.83	(0.80; 0.85)	0.10	(0.01; 0.20)	0.84	(0.80; 0.88)	8699	7329	609	513
Vanpool	0.88	(0.82; 0.94)	0.10	(0.01; 0.20)	0.89	(0.82; 0.95)	1988	1774	139	124
Intercity rail	0.27	(0.00; 0.57)	0.05	(0.00; 0.10)	0.30	(0.00; 0.61)	1367	412	96	29
Air	0.65	(0.55; 0.75)	0.33	(0.16; 0.51)	0.77	(0.62; 0.88)	1491	1142	104	80

* ε_V^P values are based on Table 1; ε_e^o and AEF are based on the literature, as described in the Methods.

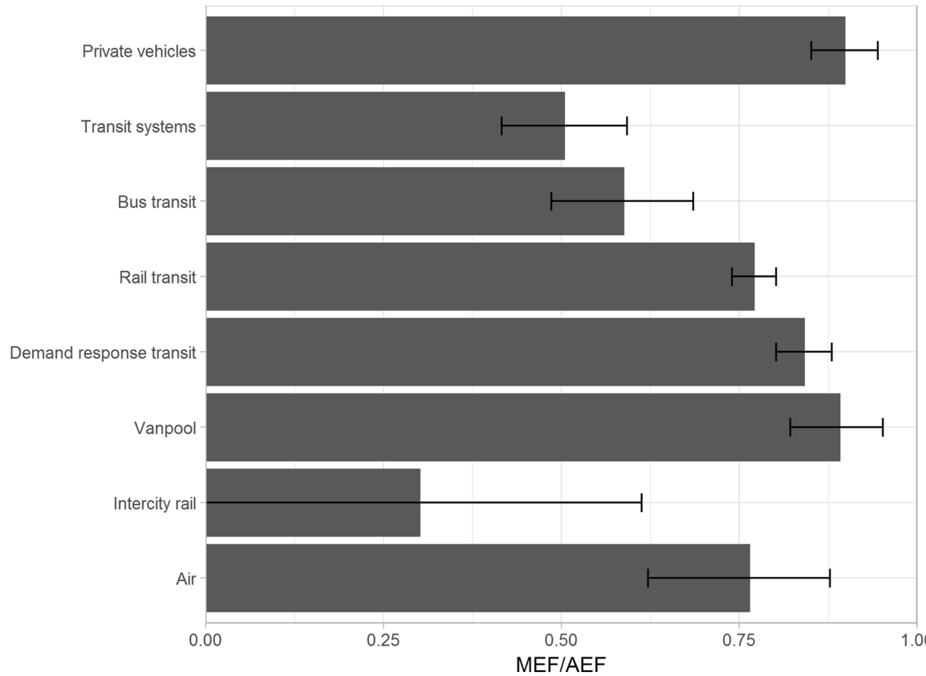

Fig. 1. Marginal to average emission factor ratios by travel mode.

Considering marginal intensities, public transit is more energy efficient and environmentally favorable than average-intensity measures and studies suggest. This finding reinforces policy initiatives aimed at transitioning passenger travel away from private vehicles and toward public transit. It also confirms that there are greater potential emission benefits from shifting travel to lower occupancy modes, as previously suggested [9]. Future work to educate travelers about the environmental impacts of their travel choices [6] should consider the marginal perspective, which could help illuminate the environmental benefits of public transit and could also be used to encourage marginal-focused private vehicle strategies such as carpooling.

This study characterizes broad, systematic differences in MEF and AEF by travel mode, but there are other dimensions and contexts over which marginal emission factors will vary. MEF is influenced by the determinants of AEF, such as vehicle and fuel technology [21,39] and average passenger load [9,10]. Changes in these factors will affect MEF proportionally to AEF, if the relationships characterized by the elasticities (ε_V^P and ε_e^o) are maintained. Elasticity of VKT to PKT likely depends on the time scale under consideration, with long-run elasticity expected to be higher than short-run elasticity [40,41]. Elasticity is also expected to be higher where greater travel options and volumes exist, such as in urban areas (as seen in the interaction effects) or between large city pairs with multiple travel services. Elasticity for multi-modal transit systems is lower than for bus or rail transit services individually

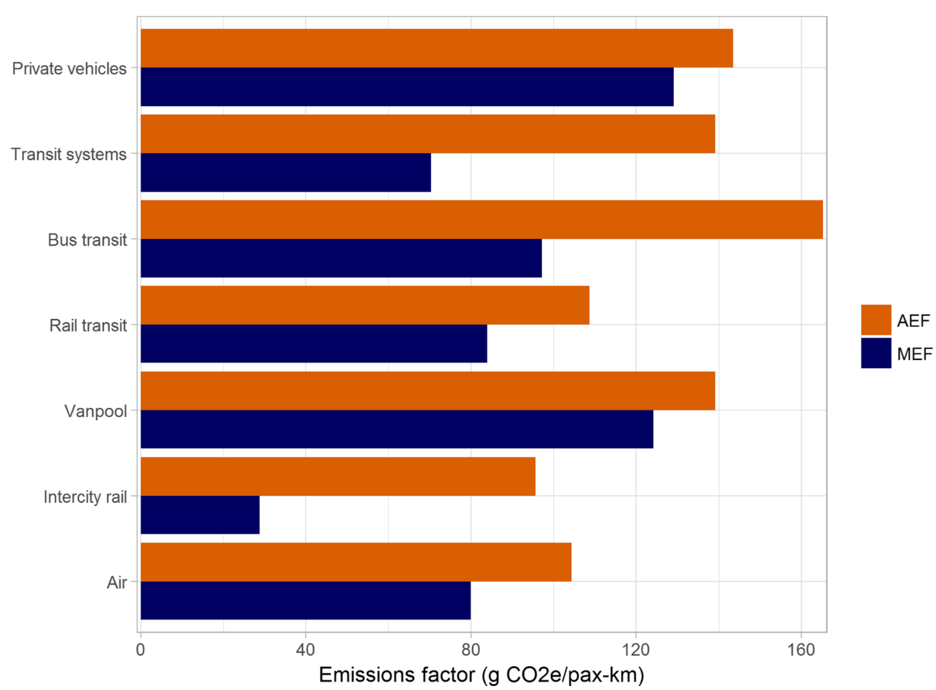

Fig. 2. Marginal and average GHG emission factors by travel mode.

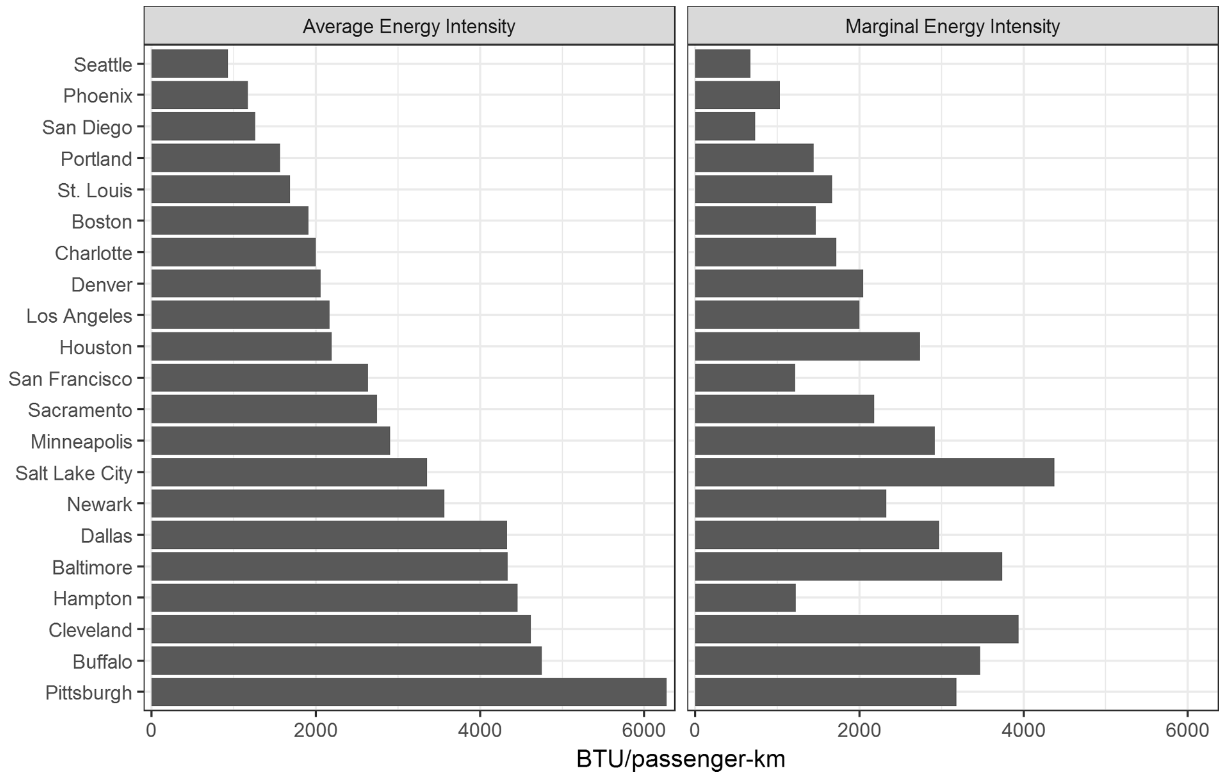

Fig. 3. Comparison of light rail average and marginal energy intesities by city.

(Table 1), likely due to substitution among transit modes within a city. A shift in transit service provision within a system to improve service quality can increase PKT with a smaller net change in system VKT than for individual transit services. In addition, this analysis uses capacity-independent VKT, so a shift toward higher-capacity transit vehicles (such as from bus to rail services) would dampen estimated ε_V^P in a multi-modal transit system (and also impact ε_e^o and AEF).

A limitation of the analysis is that only energy and emissions related to transportation operations are considered, not life-cycle impacts of transportation systems [8,10]. On a life-cycle basis, MEF/AEF ratios would most likely be lower because of fixed infrastructure and rolling stock factors, particularly for rail transit. Even allowing for variable long-run capital factors, life-cycle MEF/AEF ratios would likely be lower due to economies of scale in transportation infrastructure (which is generally expected, with some exceptions such as new roadways in highly dense cities or near a capacity threshold of a "lumpy" infrastructure system) [41,42]. Future work should evaluate the marginal life-cycle emissions associated with transportation systems.

Another aspect of the research that warrants further examination is the time precedence and causality between changes in PKT and VKT. Private vehicle VKT is more directly determined by demand than public transit VKT. From a reactive operations perspective (i.e., PKT determines VKT), transit services that are more responsive to demand will have higher elasticity, for example due to operational flexibility (vanpool) or service definition (demand response). Conversely, low-ridership public transit operations that are constrained by standards of service minimums will have low elasticity [43]. Intercity rail elasticity is the lowest of all the modes and most highly uncertain; it is the only single-system monopoly service in the analysis, and its operations are likely less responsive to demand fluctuations than other modes. From a proactive operations perspective (i.e., VKT induces PKT), transit services are expected to have higher elasticity when ridership is more responsive to service quantity and quality. Hence, elasticity will be higher in systems serving a greater percentage of "choice" transit users rather than "captive" users, which is typical for rail versus bus transit [44,45]. By extension, transit systems with a higher share of captive riders would benefit more from a transition to a marginal emissions perspective in transportation.

In summary, there is still work to be done to characterize the marginal energy and emission factors of transportation systems in various contexts. Future research should examine spatial and temporal variability in marginal emission factors (such as peak versus off-peak), similar to previous research on electricity production [13]. Marginal energy and emission factors should also be examined and compared in other countries, particularly for rail systems in Europe and Asia, and for freight transportation. This paper is a first step, introducing marginal emission factors for transportation system operations and showing that the current reliance on average emission factors is systematically biased against public transit modes.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.apenergy.2019.03.172.

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