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ANALYSIS

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A holistic analysis of passenger travel energy and greenhouse gas intensities

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Transportation is a major energy consumer and emitter of greenhouse gases (GHGs). Exploring the opportunities for energy savings and GHG emissions reductions requires understanding transportation energy or GHG intensity, which is defined as energy use or GHG emissions per unit activity, here passenger-kilometres travelled. This aggregate indicator quantifies the amount of energy required or GHGs emitted to provide a generic transportation service. We show that the range of observed energy and GHG intensities of major transportation modes is remarkably similar and that occupancy explains about 70–90% of the variation around the mean; only the remaining 10–30% is explained by differences in trip distances and other factors such as technology and operating conditions. Whereas average occupancy levels differ vastly, they translate into roughly similar levels of energy and GHG intensity for nearly all major transportation modes.

Nearly all studies exploring the energy or GHG intensity of transport systems across modes or countries focus only on averages per mode—whether as a basis for modal comparisons at a given point in time[1–5], cross-country comparisons of its longitudinal development for specific transportation modes[6,7] or as a key performance indicator in benchmarking studies[8]. However, because these intensities are determined by the technology employed, operational characteristics, traffic conditions and other factors, their value—or a comparison thereof—cannot easily be interpreted in the absence of these determinants unless we understand their influence on energy and GHG intensity. Nevertheless, there does not seem to exist any systematic analysis of the key factors affecting energy and GHG intensities of passenger transport modes. Only one recent freight study explained the energy intensity of major modes by the amount of cargo transported per vehicle, vehicle speed, engine technology and other factors[9].

To fill that gap, this study identifies the key determinants of energy and GHG intensities for the four major modes of passenger travel—that is, light-duty vehicles, buses, railroads and aircraft. Whereas existing approaches simply (and wrongly) concluded that passenger aircraft are the most energy- and GHG-intensive mode, followed by first automobiles and then buses or railways, typically visualized by a simple bar chart[1–5], the more systematic approach pursued here yields a characteristic trajectory of energy and GHG intensity versus vehicle occupancy for each transport mode. These trajectories enable a more robust analysis of the energy and environmental performance of competing transportation modes.

Energy intensity and the square–cube law

A good starting point is the definition of energy intensity, here the ratio between energy use (E) and passenger-kilometres (pkm) travelled (PKT)—that is, E/PKT. This expression can easily be expanded to energy use per vehicle-kilometre (vkm) travelled (E/VKT) divided by vehicle occupancy (PKT/VKT)—that is, the distance-weighted number of passengers per vehicle. Vehicle occupancy, in turn, is the product of load factor (the average number of passengers per seat—that is, PKT per available seat-kilometre (ASK)) and vehicle capacity (the average number of seats per vehicle—that is, ASK/VKT). The inverse relationship between energy intensity and the load factor is intuitive. The more passengers that are accommodated in a vehicle, the larger the denominator of energy intensity. Although the additional weight from the larger number of passengers also increases E/VKT, the rise in PKT/VKT is always larger, thus leading to a net decline in energy intensity. In contrast, the inverse relationship between energy intensity and vehicle capacity is a consequence of the square–cube law. The latter states that an increase in the size of a body causes its volume to rise more strongly than its surface area (that is, cube versus square). Because aerodynamic drag is partly surface area related, the drag per unit volume or seat capacity declines with increasing size. Guided by the same principle, the larger and more powerful heat engines required for larger vehicles are more energy efficient than their smaller counterparts, because the surface-related losses of friction and heat transfer are smaller in relation to the volume-related power output. Hence, as with the load factor, growing vehicle size translates into lower energy intensity.

Modal comparison

The inverse relationship between vehicle occupancy and energy or GHG intensity is depicted in Figs. 1 and 2 for light-duty vehicles, buses, commuter railways and fixed-wing aircraft. The double-logarithmic scale linearizes the hyperbolic decline in energy and GHG intensity with rising vehicle occupancy. Jointly, the modal trajectories stretch over two to nearly three orders of magnitude in occupancy levels, yielding almost similar differences in energy and GHG intensity. Even for individual modes, differences in vehicle occupancy can cause changes in energy and GHG intensity of up to one order of magnitude. On an aggregate fleet level, light-duty vehicles, urban buses, commuter railways and commercial aircraft experience average energy intensities between 1 and 10 MJ pkm^{-1}, despite operating in different markets (local, regional and intercity) and at different speeds. At the other extreme, commercial aircraft operate at speeds that are about ten times as high compared to other modes of intercity travel. Nevertheless, their higher occupancy level of two to nearly three orders of magnitude yields a range of energy intensities similar to those of urban buses, commuter and intercity

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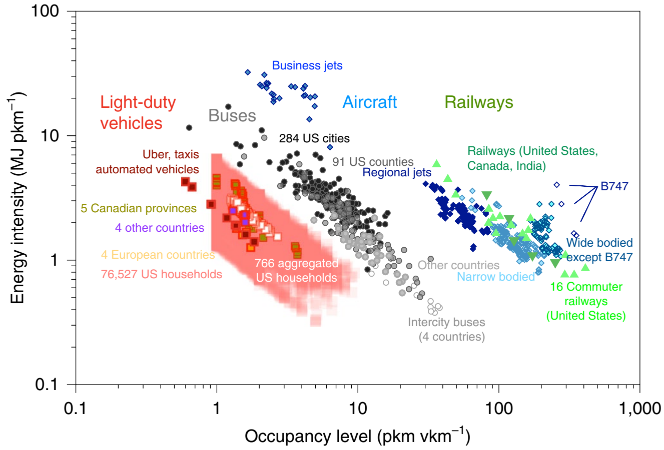

Fig. 1 | Energy intensity versus vehicle occupancy for light-duty vehicles, buses, railways and fixed-wing aircraft. See Supplementary Information for a description of the data. On an aggregate level, most modes experience energy intensities of 1–10 MJ pkm^{-1}. However, the energy intensity of variants operating in special market segments can differ by nearly two orders of magnitude, ranging from 0.4–0.8 MJ pkm^{-1} for intercity buses to 20–30 MJ pkm^{-1} for business jets. The energy intensities of light-duty vehicles in the United States and five other countries (Australia, Canada, Costa Rica, Japan and South Korea) evolve along roughly the same trajectory; smaller-sized vehicles operating in four European countries (France, Germany, the United Kingdom and Switzerland) are aligned with a less energy-intensive path. Energy use per PKT of buses operating in US cities and counties is higher compared with those operating elsewhere. The trajectories of aircraft and railways seem to overlap, despite vastly different levels of speed. Only petroleum-fuelled transport systems are shown, to ensure comparability. Supplementary Information shows that diesel and electric locomotive-propelled trains evolve along a similar trajectory. B747, Boeing 747.

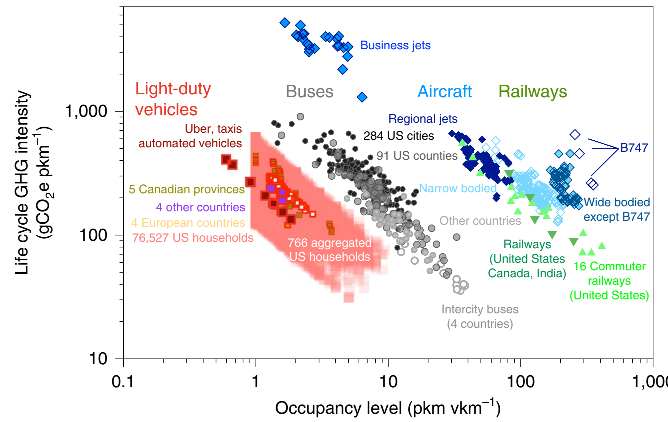

Fig. 2 | Life-cycle GHG intensity versus vehicle occupancy for light-duty vehicles, buses, railways and fixed-wing aircraft based on data in Fig. 1. The warming impact of aviation is assumed to be twice that of CO_2 alone, if excluding the highly uncertain effect of contrail-induced cirrus clouds[19], thus leading to a higher aircraft GHG intensity compared to other modes. Well-to-tank GHG emissions, which include non-CO_2 GHGs, are described in Supplementary Information, along with a description of the data. Only petroleum-fuelled transport systems are shown, to ensure comparability. The GHG emission factors (well-to-wheel) are based on the GREET1_2017 model[20]. CO_2e, CO_2 equivalent.

railways and light-duty vehicles. (In contrast, owing to their low occupancy, business jets experience the highest levels of energy and GHG intensities.) The similarity in the ranges of commercial aircraft average energy and GHG intensities to those of other passenger modes is in contrast to the freight transportation system, where dedicated freighter aircraft are unable to exploit more strongly the scale (tonnes per vehicle) and thus experience higher intensities of one to three orders of magnitude than railroads and water vessels[9]. Intercity buses experience energy intensities <1 MJ pkm^{-1}, mainly as a consequence of their relatively high occupancy and steady speed, which result in reduced acceleration losses.

Some of the occupancy levels of light-duty vehicles and buses are below unity, a condition that leads to particularly high energy and GHG intensities. These very low vehicle occupancies can be attributed to the high share of non-revenue-generating VKT, which is 60% for taxis[10], 40% for ride-sharing[11], 8–33% for single-occupancy simulation study-based automated vehicles and 2–20% for shared automated vehicles[12–16].

Energy and GHG intensities by mode also differ due to other variables, the impact of which is reflected by differences of typically up to a factor of two at a given occupancy level. Figure 3 depicts the dependency of energy intensity on the average trip distance. The latter ranges from a few hundred metres for light-duty vehicles to around 7,000 km for aircraft operating in domestic US traffic. Because light-duty vehicles experience higher occupancy levels with growing travel distance (due to the increasing share of vacation-related and thus more social trips), and because longer average trip distances translate into more steady speeds and less acceleration losses (due to the larger share of highway-driving), their energy intensity tends to decline with increasing trip distance. In contrast, the energy intensity–trip distance relationship for public surface modes is comparatively weak. In air transportation, energy intensity declines with longer average trip distance because the longer cruise stage is less energy intensive than take-off and climb. However, at a distance of around 2,000 km, average energy intensity starts to increase again because of the weight penalty associated with the extra fuel required for longer distances.

Explaining energy intensity

The data displayed in Figs. 1 and 3 can be used to explain the energy intensity of transport modes. In addition to regressing energy intensity over vehicle occupancy and average travel distance, regional differences can be measured by indicator variables (see Methods). The results of our statistical analysis show that vehicle occupancy per se explains about 70–90% of the variation around the mean energy intensity of all transport modes examined (see Supplementary Information). Depending on the mode, a substantial part of the remaining 10–30% is explained by trip distance. The remaining unexplained variability is then due to different technology and operating conditions not explicitly captured by the variables employed here. The regression analysis also indicates that a 10% increase in average vehicle occupancy leads to a 6–9% reduction in energy intensity, dependent on the mode—the decline in energy intensity due to higher occupancy per se is partially offset by the simultaneous increase in E/VKT. Thus, all trajectories in Figs. 1 and 2 decline at a ratio slightly lower than 1:1—that is, evolving at an angle slightly greater than 135° (see also Extended Data Figs. 1–4). In comparison, trip distance elasticity is considerably smaller—a 10% increase in trip distance results in a decline of only 0.1–2% in energy intensity, dependent on the mode. Although longer-distance trips result in slightly lower average energy intensities, the impact on total trip-related energy use is small due to the direct relationship with trip distance.

Our statistical analysis also suggests that regional differences are relevant to average energy intensity levels. Light-duty vehicles operating in European countries (here France, Germany, the United Kingdom and Switzerland) experience an energy intensity 40% lower than those operating in Canada on average, everything else

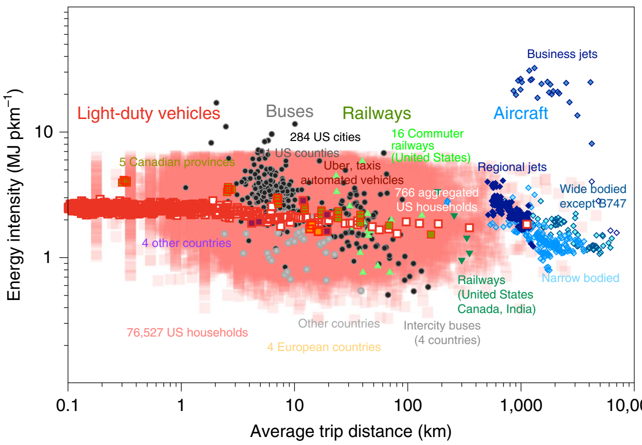

Fig. 3 | Energy intensity versus average trip distance for the transport modes shown in Figs. 1 and 2. Longer trip distances generally lead to lower energy intensity, all other factors being equal. In regard to surface transportation, longer trip distances relate to higher vehicle occupancies, more elevated average speeds and smoother driving (and thus reduced acceleration losses). In air transportation, longer average trip distances translate into a longer cruise stage, which is less energy intensive than take-off and climb. Hence, average energy intensity declines with rising trip distance before it starts to increase again because of the weight penalty of the extra fuel required for longer distances. No trip distance data were available for intercity buses. See Supplementary Information for a description of the data.

being equal. This difference can be attributed to the smaller vehicle size, roughly one segment, of European vehicles compared to their North American counterparts[17]. Similarly, urban and regional buses operating in European cities, Swedish regions and Taiwanese provinces experience 19, 32 and 40% lower energy intensity, respectively, compared to their US counterparts on average, after controlling for occupancy level and average travel distance. These country differences in energy intensity are in part due to differences in traffic flows (which are also dependent on the existence of dedicated bus lanes), technology characteristics defining driving resistances (such as vehicle weight) and drive-train efficiency, the use of air conditioning and other factors. Our results also show that diesel railways operating in north-eastern and north-western India are 38% more energy intensive than those in the United States, at identical occupancy and travel distance. This could be a result in part due to mountainous terrain, resulting in larger driving resistances. Moreover, business jets and wide-bodied aircraft consume around 100 and 70%, respectively, more energy per revenue passenger kilometre than narrow-bodied aircraft at the occupancy levels and stage lengths observed in the dataset.

Discussion

Figures 1 and 2 suggest that the range in observed energy and GHG intensities of most passenger transportation modes is surprisingly similar, irrespective of the vast differences in operating characteristics. Within the range in energy intensities, the key factor affecting a specific energy intensity level is not technology but, rather, is rooted in individual travel and industry behaviour—that is, vehicle occupancy. Whereas the average occupancy levels of light-duty vehicles, urban and intercity buses, railways and aircraft differ vastly, they translate into roughly similar levels of energy and GHG intensity for most transport modes. The roughly similar levels of energy intensities found for railways, aircraft and more efficient household vehicles in intercity travel imply that the key determinant of trip-related energy use and GHG emissions by mode is travel distance. Because aircraft operate over the longest distances (see Fig. 3), they typically experience by far the highest trip-based energy use and GHG emissions per person.

The trajectories shown in Figs. 1–3 are based on multiple data sources. Whereas the energy and GHG intensities of urban and regional buses, railways and aircraft are derived from fuel consumption and passenger records, the Australian and US intercity bus data points represent only estimates. The reliance on estimates is still larger for light-duty vehicles, as only the Canadian and Costa Rican data points represent measurements—all others are based on calculations from national government agencies. In addition, the aggregation level among data sources differs widely, ranging from individual (household) level for US light-duty vehicles to operator-specific data of US bus and railroad companies. Whereas these differences do not affect the general validity of the relationships shown in Figs. 1–3, they would influence the typical ranges of energy and GHG intensities around the mean and are thus not pursued further.

Figures 1 and 2 also show that intercity buses are the least energy and GHG-intensive mode, a result that is consistent with other studies—for example, refs. [1,4]. Nevertheless, identifying a clear 'winner' is problematic, as the quality of the transportation service—that is, PKT—differs markedly across modes. For example, light-duty vehicles offer more convenience, better comfort and higher speed than intercity buses but at a threefold energy and GHG intensity level. At the other extreme, aircraft have an energy and GHG intensity higher by five- and tenfold, respectively, than intercity buses, but operate at tenfold their average speed. Moreover, an intercity bus would experience roughly a threefold energy intensity under urban traffic and occupancy conditions.

Implications. Due to its paramount importance, vehicle occupancy per se could be used to carry out first-order estimates of a transport mode's energy intensity. This determinant's importance also implies that future changes in occupancy will affect energy and GHG intensity. Industry behaviour aims at maximizing profits and thus occupancy levels of commercial transport modes. For example, the economic viability of aircraft is measured in terms of 'minimum load factor requirements' for a given seat capacity[17]. In contrast, the utility maximization behaviour of consumers could lead to lower occupancy levels. Already in the past, light-duty vehicle occupancy in the United States and other industrialized countries has declined due to rising car ownership and use which, in turn, was driven by several factors ranging from income growth to the increasing participation of women in the labour force[18], thus leading to higher energy intensity levels. The advent of automated light-duty vehicles, either individually owned or through private use within a sharing economy, could lead to another systemic drop in occupancy levels and thus to a further increase in energy intensity. As shown in Fig. 1, automated vehicles, if not shared, will experience average occupancy levels well below 1 pkm vkm^{-1}, due to empty trips between passenger drop-off and pick-up and searching for a parking spot. This could lead to even a tripling in light-duty vehicle energy intensity, an increase that would be difficult to compensate by fuel-saving technology. In the absence of transport policy interventions aimed at increasing vehicle occupancy, the increase in GHG emissions due to a possible trend towards ever higher energy intensities in light-duty vehicle travel could be reduced most effectively through electrification of passenger transport technologies, in combination with a reduction in the GHG intensity of electricity.

Our analysis relates only to internal combustion engine vehicles. Although electrification could lead to different absolute levels of (primary) energy intensity, the basic physics underlying the trajectories is sufficiently similar and thus the relative energy intensities between electrically propelled modes would broadly remain unchanged.

Methods

Based on Fig. 1, equation (1) relates energy intensity (*E*/PKT) to vehicle occupancy (PKT/VKT) and average trip distance (ATD):

$$\frac{E}{\mathrm{PKT}} = \beta_0 \times \left(\frac{\mathrm{PKT}}{\mathrm{VKT}}\right)^{\beta_1} \times \mathrm{ATD}^{\beta_2} \times \varepsilon \qquad (1)$$

where β_i are parameters to be estimated and ε is the error term. In addition, energy intensity is affected by operating conditions and the technology and size of aircraft and light-duty vehicles (which may differ across countries), here measured by a dummy variable (I). Equation (2) shows the resulting regression equation in log-linear form:

$$\ln\left(\frac{E}{\mathrm{PKT}}\right) = \beta_0 + \beta_1 \ln\left(\frac{\mathrm{PKT}}{\mathrm{VKT}}\right) + \beta_2 \ln(\mathrm{ATD}) + \sum_{n=3}^{N} \beta_n I_n + \varepsilon \qquad (2)$$

Supplementary Table 1 reports the detailed regression results. In summary, occupancy alone explains about 70–90% of variation around the mean energy intensity of all examined transport modes. A substantial part of the remaining 10–30% is explained by trip distance and other factors, such as technology and operating conditions. The remaining unexplained variability is then due to different technology and operating conditions not explicitly captured with the variables employed here.

Reporting Summary. Further information on research design is available in the Nature Research Reporting Summary linked to this article.

Data availability

All data were derived from public databases. The datasets used in the analysis have been deposited at https://doi.org/10.5281/zenodo.3727541.

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Author contributions

A.W.S. led the data collection, data analysis and preparation of the manuscript. S.Y. contributed to data collection, data analysis and preparation of the manuscript.

Competing interests

The authors declare no competing interests.

Additional information

Extended data is available for this paper at https://doi.org/10.1038/s41893-020-0514-9.

Supplementary information is available for this paper at https://doi.org/10.1038/s41893-020-0514-9.

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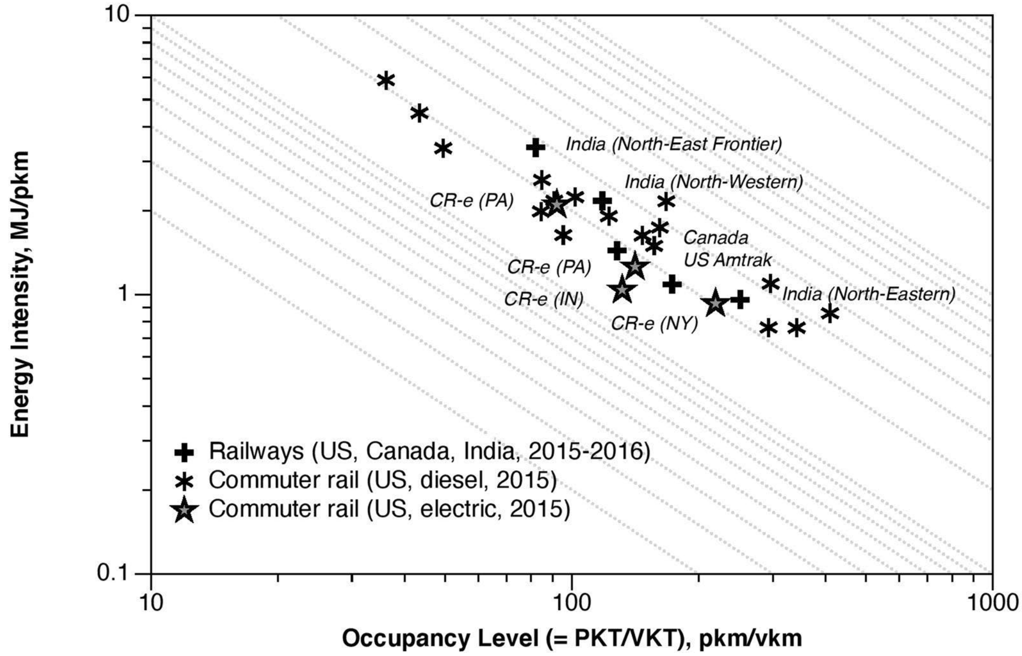
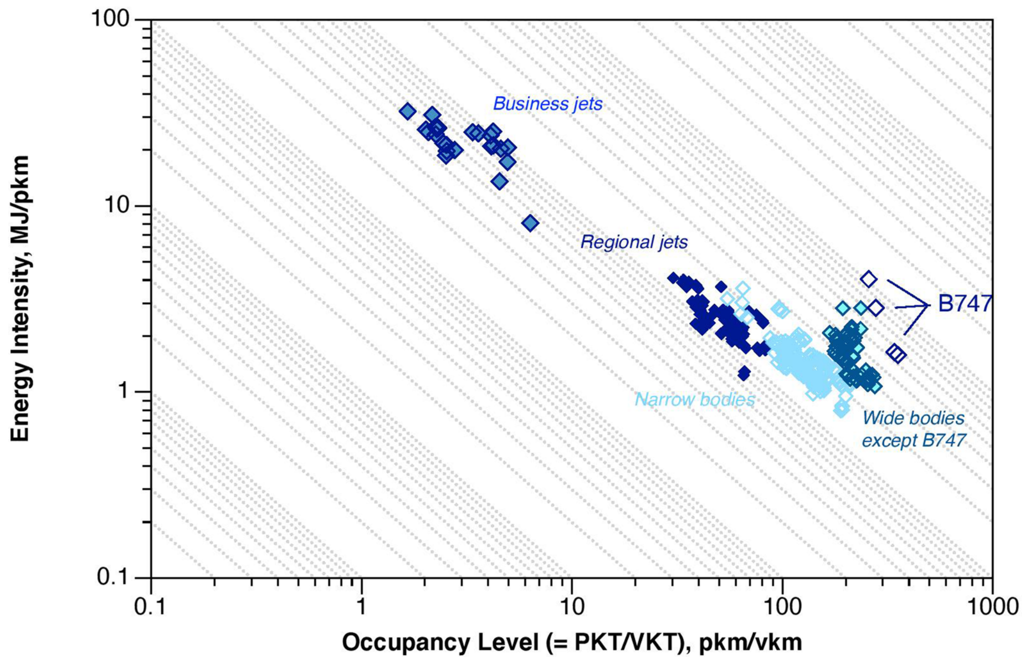
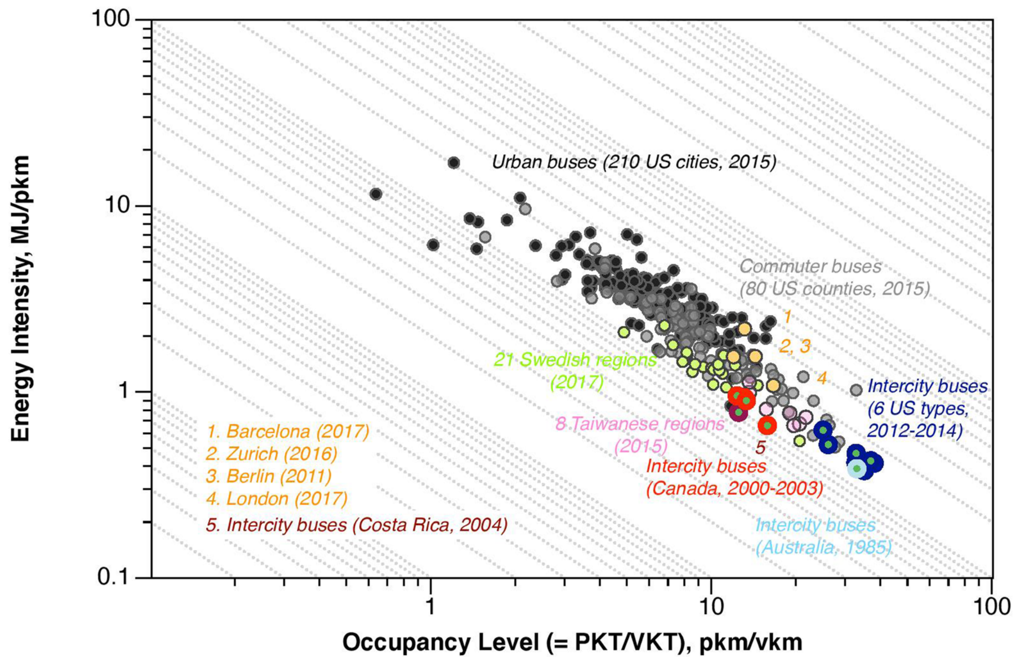


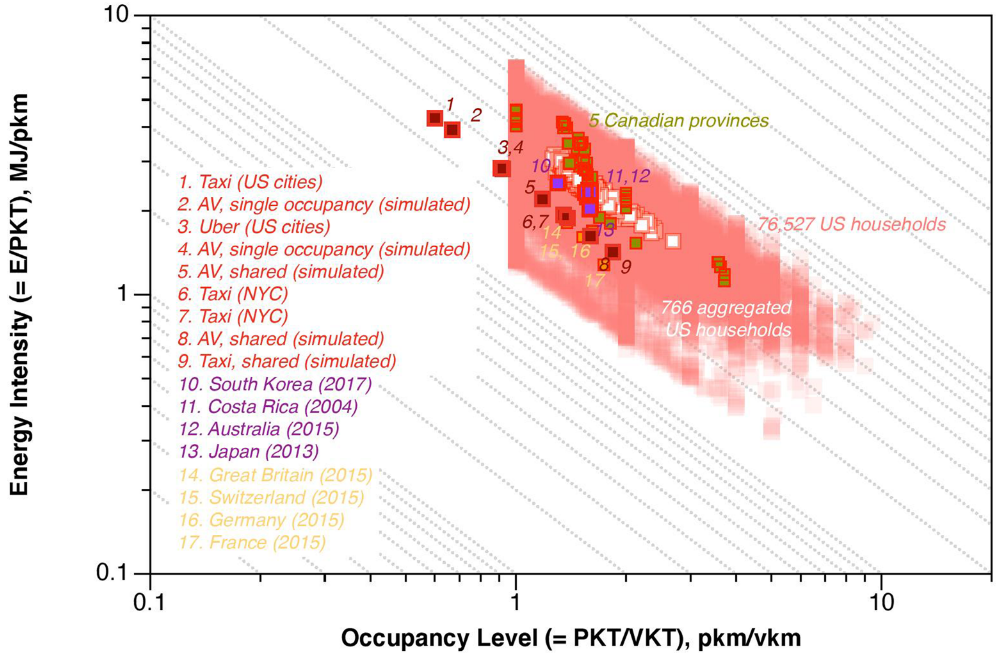
Extended Data Fig. 1 | Energy intensity versus occupancy for railways in Canada, India, and the US. Four electric commuter railways in the US are added to the figure. The energy intensities of electric railways are 0.49, 0.91, 0.55 and 0.45 MJ electricity/pkm for NY, PA, PA and IN, respectively. To ensure consistent comparisons, the final energy (electricity consumed) is converted to the secondary energy required to generate electricity in the corresponding US state, and multiplied by the final-to-secondary energy ratio for diesel fuel, which is 0.83 according to the latest GREET model. For example, the fossil-fuel equivalent EI of 0.55 MJ electricity/pkm is 0.55 /0.36 x 0.83 = 1.26 MJ/pkm, given the secondary-to-final energy efficiency of 36% for the electric power system in PA. The dotted lines represent a hypothetical 1:1 decline in energy intensity with vehicle occupancy, the limiting case of zero-weight passengers. All trajectories thus need to decline at a lower than 1:1 ratio.



Extended Data Fig. 2 | Energy intensity versus occupancy for fixed-wing aircraft operating in US domestic travel. All data relate to US domestic air travel in 2015. The dotted lines represent a hypothetical 1:1 decline in energy intensity with vehicle occupancy, the limiting case of zero-weight passengers. All trajectories thus need to decline at a lower than 1:1 ratio.



Extended Data Fig. 3 | Energy intensity versus occupancy for intercity, regional, and urban buses in Australia, Canada, European cities, Sweden, Taiwan, and the US. The dotted lines represent a hypothetical 1:1 decline in energy intensity with vehicle occupancy, the limiting case of zero-weight passengers. All trajectories thus need to decline at a lower than 1:1 ratio.



Extended Data Fig. 4 | Energy intensity versus occupancy for light-duty vehicles. The dotted lines represent a hypothetical 1:1 decline in energy intensity with vehicle occupancy, the limiting case of zero-weight passengers. All trajectories thus need to decline at a lower than 1:1 ratio.

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Data collection	The data sources are described in the SI.
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Study description	The study identifies the key determinants of passenger travel energy intensity.
Research sample	The data set underlying the regression analysis was assembled using observations from the open literature.
Sampling strategy	N/A
Data collection	N/A
Timing and spatial scale	N/A
Data exclusions	Observations that were deemed implausible as they violated the laws of physics and observations that included also different transport technologies/modes were excluded from the data set.
Reproducibility	N/A
Randomization	N/A
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Methods

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