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Does electric mobility display racial or income disparities? Quantifying inequality in the distribution of electric vehicle adoption and charging infrastructure in the United States

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HIGHLIGHTS

- Documents historic inequality of electric vehicle infrastructure.
- Illustrates significant spatial variation across different cities and states.
- Proposes novel metrics such as Racial Gap Index to characterize inequality.
- Develops equity strategies tailored to local and regional contexts.
- Evidences a need for more coordinated inter-state charging infrastructure across the country.

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ABSTRACT

Based on high-resolution spatial and temporal analysis, we quantify and evaluate the equality of plug-in electric vehicle adoption and public charging infrastructure deployment in the United States, examining current and historical trends, as well as racial and income-based disparities. Our results show that the current and historical distribution of conventional vehicle ownership and gas stations shows much more equality, in contrast to electric vehicles and charging infrastructure. With regards to the distribution of electric vehicle adoption, the more electrified vehicle technology is adopted, the more significant income inequality becomes, on a national scale. Over the last several years, almost all states ameliorated income and racial/ethnic inequality for plug-in electric vehicle adoption, but that is not the case for charging infrastructure. The income inequality of the distribution of nationwide charging infrastructure is three times larger than that of gas stations. Individual states, as well as some of the largest urbanized areas, demonstrate a wide range of inequality associated with income and race/ethnicity. There is a need to better understand what drives this significant spatial heterogeneity, as it implies that additional strategies tailored to local and regional contexts may be necessary to achieve more equal distribution of infrastructure as electric vehicles become common beyond early adopters. Improving consistency and coordination of development of charging infrastructure across different states/regions would likely benefit inter-state travelers.

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1. Introduction

In the U.S., the number of plug-in electric vehicles (PEVs) – plug-in hybrid-electric vehicles (PHEVs) and battery electric vehicles (BEVs) – as well as associated charging infrastructure, has grown exponentially over the last decade [1]. As of the end of 2021, the U.S. had about 2 million PEVs on the road [2,3]. The total number of non-residential PEV charging stations across the country is now approximately 50,000, hosting 130,000 charging ports. The growth of PEV adoption and corresponding charging infrastructure (or electric vehicle supply equipment [EVSE]) in the U.S. is only expected to rise in the coming years, in part owing to policy and market momentum [4,5].

As for the deployment of PEVs and EVSEs in the U.S., existing studies suggest that there is a persistent issue of inequality (e.g., significant bias towards high-income, white population, etc.), whether it is for cities [6,7] or states [8,9]. Although those previous studies provide meaningful insights as to the city- or state-wide inequality of vehicle electrification, it is not clear to what extent the inequality exists for nation-wide PEV adoption and EVSE deployment. Furthermore, a comparative investigation of inequality between different cities, states, and years is lacking in the existing body of literature. To fill that knowledge gap, we quantify and evaluate the income and race/ethnicity inequality in the current and historical diffusion of PEVs and non-residential EVSEs in the contiguous U.S. (i.e., all states excluding Hawaii and Alaska).

Overall, the contribution of this study is to: (1) provide a comprehensive national and state-by-state assessment of equality in current and historical PEV adoption and public EVSE deployment; (2) compare the distribution of PEV and conventional non-PEV technologies, as well as corresponding public refueling infrastructure (gas stations and charging stations); and (3) develop and apply new metrics (built upon the concepts behind Lorenz curves and Gini coefficients) that can be helpful to quantify and evaluate the evolution of inequality in the space and time domains.

In this study, we differentiate equality (considered) and equity (not considered). Equality is mainly concerned with treating everyone equally – for example, equal/even distribution of PEVs or charging stations (e.g., per capita). On the other hand, the concept of equity involves acknowledging different needs/challenges that different people or communities may have and addressing them, which may require treating people differently according to their needs/challenges (rather than treating everyone equally) [10]. Equity requires a much more complex analysis (e.g., an examination of who is benefiting or not; and/or who is bearing the burden or not). Nonetheless, the results of this analysis - quantification of the equality of PEV adoption and charging infrastructure, in comparison with conventional non-PEV technologies and gas stations - will help inform more equitable distribution of the benefits or burdens of vehicle electrification in the future.

2. Methods

2.1. Analysis of variance

We first conduct a descriptive statistical analysis to see whether there are statistical differences in PEV adoption and EVSE deployment in terms of income and race/ethnicity. For this, we utilize analysis of variance (ANOVA) and estimate correlations between those variables. However, as is often the case, descriptive statistical analysis reveals somewhat limited information and thus is not always very helpful for systematically quantifying the quantity and structure of inequality for the nation, regions/states, or cities. Therefore, in addition to descriptive statistical analysis (e.g., ANOVA), we employ alternative approaches and metrics to characterize the income and racial inequality of PEV adoption and EVSE deployment.

2.2. Gini coefficient

For the national analysis, we use Lorenz curves and Gini coefficients to quantify any inequalities ("an uneven or unfair share") in the distribution of nation-wide PEVs and charging infrastructure in relation to median household income by census block group (CBG). The Lorenz curve is a graphical representation of the relationship between the cumulative proportion of the population and its cumulative proportion of income. The Gini coefficient is a unit-less statistic (ranging from 0.0 [perfect equality] to 1.0 [perfect inequality]) that indicates the gap between perfect equality and the Lorenz curve for a given setting. Here, perfect equality refers to an equal share of income across the population. In other words, equality (in Lorenz curves and Gini coefficients) does not mean that each census block group must have the exact same number of PEVs or chargers. Rather, it is about the relative share across income groups – for example, 50 % of PEVs adopted in the group of census block groups with lower income, and the other 50 % in the group of census block groups with higher income. The Lorenz curves and Gini coefficient have been widely used for various analyses of income inequality in energy and transportation systems [11–17], despite certain limitations [18]. Numerous organizations publish Gini coefficients on a regular basis, either assessing it at the national level [19] or comparing income inequality across different countries [20].

When applying the Gini coefficient (based on the Lorenz curve), we consider each and all census block groups (CBGs) in the U.S. [21] and annual income for individual households in each CBG, for which we use the 2015–2019 American Community Survey (ACS) 5-year estimates [22]. To develop Lorenz curves for PEV adoption, we utilize historical annual vehicle registration data [3] at the CBG spatial resolution between 2016 and 2021. For EVSE deployment, we employ monthly EVSE data [1] as coordinates (longitude and latitude – assigned/paired to corresponding CBGs) between 2015 and 2021. Regarding public charging infrastructure, as noted earlier, because this study is focused on equality (not equity), our analysis is solely based on the location of chargers, without accounting for exactly who is benefiting from them and/or bearing potential burdens, which lies in the realm of equity discussions. It is acknowledged that a significant proportion of PEV charging that occurs at public charging infrastructure is done outside the census block group (e.g., at work, at shopping centers, during long-distance travels) where the home of the driver is. However, such equity-oriented investigation would require much more complex assessment and data associated with vehicle movement, refueling behavior, destination types, electric driving range, the dynamic between home and public charging, and so on, which is beyond the scope of this study.

For each CBG, we estimate median household income, as well as aggregate vehicle registration by technology and public EVSE port count. We then sort the CBG-by-CBG integrated data based on its median household income (from the lowest to highest) and develop the cumulative distribution for the entire country. We also generate a cumulative distribution for vehicle registration and charging port count, respectively. Based on the Lorenz curves (i.e., relationship between the cumulative share of the CBGs for income and vehicle registration or charging port count), we estimate the Gini coefficients (i.e., scaled difference between Lorenz curves and the perfect equality line). For the Gini coefficient, we employ the method proposed by Sen [23]:

$$Gini = 1 + \frac{1}{N} - \frac{2}{N^2 \overline{y}} \sum_{i=1}^{N} (N + 1 - i) y_i \tag{1}$$

where N is the total number of CBGs, $\overline{y}$ is the mean value across all CBGs ($\overline{y} = \frac{\sum_{i=1}^{N} y_i}{N}$), and y_i is the number of PEVs or EVSEs in the i-th CBG.

2.3. Per-capita share of low-income neighborhoods (PCS-LIN)

In addition to the Gini coefficient, we define and utilize two new metrics, PCS-LIN (per-capita share of low-income neighborhoods, using census block group level data) and RGI (racial gap index), to characterize inequalities, associated with income and race, respectively, of PEV adoption and EVSE deployment for individual states as well as for urbanized areas. Both PCS-LIN and RGI are based on the similar concept of cumulative proportions (or relative share) as expressed in the Gini coefficient. However, unlike the Gini coefficient, these two new metrics (PCS-LIN and RGI) are more intuitive and less sensitive to sample size. For example, the Lorenz curve can become less meaningful when the sample size is small, leading to a less-than-meaningful Gini coefficient, which is oftentimes the case for PEV adoption or EVSE deployment in their early stages, especially for smaller geographies such as states and cities. In contrast, PCS-LIN and RGI both generate workable and helpful inequality measures, even when the sample size and/or geography of interest is small. Furthermore, the Gini coefficient may not produce meaningful results for multi-variate parameters (e.g., race). As illustrated in Table 1, PCS-LIN and RGI can fill the gap by allowing us to tackle the types of questions that Gini cannot answer.

Fig. 1 (left) shows cumulative distribution of charger/port count (vertical axis) in each state in December 2021, sorted by CBG-by-CBG median income (horizontal axis), similar to the Lorenz curve. It must be noted that the EVSE port count is normalized by population for each state and CBG, to account for the heterogeneity of population between different states or CBGs. Also, in PCS-LIN, the heterogeneity in income level of different states/areas is also taken into consideration. If an area has perfect equality in terms of the relationship between the distribution of EVSEs and income, the PCS-LIN would be 0.5, which means that CBGs that account for up to the state-wide median income value collectively represent 50 % of state-wide EVSEs.

PCS-LIN is formulated as:

$$\mathrm{PCS-LIN} = \frac{Z_j\big|_{(s.t. x_j = X_M)}}{Z_L} \tag{2}$$

$$Z_j = \frac{1}{\sum_{i=1}^{L} h_i} \sum_{i=1}^{j} q_i \tag{3}$$

where Z_j is a cumulative distribution function of the number of per-capita PEVs or EVSEs (q_i) up to the j-th CBG ($i = 1, \dots, j$) in each state or urbanized area; h_i is human population in the i-th CBG ($i = 1,\dots,L$); Z_L is $Z_j\big|_{j=L}$ which is essentially (state- or area-wide) total number of per-capita PEVs or EVSEs in the state or urbanized area, as Z_j is a cumulative distribution function; $\frac{1}{Z_L}$ is a scaling factor to make the vertical axis (Fig. 1) vary from 0 % to 100 %; X_M is state- or area-wide median income. Note that CBGs ($i = 1,\dots,L$) are indexed or sorted based on CBG-by-CBG median income (x) so that $x_{i-1} \le x_i$, similar to the Lorenz curve.

Two example states are shown in Fig. 1. In the case of Mississippi, state-wide median household income is 45,000 US dollars (in constant 2019 value). If one accounts for all CBGs that have a median income below that state-wide median value, then the corresponding EVSE port count in those CBGs collectively represents 70 % of all charging ports available in Mississippi. Therefore, the PCS-LIN value for Mississippi in December 2021 is 0.7. In the case of New Jersey, which has a median income of 83,000 US dollars, a collection of CBGs that account for up to the state-wide median income account for 42 % of all EVSEs in the state, leading to PCS-LIN value of 0.42. This means that in terms of the distribution of EVSEs, whereas New Jersey has a marked bias towards more affluent CBGs, Mississippi displays a bias in favor of lower income areas.

2.4. Racial gap index (RGI)

For the RGI, we take a similar approach as to PCS-LIN, but focus on racial groupings (as defined by the U.S. Census). The main objective of RGI is to quantify the difference between individuals inhabiting these different racial groupings in terms of their share of PEV adoption and EVSE deployment. However, "race", as the Census labels these groupings, is a more complex variable than income. Race, as defined within the context of the Census and individual responses to it, is inherently categorical and multi-variate (White, Hispanic White, Asian, African American, Native American Indian, and so on). Therefore, unlike with income, it is difficult to represent the cumulative proportions (of PEV adoption or EVSE deployment) for different races or ethnicities with one Lorenz curve or Gini coefficient (unlike income). As it is possible that different racial groupings have completely different spatial distribution across the geographic dimensions (e.g., states or urbanized areas), developing cumulative share based on one variable (e.g., income) would not work. For those reasons, when estimating RGI, we take a different approach from the Gini coefficient or the PCS-LIN. We develop a cumulative proportion curve for each racial grouping separately, and, in doing so, we sort the CBG-by-CBG data for each racial grouping by population of each "race" category.

RGI is formulated as:

$$\mathrm{GI} = \frac{1}{100} \frac{\sum_{i=1}^{L} h_i}{\sum_{i=1}^{L} q_i} \sum_{p=0}^{100} (u_p - v_p) \tag{4}$$

$$u_p = \frac{1}{\sum_{i=1}^{L} h_i} \sum_{i=1}^{r_{NW}} q_i \tag{5}$$

$$r_{NW} = i \; when \; p = 100 \left(\frac{\sum_{i=1}^{r_W} h_{NWi}}{\sum_{i=1}^{L} h_{NWi}} \right) \tag{6}$$

$$v_p = \frac{1}{\sum_{i=1}^{L} h_i} \sum_{i=1}^{r_{NW}} q_i \tag{7}$$

Table 1
Different research questions that Gini, PCS-LIN, and RGI can answer.

Inequality metric	Research question addressed	Description
Gini coefficient	How evenly distributed are things or people across income spectrum?	Widely used inequality metric. Inherently univariate. Not helpful when sample size is small
PCS-LIN	For neighborhoods with median household income below state-wide median value, what is the percentage share of things/technologies?	Gini tends to be focused on the overall distribution and its evenness, not necessarily the share of certain income groups. That is why PCS-LIN is helpful
RGI	For different race/ethnicity groups – inherently not univariate unlike income, how does inequality compare in terms of the distribution of things/technologies?	Gini does not allow multi-variate inequality evaluation, for example, race and ethnicity, which is addressed by RGI

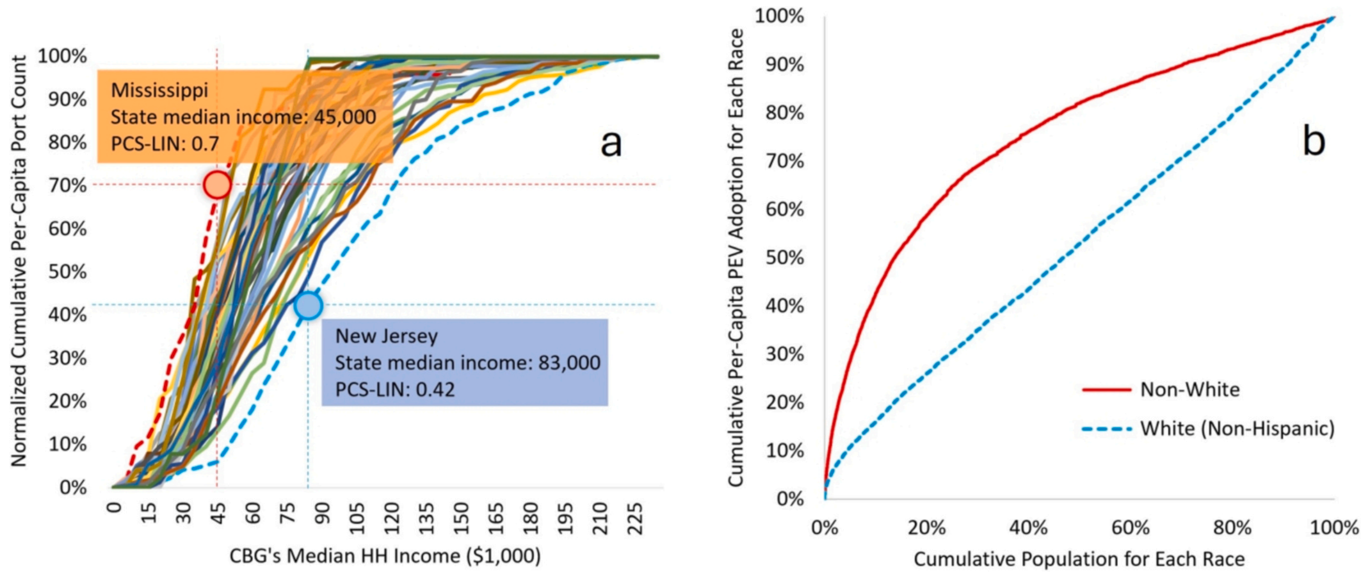


Fig. 1. (a) Illustration of PCS-LIN (per-capita share of low-income neighborhoods) for public EVSE deployment across different states, showing cumulative per-capita share (%) of charger counts by cumulative median household income; and (b) illustration of the racial gap index (RGI) for PEV adoption in New York – Newark (right).

$$r_W = i \text{ } when \text{ } p = 100\left(\frac{\sum_{i=1}^{r_W} h_{Wi}}{\sum_{i=1}^{L} h_{Wi}}\right) \tag{8}$$

where u_p is a cumulative distribution function for the number of PEVs or EVSEs (q_i) for the CBGs ($i = 1, \dots, r_{NW}$) that collectively represent the p-th percentile of non-white population (h_{NW}) in the state or urbanized area; v_p is a cumulative distribution function for the number of PEVs or EVSEs (q_i) for the CBGs ($i = 1, \dots, r_W$) that collectively represent the p-th percentile of white population (h_W) in the state or urbanized area; p is an integer variable that indicates the p-th percentile; and h_i is total human population in the i-th CBG. Note that CBGs are indexed based on population share for each race/ethnicity group, from the smallest to the largest, so that ($h_{Wi-1} \le h_{Wi}$) and ($h_{NWi-1} \le h_{NWi}$), respectively.

An example of RGI curves for (non-Hispanic) "white" vs. "non-white" is shown in Fig. 1 (right). It is worth discussing five elements of RGI curves. First, as RGI curves are designed to compare a disparity between different racial groupings, we use the gap between the curves as a measure of inequality (similar to the difference between the perfect equality line and the Lorenz curve for the Gini coefficient) – a wider gap between the curves indicates a larger racial gap. Second, borrowing the ratio concept from the Lorenz curve and the Gini coefficient, RGI is a unit-less statistic – the difference between the curves divided by the entire area (maximum of horizontal axis and maximum of vertical axis). Third, the shape of each RGI curve may have a linear or non-linear pattern (as illustrated in Fig. 1). If an RGI curve has a linear shape, it means that (for that race category) PEV adoption or EVSE deployment is relatively evenly distributed across the population of its own race category. On the other hand, if the curve has a non-linear pattern, it implies uneven distribution or representation of the population of that race category. However, regardless of the shape (linear, non-linear, or skewed), RGI is determined by the difference between the curves. Fourth, as can be more easily explained by examining Fig. 1 (right), note that the RGI curve for non-whites in Fig. 1 is above the curve for their white counterparts. This should be interpreted to mean that PEV or EVSE deployment is mostly driven by or correlated with the white population, and therefore, the cumulative proportions of the non-white population do not really affect the geography-wide PEV or EVSE deployment, which is exactly what RGI is aimed to characterize. Fifth, RGI can range from −1.0 to 1.0, with 0.0 indicating perfect equality between races or their categories (white vs. non-white as in our analysis). Again, looking to Fig. 1, it can be seen that as we use white as our reference "race" for RGI, the example shown in that figure (bottom right) will have a positive RGI value (but not greater than 1.0). However, as the RGI curve for whites can sometimes be above the curve for the non-white counterpart, the RGI value will be negative in those cases (and no smaller than −1.0).

From the example shown in Fig. 1 (right) for PEV adoption in the New York – Newark area, we can see that the RGI curve for non-whites is above the one for their white counterparts, meaning, as noted above, that the overall distribution of PEV adoption in the area is dominated or driven by the white population. Also, we can see that the curve for the white population has a linear pattern, while the one for non-white is skewed to the right (i.e., with or a spike on the left side). This means that, compared to its white counterpart, a smaller share of the non-white population has a very large share of PEVs within that race category, and this particular group of non-white population (representing a large share of PEV adoption) tends to live in CBGs that have a relatively small number of non-white residents but rather which have a larger shares of white population and/or more affluent communities (contributing to a larger share of PEVs in those CBGs, despite a small share of non-white population). All things considered, the RGI for PEV adoption in the New York – Newark area is 0.22, which means a bias in PEV adoption towards the white population in the area by 22 %.

Although the RGI example shown in Fig. 1 has one linear curve (for white) and one non-linear curve (for non-white), in some cases, both curves may be skewed to the right (or with a steep increase/slope on the left, similar to the curve for non-white in Fig. 1). In those cases, regardless of the race category (white or non-white), a significant portion of PEVs or EVSEs is highly concentrated in less-populated areas, such as non-residential (e.g., commercial) and/or rural areas. A good example is Nevada, where many chargers are installed in or around places like resorts and such. In other words, the RGI curves not only tell us the population-normalized gap between different racial groupings (used for the RGI score), but also reveal the concentration of chargers in each geography as a function of population across race.

3. Results

3.1. Variance and correlation with income and race/ethnicity

ANOVA results in Table 2 indicate that CBGs that have one or more PEVs or EVSEs tend to have different income and race/ethnicity characteristics from those that have no PEVs or EVSEs. For example, mean value of CBG-by-CBG median household income is about $44,000 for CBGs with no PEVs, whereas it is approximately $74,000 for CBGs with one or more PEVs, for which the difference (based on ANOVA) seems to be meaningfully different at the significance level of 5 % (p-value ≤ 0.05). Similarly, non-white population share for CBGs with no PEVs is 44 %, 8 % greater than that for CBGs with one or more PEVs. This means that the two groups of CBGs (one group with no PEVs, and the other with one or more PEVs) have statistically distinct distributions along the spectrum of CBG-by-CBG median household income or non-white population share.

The same applies to EVSE deployment – L2 or DCFC. ANOVA results imply that CBGs with no EVSE ports have statistically significant difference from CBGs with one or more EVSE ports in terms of CBG-by-CBG median household income or non-white population share. However, compared to PEV adoption, EVSE deployment has lower difference in terms of median household income or non-white population share.

By and large, ANOVA reveals the existence of meaningful difference (i.e., inequality) between CBGs with vs. without PEVs or EVSEs in terms of income or race/ethnicity. However, it is worth noting that correlation coefficients are low. This implies that correlation analysis or linear regression may not be very helpful or effective to explain or evaluate the relationship between PEV/EVSE deployment and CBG-by-CBG income or race/ethnicity. Furthermore, the descriptive statistics in Table 2 does not explain the structure of the inequality that the Lorenz curves, PCS-LIN, or RGI can shed light on (as illustrated in Fig. 1).

3.2. National Inequality of PEV adoption and charging infrastructure

Fig. 2 illustrates Lorenz curves for vehicle registration and refueling infrastructure in the U.S. in 2021. Regardless of vehicle technology, the Lorenz curves for vehicle registration are far away from the perfect equality line. Among different vehicle technologies, the more electrified vehicles are, the wider the gap between the Lorenz curves and the perfect equality line for vehicle registration becomes. For example, in 2021, the Gini coefficient (dimensionless indicator of the gap between Lorenz curves and equality line) for internal combustion engine vehicle (ICEV) is 0.25, which is lower (and thus more equal) than the value (0.36) for hybrid-electric vehicle (HEV) and about half the value for PEV (0.47–0.44 for PHEV and 0.5 for BEV). These differences are about 10 % lower than values for 2015–2016. This decline suggests that there has been some reduction in income inequality of nation-wide PEV adoption.

The Lorenz curve for gas stations (for ICEV, HEV, and PHEV) is very close to the perfect equality line (Fig. 2). The lack of inequality for gas stations is not very surprising, given the ubiquity of gas stations. Conversely, the Lorenz curves show a large gap for public electric vehicle supply equipment (EVSE, or charging port) that is roughly three times larger (higher level of inequality) than that for gas stations. As of 2021, the Gini coefficient for gas station is 0.09, but it is 0.27 for Level 2 (L2) and 0.24 for DC fast charging (DCFC). Unlike PEV adoption, the Gini coefficients increased by 4 % for L2 and 10 % for DCFC between 2015 and 2016 and 2021, indicating the lack of improvement of equality.

The EVSE infrastructure in the U.S. has grown 350 %, from 0.085 charging ports per 1000 people in 2015 to 0.38 in 2021. This growth (of the gross number of EVSEs) does not seem to ease inequality. The Gini coefficients imply that most of the recharging infrastructure added since 2015 has been deployed in areas that have income characteristics similar to those that had such equipment in 2015. These results suggest that public PEV refueling infrastructure continues to be distributed unequally.

3.3. Per-capita share of low-income neighborhoods (PCS-LIN)

Unlike in the national analysis above, when characterizing income-related inequality, we do not employ the Lorenz curve and Gini coefficient. As some states have a very small number of PEVs and/or EVSEs (e.g., there are only 70 DCFC ports in Mississippi), Lorenz curves (and corresponding Gini coefficients) can become very skewed or less-than-meaningful and thus do not always accurately represent reality, especially when used to illustrate state-by-state comparisons. For this reason, we use our own metric, called Per-Capita Share of Low-Income Neighborhoods (PCS-LIN), which accounts for heterogeneous demographics and income level within and across states.

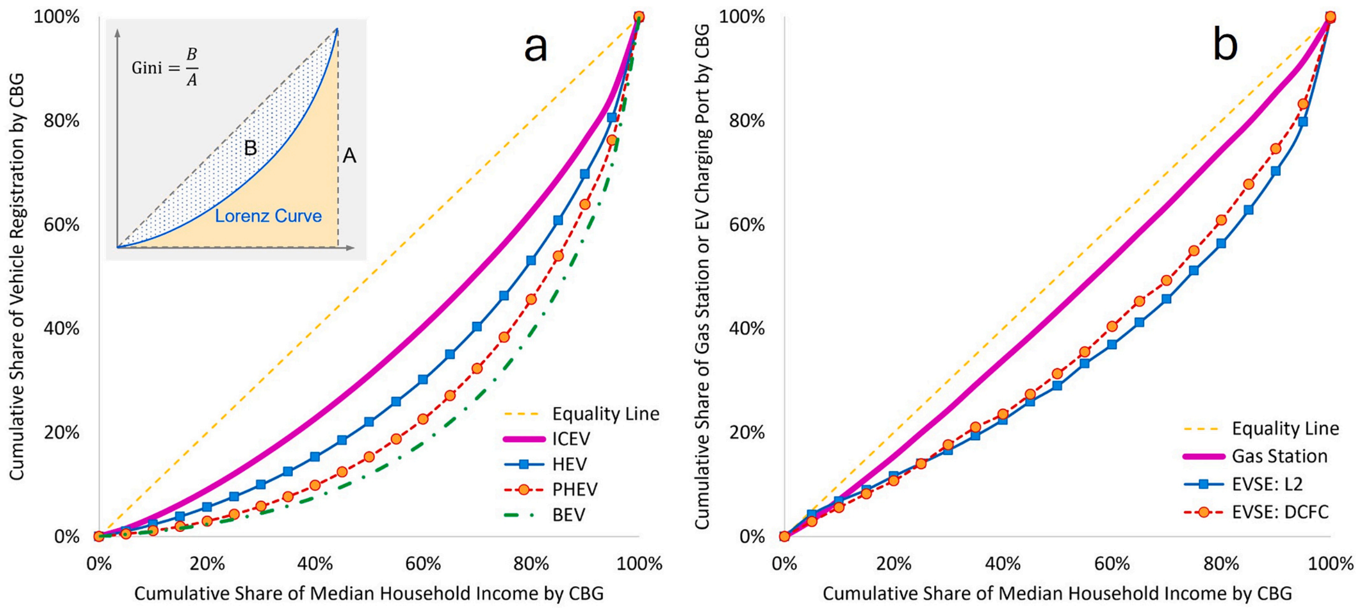
PCS-LIN shows how well low-income neighborhoods, using census block group data, are represented in the overall deployment of PEVs or EVSEs; and how the equal or fair representation changes over time (improving or worsening). If deployment within a state is perfectly equal, the PCS-LIN for that state would be 50 % (evenly distributed between low- and high-income neighborhoods). As noted earlier for the Lorenz curves and Gini coefficients, equality here does not require the exact same number of PEVs or EVSEs to exist in each neighborhood. It is

Table 2
ANOVA and correlation of PEV adoption and EVSE (L2 and DCFC) associated with CBG-by-CBG median income and race/ethnicity as of December 2021.

		Median Household Income (in 1000 US dollars, per CBG)			Percentage of Non-White (including Hispanic White) Population		
		Mean (Std. Dev.)	ANOVA F-value (p-value)	Corr. (p-value)	Mean (Std. Dev.)	ANOVA F-value (p-value)	Corr. (p-value)
PEV	No PEV	43.6 (20.4)	36,220[a] (0.2 × 10^{-16})	0.26[b] (0.2 × 10^{-16})	0.44 (0.38)	538[a] (0.2 × 10^{-16})	0.004[b] (0.2 × 10^{-16})
	1 or more PEVs	73.5 (38.1)			0.36 (0.3)		
EVSE: L2	No L2 ports	66.5 (36.8)	647[a] (0.2 × 10^{-16})	0.004[b] (0.2 × 10^{-16})	0.38 (0.32)	268[a] (0.2 × 10^{-16})	0.002[b] (0.2 × 10^{-16})
	1 or more L2 ports	74.2 (40)			0.37 (0.27)		
EVSE: DCFC	No DCFC ports	67.1 (37.1)	119[a] (0.2 × 10^{-16})	0.024[b] (0.2 × 10^{-16})	0.38 (0.32)	170[a] (0.2 × 10^{-16})	0.01[b] (0.2 × 10^{-16})
	1 or more DCFC ports	72 (36.1)			0.4 (0.27)		

[a] F value for the variance between CBGs with no PEV/EVSE vs. CBGs with one or more PEV/EVSE, in terms of median household income (log-transformed) and percentage of non-white population (log-transformed).

[b] Dependent variable: Per-capita PEV/EVSE count (log-transformed). Independent variable: Median household income or percentage of non-white population (log-transformed).



	Year	ICEV	HEV	PHEV	BEV	PEV	Gas station	EVSE-L2	EVSE-DCFC	EVSE-All
Gini Coefficient	2015-2016	0.25	0.37	0.49	0.54	0.5	0.09	0.26	0.22	0.25
	2021		0.36	0.44	0.5	0.47		0.27	0.24	0.27

Fig. 2. Lorenz curve (for 2021) and Gini coefficient (for 2015–2016 and 2021) for different light-duty passenger vehicle technologies (a) and refueling infrastructure types (b). A Lorenz curve denotes, in this analysis, a graphical representation of the relationship between the cumulative proportions of the population with registered vehicles and/or living nearby refueling infrastructure and its cumulative proportions of income. Note that the Lorenz curves are based on the cumulative distribution of y_i and that CBGs on the horizontal axis are sorted according to the CBG's median income, from the smallest to the largest.

rather about equal share between lower and higher income neighborhoods. For example, if a state has 200 PEV chargers distributed evenly between the neighborhoods (hosting 100 chargers, 50 % share) that have income below the state-wide median income value and those neighborhoods (hosting 100 chargers, 50 % share) that have income above the state-wide median value, the PCS-LIN value for the state will be 50 %. If the state has only 50 chargers (among the 200, and thus 25 % share) in the neighborhoods that have median income below the state-wide median value, then the PCS-LIN value becomes 25 %, implying the uneven distribution of PEV chargers (biased towards the relatively more affluent neighborhoods). A more detailed description and visualization for the PCS-LIN metric are available in the Experimental Procedures section.

As illustrated in Fig. 3, the PCS-LIN value for PEV adoption is below 50 % (equality line) for all states, which means that PEVs are disproportionately less represented in low-income neighborhoods. The bias towards high-income neighborhoods as such (the further below the equality line, the more severe) shows a wide variation between states. In Virginia, low-income neighborhoods represent only 23 % of state-wide PEV adoption, whereas it is 45 % (very close to the equality line) in Vermont. In most states, PCS-LIN values for PEV adoption get closer to the equality line over time (from 2016 to 2021), which suggests a longitudinal improvement in equality. Spatial and temporal variation of PCS-LIN reveals that income inequality in the space and time domains is much more complex than what was characterized by Lorenz curves and Gini coefficients above. This illustrates why it is important to examine the inner structure of inequality across different areas/locations as well over time.

For EVSE deployment, it is interesting that the overall longitudinal variations are greater than that for PEV adoption, indicating potentially greater flexibility of EVSE deployment and its equality impact, in comparison with PEV adoption. In other words, improving income equality of public EVSEs could be relatively easier than tackling the income inequality in PEV adoption, although the historical and longitudinal variation of PCS-LIN values alone cannot confirm the relative easiness in improving equality in EVSE deployment vs. PEV adoption. Furthermore, it is recognized that household income alone may not be the most effective variable to measure or characterize the longitudinal change in equality of public charging infrastructure, because a significant portion of the public EVSEs is in non-residential areas (e.g., shopping centers, office parks, schools) that may have skewed representation of household income on a census block group level.

Unlike PEV adoption (all states below the equality line), for EVSE deployment, about half of the states have PCS-LIN values above 50 % (equality line). In those states, relatively more EVSEs are deployed in neighborhoods that have income below state-wide median value in 2021 (Fig. 3). Although the contrast between PCS-LIN values for PEV adoption and EVSE deployment may be surprising, it must be noted that PEV adoption tends to be concentrated in high-income and residential areas, whereas EVSEs are usually located in predominantly commercial areas (that may or may not be strongly correlated with income). Nonetheless, like PCS-LIN values for PEV adoption, there is a wide variation of PCS-LIN values for EVSE deployment between states – 20 % above the equality line (biased towards low-income) in Utah, and 20 % below the equality line (biased towards high-income) in Kansas.

Longitudinal patterns indicate the decline in PCS-LIN values over time in most states, except some (e.g., Iowa, New Hampshire, Louisiana, West Virginia, Oklahoma). This implies a worsening equality over time, in which more and more public EVSE ports are preferentially deployed in the areas that have income values higher than the state median value. In the case of Iowa and New Hampshire, the PCS-LIN values increased but from a starting point that was already above the equality line – in other words, they became more unequal due to preferential deployment to neighborhoods that have incomes lower than the state median value. While the PCS-LIN values for Louisiana, West Virginia, and Oklahoma increased, they got much closer to the equality line.

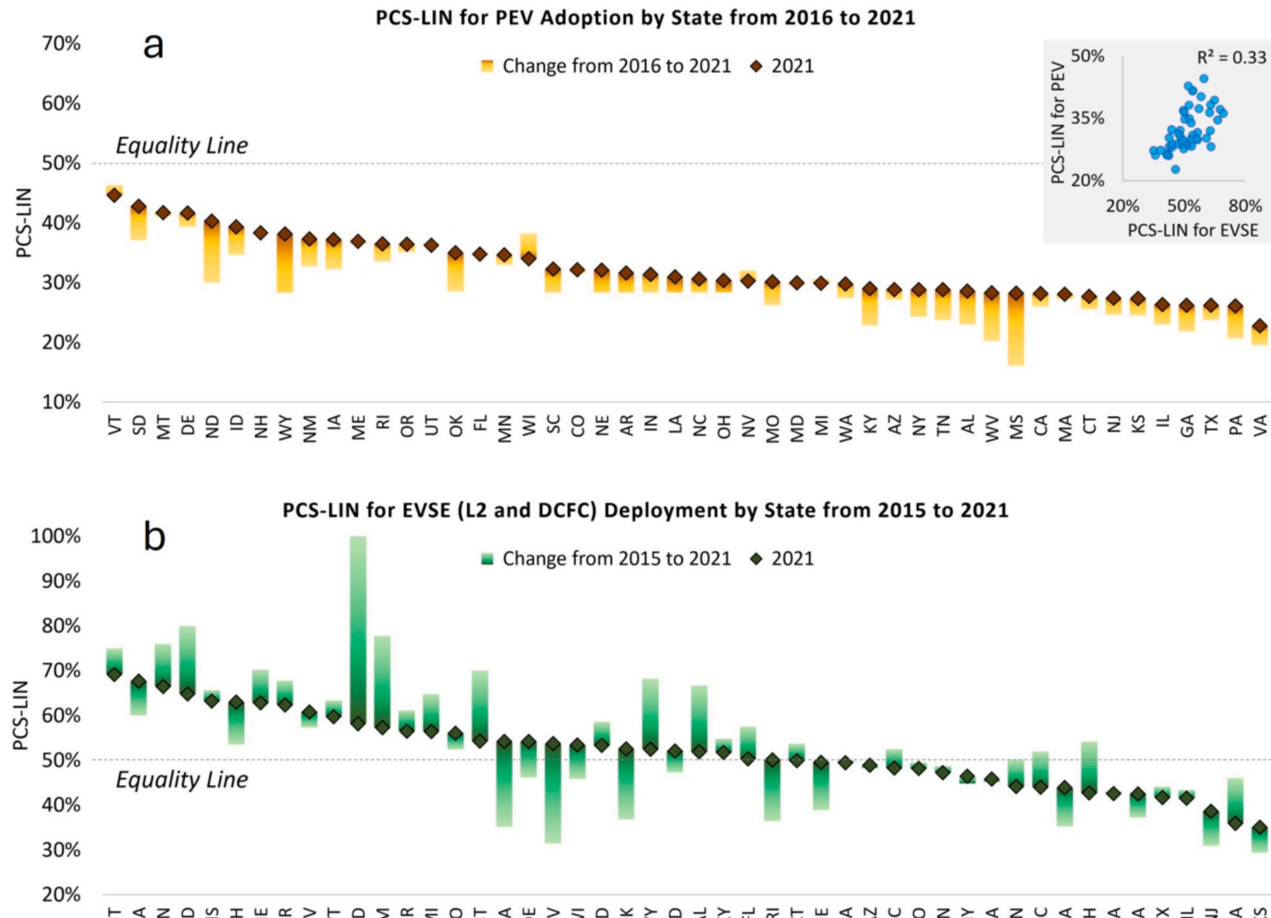


Fig. 3. Per-capita share of low-income neighborhoods (PCS-LIN) by state, and historical change over the last several years, for PEV adoption (a, top) and EVSE deployment (b, bottom). PCS-LIN shows how well low-income neighborhoods or census block groups are represented in the overall deployment of PEVs or EVSEs. If deployment within a state is perfectly equal, the PCS-LIN for that state would be 50 %. Above the perfect equality line (50 %) – a bias towards low-income; below the equality line – a bias towards high-income (i.e., lower representation of low-income neighborhoods).

Evaluating Figs. 2 and 3 together leads to two intriguing observations. First, the Gini coefficients in Fig. 2 reveal that the overall nationwide income inequality for vehicle ownership is generally greater than the inequality for refueling infrastructure. For both electric (PEV – PHEV and BEV) and non-electric (ICEV and HEV) vehicle technologies, the Gini coefficients for vehicle ownership or technology adoption are larger (greater inequalities) than those for corresponding refueling infrastructure (EVSEs or gas stations). Second, the state-by-state analysis in Fig. 3 in part explains the overall difference of the Gini coefficients (Fig. 2) between PEV adoption and EVSE deployment. Fig. 3 shows that there is a widespread income inequality for PEV adoption in all states, and the inequality is biased towards high-income neighborhoods, which contributes to relatively bigger Gini coefficients for vehicle technology adoption (compared to refueling infrastructure) in Fig. 2. Interestingly, state-by-state PCS-LIN values for EVSE deployment also indicate significant income inequalities in most of the states, but (unlike PEV adoption) they are spread in both directions – some states above the equality line (biased towards low-income), and others below the line (bias towards high-income). Owing to this spread above and below the equality line (Fig. 3), when aggregated for the entire country, the overall income inequality for EVSE deployment becomes relatively smaller (compared to PEV adoption), as can be seen in Fig. 2. Ironically, this also shows why the Lorenz curves and Gini coefficients (Fig. 2) can sometimes be misleading, and why we need alternative metrics such as PCS-LIN (Fig. 3).

Fig. 4 shows the historical evolution and latest status of PEV adoption and EVSE deployment in each state. Figs. 3 and 4 reveal three interesting aspects. First, although California has the largest per-capita number of PEVs (and the second largest per-capita EVSEs, next to Vermont), California is one of the states that has the most severe income inequality in PEV adoption and EVSE deployment (Fig. 3). The example of California implies that simply increasing the number of PEVs or EVSEs (Fig. 4) does not necessarily or automatically improve equality (at least at current levels of adoption) (Fig. 3), and it requires purposeful efforts and effective strategies to achieve both a wider PEV adoption (or EVSE deployment) and equality at the same time. In comparison with California, Washington shows a little more complex of a pattern – worse than average income inequality for PEV adoption, but almost perfect equality for public EVSEs. This may mean that PEV owners (in Washington) predominantly reside in high-income neighborhoods but benefit from public EVSEs in both high- and low-income neighborhoods. It may also mean that government incentives for EVSEs have been skewed towards low-income neighborhoods with the anticipation that PEV adoption will follow.

Second, Utah and Kansas, positioned at opposite ends of the spectrum in terms of PCS-LIN for EVSE deployment (Fig. 3) highlight the complex inequality conditions within and between states. The PCS-LIN value for Utah, 20 % above the equality line, indicates a bias towards low-income neighborhoods, whereas it is 20 % below the line for Kansas, implying a bias towards high-income. Utah and Kansas are both relatively rural states, and they have approximately the same number of per-capita ICEVs and gas stations (Fig. 4). Furthermore, in both states, a

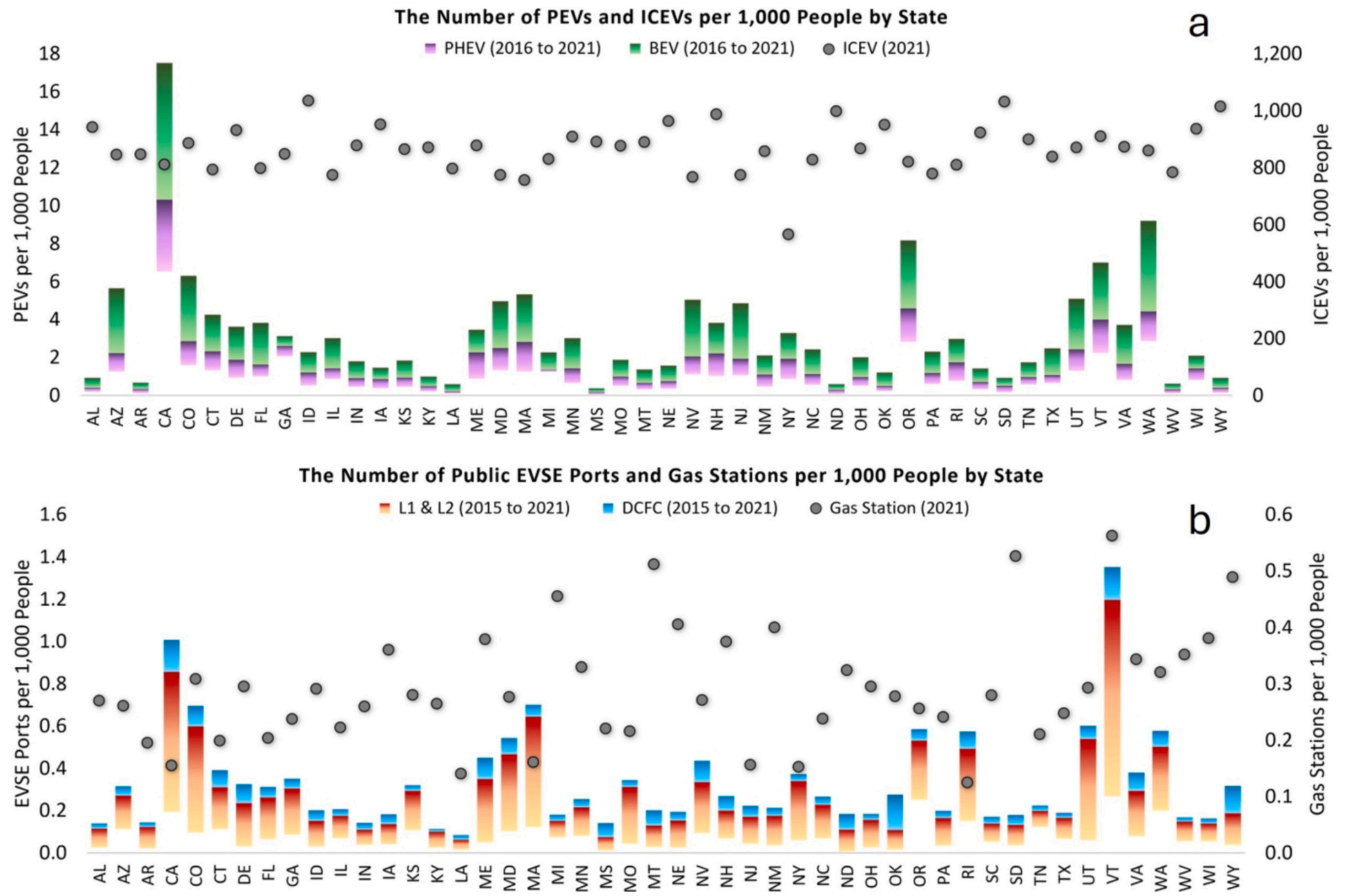


Fig. 4. Historical evolution of state-by-state PEV and ICE vehicle adoption (a, top) and EVSE and gas station deployment (b, bottom), on a per-capita basis, compared to conventional vehicle and corresponding refueling infrastructure. Detailed discussion is provided in Appendix.

significant portion of EVSEs are concentrated in the states' largest cities (Salt Lake City in Utah, and Overland Park [near Kansas City in Missouri] in Kansas). Despite those similarities, why do the two states have the largest, yet completely opposite, income inequality? Two factors may be contributing to this. In Utah, a good chunk of EVSEs in Salt Lake City are in lower-income neighborhoods, whereas it is the opposite in Overland Park in Kansas – see Figs. A1 and A2 in Appendix. Another factor is the overall state-wide distribution of EVSEs. Utah has relatively better spatial spread of EVSEs across the state, in part owing to a greater number of EVSEs placed along interstate highways, rural areas, and national parks (that tend to be lower-income neighborhoods). On the other hand, Kansas does not yet have similarly significant number of EVSEs spread along the interstate highways and/or in rural areas (beyond population centers).

Third, the longitudinal variation of PCS-LIN values in each state (Fig. 3) seems to be somewhat correlated with the level of electrification (Fig. 4). States (e.g., California, Oregon, and Washington) that have relatively more established PEV adoption (or EVSE deployment) do not show much variation in the longitudinal evolution of PCS-LIN values (at least over the past several years). On the other hand, those that have relatively lower level of PEV adoption (or EVSE deployment) show greater longitudinal variations over the past several years. For those states with relatively more established PEV adoption, it is uncertain whether the lack of longitudinal variations (or improvements) in inequalities would remain the same in the future, but it is discouraging that the data indicate less-than-meaningful improvement in inequalities in those states over the past several years.

3.4. Racial gap index (RGI)

We characterize racial inequality in PEV adoption and EVSE deployment using the racial gap index (RGI), which measures how well different races are represented, by quantifying the disparity between different racial groupings and where a wider gap between the curves indicates a larger racial gap. For simplicity, we analyze only non-Hispanic white (white) vs. non-white. If the deployment of PEVs and EVSEs proceeds equally in white and non-white populations, they will have the same share of PEVs or EVSEs, resulting in an RGI score of zero (perfect equality). Fig. 5 shows RGI results for PEV adoption and EVSE deployment in each state. A positive RGI value implies a bias towards the white population, in which the distribution of white population disproportionally represents a larger share of the distribution of PEVs or EVSEs. Accordingly, a negative RGI value suggests a bias towards non-white population. If the distribution of PEVs or EVSEs is perfectly equally represented across white and non-white populations, the RGI value would become 0. More detailed description and visualization for the RGI metric are available in the Experimental Procedures section.

Whether it is PEV adoption or EVSE deployment, as of today, our RGI results indicate that there is a wide-spread bias towards the white population in almost all states. Longitudinal changes between 2015 and 2021 indicate that the racial gap has been narrowing slowly (RGI values getting closer to the equality line) for PEV adoption in most of the states. Conversely, the racial inequality has worsened for public EVSE deployment in most of the states.

Regarding the inequality in PEV adoption, for both income (Fig. 3) and race/ethnicity (Fig. 5), the results seem to show a consistent pattern – a widespread (income or race/ethnicity) inequality in all states, but

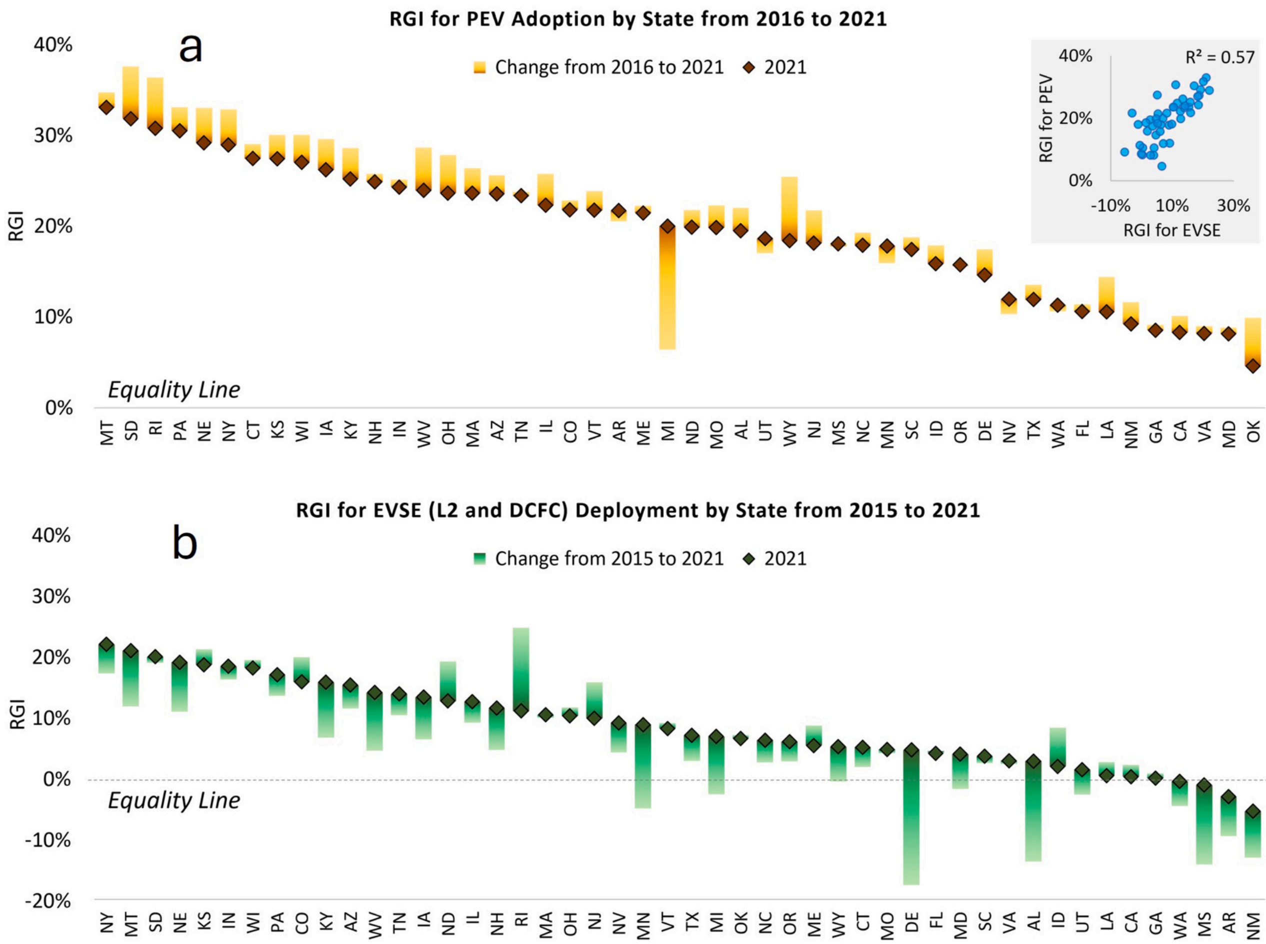


Fig. 5. State-by-state racial gap index (RGI), and its historical change from 2015 to 2021, for PEV adoption (a, top) and EVSE deployment (b, bottom). RGI measures how well different races are represented (spatially) in the deployment of PEVs and EVSEs. If the deployment of PEVs and EVSEs proceeds equitably for the white and non-white populations, they will have the same share of PEVs or EVSEs and have an RGI score of zero. Above the perfect equality line (0 %) – a bias towards white (lower representation of non-white population); below the equality line – a bias towards non-white (including Hispanic).

slowly improving over time (getting closer to the equality lines). As for EVSE deployment, it is a little more complicated. From the income perspective (PCS-LIN in Fig. 3), about half of the states are above the perfect income equality line (with the other half below the equality line) – some states are biased towards high-income, while others biased towards low-income. However, from the race/ethnicity standpoint (RGI in Fig. 5), almost all states are above the racial equality line. This means that racial/ethnic inequality (in EVSE deployment) has a predominant bias towards the white population in almost all states, of which the bias (and thus inequality) is more severe and widespread compared to income inequality (PCS-LIN in Fig. 3).

States that have the largest racial inequality (for PEV and EVSE deployment) include New York, Montana, South Dakota, and Nebraska. On the other hand, California and Georgia are among the states with the smallest racial inequality in both PEV adoption and EVSE deployment. One might suspect that relatively lower racial inequality in California or Georgia may be just a byproduct of the greater share of non-white populations in those states, but that does not fully explain the RGI values across different states. A good example is Georgia vs. New York in terms of RGI values for EVSE deployment. While the two states have a similar share of non-white population in each state, Fig. 5 shows that the RGI value of Georgia (for EVSE deployment) is very close to the equality line, but the RGI value for New York is the furthest away (among all states) from the equality line (worst racial equality).

When it comes to racial inequality of public EVSE deployment, the Utah vs. Kansas comparison discussed above (for PCS-LIN) presents another interesting case. In addition to the similarities between those two states described earlier, Utah and Kansas have a similarly high share of white population (relative to other states). However, the RGI value for Utah is very close to the equality line (Fig. 5), while the RGI for Kansas shows one of the most severe racial inequalities (for public EVSE deployment) in the country. Overall, in terms of EVSE deployment, Utah seems to have relatively better income and racial equality in comparison with Kansas, in part owing to the more even distribution in Salt Lake City as well as across the state (as mentioned above) – see Figs. A1–A4 in Appendix.

3.5. Inequality comparison for 20 largest urbanized areas

Our analyses thus far clearly show that high-level national characterization of income inequality for PEV adoption or EVSE deployment (based on Lorenz curves and Gini coefficients in Fig. 2) does not tell the whole story, and therefore it is important to investigate the spatial and temporal heterogeneity of inequality (e.g., using PCS-LIN and RGI as in this study). To that end, in addition to state-by-state analyses above (Figs. 3 through 5), we now also evaluate the inequality of PEV adoption and EVSE deployment in the 20 largest (i.e., most populous) urbanized areas (as defined by the US Census Bureau to indicate areas smaller than metropolitan areas, but larger than cities, focused more on densely-populated urban cores) [24]. Together, these 20 largest urbanized areas cover about 1 % of the land area of the lower 48 states, are home to about 30 % of the US population, and account for 26 % of the light-duty vehicle stock, 42 % of PEVs, and 37 % of public EVSE ports. These areas are analyzed using the same data and methodology adopted above.

Fig. 6 illustrates PEV adoption, public charging stations, household income, and race on a census block group level for three example cities (Chicago, Manhattan-Bronx area of NYC, and Houston) that are part of the urbanized areas assessed. In Chicago, Manhattan-Bronx, and Houston, there is a strong positive correlation between income and PEV adoption or EVSE deployment – affluent areas have more PEVs and/or EVSEs (Fig. 6). Generally, downtown areas have greater concentrations of EVSEs (L2 in particular). PEVs or EVSEs are less prevalent in less affluent areas that also tend to be home to a higher share of the non-white population. Those patterns are apparent in downtown and northwest of Chicago vs. southeast of Chicago; Manhattan vs. Bronx; and downtown and west of Houston vs. the rest of the city. More systematic evaluations are summarized in Table 3.

For EVSE deployment, of the twenty urbanized areas analyzed, the New York – Newark area has a PCS-LIN value (0.25) that is the furthest away from the perfect equality line (0.5). This means that the census block groups that have incomes lower than the area-wide median value represent only 25 % of per-capita EVSEs in the New York – Newark area. In contrast, those lower income census block groups account for 70 % of all EVSEs in the Tampa – St. Petersburg area, as illustrated by PCS-LIN value of 0.7 (20 % above the equality line [0.5], meaning a significant bias towards low-income neighborhoods).

In general, for EVSEs, half of the urbanized areas have PCS-LIN values below 50 % (equality line), which implies a bias towards more affluent neighborhoods (or census block groups). This is consistent with the pattern illustrated in Fig. 3 – about half of the states are above the equality line and the other half are below that line. For gas stations, however, the values of PCS-LIN are greater than 50 % in all but three urbanized areas. This indicates that gas stations are disproportionately located in less affluent neighborhoods, which may raise pollution and health concerns in those neighborhoods [25–28].

For PEV adoption and income equality, the New York – Newark area again has the worst income equality (as was the case for EVSE deployment), among the twenty urbanized areas evaluated – with a PCS-LIN value (0.25) furthest away from the equality line (0.5). It is worth noting that the state of New York has about the same income equality (PCS-LIN of 0.29 for PEV adoption) as the state of Georgia (0.26) – see Fig. 3, but the urban area of New York – Newark area (0.25) in New York state has much worse income equality than the Atlanta area (0.4) in Georgia – recalling that the further away from the equality line (0.5), the worse inequality. This highlights again why it is important to investigate inequality at different geographical scales.

Notably, almost all of the twenty urbanized areas have PCS-LIN values close to 50 % (perfect equality) for conventional gasoline

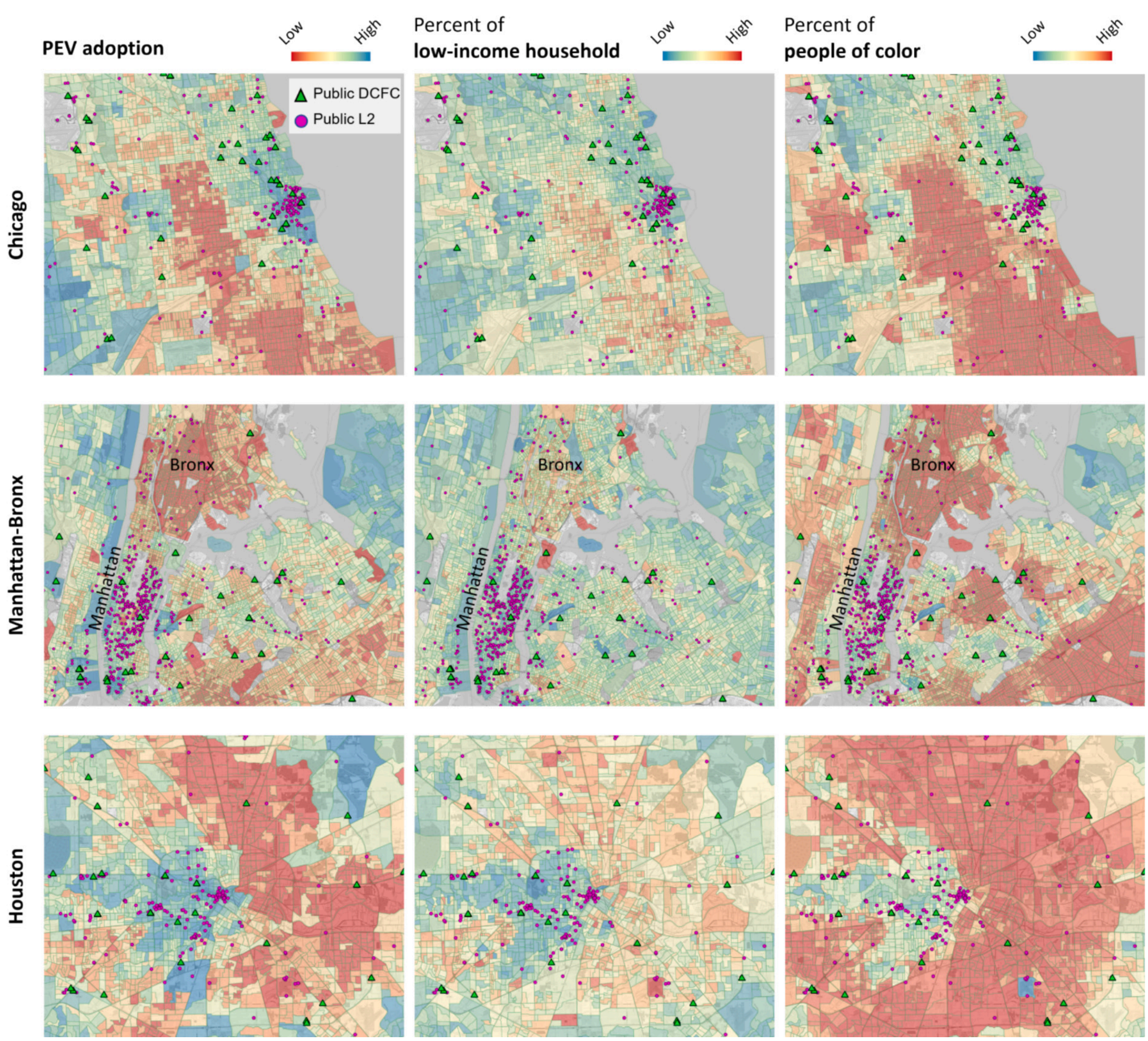


Fig. 6. Spatial relationship between PEV adoption, EVSE deployment, percent of low-income households, and percent of non-white (people of color, including Hispanic), by census block group, for three example cities (Chicago, Manhattan-Bronx area of NYC, and Houston) in 2021.

Table 3
Human population, median household income, EVSE deployment, PEV adoption, PCS-LIN, and RGI for the 20 largest (most populous) urbanized areas – PCS-LIN and RGI values are to be interpreted in terms of the level of deviation from the perfect equality line (0.5 for PCS-LIN and 0 for RGI) as illustrated in Figs. 3 and 5 above.

Urbanized Area	State	Population (1000)	Median Income ($1000)	PCS-LIN (Perfect Equality: 0.5)				RGI (Perfect Equality: 0)			
				EVSE	Gas Station	PEV	ICEV	EVSE	Gas Station	PEV	ICEV
New York – Newark	NY, NJ, CT	17,800	77	0.25	0.42	0.25	0.38	0.12	0.07	0.22	0.08
Los Angeles – Long Beach – Anaheim	CA	12,300	71	0.53	0.47	0.31	0.48	0.03	−0.04	0.09	−0.16
Chicago	IL, IN	7900	69	0.46	0.61	0.28	0.50	0.16	−0.02	0.23	0.02
Miami	FL	5700	56	0.58	0.59	0.37	0.49	0.05	−0.08	0.08	−0.12
Dallas – Fort Worth – Arlington	TX	5200	65	0.63	0.67	0.33	0.52	0.09	−0.09	0.14	−0.07
Philadelphia	PA, NJ, DE, MD	4900	68	0.41	0.52	0.26	0.45	0.18	0.14	0.27	0.11
Houston	TX	4700	62	0.42	0.64	0.27	0.55	0.09	−0.14	0.11	−0.14
Washington, DC	DC	4600	102	0.50	0.53	0.30	0.44	0.10	−0.09	0.13	−0.05
Atlanta	GA	4200	68	0.42	0.62	0.33	0.50	0.04	−0.02	0.12	−0.05
Boston	MA, NH, RI	3800	86	0.32	0.40	0.27	0.44	0.12	0.19	0.22	0.17
Phoenix	AZ	3700	61	0.41	0.53	0.33	0.50	0.17	0.02	0.25	0.05
Detroit	MI	3500	58	0.65	0.73	0.27	0.51	−0.02	0.01	0.16	0.11
San Francisco – Oakland	CA	3200	100	0.35	0.48	0.34	0.48	0.03	−0.03	0.05	−0.12
Seattle	WA	3100	87	0.56	0.57	0.30	0.48	−0.01	−0.01	0.12	0.06
San Diego	CA	2900	76	0.40	0.57	0.35	0.50	0.13	0.04	0.15	−0.04
Minneapolis – St. Paul	MN, WI	2500	75	0.62	0.62	0.44	0.51	0.14	0.15	0.19	0.13
Denver – Aurora	CO	2400	76	0.39	0.56	0.40	0.48	0.23	0.04	0.22	0.09
Tampa – St. Petersburg	FL	2300	53	0.70	0.54	0.42	0.52	0.08	0.05	0.15	0.09
Baltimore	MD	2000	76	0.54	0.67	0.37	0.52	0.02	0.02	0.06	0.02
Las Vegas – Henderson	NV	2000	58	0.67	0.67	0.34	0.52	0.07	−0.05	0.12	−0.03

vehicles. In the case of PEV adoption, none of the urbanized areas has a PCS-LIN value that is closer to the equality line (0.5) compared to ICEV ownership (for which PCS-LIN values are all very close to the equality line, ranging from 0.38 to 0.55). For the twenty urbanized areas, the variation in the difference between PCS-LIN values for PEVs and ICEVs ranges from 0.07 (for the Minneapolis – St. Paul area) to 0.28 (for the Houston area) – the greater the difference, the more severe inequality between PEVs and ICEVs.

With regards to racial equality (characterized by RGI values), our analysis indicates that almost all urbanized areas evaluated demonstrate marked underrepresentation of the non-white population. In the Denver – Aurora area (RGI of 0.23), the white population has a 23 % higher share of public EVSE ports than the non-white counterpart on a per-capita basis. In contrast, in the Seattle area, public EVSE ports are distributed almost equally (on a per-capita basis) between white and non-white populations. This is consistent with the state-level results in Fig. 4 – Colorado has an RGI value 36 % above the equality line (biased towards the white population), while Washington's RGI value is very close to the equality line. In contrast, RGI values for gas stations in both areas (Denver – Aurora and Seattle) are very close to perfect equality.

Across the twenty urbanized areas investigated, the adoption of PEVs occurs at higher rates among the white population than the non-white population, with RGI values ranging from 5 % (San Francisco – Oakland) to 27 % (Philadelphia) – all are above the equality line (a bias towards white population). It is worth noting that the non-white populations exhibit a higher share of per-capita ICEV ownership – see negative RGI values in many of these urbanized areas. In the Houston area, the non-white population has a 14 % higher per-capita share of ICEVs than its white counterpart. In the Boston area, however, RGI values are above 20 % for both PEVs and ICEVs, which may be associated with an underlying bias in personal vehicle ownership across all technologies towards the high-income and/or white population in that area. In the Chicago area, RGI for ICEV ownership is 2 % (implying almost perfect racial equality), whereas it is 23 % for PEVs (significant inequality compared to ICEVs). Overall, differences in the range of RGI values between PEV (5 % to 27 %) and ICEV (−16 % to 17 %) illustrate racial inequalities that persist in some of the largest urbanized areas in the U.S.

As shown in Fig. 5, California is one of the states that has the best racial equality for PEV adoption and EVSE deployment, despite being one the states with the most severe inequalities based on income (Fig. 3). Within California, the comparison between two areas, San Francisco – Oakland vs. San Diego (Table 3), shows a significant variation of racial inequality across different cities/areas in the same state. The San Francisco – Oakland area's RGI for PEV adoption is 5 % above the equality line (0 %), meaning a slight bias towards white population (and lower than the state-wide value [8 %]), whereas the San Diego's RGI is three times larger (15 % above the equality line, and greater than state-wide value). Note that the two areas have almost the same income inequality for PEV adoption (PCS-LIN: 35 % above the equality line in the San Francisco – Oakland area; 34 % above in the San Diego area; and thus a significant bias towards high-income neighborhoods in both urbanized areas). Despite the same income inequality, racial inequality for PEV adoption is apparently very different between those two areas. The racial inequality gap between the two areas gets even bigger for EVSE deployment, as the San Francisco – Oakland area has an RGI value of 3 %, whereas it is 13 % (more than four times greater) for the San Diego area. A similar observation (significant variation within the state) can also be made between the Miami area (RGI for EVSE deployment: 8 %) vs. the Tampa – St. Petersburg area (15 % - about twice greater inequality), while the state-wide RGI value for Florida is about 7 % (Fig. 5).

This study's use of a binary definition of race (non-Hispanic white vs. non-white, including Hispanic) creates limitations in terms of implications, however spatial comparisons of the relationships between race or income and PEVs and EVSE show examples patterns of both equality and inequality. In terms of the comparison of racial inequality between EVSEs and gas stations, our data for the Baltimore area shows an inverse relationship between income and race. RGI values for EVSEs and gas stations are the same (0.02) and very close to the equality line (0), which means that both EVSEs and gas stations are relatively evenly distributed between white and non-white dominant neighborhoods in the area. This seems to be in part due to relatively even distribution of white and non-white households in the area (despite some sign of segregation) – see Figs. A5 and A6 in Appendix. On the contrary, the comparison between PCS-LIN values for EVSEs and gas stations in the area presents a different picture. PCS-LIN for EVSEs in the Baltimore area is 0.54 (very close to the equality line [0.5]), whereas PCS-LIN (0.67) for gas stations is further away from the equality line. This is partly due to the spatial coincidence of the higher concentration of low-income neighborhoods and EVSEs in the downtown area of Baltimore, which is not the case for gas stations. This example (PCS-LIN vs. RGI for EVSEs and gas stations in the Baltimore area) highlights that the pattern of income inequality related to electrification does not always translate into the same pattern of racial inequality, or vice versa. On a state-level, Colorado is a good example for this – almost perfect income equality for EVSE deployment (Fig. 3), but one of the states with the most severe racial inequalities in the country (Fig. 5).

4. Discussion: Reflections, limitations and future gaps

Our results are the first to quantify the current and historical inequalities across income and race regarding the distribution of PEV adoption and EVSE deployment, compared to conventional vehicles or gas stations, across local, regional, and national scales.

Nonetheless, our analysis contains some limitations. As noted at the beginning, our analysis is based on the location (longitude and latitude) of public EVSEs and does not include the broader characteristics of those who use public EVSEs (where they live, work, shop, etc.) or the interaction between home charging access and the utilization of public EVSEs. One example of such interaction is that the charging duration for electric vehicles is significantly longer compared to refueling an ICE vehicle at a gas station, resulting in a stronger correlation between the number of PEVs and charging demand, meaning that absolute equality in EVSE deployment may not align linearly with the broader goals of PEV adoption. To account for such considerations, a much more complex analysis will be required, involving home charging access (as a function of housing type, parking options, and power outlet availability), electric driving range (or battery size), vehicle utilization (how often and far people drive), refueling behavior (where, how often, and how long people charge their PEVs), destination types (work, shopping, exercise, etc.), and so forth.

Furthermore, our analysis is primarily focused on distributional equality with respect to income and race/ethnicity, but there are other important dimensions (e.g., housing, jobs, education, pollution, decarbonization, resilience, etc.) that were not addressed in this study. In addition, as acknowledged at the beginning, this study is strictly focused on equality (or the lack thereof), not equity. The design of equitable PEV and EVSE deployment must be grounded upon a clear understanding of who is benefiting or bearing burdens, and to what degree, which is beyond the scope of this study. Nevertheless, the data and methods (equality metrics) in this study could also be applied to equity analyses if the unit of analysis is converted to benefits or burdens [29–31]. Examples of considerations in an equity analysis include more categories for race or ethnicity, and controlling for income.

Given that most EVSE locations are public and are built and situated not necessarily where the users live, analyzing the number of gas stations instead of income or race might also show interesting patterns of spatial heterogeneity that we encourage future researchers to explore. Same with possible rates of charging malfunctions, or spatial data on the sales of EVs and availability of stock within urban locations.

Lastly, although this analysis provides critical information as to what type of and how much inequality exists at different spatial and temporal scales based on novel equality metrics (Gini, PCS-LIN, and RGI), those equality quantification methods may have some limitations [32,33]. For example, even when the two cases have the exact same Gini coefficients, they may have very different income distributions (or shapes of the Lorenz curves). Furthermore, equality metrics (distilled down to a single number) may not sufficiently reveal sub-group characteristics (e.g., for the poorest of the poor). For PCS-LIN and RGI, potential sensitivity or the lack therefore would also need to be examined carefully to shed light on the robustness of those metrics. These limitations may also apply to PCS-LIN and RGI metrics developed in this study, as they are built upon the same concept as in the Lorenz curves and Gini coefficients. Nonetheless, some of those issues regarding the equality metrics can be alleviated to an extent by carefully investigating the inner structure of distributions (beyond numeric values). That is why we conducted visual examination (e.g., maps) alongside numerical quantification of inequality in this study. All in all, despite some limitations, the inequality metrics adopted in this study do provide a consistent and scalable platform upon which different areas and times can be compared against each other at different geographical scales. A logical future extension of this work would be to incorporate other equity considerations, including the fact that quality of mobility and access are not tied to a single mode such as personally-owned vehicles.

5. Conclusion

Two core measures of equality, income and race, strongly shape and connect with the adoption of conventional cars, spatial patterns of EV diffusion, and the distribution of EVSE charging stations. This leads to disparities in adoption patterns, impacts travel patterns and urban morphology, and generates differential responses to pressing energy and mobility problems. All states examined, except New York, have approximately the same per-capita number of ICEVs (ranging from 0.8 to 1 ICEV for every person), while the number of PEVs (per capita) varies greatly from one state to another. State-level public EVSE count tends to be correlated with PEV adoption on a per-capita basis, meaning that EVSE deployment also has significant unequal distribution across states. It is uncertain whether and how long such stark contrast between ICEVs (almost evenly distributed across the country on a per-capita basis) and PEVs (significantly unequal distribution) will remain the same or not in the future. Nonetheless, it is worth considering the impacts of the inequality and whether policy or market intervention are warranted to address the disparity.

Compared to public EVSE deployment, our analysis shows that PEV adoption has widespread income and race inequalities in all states. As PEV owners are the ones who benefit the most from public EVSE deployment, the severe inequalities associated with PEV adoption may also spill over to public EVSE deployment (although the interaction/dynamic between PEV adoption and public EVSE deployment was not considered in this study). In some states, public EVSEs are more concentrated in lower-income areas (e.g., 63 % in Nebraska), while most PEV owners live in high-income neighborhoods (e.g., 70 % in Mississippi). The interaction between EVSE access and PEV adoption may mean that installing more public EVSEs in low-income neighborhoods, without concerted efforts between PEV adoption and public EVSE deployment in less-affluent areas, might only benefit high-income PEV owners who live outside of those areas. At the same time, public EVSE deployment can also support PEV adoption over time in less-affluent areas.

Our results suggest future research can help us understand what works and what doesn't work in terms of equalizing access to PEVs and EVSE. This is because our findings indicate that there is really no one good state or city that can be used as a benchmark for improving income and/or racial equalities in PEV adoption or public EVSE deployment across the country. South Dakota has one of the best income equalities for both PEVs and EVSEs (see Fig. 3 – very close to the equality line), but the state has the most severe racial inequalities for both PEVs and EVSEs (Fig. 5 – furthest away from the equality line). California is completely the opposite – one of the most severe income inequalities for PEVs and EVSEs, but one of the best racial equalities. Even within California, different cities show different characteristics, as illustrated previously with the comparison of PEV adoption in the San Francisco – Oakland vs. San Diego areas (similarly biased towards high-income, but the San Diego area has three times more severe racial inequalities). Furthermore, the Baltimore area example presented earlier exemplifies the heterogeneity in the relationship between income, race/ethnicity, PEVs, and public EVSEs.

Different cities and states may want to consider different approaches based on their own needs and conditions, and incorporate relevant transportation equity considerations. In that regard, it is worth mentioning that federal and state policies around PEVs and EVSEs tend to be uniform – no geographical considerations (between states or cities). Therefore, in addition to federal and state entities, city governments and businesses (e.g., utility companies) may also have an important role to develop and implement local strategies to achieve better equality of mobility, so that equality may not only become a goal but a reality.

CRediT authorship contribution statement

Dong-Yeon Lee: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Alana Wilson:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Melanie H. McDermott:** Writing – review & editing, Writing – original draft, Validation, Resources, Methodology, Investigation, Conceptualization. **Benjamin K. Sovacool:** Writing – review & editing, Writing – original draft, Visualization, Validation, Resources, Methodology, Investigation, Conceptualization. **Robert Kaufmann:** Writing – review & editing, Writing – original draft, Visualization, Validation, Resources, Methodology, Investigation, Conceptualization. **Raphael Isaac:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Resources, Methodology, Investigation, Funding acquisition, Conceptualization. **Cutler Cleveland:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Methodology, Conceptualization. **Margaret Smith:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Methodology, Funding acquisition, Conceptualization. **Marilyn Brown:** Writing – original draft, Visualization, Methodology. **Jacob Ward:** Supervision, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Dong-Yeon Lee reports financial support was provided by US Department of Energy.

Data availability

Data will be made available on request.

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Appendix A. Appendix

A.1. Discussion on Historical State-by-State PEV and EVSE Deployment

As illustrated in Fig. 4 in main text, on a per-capita basis (normalized by state population), there has been significant growth in PEV adoption (mostly BEVs) in all states between 2016 and 2021 – Mississippi with the highest growth (by 700 %, albeit from a very low baseline) and Georgia with the lowest (by 50 %). As of 2021, California has the highest per-capita PEV adoption rate, followed by those states that have state-wide goals/ mandates for zero-emission vehicle (ZEV) deployment, such as Oregon, Washington, Vermont, Colorado, etc. In the case of ICEVs, except New York, there is approximately one ICEV for every person in each state, which contrasts with the PEV adoption pattern that is dominated by one state (i.e., California). Also, the relatively small variation of ICEV concentration across states (except New York), ranging from 800 to 1000 (per 1000 people), implies that ICEV population is generally correlated with human population (and thus there are relatively small variation across different states in terms of per-capita ICEV count), but that is not the case for the PEV population.

If state-level ICEV ownership (normalized by human population in each state) is any indication of the potential level of future penetration of PEV technologies, Fig. 4 (in main text) illustrates the wide-ranging gap between the electrification potential (ICEV density [per 1000 people]) and reality (current PEV adoption) across different states. For instance, California and Louisiana have approximately the same number of ICEVs (800 per 1000 people), but the current number of PEVs in Louisiana is approximately ten times smaller compared to California. Another good example is Oregon vs. Rhode Island – the same number of ICEVs (800 per 1000 people), but Rhode Island's PEV adoption is twice lower than that of Oregon. If equality is about "equal access for all" to electrification (e.g., whether people live in California or Louisiana), this drastically uneven distribution between states (Fig. 4 in main text) implies a great inequality across the nation for access to PEVs. This between-state inequality tends to be taken for granted, but it is worth asking why such inequality persists and whether something is to be done to decrease such inequality.

Deployment of public EVSE shows a very different pattern from PEV adoption. For example, California is no longer the most dominant state, and Vermont has the highest density of per-capita EVSE ports (as well as gas stations). Nevertheless, per-capita EVSE port count generally appears to have a positive correlation (0.6 in log-log scale) with the per-capita PEV adoption. However, this correlation does not necessarily imply causation. Conversely, longitudinal growth shows a weak correlation (less than 0.3) between PEV adoption and public EVSE deployment. Tennessee had the lowest growth in EVSE deployment, 80 % from 0.12 to 0.23, while PEV adoption has grown 200 % from 0.6 to 1.8. On the other hand, the EVSE port count in North Dakota increased 2600 % from 0.007 to 0.19, while the rate of growth of PEV adoption was around 500 % from 0.1 to 0.6.

For the state-by-state public EVSE port count (in comparison with gas stations), unlike PEV adoption (in comparison with ICEV population – see the discussion above), we cannot draw strong inequality implications from the per-capita values for two reasons. First, while ICEVs solely rely on public refueling infrastructure (gas stations), most PEVs are primarily charged at home, with public charging stations being secondary refueling locations. Second, as Fig. 4 (in main text) illustrates, because state-level EVSE port counts are generally proportional to state-level PEV adoption (not human population), inequality discussions based on the gap between the number of EVSE ports and the number of gas stations may not be very meaningful.

For example, California and Louisiana have similar per-capita number of gas stations (and ICEVs), but that doesn't necessarily mean that those two states are supposed to have equal number of EVSE ports (when normalized by the same unit [1000 people]). Despite almost the same number of gas stations and ICEVs between California and Louisiana, California's PEV adoption is ten times higher than Louisiana, and that is also true for public EVSE port count (about ten times larger). Nonetheless, if we look at Montana and Vermont, those two states also have similar per-capita number of gas stations and ICEVs (as in the example of California vs. Louisiana), but Vermont has four times higher PEV adoption than Montana, while the number of public EVSE ports in Vermont is seven times greater than Montana. In general, except some outliers such as Vermont, given the correlation between the number of EVSE ports and the number of PEVs in each state (0.6 in log-log scale, as mentioned earlier), the inequality of public EVSE port distribution across different states seems to be closely aligned with the inequality in state-by-state PEV adoption.

Despite wide variations across states, it is evident that there has been universal growth of PEV adoption and EVSE deployment in all states (Fig. 4 in main text). A key question that remains is to what degree this growth has been unequal in each state (i.e., the inner structure of the growth). To answer that, we now evaluate each state's unequal (uneven) distribution of PEV adoption and EVSE deployment, focusing on household income and racial groupings (non-Hispanic white and non-white including Hispanic). Within non-white racial grouping (including Hispanic), there could be some variations across races or ethnicities in terms of the equality of PEV adoption and EVSE deployment, but we use dichotomous racial groupings in this study for simplicity.

Examples for Utah vs. Kansas; and the Baltimore Area in Maryland

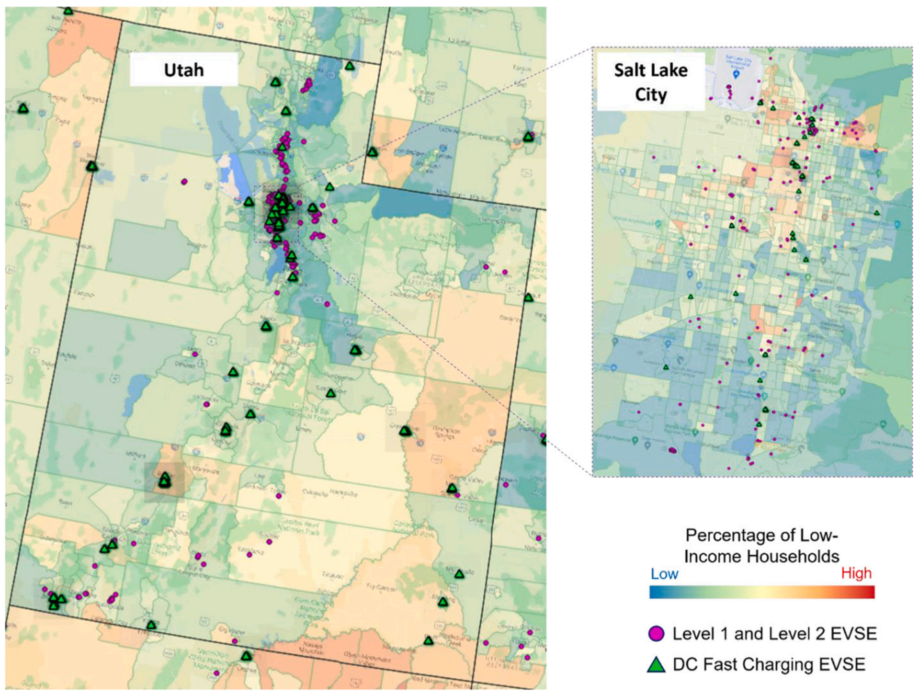

Fig. A1. Distribution of low-income households (by CBG) and public EVSEs in Utah (left) and Salt Lake City, UT (right).

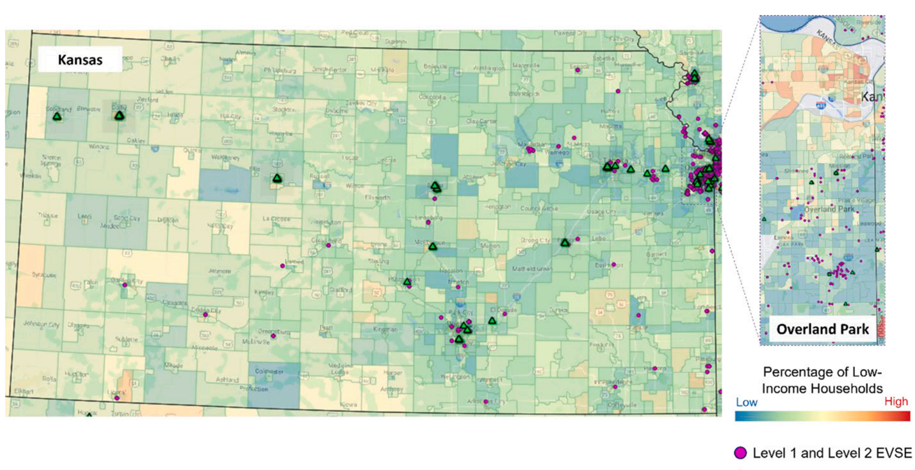

Fig. A2. Distribution of low-income households (by CBG) and public EVSEs in Kansas (left) and Overland Park, KS (right).

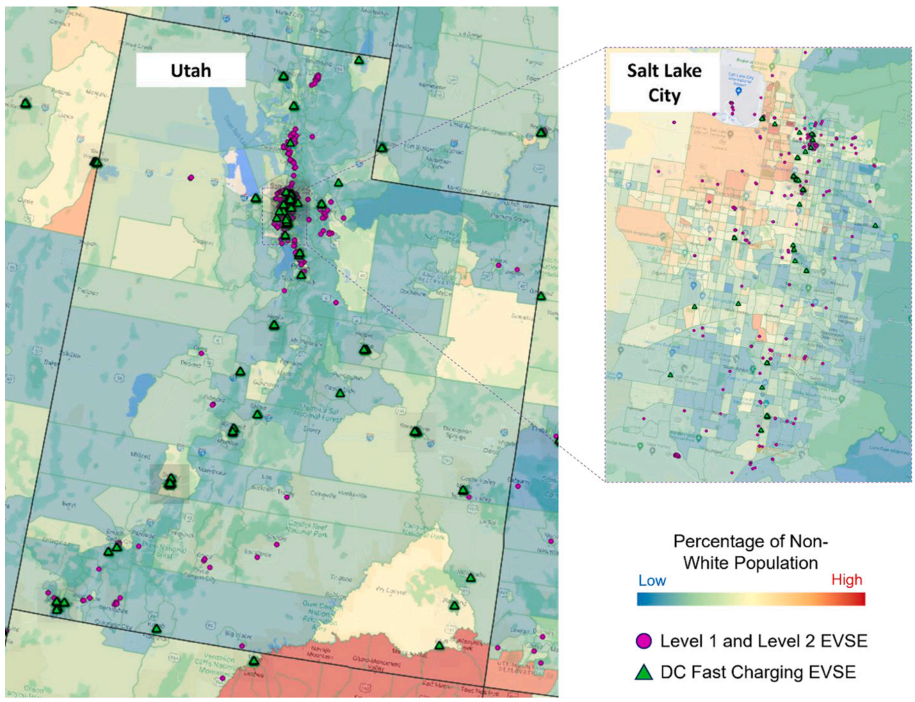

Fig. A3. Distribution of non-white population (by CBG) and public EVSEs in Utah (left) and Salt Lake City, UT (right).

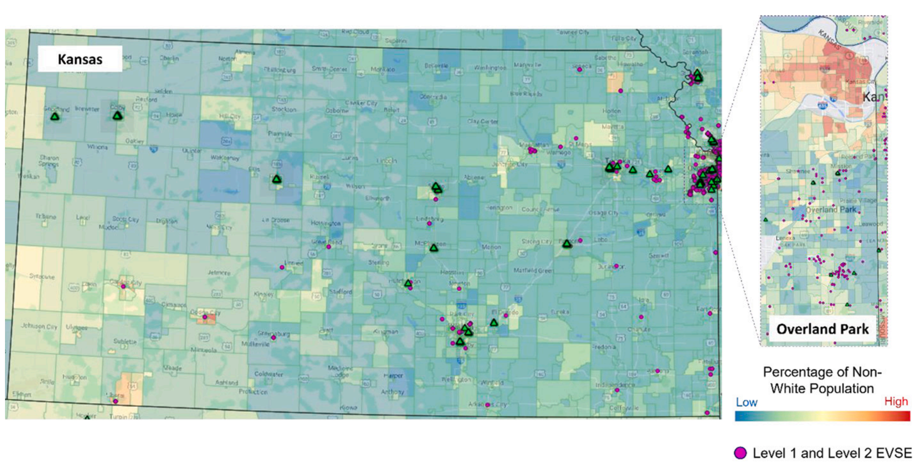

Fig. A4. Distribution of non-white population (by CBG) and public EVSEs in Kansas (left) and Overland Park, KS (right).

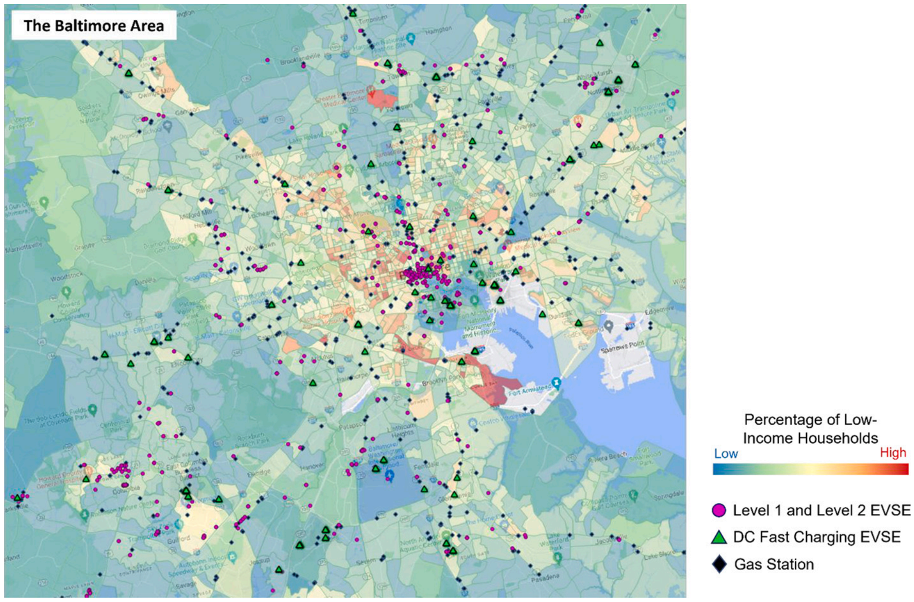

Fig. A5. Distribution of low-income households (by CBG), public EVSEs, and gas stations in the Baltimore urbanized area in Maryland.

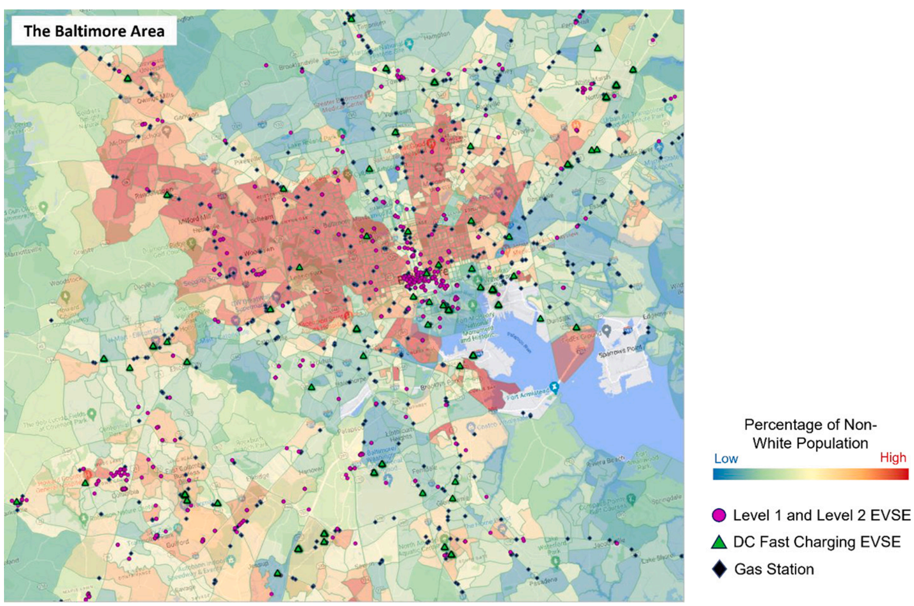

Fig. A6. Distribution of non-white population (by CBG), public EVSEs, and gas stations in the Baltimore urbanized area in Maryland.

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