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Article

Environmental Injustices of Leaks from Urban Natural Gas Distribution Systems: Patterns among and within 13 U.S. Metro Areas

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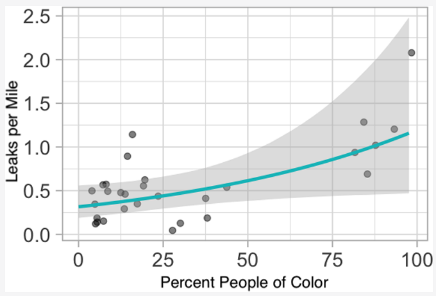
ABSTRACT: Natural gas leaks in local distribution systems can develop as underground pipeline infrastructure degrades over time. These leaks lead to safety, economic, and climate change burdens on society. We develop an environmental justice analysis of natural gas leaks discovered using advanced leak detection in 13 U.S. metropolitan areas. We use Bayesian spatial regression models to study the relationship between the density of leak indications and sociodemographic indicators in census tracts. Across all metro areas combined, we found that leak densities increase with increasing percent people of color and with decreasing median household income. These patterns of infrastructure injustice also existed within most metro areas, even after accounting for housing age and the spatial structure of the data. Considering the injustices described here, we identify actions available to utilities, regulators, and advocacy groups that can be taken to improve the equity of local natural gas distribution systems.



KEYWORDS: *environmental justice, natural gas, infrastructure, methane, spatial modeling*

1. INTRODUCTION

Environmental justice (EJ) broadly refers to the principle that various sociodemographic groups equitably share the benefits of environmental amenities and the burdens of environmental hazards.[1,2] Furthermore, work to develop an environmentally just system seeks to eliminate environmental hazards altogether. Researchers have conducted EJ analyses of a wide variety of environmental burdens and benefits, from exposure to air pollution[3,4] to access to urban green spaces.[5] In this article, we consider EJ as it relates to the quality of pipeline infrastructure used in urban natural gas (NG) distribution systems.

NG distribution systems are an integral part of many U.S. metropolitan (metro) areas. According to the American Community Survey (ACS), 48% of occupied American housing units use NG for house heating.[6] NG is routed through metro areas and delivered to homes via a network of NG pipelines, typically located underground along city streets. A high leak density (leaks per mile of pipeline) is indicative of degraded infrastructure integrity, which often occurs as pipelines age[7] and can be a type of infrastructure injustice when the degraded pipe is nonrandomly distributed.

Natural gas leaks can lead to environmental hazards of varying severity. In some rare cases, the accumulation of NG from these leaks can develop into an explosion hazard, threatening both property and human safety. These events often capture national attention due to their unexpected occurrence and sometimes enormous impact on lives and property. In February 2018, a gas leak caused a home explosion, resulting in the death of a 12-year-old girl in a predominantly Hispanic Dallas neighborhood. The Dallas event raised questions about the co-location of leak-prone steel pipes and communities with high densities of people of color (PoC)[8] and what exactly are the impacts of NG leaks on community members. In September 2019, an 18-year-old man was killed, at least twenty more people were sent to the hospital, and at least 130 structures sustained damage after natural gas fires and explosions impacted three towns in the Merrimack Valley of Massachusetts.[9] In most cases, leaks are not immediately hazardous to human health but still represent an economic loss due to the value of the leaked gas, an environmental harm because they emit the potent greenhouse gas methane (CH_4) and can otherwise negatively impact the quality of life.

Several studies have now documented the burdens, benefits, and injustices of the oil and gas industry and its infrastructure.[4,10] These studies document the EJ impacts of oil and gas production, especially those related to fracking.[11−14] Looking at the location of natural gas gathering and transmission pipelines, Emanuel et al.[15] found that counties

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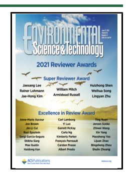

Table 1. Summary of the ALD Survey Results from Each Metro Area after Quality Control Filtering[a]

location	abbreviation	tracts (n)	leak indications (LI)	total road miles surveyed	leak density (LI/mile)
Birmingham, AL	Birm	8	114	213	0.54
Boston, MA	Bos	218	1998	2663	0.75
Burlington, VT	Burl	11	13	173	0.08
Chicago, IL	Chi	115	402	1153	0.35
Dallas, TX	Dal	29	414	804	0.51
Indianapolis, IN	Indy	7	1	82	0.01
Jacksonville, FL	Jax	26	81	1340	0.06
Long Island, NY	Long	367	1652	4574	0.36
Los Angeles, CA	LA	100	335	1686	0.20
Mesa, AZ	Mesa	14	1	194	0.01
Pittsburgh, PA	Pitt	30	226	348	0.65
Staten Island, NY	SI	105	967	1220	0.79
Syracuse, NY	Syr	53	211	624	0.34
total		1083	6415	15 074	0.43

[a]Each tract had at least 50% of its roadway surveyed. The average leak density across metro areas was 0.36 leaks per mile. The overall average leak density is higher because more miles of roadway were surveyed in metro areas with higher leak density.

with a high social vulnerability index (SVI) have higher pipeline concentrations than counties with a lower SVI. The SVI includes factors such as socioeconomic status, household composition and disability, nonwhite non-Hispanic population and language, and housing type and transportation.[16] Di Gregorio and Jordan[17] found that natural gas leaks from distribution systems were allowed to persist longer in census block groups that displayed more ethnoracial and linguistic diversity.

We explore variations in the frequency of leak indications derived from our previous urban methane surveys, where we used high-sensitivity methane analyzers deployed in Google Street View cars.[18] The technological approach for gathering this leak indication data, now commonly known as advanced leak detection (ALD)[19,20] has been identified as a best practice for finding natural gas leaks and estimating their size.[20] Our survey data included atmospheric methane concentrations in 13 U.S. metro areas, covering neighborhoods that are home to 4.5 million people. Within these metro areas, we characterize the relationship between the density of NG leak indications and demographic and infrastructure information at the census tract scale. Local distribution system infrastructure inequalities can arise due to multiple factors, such as historical policies, constraints imposed by regulatory oversight, lack of leak reporting by residents, utility leak repair practices and investment, or historic inequities. Considering these factors, our statistical approaches account for spatial correlation and use a multivariate approach to develop our conclusions. Such an approach for examining the patterns of leaks could also be used by local gas distribution utilities to assess potential inequalities and reveal areas where infrastructure investment or energy transition could be most beneficial.

2. METHODOLOGY

2.1. Data Description. We conducted surveys for natural gas leak indications in 13 U.S. metro areas: Birmingham, Boston, Burlington, Chicago, Dallas, Indianapolis, Jacksonville, Long Island, Los Angeles, Mesa, Pittsburgh, Staten Island, and Syracuse (see Table 1). These surveys used ALD to detect NG leaks in local distribution systems. The methodology and results of these surveys have been described in detail elsewhere.[18,21,22] Below, we summarize the most relevant features of the survey, data, and data processing for our EJ analysis.

Google Street View cars equipped with methane analyzers manufactured by Picarro or Los Gatos Research were used to identify methane-emitting sources in several metro areas. The data from these platforms were collected at 2 Hz and included atmospheric methane concentrations with part-per-billion (ppb) precision and GPS coordinates with a typical precision of less than 1 m. These data were processed to develop locations of methane point sources, called leak indications. Previously, we have demonstrated that the majority (>75%) of these leak indications correspond to NG leaks from local distribution pipelines.[22]

We identified multiple regions within each metro area as study areas for the ALD surveys. For the metro areas included in this analysis, these regions were chosen to capture the diversity of demographic and infrastructure features of the metro area, based on information available from the U.S. Census data.[23] Within each survey region, we drove each roadway in the selected areas two or more times, with the two drives occurring on different days. We used the vehicle's GPS data and the census' TIGER/Line[24] shapefiles to monitor the roadway coverage of the survey. The surveys were conducted only during favorable weather conditions (i.e., not raining, with dry road surfaces) during months of the year when soils were not frozen.

After completion of our survey, we used geographic information system (GIS) analyses to assign leak indications to census tracts. Additionally, we utilized the GPS data and TIGER/Line database to compute the total miles of roadway and the total miles of roadway surveyed within each tract. We designated a roadway section as surveyed if the vehicle drove the roadway on at least two occasions that were separated by at least 30 s. We used the count of leak indications and road miles surveyed to compute the leak indication density, given by leak indications per mile, in the census tract. Hereafter, we refer to the rate of leak indications per mile of roadway surveyed as the leak density.

We used the ACS[23] to obtain sociodemographic characteristics of the census tracts where we conducted our ALD surveys. We used the 5-year ACS estimates spanning the period of 2014−2017 because this time span aligns with the time when most of our leak surveys were conducted. For each

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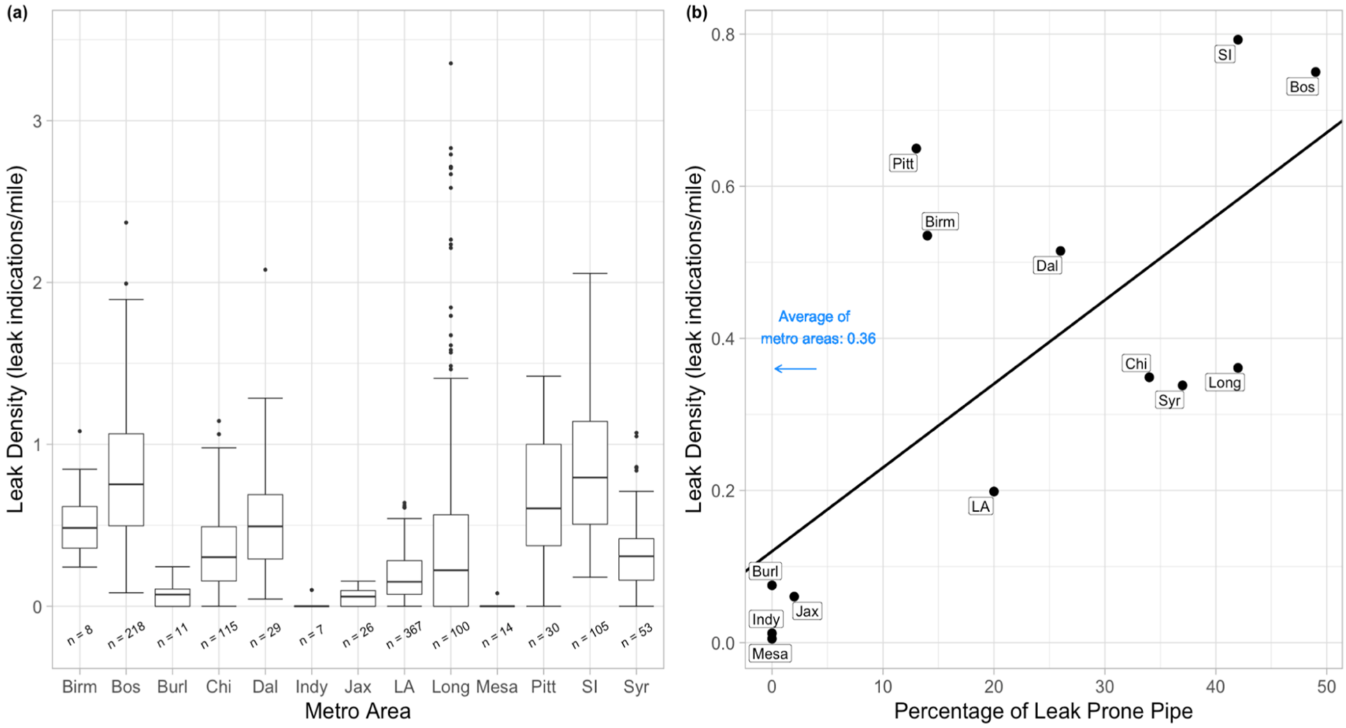

Figure 1. Variation in leak density within metro areas (a) and the relationship between leak density and percent of leak-prone pipes across metro areas (b). See Table 1 for metro area abbreviations. The boxplots in panel (a) show the distribution of leak density among surveyed census tracts within metro areas. The numbers below the boxplots indicate the number of surveyed census tracts. Panel (b) shows the range of leak density observed among metropolitan areas, and the regression line illustrates that higher leak density is associated with greater percentages of leak-prone pipes.

census tract, we computed the percentage of the population that met the description of indices defined by the Environmental Protection Agency's environmental justice screening and mapping tool (EJSCREEN).[25] These characteristics included the percent of the population consisting of PoC, percent of the population under age 5, percent of the population over age 64, and percent of households in linguistic isolation. We calculated percent PoC as the percentage of the tract's estimated population that does not identify as "white alone" in the ACS reporting. Linguistic isolation was calculated on a household basis and defined as the percent of households that are limited English speaking. We also extracted the median household income in each census tract. Collectively, we refer to these variables as EJ predictors. We have previously demonstrated that pipeline age is moderately correlated (r = 0.44) with housing age[7] and hypothesized that housing age could explain the variation in leak density. We used median housing age as a proxy for the age of the pipeline infrastructure within the census tract in our regression models.

We used several filtering criteria to remove unusual or missing observations from our data. There were many census tracts that had very little survey coverage. We excluded census tracts with less than 50% roadway coverage, where roadway coverage is defined as the percentage of the miles of roadway in the tract that was surveyed two or more times. A sensitivity analysis of this threshold indicated that, for most metro areas, the choice of threshold (e.g., 25% vs 50%) did not have a meaningful impact on the percentage of tracts that were excluded from the analysis. We also removed census tracts where one or more of the ACS variables were missing. Again, this filtering criteria resulted in just a small percentage of census tracts being dropped from the analysis. In total, our cleaned and filtered data consisted of 1083 census tracts with an estimated total population of 4 472 000 people. Table 1 lists the metro areas, metro area abbreviations, and the number of census tracts that are included in our analyses after filtering. The numbers reported in Table 1 will vary slightly from our previous publications of these data because of the filtering criteria used here.

For each metro area, we used pipeline data reported to the Pipeline and Hazardous Material Safety Administration (PHMSA) in 2015[26] to determine the percentage of leak-prone pipeline mains in the local distribution system. We defined a leak-prone pipe as a pipeline that is made of unprotected steel, cast iron, or wrought iron. Utilities are required to report the total miles of each pipe material in their distribution system on an annual basis.

2.2. Statistical Methodology. We conducted several analyses to model the density of natural gas leaks in urban areas. We first explored leak density variation within metro areas. Next, we examined the relationship between leak density and the percentage of leak-prone pipes in the local distribution system of those metro areas. Then we developed models to estimate the relationship between leak density and demographic and infrastructure characteristics across all our surveyed metro areas and within metro areas. We provide the details on these models and analyses in the Supporting Information (Sections SM1 and SM2). Briefly, we used Bayesian, negative binomial regression models to estimate the relationship between leak density and the EJ predictors, median household income, and median housing age. We standardized many of the predictor variables using z-scores to account for relative differences across metro areas (e.g., in

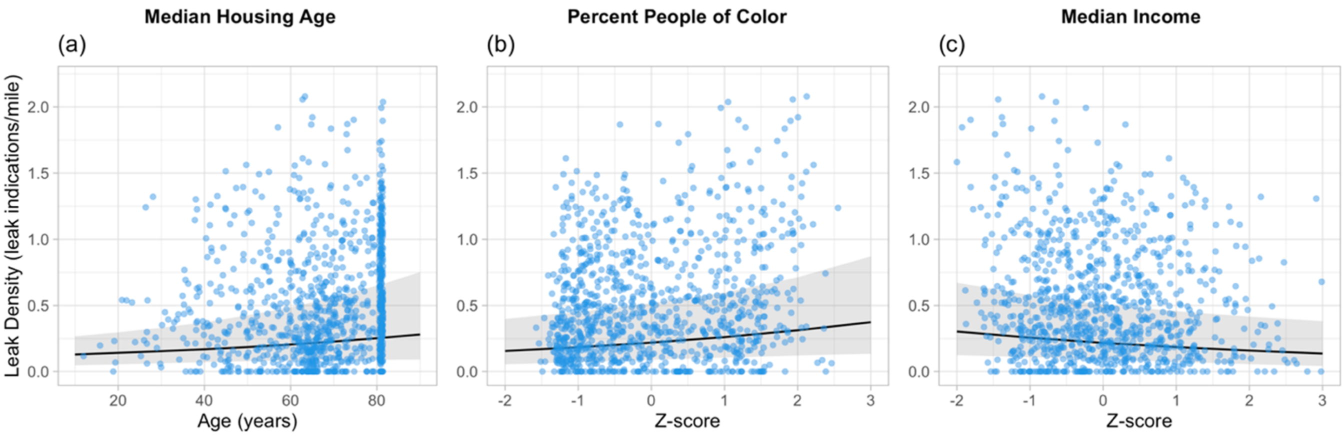

Figure 2. Combined relationship between median housing age (a), percent PoC (b), median income (c), and leak density. Each point in the figure represents a single census tract, where observations have been combined across all metro areas. There is statistical evidence of increasing leak density with both older housing and a greater percentage of people of color. The y-axis is truncated at 2.2 leaks/mile to facilitate comparisons and visualization of the trend lines. There are 14 census tracts (1.3% of the total observations) that are not shown due to this truncation.

income). All analyses were conducted using R software v4.0.4.[27]

3. RESULTS

3.1. Observed Leak Densities. Leak density varies within metro areas. The boxplots in Figure 1a demonstrate the variation in leak density among surveyed census tracts in the 13 metro areas. In many metro areas, the leak density varies among census tracts from near-zero to over 0.75 leaks per mile. In several census tracts, the leak density is greater than two leaks per mile. The remainder of our analyses examined how these leak densities vary both among and within metro areas as a function of sociodemographic factors.

There is a large variation in the leak density among metro areas (Figure 1b). Some metro areas, like Indianapolis and Mesa, have leak densities near zero, falling far below the survey average of 0.36 leaks per mile. Other metro areas, like Boston and Staten Island, have relatively high leak densities, as large as 0.75 leaks per mile. The variation in leak densities among metro areas can be partially explained by the quality of pipeline infrastructure. Leak density is moderately positively correlated ($r = 0.72$) with the percentage of leak-prone pipes in the metro area's distribution system. The results of a linear regression model between these two variables indicate that metro areas without leak-prone pipes still have an average leak density of 0.1 and that every additional 10% difference in leak-prone pipe abundance is associated with an increase of 0.1 leaks per mile, on average.

3.2. Combined Analysis: Single Predictor Models. In this section, we examine the relationship between our various EJ predictors and leak density combined across the surveyed metro areas. The results of our combined analysis reveal overall trends in our results by including all metro areas in a single analysis. In these models, metro areas are modeled with a random effect. While these results assume observations are correlated within a metro area, they do not explicitly account for the spatial correlation within metro areas, which is explored in the metro-by-metro analyses. We compare these relationships among metro areas in the following sections, Sections 3.3 and 3.4. We report effect estimates (slope term of the regression models) and uncertainty of these estimates in parentheses using 95% credible intervals. When the 95% credible interval for an effect does not contain zero, we define that as sufficient statistical evidence for the presence of a relationship. Hereafter, we use the term statistical evidence.

Our combined analysis of leak density and median housing age suggests that leak density increases with increasing housing age. The estimated combined trend is shown with the black curve in Figure 2a. A 10-year increase in median housing age is associated with an estimated 10% increase in leak density (95% Credible Interval, CrI: −1, 19%). Variation among metro areas is shown in the Supporting Information (Figure SM2d). We further explore the metro-by-metro trends in Section 3.3.

The results of our combined analyses provide statistical evidence that leak density increases with percent PoC (Figure 2b). The combined trend indicates that for a one-standard deviation additional difference in percent PoC, leak density increases by an estimated 19% (CrI: 5, 36%). On average, a one-standard deviation difference in percent PoC is 32%, and across our 13 surveyed metro areas, the average percent PoC was 37%. To put these changes in comparative terms, for census tracts with 5% PoC (one standard deviation below the mean), the estimated average leak density is 0.19 leaks per mile, while for census tracts with 69% PoC (one standard deviation above the mean), the estimated average leak density is 0.26 per mile. Thus, we estimate that average leak density increases by 37% when comparing census tracts having a predominantly white population with those having a majority population of PoC. Variation among metro areas is shown in the Supporting Information (Figure SM2e). We further explore the relationship between percent PoC and leak density for individual metro areas in Section 3.3.

Similarly, the combined analysis of median household income found statistical evidence for a decrease in leak density with increasing income (Figure 2c). To account for differences in income among metro areas, we standardized median income in the same way that we standardized percent PoC. For this variable, leak density decreases by an estimated 14% (−30, −4%) for each one-standard deviation additional difference in median income. Across metro areas, the average standard deviation of median income was ∼\$26 000 and the average median income was ∼\$42 000. Census tracts at this average are estimated to have 0.22 leaks per mile (one leak every 4.5 miles), while census tracts with a median income of \$92 000 (a two standard deviation increase) are estimated to have 0.16 leaks per mile (one leak every 6.3 miles). This represents an

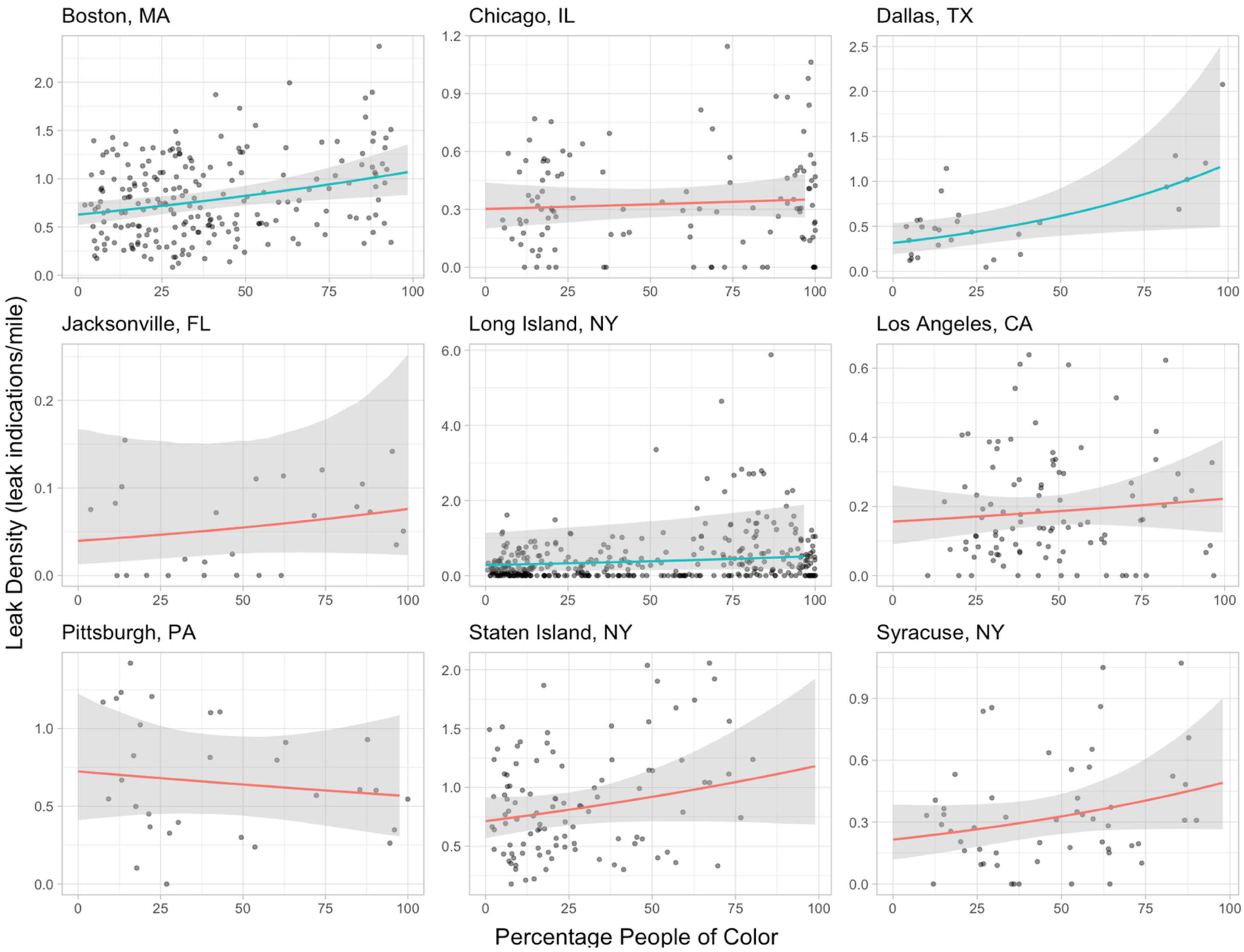

Figure 3. Relationship between percent people of color (PoC) and leak density from surveyed census tracts in each of nine of the metro areas. In eight of the nine metro areas, leak density is estimated to increase with increased percent PoC. Both the magnitude of this association and the overall leaks/mile vary among metro areas. Blue lines indicate that there is statistical evidence to conclude that leaks/mile increase with increasing percent PoC. Note that the *y*-axes vary across metro areas.

~26% decrease in leak density between an average income tract and a relatively high-income tract. Variation among metro areas is shown in the Supporting Information (Figure SM2f). We further explore this relationship in individual metro areas in Section 3.3.

We performed the same combined analyses for three other EJ predictors: percent linguistic isolation, percentage of population under age 5, and percentage of population over age 64. There was little statistical evidence of a relationship between leak density and these three other predictors. We provide additional details on within metro analyses of these variables in the Supporting Information (Section SM5).

3.3. Within Metro Areas. In this section, we examine the relationship between leak density and EJ predictors within individual metro areas. The results of our previous analysis revealed combined trends by including all metro areas in a single analysis. In those models, metro areas were modeled with a metro area-specific random effect. The results shown here are based on a regression model that explicitly accounts for the spatial correlation within metro areas using a census tract-specific random effect. Explicitly accounting for spatial correlation within metro areas produces a more conservative inference (e.g., wider credible intervals) relative to our previous analysis that combines all metro areas into a single model. Additionally, the uncertainty derived from these results accounts for differences in the number of surveyed census tracts across the various metro areas. Metro areas with greater survey coverage and therefore more surveyed census tracts tend to have narrower credible intervals.

Our metro-by-metro analysis of leak density and median household age indicates that leak density increases with increasing housing age in eight of the nine metro areas considered for this analysis. Areas with older housing also tend to have older pipeline infrastructure, which tends to be more leak-prone.[7] In Boston and Staten Island, there is statistical evidence to conclude that there is an association between median housing age and leak density. Among these three metro areas, the largest effect is in Staten Island, where a 10-year additional difference in median housing age is associated with an estimated increase of 15% (7, 25%) in leak density. In Boston, the increase is an estimated 13% (6, 20%). In two metro areas, there is an estimated decrease in leak density with increasing housing age: Los Angeles, −7% (−18, 6%) and Jacksonville, −3% (−37, 44%). The observed leaks per mile as a function of median housing age with the model fit are shown in the Supporting Information (Figure SM3).

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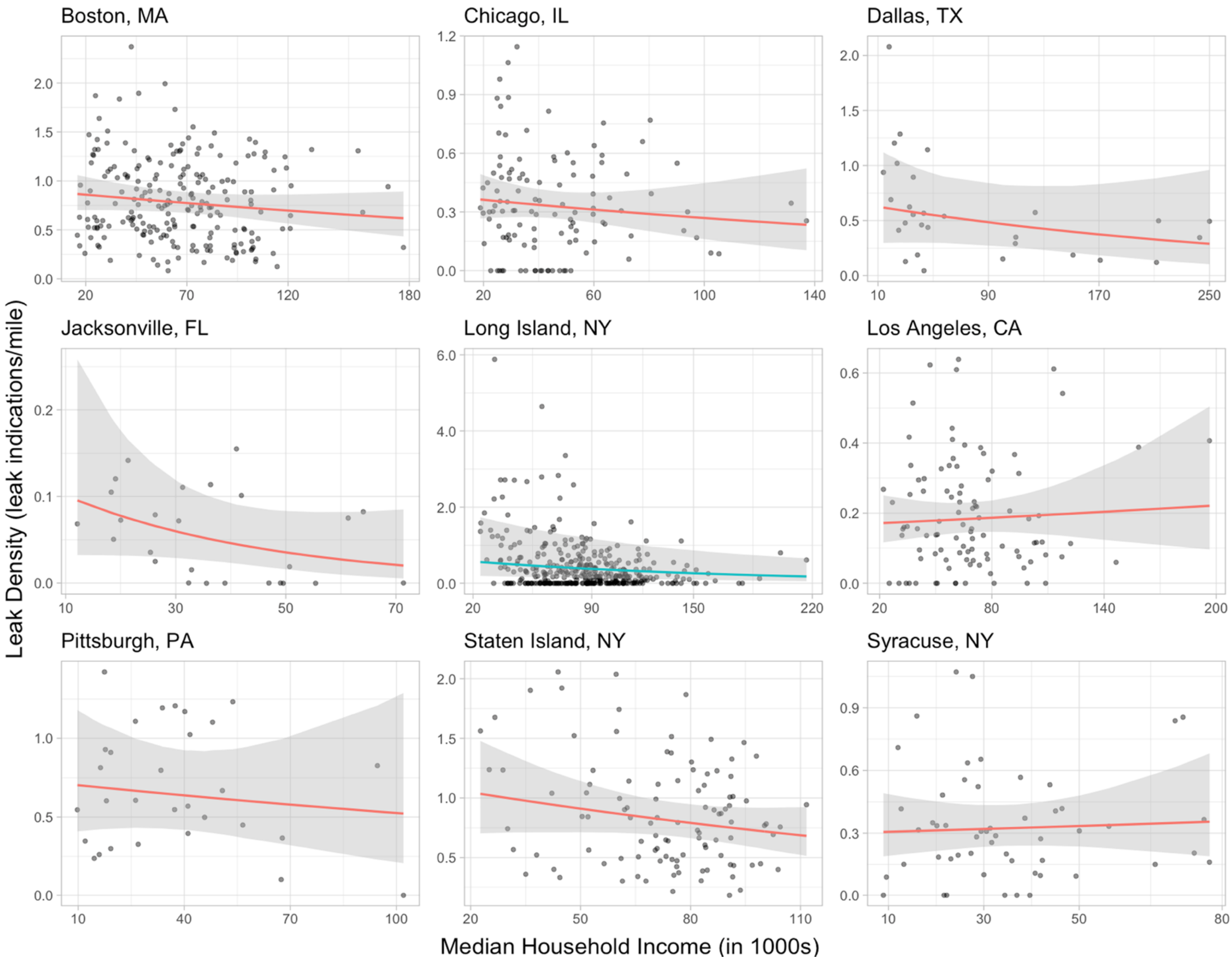

Figure 4. Relationship between median household income (in US dollars) and leak density from surveyed census tracts in each of nine of the metro areas. In seven of the nine metro areas, leak density is estimated to decrease with increasing income. In Long Island (blue line), there was statistical evidence to conclude that leak density decreases with increasing income. Note that the *x*- and *y*-axes vary across metro areas.

Across most metro areas, we found a higher leak density, on average, in areas with greater percentages of PoC. Our metro-by-metro analysis of leak density and percent PoC indicates that leak density increases with increasing percent PoC in eight of the nine metro areas considered for this analysis. Figure 3 displays the observed leak density as a function of percent PoC with the model fit. In Boston, Dallas, and Long Island, there is statistical evidence to conclude that leak density increases with percent PoC. Among these three metro areas, the largest effect is in Dallas, where a one-standard deviation additional difference in percent PoC is associated with an estimated increase of 52% (4, 111%) in leak density. Similarly, in Long Island, the same effect is estimated at 23% (1, 51%) and in Boston, the estimate is 15% (5, 26%). Pittsburgh was the only metro area where average leak density was estimated to decrease with percent PoC, but there was not enough statistical evidence to conclude that leak density decreases with percent PoC. We provide additional comparisons among metro areas in Section 3.4 (see Figure 5).

In nearly all metro areas, there was lower leak density, on average, in areas with higher incomes. Leak density decreased with increasing median income in seven of the nine metro areas in our analysis. The data from each metro area and model fits are shown in Figure 4. There was just one metro area, Long Island, where there was statistical evidence to conclude an association between leak density and median income. In Long Island, a one-standard deviation ($30 500) additional difference in median income is associated with an estimated decrease of 16% (2, 28%) in leak density. There were two metro areas, Los Angeles and Syracuse, where higher incomes were associated with greater leak density. In these metro areas, the estimated increases in leak density associated with a one-standard deviation increase in median income were both near-zero.

In seven metro areas (exceptions were Chicago and Jacksonville), leak density was estimated to increase with increasing percent linguistic isolation. However, there was large uncertainty in these estimates, and only one metro area, Long Island, had a credible interval that did not include zero. In Long Island, an additional one-standard deviation difference in percent linguistic isolation was associated with an estimated 36% (7, 70%) increase in leak density. In the other metro areas with positive estimates, these estimated effects were smaller, varying from 1 to 14%. We show the results of the linguistic isolation analysis in the Supporting Information (see Figures SM6 and SM9). As detailed in the Supporting Information

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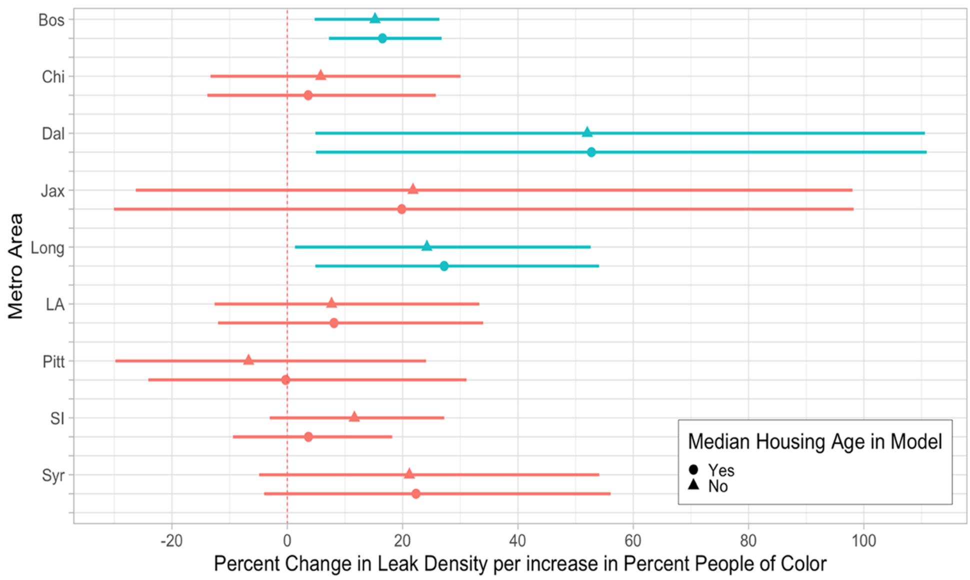

Figure 5. Estimated relationship (i.e., slope) between percent PoC and leak density with and without median housing age in the model. The *x*-axis shows the estimated percent change in leak density associated with a one-standard deviation additional difference in percent PoC. Blue credible intervals do not contain zero, indicating that there is statistical evidence of a relationship between percent PoC and leak density in the corresponding metro area.

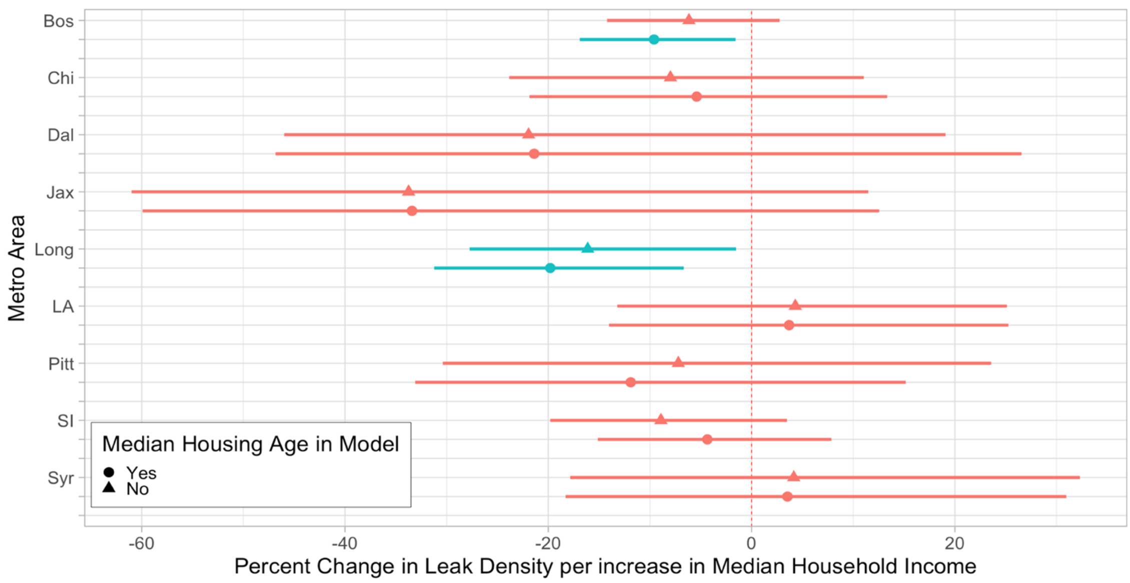

Figure 6. Estimated relationship (i.e., slope) between median household income and leak density with and without median housing age in the model. The *x*-axis shows the estimated percent change in leak density associated with a one-standard deviation additional difference in median income. Blue credible intervals do not contain zero, indicating that there is statistical evidence of a relationship between median household income and leak density in the corresponding metro area.

(Section SM5), there was no clear association between leak density and population age characteristics (percent under age 5, percent over age 64) across the nine metro areas.

3.4. Within Metro Areas: Controlling for Median Housing Age. In this section, we examine the results of spatial models fit to each metro area that included both an EJ predictor and median housing age in the same regression model. We use these models to assess the relationship between leak density and the EJ predictors while controlling for median housing age. Recall that in eight of the nine metro areas, leak density is estimated to increase with median housing age.

When we included both median housing age and percent PoC in the same model, there was little change in the estimated relationship between leak density and percent PoC. In other words, the relationship between leak density and percent PoC persists even after controlling for housing age. A comparison of the estimated effects of percent PoC, with and without controlling for median housing age is shown in Figure 5. The only notable differences in these effects are in Pittsburgh and Staten Island. In Pittsburgh, the estimated relationship between leak density and percent PoC moved from negative to near-zero after controlling for housing age. In Staten Island, the estimated effect decreased from 11 to 3% when including housing age in the model.

Like percent PoC, the estimated relationship between leak density and median income changed very little when controlling for median housing age. A comparison of the estimated effects of median income, with and without controlling for median housing age, is shown in Figure 6. In Boston, the inclusion of median housing age in the model increased the estimated effect of income from −6 to −10%, and there is now statistical evidence (95% CrI: −17, −2%) to conclude that leak density decreases with increasing median income while controlling for housing age. In Long Island, controlling for housing age also increased the estimated effect of household income from −16 to −20%. Conversely, this effect notably decreased in Chicago (−8 to −5%) and Staten Island (−9 to −4%).

We also examined the relationship between leak density and each of the three other EJ predictors (linguistic isolation, age under 5, and age over 64) in models that also included median housing age. For most metro areas, the effects of linguistic isolation, age under 5, and age over 64 on leak density were similar with and without median housing age. Details on these analyses can be found in the Supporting Information (Section SM6).

4. DISCUSSION

The results of our analysis reflect the state of the infrastucture at the time the survey data were collected (2014−2017). Our combined analysis of all metro areas reveals a disturbing inequality: leak density increases with both increasing percent PoC and decreasing income. We also find statistical evidence that leak density increases with housing age. However, when we control for housing age in our metro-by-metro area analysis, we see the persistence of the concerning relationship between leak density and percent PoC and median income in several metro areas. The sizes of these effects vary in their magnitude and uncertainty across metro areas, but their existence points to an unequal distribution of NG infrastructure quality. The results of our analyses suggest that the burdens associated with natural gas leaks resulting from degraded pipelines are not equally distributed across race or income and thus present an environmental injustice.

4.1. Impacts of Unequal Distribution of Natural Gas Leaks. Communities impacted by natural gas leaks and degraded pipeline infrastructure are subjected to multiple burdens. We broadly classify these burdens into three categories: safety, economic, and environmental/public health burdens. These burdens range from chronic to acute and likewise vary in severity, as has been documented for a variety of other EJ burdens.[15,28,29]

The most acute and local safety concern associated with natural gas leaks is explosions. The U.S. Pipeline and Hazardous Materials Safety Administration (PHMSA) has collected gas distribution incident reports since 1970. Most reported incidents are attributable to dig-in mishaps. However, over the time period of 2010−2020, there were a total of 256 significant[a] NG distribution pipeline incidents that were attributable to corrosion or equipment failure, incorrect operation, or material failure.[30] From these incidents, there were 13 fatalities, 161 injuries requiring inpatient hospitalization, and an estimated total cost (including property damage, emergency response, and gas released) of $1.7 billion. Our previous work has estimated that there are over 650 000 natural gas distribution leaks in the United States at a given time.[7] Many nonhazardous leaks are allowed to remain in distribution systems for years and can thus evolve from nonhazardous to hazardous over time.[31] Given that a few dozen explosions from distribution systems are reported each year, the probability of a leak causing an explosion is small, but explosions do happen. Though rare, the impact of a natural gas leak explosion is typically enormous, and our analysis suggests that these impacts are more likely to occur in neighborhoods with lower income or higher percent PoC.

Natural gas leaks can have health or nuisance odor impacts[32] due to added mercaptan. When a storage gas well began leaking in Aliso Canyon, CA, the odor was described as nauseating and sickening[33] and an estimated 2500 families were displaced for several weeks.[34] Buildup of methane in a poorly ventilated space can displace the ambient air, and inhalation can cause asphyxiation or hypoxia.[35]

Additional local impacts of natural gas leaks include economic burdens. In most utility rate structures, the expense of gas lost from these leaks (usually called lost and unaccounted for or LAUF gas) is passed to the consumer.[36] Consumers pay for infrastructure improvements such as pipe repair or replacement, and our findings suggest that these improvements may not be equally distributed. Additionally, natural gas leaks can cause vegetation to die,[37,38] adversely affecting neighborhood aesthetics, shade and cooling, and potentially reducing property value. This can have cascading impacts on the sense of neighborhood satisfaction and can impact the sense of life satisfaction.[39]

There are also broader impacts associated with natural gas leaks. These impacts do not necessarily occur in the same location as the leak locations, but they create environmental and public health burdens. Natural gas is primarily composed of the greenhouse gas methane, and an estimated 20% of current warming is attributable to methane.[40,41] Climate change effects are not always immediately obvious or easily quantified, but by many measures, they disproportionately affect vulnerable populations.[42] On a regional or global level, methane can also contribute to the formation of tropospheric ozone,[43] which can contribute to respiratory issues in vulnerable populations.[44−46]

Cumulatively, the burdens of poor infrastructure as indicated by natural gas leaks raise concerns on many levels, and this work adds documentation to the litany of injustices already faced by vulnerable populations. In the case of the natural gas distribution infrastructure, we find that the burdens are not always immediately visible, but many small failures can cumulatively increase the risk to life, health, and property and the environment experienced by vulnerable populations. Gas utilities are required to undertake routine analysis to identify and mitigate threats to their systems.[31,47] These routine analyses represent an immediate opportunity to improve social and environmental justice by eliminating disparities in natural gas leak densities. Elimination of disparities could be achieved through equitable leak repair, pipeline replacement, or pipe retirement to accommodate a non-pipeline alternative.

4.2. Pathways for Improving Equity of Local Distribution Systems. Considering the patterns revealed by our analysis, we identify possible pathways for stakeholders that could create a more equitable energy system. These stakeholders include utilities, regulators, and concerned community members. In many cases, there are numerous, complex factors that give rise to these documented inequalities, and as a result, require an intentional, multifaceted, and collaborative approach to resolution. Naturally, approaches

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must be customized because each utility and community faces a unique set of constraints.

The prioritization, management, and transparency of utilities can improve the equity of the distribution systems they oversee. Utility companies could prioritize repair and replacement in EJ communities when all other risks and costs are equal. Leak surveillance with advanced leak detection methods reduces the burden of leak detection on the public, which is critical because some populations may be less able to detect leak odors, be unwilling to report them, or face barriers to reporting (e.g., lack of language accommodation). Finally, the public reporting of data on leak locations, repairs, and pipeline incidents enables transparency in the quality of infrastructure, attention dedicated to different segments of the distribution system, and any systematic aspects of incidence occurrences.

As agencies that provide oversight to utilities, regulators can ensure just local distribution systems by mandating public reporting and equitable long-term planning. In this context, regulators include the state public utility commissions; state agencies associated with pipeline safety, environmental justice, and air quality; and federal agencies, including the Department of Transportation's Pipeline and Hazardous Materials Safety Administration (PHMSA), Department of Energy, and the Environmental Protection Agency. Should public reporting be mandated, regulators can support hosting this data and/or encouraging its availability in an accessible and georeferenced format (e.g., at the census tract-level), thus ensuring that public input is informed by this. The data can have the strongest impact when used for decision-making and long-term planning to ensure a more just, safe, and reliable energy system. The presence of disparities in leak densities as a function of demographic characteristics suggests a need for public input processes to actively include and accommodate populations that have greater exposure to high leak densities.

Community members may want to share observations and voice concerns about the safety, economics, justice, or environmental issues associated with natural gas leaks. These concerned community members can participate in regulatory processes and engage in discussions with their utility or regulatory agencies to address disparities in leak densities. Opportunities for participation and discussion may include rulemakings, broader comment periods, direct outreach to the utility or regulator, and more.

Scientific studies can document the patterns in system integrity, illustrate the causes and impacts of failures in systems, and reveal pathways to better management. Community members, utilities, and regulators can collaborate with scientists to design studies that will further evaluate the reasons for demographic disparities in leak densities. Further research combined with the analytical framework presented here can be used to improve the safety, reliability, and equity of local natural gas distribution systems.

■ ASSOCIATED CONTENT

Supporting Information

The Supporting Information is available free of charge at https://pubs.acs.org/doi/10.1021/acs.est.2c00097.

> Additional details on the statistical methodology (Section SM1), model estimation (Section SM2), ALD vehicle survey coverage (Section SM3), and results of our data analysis (Sections SM4−SM6) (PDF)

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Notes

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■ ADDITIONAL NOTE

[a]PHMSA defines significant incidents as those resulting in any of the following: (1) Fatality or injury requiring inpatient hospitalization; (2) \$50 000 or more in total costs, measured in 1984 dollars; (3) Highly volatile liquid releases of five barrels or more or other liquid releases of 50 barrels or more; or (4) Liquid releases resulting in an unintentional fire or explosion.[48]

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