Driving Displacement: Energy, Social, and Environmental Determinants' Roles in Urban Gentrification

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ABSTRACT

Energy equity and insecurity is a growing concern in the U.S. as nearly one in three households find it challenging to meet their basic energy necessities; 20% of households forgo fundamental needs like food and medicine to pay energy bills, and more than 10% report keeping their homes at unsafe and unhealthy temperatures (EIA 2017). Cities have adopted clean energy goals that center equity and are exploring different means of achieving these targets.

Research has shown that lower income households experience higher energy burdens (the percent of household income spent on utility bills), but its relationship to community displacement and gentrification is less well understood. In this study, novel datasets and machine learning modeling techniques are applied to evaluate the relationship between urban tree canopy, energy burden, redlining, energy use intensities, population migration, socio-economic indicators, and displacement, among others, at the neighborhood level in three U.S. cities. This research investigates how these variables may serve as indicators for gentrification in the U.S. Finally, the current policy landscapes for these cities are briefly investigated and compared against the ACEEE State and Local Scorecards to provide some context for future policy discussions focused on improving equity outcomes.

INTRODUCTION

With the combination of inflation and the lifting of the COVID-19 eviction moratorium, families across the U.S. could face an increased risk gentrification, which is a process of neighborhood change that occurs due to economic development, usually because of a shift in average income and education levels and racial composition of its neighborhoods (Chapple 2021). The process of gentrification was initially perceived to reverse decades of urban decline where it had the potential to bring broad new benefits to cities through a growing tax base, increased socioeconomic integration, and improved amenities (Vigdor 2002; Diamond 2016). Instead, the highly visible changes occurring in gentrifying neighborhoods were driven by the direct displacement of original residents, making them worse off and preventing them from sharing in the benefits (Quentin Brummet and Davin Reed, 2019). Displaced residents face housing instability and high levels of stress with increased levels of homelessness and disrupted community ties taking additional tolls on mental health (Hannah De los Santos 2022).

The risk for displacement is not evenly distributed. Low-income households and communities of color often experience greater risk for displacement. In addition to demographic factors, there are many social determinants such as housing, economic, and environmental indicators that may contribute to this risk across the U.S.

Housing Indicators

Housing factors contributing to displacement risk may include the cost of housing, the type and ownership structure of housing, or residing in a formerly redlined neighborhood. Redlining was an American real estate practice where areas were designated as hazardous for investment with red ink on maps as a warning to mortgage lenders. The presence of racial minorities was a strong determinant in designating an area as hazardous, effectively isolating Black residents into areas that would receive lower levels of investment than their White counterparts (Perry & Harshbarger 2022). Though redlining was outlawed decades ago, many communities are still impacted today, experiencing lower access to tree coverage, increased risk of preterm births, and increased risk of fatal police encounters (Nowak 2022; Krieger 2020; Mitchell 2021). Additionally, without price protection policies, renters are exposed to greater housing cost variability than owners when the market cost of housing is incorporated in a new lease agreement. Nationally, rent prices have increased 17% in the past year and are expected to increase by another 10% over the next year (Bachaud 2022). Unaffordable rents can lead directly to displacement.

Economic and Environmental Indicators

Many economic factors also contribute to the risk for displacement. The most obvious is median household income. Low-income households may sometimes have difficulty paying rent and utility bills. Households that cannot afford to pay energy bills frequently cannot afford other costs of living such as rent, creating eviction risks that can result in displacement (Haider 2020, Body 2019). Energy burden (the percentage of annual household income spent on gas and electricity bills) is a key concept in understanding this relationship. Nearly 13% of families across the U.S. are paying more than 10% of their annual income on utility bills, making them severely energy burdened (Drehobl, et al., 2020). High Energy Use Intensity (EUI) (energy per square foot) can also contribute to high energy bills. In addition to the potential displacement implications of high household energy burdens, the concept of “green gentrification” has recently received increased attention. Green gentrification occurs when environmental improvements lead to increases in perceived local desirability that result in higher property values and rents (Green Gentrification n.d.). Such efforts can harm renters if housing costs become unaffordable, increasing the risk for displacement.

Health Indicators

In addition to the housing factors associated with displacement, mental health can also act as a risk factor for displacement. Mental health conditions can include depression, anxiety, lack of sleep, or addictive behaviors. Poor housing conditions, high energy bills, and economic hardships can trigger mental health episodes. For many households, stress from high energy bills and the possibility of losing electricity service altogether can exacerbate mental health conditions (Brown, et al., 2020). Reminders of service shut offs due to late or missed payments, coupled with societal shame and potential worries of deteriorating housing conditions, can exhaust mental reserves and prompt families to relocate to avoid shame and discomfort (Hernández, 2016). These issues may not resolve immediately upon relocation and may also be exacerbated by non-energy stressors, leading to the emergence of mental health conditions like depression. Coping with mental health episodes can make it difficult to go to work or earn income in other ways that could help lower the risk of being displaced (Tran 2018).

To mitigate the risk of displacement, there needs to be a greater understanding of the relationship between different socio-economic determinants such as those mentioned earlier. The goal of this study is to understand how these different factors can exacerbate these risks in three major cities across the U.S.: San Francisco, Atlanta, and Chicago.

Table 1. City Characteristics for Atlanta, Chicago, and San Francisco

	Atlanta	Chicago	San Francisco
City Characteristics			
Tracts	165	842	190
Median Income	$70,499	$63,468	$113,271
Energy Burden	4%	5%	2%
Percent Renters	52%	52%	59%
Percent Multi Family Units	48%	65%	63%
Median EUI (kWh/ft^2)	10	14	5
Racial Demographics			
White	41%	38%	44%
Black	47%	28%	4%
Asian	4%	6%	33%
Multi	2%	2%	4%
Hispanic or Latino	6%	25%	14%

Table 1 outlines characteristics for each of the three chosen cities. The cities selected for this study were chosen for their location, demographic, climatic diversity, and data availability. A closer look at how our findings interact with existing city-level energy policies outlined in ACEEE's *2021 Clean Energy Scorecard* are found in the discussion.

METHODOLOGY

Data Gathering

Displacement is a complex topic driven by historical conditions, disinvestment, and development patterns (Chapple 2021). The Urban Displacement Project (UDP) is a research initiative out of the University of California, Berkeley that strives to understand the nature of gentrification and displacement. Data on displacement that highlight neighborhood change across census tracts in Atlanta, San Francisco, and Chicago were gathered from the UDP to better understand current displacement risk within the 3 cities. In this data, tracts are characterized across a spectrum of displacement (from low-income/susceptible to displacement to stable/advanced exclusive). Data on the number of people that moved inter- and intra-city were extracted from the

UDP database to observe neighborhood change on a census tract level specific to population counts.

The American Community Survey (ACS) includes annual survey responses by American residents regarding several economic, geographic, and household indicators, including utility spending and household income. Across Atlanta, Chicago, and San Francisco, data for approximately 1,200 census tracts were analyzed based on 2019 five-year estimates from ACS.

Energy related determinants such as energy burden and energy use intensity (EUI) were also evaluated as part of the analysis. EUIs provide insight into household energy performance and are calculated by dividing the annual energy usage by median square footage for a given census tract. The median square footage is extracted from Zillow's database based on the median year built for houses on a zip code level for each city. Energy spend data is used alongside average utility rates taken from the EIA-861 Annual Electric Power Industry Report to derive household energy usage and then divided by the median square footage for the corresponding ZIP code to get EUIs for each census tract. Due to data limitations, EUIs were only able to be calculated on a ZIP code level. Energy burdens are taken from the Greenlink Equity Map (Greenlink Equity Map 2022).

The survey data, energy use intensities, and gentrification data were combined with tree canopy cover extracted from the National Land Cover Database (NLCD), University of Richmond's Digital Scholarship Lab Redlining dataset, and Center for Disease Control's (CDC) chronic disease risk factors.

Model Development

To assess the effects of key environmental and socio-economic determinants on displacement likelihood and identify tracts at-risk for future displacement, a descriptive model was developed. Several independent variables were compared against the dependent variable of displacement risk to narrow down the specific determinants that have a lasting impact on displacement for each city. The independent variables evaluated are *urban tree canopy (UTC), energy burden, EUI, and redlining*, alongside several other socio-economic variables gathered from the survey data such as *median income, housing characteristics, migration, and gross rent.* The independent variables were fitted against the dependent variable of *displacement risk* based on the categories assigned by the Urban Displacement Project.

Many of the independent variables are indicators of gentrification. Displacement risk can be exacerbated by gentrification, particularly when community stabilization policies are not in effect (Chappel 2021). The displacement typology categories describe different stages of transition risk, ranging from gentrification, displacement, stability, and exclusivity. Before training the machine learning (ML) model, census tracts undergoing displacement and gentrification were grouped into a single category of "*displacement*" while exclusive census tracts were grouped into "*exclusive"*. The "*displacement*" group includes tracts that are susceptible to displacement or with ongoing displacement and includes already gentrified census tracts. *"Exclusive*" includes tracts that are advanced exclusive or have already been gentrified and are now experiencing high rents such that low-income residents are excluded. Stable census tracts can be identified as tracts that have been gentrified but are not currently at risk of becoming exclusive or ones that experience long-term exclusivity (The Urban Displacement Replication Project 2022). These neighborhoods were excluded from the model to focus its learning on characteristics indicative of the previous two categories. For example, by building a binary-classification model (instead of a multiclass classification), using 'gentrification' and 'exclusive' as the categories, the model was able to have more frequent occurrences to learn from. This aggregation allowed the model to learn against the true categories of interest in this research; each census tract is assigned to one of the two displacement typology categories. The data was then randomly split into an 80/20 training and testing set, where 80% of the data was trained on and 20% was used for testing how accurately the model could predict the census tracts experiencing displacement.

Several tests like checking for multicollinearity, skewness and unbalanced data were employed to ensure the data could be properly analyzed before moving forward with model learning. High intercorrelations (multicollinearity) among two or more independent variables used to train the model could lead to skewed or misleading results as change in one variable would also lead to a change in another variable leading towards fluctuating results with large standard errors and wider confidence intervals. To address multicollinearity, specific variables that are identified as most collinear with other independent variables were removed. For instance, median income was removed to reduce multicollinearity from the model as it is highly collinear with energy burden and the median house value of owner-occupied units. The Variance Inflation Factor (VIF) was used alongside a correlation matrix to ensure that no two interdependent determinants were used to fit the model, ensuring the lowest correlations between the independent variables. Data was first standardized to bring all independent variables to the same scale so that the model does not interpret variables with high scalar values as having higher importance during training. Next, skewness in the data was addressed to avoid degradation of model performance as rare cases and extreme values (outliers) could lead the model to poorly describe the typical behavior of data. A Yeo-Johnson power transformation function was applied to convert the data into a Gaussian-like distribution to address skewness (Yeo 2000).

The model was trained using the balanced dataset to learn and understand the relationship between different environmental and socio-economic determinants and their impact on displacement risk for each census tract within the three cities. A baseline model captured the performance of a random classification model without any tuning or customizations to see if the model was able to identify the relation of the majority class represented. After fitting the baseline model, data was trained and tested for performance on five different models before choosing the best one for final training (Table 2).

All models were evaluated based on prediction accuracy to determine the best fit for evaluating displacement risk. Accuracy is defined by the percentage of tracts that are correctly identified by the model. After analyzing the performance metrics, the model with the best outcome was the Random Forest Classifier for all three cities but with different hyperparameters**.** This model was then tuned to find the optimal hyperparameters using a grid search cross validation (GridSearchCV) method to protect against overfitting.

Table 2. Model Training Performance (Accuracy) of Models for Each City

Model	San Francisco	Atlanta	Chicago
Logistic Regression (LR)	80.3%	89.3%	88.0%
Support Vector Machine (SVM)	76.5%	86.3%	88.0%
K Nearest Neighbors (K-NN)	70.2%	89.7%	84.2%
Bagging Classifier	76.9%	89.7%	84.8%
Random Forest Classifier	**81.7%**	**91.0%**	**86.7%**

The final model was then used to classify tracts into "*displacement*" and "*exclusive*" while evaluating the indicators which have the strongest influence in each of the classifications to accurately understand and describe the impact of the different determinants on displacement risk.

In addition, the independent features used in each city's modeling were plotted against health indicators (Poor Mental Health, Coronary Heart Disease and Asthma rates) on a census tract level taken from Greenlink Equity Map (GEM) to understand their correlations within each city, shown in Table 4 (Greenlink Equity Map 2022).

RESULTS

After employing several tests and transformations to address missing values, multicollinearity and data skewness, the model hyperparameters were tuned for quality and accuracy. The values in Table 3 show the determinants because of the Random Forest model with their associated feature importance ranks, a measure of the model's understanding of correctly determining the final classifications through a specific indicator, and level of significance, or p-value. Determinants with a p-value < 0.05 were observed as significant and listed with an asterisk (*) beside them. Although the determinants vary among the three cities, the final significant outputs generally highlight migration patterns, education levels, energy burden, and housing imbalances as leading indicators increasing the threat of displacement risk. Shown in Table 3, the models determined there are five significant indicators for Chicago, three for San Francisco, and two for Atlanta. San Francisco's significant features were *households under severe energy burden*, *median square feet*, and *number of people moving from abroad*. In Chicago, displacement risk was guided by *redlining* (whether or not a census tract was previously redlined), *number of single-family units*, *households under high energy burden*, *median home value of owner-occupied units*, and *population (>25yrs) with a master's degree*. Displacement for Atlanta was similarly transformed by energy burden and migration patterns. *Households under energy burden* and *number of people moving from outside the city* hold the greatest weight when defining displacement risk for Atlanta. In general, the model indicates that Atlanta shows fewer significant indicators for describing displacement risk. This could be for a variety of reasons such as Atlanta containing fewer census tracts in the analysis compared to the other cities or the absence of a significant trend in the data if gentrification has been recently introduced to the city.

Several health-related indicators showed high multicollinearity with the socioeconomic indicators listed in Table 3 and were therefore removed from the analysis. However, to better understand the relationships between them, an additional correlation analysis was implemented between each model's features and three tract-level health indicators: *prevalence of poor mental health*, *prevalence of asthma*, and *prevalence of coronary heart disease*. The correlation analysis labels the strength of the relationship by using a correlation coefficient, ranging from -1 and +1, where an absolute value of > 0.6 indicates strong correlation, 0.4 - 0.6 indicates a moderate correlation, and < 0.4 is regarded as weak correlation. When evaluating results for Atlanta, all three health indicators showed a strong correlation with energy burden and the number of residents with a master's degree. Poor mental health and asthma had a strong correlation with the median home value of owner-occupied units and number of residents with a PhD. Asthma also had a strong correlation with eviction rates for Atlanta. Similarly, both mental health and asthma in Chicago have a strong correlation with energy burden while asthma alone has a strong relationship with eviction. All three health indicators for Chicago indicate a strong correlation with the median value of owner-occupied units, as well. Although no indicators had a strong correlation with any of the health indicators for San Francisco, energy burden and eviction rate did have a moderate correlation with a few of the health indicators (Table 4).

Table 3. Ranked Model Determinants with Associated P-Values for the Three Cities

	San Francisco	Atlanta	Chicago
Percent Urban Tree Canopy, 2019	Rank 15 (0.9131)	Rank 11 (0.0863)	Rank 17 (0.6956)
Redlined	Rank 14 (0.8333)	Rank 15 (0.372)	Rank 16 (0.0325)*
Median income, 2018	-	-	-
Electricity and gas burden, 2018	Rank 5 (0.0896)	Rank 1 (0.8437)	Rank 1 (0.0818)
Households Under Energy Burden, 2018	Rank 10 (0.0724)	Rank 10 (0.0174)*	Rank 10 (0.3606)
Households Under High Energy Burden, 2018	Rank 11 (0.4368)	-	Rank 12 (0.0076)*
Households Under Severe Energy Burden, 2018	Rank 9 (0.0373)*	Rank 7 (0.2224)	Rank 8 (0.2966)
Eviction rate, 2017	Rank 8 (0.6529)	Rank 5 (0.0968)	Rank 7 (0.8026)
Median Sq. Ft., 2018	Rank 1 (0.0006)*	Rank 6 (0.1122)	-
Median Energy Usage Intensity, 2018	Rank 13 (0.1305)	-	Rank 11 (0.1134)
Number of occupied housing units, 2018	-	-	-
Number of owner occupied units, 2018	-	-	-
Number of single family units, 2018	Rank 4 (0.4043)	Rank 14 (0.3321)	Rank 4 (0.000)*
Median home value of owner occupied units, 2018	-	Rank 2 (0.1447)	Rank 3 (0.000)*
Median gross rent, 2018	-	-	-
Total units built, 2018	-	-	-
Total population, 2018	-	-	-
Population (>25yrs) in 2018	-	-	-
Population (>25yrs) with a Bachelor's degree in 2018	-	-	-
Population (>25yrs) with a Master's degree in 2018	-	Rank 4 (0.1809)	Rank 2 (0.0171)*
Population (>25yrs) with a PhD degree, 2018	Rank 2 (0.0878)	Rank 3 (0.2374)	Rank 5 (0.5263)
Number of people (with income) who moved within city, 2018	Rank 7 (0.769)	Rank 12 (0.1167)	Rank 14 (0.7425)
Number of people (with income) who moved in from outside the city, 2018	Rank 6 (0.0908)	Rank 9 (0.0293)*	Rank 13 (0.2946)
Number of people (with income) who moved in from outside the state, 2018	Rank 3 (0.1136)	Rank 8 (0.1615)	Rank 9 (0.5811)
Number of people (with income) who moved from abroad, 2018	Rank 12 (0.0371)*	Rank 13 (0.7506)	Rank 15 (0.5379)

**p<.05*

Table 4. Health Correlations with Model Determinants in the Three Cities

	San Francisco			Atlanta			Chicago		
	MHLTH	ASTHMA	CHD	MHLTH	ASTHMA	CHD	MHLTH	ASTHMA	CHD
Percent Urban Tree Canopy, 2019	-0.14	-0.09	0.09	-0.1	0.07	0.23	-0.1	-0.06	0.06
Redlined	0.19	0.18	-0.05	0.2	0.12	-0.08	0.17	0.22	0.09
Median income, 2018	-	-	-	-	-	-	-	-	-
Electricity and gas burden, 2018	0.49	0.48	0.19	**0.77**	**0.76**	**0.62**	**0.68**	**0.66**	**0.6**
Households Between 3% and 6% Energy Burden, 2018	-0.03	-0.13	0.04	-0.2	-0.13	-0.13	-0.27	-0.28	-0.11
Households Between 6% and 10% Energy Burden, 2018	0.18	0.06	0.03	-	-	-	0.06	-0.03	0.15
Households Above 10% Energy Burden, 2018	0.33	0.27	0.2	0.43	0.46	0.39	0.35	0.35	0.39
Eviction rate, 2017	0.43	0.34	0.24	0.59	**0.67**	0.52	**0.52**	**0.67**	**0.46**
Median Sq. Ft., 2018	-0.1	-0.1	-0.07	-0.3	-0.31	-0.24	-	-	-
Median Energy Usage Intensity, 2018	0.09	0.03	0.12	-	-	-	0.1	0.12	0.08
Number of occupied housing units, 2018	-	-	-	-	-	-	-	-	-
Number of owner occupied units, 2018	-	-	-	-	-	-	-	-	-
Number of single family units, 2018	-0.21	-0.27	0.19	-0.18	-0.01	0.23	-0.12	-0.01	0.22
Median home value of owner occupied units, 2018	-	-	-	**-0.74**	**-0.74**	-0.5	**-0.66**	**-0.61**	**-0.67**
Median gross rent, 2018	-	-	-	-	-	-	-	-	-
Total units built, 2018	-	-	-	-	-	-	-	-	-
Total population, 2018	-	-	-	-	-	-	-	-	-
Population (>25yrs) in 2018	-	-	-	-	-	-	-	-	-
Population (>25yrs) with a Bachelor's degree in 2018	-	-	-	-	-	-	-	-	-
Population (>25yrs) with a Master's degree in 2018	-	-	-	**-0.72**	**-0.7**	**-0.6**	-0.59	-0.47	-0.47
Population (>25yrs) with a PhD degree, 2018	-0.34	-0.22	-0.35	**-0.62**	**-0.61**	-0.51	-0.4	-0.31	-0.3
Number of people (with income) who moved within city, 2018	-0.02	-0.02	-0.31	-0.08	-0.18	-0.35	-0.31	-0.3	-0.39
Number of people (with income) who moved in from outside the city, 2018	0.32	0.21	-0.23	-0.08	-0.22	-0.38	-0.27	-0.28	-0.39
Number of people (with income) who moved in from outside the state, 2018	-0.07	-0.03	-0.31	-0.31	-0.47	**-0.6**	-0.35	-0.32	-0.45
Number of people (with income) who moved from abroad, 2018	-0.03	-0.06	-0.21	-0.15	-0.32	-0.46	-0.23	-0.24	-0.23

DISCUSSION

The results of this study indicate that high energy burdens, increasing housing prices, and poor mental health are correlated with neighborhood displacement in San Francisco, Atlanta, and Chicago. Using ACEEE's 2021 Clean Energy Scorecard, we identify how existing building and energy policies within each city interact with these results and neighborhood displacement. Although often well-intentioned, some policies or programs may have adverse effects on the issues they're trying to resolve. Policies meant to increase energy efficiency within multifamily rental units, for example, have the potential to lower residential bills, improve public health, and increase grid resiliency. These policies, however, also have the potential to harm equity outcomes if landlords pass down incurred costs from efficiency investments to their residents (Hart et al., 2020). Understanding the interactions between well-intended government policy and the realities affected by them are crucial in improving equity impacts.

Consistent with existing research, our results show that higher rent and housing prices, combined with an influx of new, wealthier residents, are associated with the displacement of low-income renters in San Francisco (Verma et al. 2019). In Atlanta and Chicago, poor mental health and high energy burden are two topics of concern and are correlated with each other. Energy burden in both Chicago and Atlanta can be as high as 18% in some neighborhoods, most of which are predominantly renter occupied. Enhancing policies and programs related to equity, smart growth, transportation, and climate goals are crucial to improving energy burden and mental health issues that we have shown as correlated with displacement.

Both Atlanta and Chicago have adopted building energy consumption disclosure policies intended to reduce energy consumption in commercial and residential buildings. Atlanta currently requires large commercial and multifamily buildings to disclose their energy consumption and undertake energy audits if they do not meet energy performance standards. Chicago passed a benchmarking ordinance in 2014 that requires owners of buildings 50,000 square feet or greater to measure and report their energy consumption. In 2019, an Energy Rating System policy was introduced in Chicago to encourage landlords to disclose home heating costs. Benchmarking and transparency policies are beneficial because they more accurately inform prospective renters of building energy use before committing to a lease. Both cities might improve these policies by expanding them to smaller multi or single-family buildings so that more residents are reached.

As detailed in this research, a high energy burden is a primary indicator for displacement and shows a correlation with health outcomes across the analyzed cities. It is important to create policies that intentionally support individuals and households most at risk from these indicators to improve equity outcomes. While the policies mentioned within the 2021 City Clean Energy Scorecard promote energy efficiency and therefore reduce the energy use of tenants, some of them could permit landlords to pass increased costs from clean energy investments onto their tenants (Bird & Hernández 2012). Energy bills may be reduced from energy efficiency improvements, but an increase in rent simply redistributes inequitable cost burdens across this population and does little to reduce stress and mental health issues for low-income households.

Interventions intended to promote energy equity are not limited to relying on energy policies–there are several pathways available to local governments across housing, racial, economic, and environmental policy. Financial incentives or support from governments and financial institutions should be accessible to building owners who cannot afford efficiency upgrades so that these costs do not get passed on to residents. Increasing and preserving affordable housing through rent stabilization policies could be effective in neighborhoods most at risk of displacement. Community land trusts with energy efficiency at the forefront can protect neighborhood wealth and decrease or limit exclusionary growth. Leading with racial and social equity in mind can also ensure that priority access to resources can be provided to neighborhoods most in need. Developing inclusive procurement and contracting policies can change market outcomes through the purchasing power of the government and can encourage the private sector to hire from historically marginalized communities. This approach can provide an opportunity for high quality job creation and wealth-building for existing residents, enabling them to continue to live in their neighborhoods and communities and pushing back against the forces of displacement.

CONCLUSION

Each city in the U.S. has a different set of factors influencing displacement, making it critical to study the local context and not simply borrow policy from other jurisdictions. It is vital to understand and address these factors to mitigate displacement without relying on a one-size-fits-all solution. Displacement, particularly when driven by gentrification, is not just an economic and housing issue, it is also an environmental and health issue. It is intersectional and requires interdisciplinary policy considerations.

This research is a contribution to the application of newer, advanced quantitative methods to displacement research. It sheds light on the factors that have the greatest influence on displacement risk within San Francisco, Atlanta, and Chicago. Our findings suggest that when evaluating displacement risk for Atlanta and San Francisco, migration patterns have a large influence. In addition to these similarities, energy burden affects displacement risk in all three cities. We also find that health outcomes often have a strong relationship with different factors influencing displacement risk in the three cities. The factors that have a strong relationship with mental health, asthma, or coronary heart disease are energy burden, eviction rate, median home value of owner-occupied units, and education levels.

Additionally, this research can be expanded to more cities across the US to better understand the role that energy burden and other variables play in displacement risk. More research into the drivers of these relationships by various socio-economic and environmental variables addressed in this analysis is also critical when working towards achieving an understanding of how displacement risk can be addressed within cities. To achieve further insight into these causes and relationships, community engagement processes focused on developing joint meaning-making between government and residents can provide crucial answers regarding the causes of the outcomes and relationships observed in their communities. Advice on structuring such processes is detailed in resources like the GEM Process Guide (Process Guide).

This paper is one of the first steps towards building a robust database and model for describing the most impactful determinants of displacement risk. An analysis and integration of the existing policy landscape would further strengthen the literature.

The results of our analysis provide insights into the correlation between residential displacement and diverse socioeconomic variables across cities situated in different contexts. Understanding these relationships can be used to inform energy policies that improve health, income, and energy burden outcomes so that historically marginalized communities can thrive. Resources such as ACEEE’s City Clean Energy Scorecard can provide examples of how other cities have mitigated equity issues related to energy, while simultaneously working to prevent displacement within low-income communities.

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