Emergency Rental Assistance Priority Index Version 2.0

Technical Appendix

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An estimated 1.25 million people experienced homelessness at least once in 2020 (HUD 2022a), while an estimated 3.6 million eviction cases are filed against renter households each year (Eviction Lab 2018). Shortly after the pandemic began in 2020, the Urban Institute released the Emergency Rental Assistance Priority Index (ERAP Index 1.0) to support communities in more justly and effectively targeting emergency rental assistance funding provided by federal COVID-19 relief efforts to prevent evictions and homelessness.[1]

With the most acute phase of the pandemic now over and with new data available, Urban developed a revised Emergency Rental Assistance Priority Index (ERAP Index 2.0) to continue to support communities in targeting their rental assistance funds to the households that most need this help.[2] The new ERAP Index 2.0 is benchmarked against eviction filings and identifies the neighborhoods where renters are most likely to face eviction and risk of homelessness. Annual updates to the tool will provide communities with reliable and timely data into the future.

In March 2020, the federal government passed the Coronavirus Aid, Relief, and Economic Security Act (CARES Act), which provided $12 billion in COVID-19 relief funding for HUD programs. Following this, in December 2020, Congress passed the COVID-19 Economic Relief Bill under the Consolidated Appropriations Act. This bill established the Emergency Rental Assistance program, which made $25 billion in funding available to assist households that are unable to pay rent or utilities (Batko et al. 2022).

These major funding streams were a direct response to housing instability resulting from the COVID-19 pandemic. As Urban developed the Emergency Rental Assistance Priority (ERAP) Index 1.0, it responded to the pandemic by incorporating measures of pandemic vulnerability and impact; the ERAP Index 1.0 included three subindices: Housing Instability Risk, COVID-19 Impact, and Equity. In 2021, Urban updated the ERAP Index 1.0 with newly-available data, but the structure of the index remained the same.

While the most acute phase of the COVID-19 pandemic is behind us, housing unaffordability, housing instability, and risk for homelessness remain widespread, threatening the well-being of millions of Americans. Communities across the US continue to face similar challenges in identifying and supporting households at risk of homelessness—but with even fewer resources now that ARPA funding has elapsed. This makes identifying the most vulnerable households and prioritizing them for emergency rental assistance and other forms of housing supports even more critical.

To continue to support communities in equitably prioritizing and allocating housing assistance resources, Urban released the Emergency Rental Assistance Priority Index 2.0 in July of 2023. The updated index provides an interactive map and accompanying dataset that ranks neighborhoods across the country based on their risk for eviction and homelessness.[3] The updates captured in the ERAP Index 2.0 reflect multiple goals:

1. **Update the index to reflect the post-pandemic context**, including by removing discontinued, pandemic-specific data sources and replacing these measures with other indicators closely tied to risk for eviction and homelessness.
2. **Enhance the rigor of the index** by modeling indicators and subindices against eviction-filing rates, and use model results, in combination with the literature, subject matter experts' input, and feedback from communities to create empirically derived weights for each subindex.
3. **Create a sustainable framework for the index** so that indicators, subindices, and total index scores can be easily updated on an annual basis with new data, providing users a consistent and reliable data source over time to support and inform program and policy decisions.
4. **Enhance the digital interface** so that users can more clearly understand and work with index scores across the country.

The ERAP Index 2.0 is composed of three subindices that capture different domains of risk for eviction and homelessness: the Housing Subindex, the Household Demographics Subindex, and the Income Subindex. Together, these subindices are aggregated into a composite index score that correlates with risk for eviction and indicates need for emergency rental assistance. In combination with local communities' knowledge, the ERAP Index 2.0 can serve as a foundational resource for targeting policies and resources to more equitably support the households that most need assistance to remain in their homes.

The Need for the ERAP Index 2.0

In March 2020, the federal government passed the Coronavirus Aid, Relief, and Economic Security Act (CARES Act), which provided $12 billion in COVID-19 relief funding for HUD programs. Shortly thereafter, in August 2020, Urban developed and released the ERAP Index 1.0. The federal government made additional emergency rental assistance funding available through the COVID-19 Economic Relief Bill under the Consolidated Appropriations Act in December 2020 and through the American Rescue Plan Act (ARPA) in March 2021.

The primary goal of the ERAP Index 1.0 was to inform efforts to target emergency rental assistance to the households most in need of support—especially low-income households of color, which are disproportionately impacted by housing instability and most likely to experience homelessness (HUD 2022b). The ERAP Index 1.0 included three subindices: the Housing Instability Risk Subindex, the COVID-19 Impact Subindex, and the Equity Subindex.

BOX 1

Use of ERAP Index 1.0

The original index was widely used by communities across the country: by January 2023, the ERAP Index 1.0 had received more than 48,000 unique views, reflecting its relevance to pressing questions facing local and state agencies during the first years of the pandemic.[4]

- The State of Oregon integrated the index into its prioritization of applicants for emergency rent assistance. The State combined index scores with other local factors, including whether applicants had experienced hardship from wildfires in previous years.
- In the Bay Area, jurisdictions that partner with All Home built the index into their prioritization of applicants for emergency rent assistance. Like the State of Oregon, All Home encourages jurisdictions to use additional local data to complement the index.
- In Austin, Texas, the Continuum of Care lead agency ECHO used the index to develop a targeting tool in which they layered data from the index with additional data available only at the local level.

The variety and extent of the ERAP Index 1.0's use pointed to the value of data updates and other improvements. The ERAP Index 2.0 uses newer data and improves upon the tool's rigor and usability in order to promote its ongoing use.

With the pandemic at its height, and with millions of households abruptly out of work and unable to pay rent, the first version of the index incorporated neighborhood-level measures of COVID-19 impacts in the COVID-19 Impact Subindex. Recognizing that COVID-19 did not affect all households and communities equally—for example, early research found that Black and Latine households were more likely to report concerns about future job loss and reported higher rates of insurance loss than the national average[5]—this subindex included indicators measuring the percentage of low-income jobs lost and the number of uninsured people in each tract. The uninsured rate served as a proxy for vulnerability to COVID-19, while the measure for low-income job loss was taken from an Urban data tool (no longer being updated) developed to measure close-to-real-time job losses during the pandemic, which served as a proxy for economic security.[6]

Indicators and weights for the ERAP Index 1.0 were developed based on evidence from the literature, as well as from input and feedback from subject matter experts and local practitioners. After the index was published, the team evaluated the correlation between ERAP Index 1.0 scores and eviction-filing rates to better assess the strength of the overall index and each subindex (Batko et al. 2020). These analyses found that the overall index, the Housing Instability Subindex, and the Equity Subindex all had moderate or strong positive correlations with eviction-filing rates in a majority of states. The COVID-19 Impact Subindex was not strongly correlated with eviction-filing rates in any states, and for most states, it was only weakly positively associated with eviction-filing rates.

BOX 2

Housing Justice

The ERAP Index 2.0 was developed as part of the Urban Institute's Housing Justice Hub, which seeks to confront historical and ongoing harms and disparities caused by structural racism and other systems of oppression by ensuring everyone has affordable housing that promotes health, well-being, and upward mobility.[7] The Housing Justice Hub advances housing justice by convening researchers, practitioners, people with lived experience, and other stakeholders to produce relevant convenings, research, and tools. Recent research from the hub has explored the importance of housing decommodification (Fu and Velasco 2023), the correlations between historical redlining patterns and contemporary measures of housing instability (including the ERAP Index 1.0; Gerken et al. 2023), and the intersections between disability justice and housing justice.[8] A guide for practitioners and policymakers highlights interventions that can advance housing justice.[9]

Housing justice underlies the motivation for and design of the ERAP Index 2.0. Research has shown that Black and Latine renters face disproportionate rates of eviction filings (Hepburn et al. 2020) and that Black and Indigenous households are significantly overrepresented among households experiencing homelessness (HUD 2022b). The index seeks to capture racial inequities in housing instability and income and prioritize resources to ensure all households have stable and affordable housing. In the ERAP Index 2.0, our team made the decision to disaggregate many race and ethnicity categories to better capture differences in groups' need for emergency rental assistance (see box 4 for additional details).

Technical Methods

In this technical appendix, we describe the steps involved in creating the ERAP Index 2.0 and highlight key processes and decisions. The project GitHub repository provides a full accounting of how we obtained, processed, and analyzed data to produce the final ERAP Index 2.0 scores.[10]

We begin by describing our approach to selecting candidate index indicators. We started with the indicators from the ERAP Index 1.0 and then incorporated additional indicators that we believed might be relevant based on the literature and subject matter experts' input.

BOX 3

Homelessness and Evictions Data

The primary focus of emergency rental assistance funding is to keep households in their residences and prevent them from experiencing evictions and homelessness. Given that there is limited funding that is far outstripped by demand, emergency rental assistance resources are most impactful when they are provided to households that would experience homelessness if not for assistance. Theoretically, a direct measure of this risk for homelessness (which does not exist), or a very close proxy, such as homelessness rates, would be ideal for tuning the ERAP Index. However, available homelessness data is limited—nationwide, homelessness data is only consistently available at the Continuum of Care level (CoC), with individual CoCs often encompassing one or many counties. However, risk for homelessness varies significantly within individual CoCs, and governments administering emergency rental assistance funding frequently make decisions about prioritizing resources at much smaller geographies, such as the neighborhood.

Because homelessness data were not available for evaluating the ERAP Index and its constituent indicators, we instead leveraged publicly available evictions data from the Princeton University Eviction Lab.[11] These data are available at the census tract geography, which is a geographic unit that typically encompasses roughly 4,000 people; in more densely populated areas, a tract might be the size of ten square blocks, while in sparsely populated areas, a tract can cover many square miles.

Because eviction judgment records are not collected comprehensively or in a standardized manner,[12] we mirrored the approach taken by Gromis et al. (2022) and analyzed eviction-filing rates, which are more uniformly collected across the country. While Gromis et al. (2022) have published a modeled dataset that imputes data for counties without available eviction data and that addresses concerns about the accuracy of some reported data, this modeled dataset is only available at the county and state levels. Instead, we relied on the unmodeled dataset, which covers 75 percent of all tracts in the country. We provide additional details about these evictions data and approaches we took to address data quality concerns in the Limitations and Opportunities section and in Appendix A figures A1 and A2.

Using eviction-filing data as opposed to homelessness data does create some limitations, as homelessness is comparatively rarer than eviction. To account for this when considering candidate indicators, we considered the published literature in addition to empirical modeling to evaluate indicators, at times opting to include indicators that were not influential in our models because of their basis in the literature, and vice versa.

To evaluate the candidate indicators, we first obtained tract-level eviction-filing data from the Eviction Lab. Using predictive models, including a lasso regression model and a random forest model, we then evaluated how our set of candidate indicators were (or were not) predictive of eviction-filing rates. By examining variable importance scores and through reference to the literature and subject matter experts' advice, we dropped candidate indicators that were redundant, contributed marginally to our models, or that did not have strong theoretical justifications for inclusion.

The process for grouping indicators into subindices and developing subindex weights leveraged a specialized regression method called Weighted Quantile Sums (WQS) regression. First, we assigned indicators to one of three subindices (Housing, Household Demographics, or Income), each of which contained indicators that related to the corresponding dimension of risk for homelessness. Then we added these subindices to a WQS model, which allowed us to empirically create subindex weights such that the total index scores—calculated by multiplying a given tract's scores for each subindex by the corresponding subindex weights—were optimized to align with eviction-filing rates.

After we had produced a draft version of the ERAP Index 2.0, we ground-truthed the index scores with local practitioners to better understand how well the ERAP Index 2.0 aligned with local perceptions of risk for homelessness and emergency rental assistance priority and to identify any needed revisions. Feedback highlighted the usefulness of the updated index and the value of contextualizing index scores with local knowledge and data.

The final ERAP Index 2.0, including its component indicators and subindices and their correlations with eviction-filing rates, is described in table 1.

TABLE 1

ERAP Index 2.0: Subindices, Indicators, and Definitions

	Definition	Correlation	Data source
Total index		**.47**	
Housing Subindex		**.46**	
Median monthly housing cost	Median monthly housing cost of all occupied housing units with monthly housing costs	.19	ACS
Share of renter-occupied units	Share of all occupied units that are occupied by renters	.50	ACS
Share of renter-occupied units in multiunit buildings	Share of all renter-occupied units that are in structures with more than one unit	.28	ACS
Income Subindex		**.27**	
Share of cost-burdened renter households	Share of renter households with incomes of less than $35,000 that are paying 50 percent or more of their incomes on rent	.24	ACS
Share of extremely low-income renter households	Share of all renter households with incomes at or below 30 percent of the HUD area median family income	.28	CHAS
Household Demographics Subindex		**.40**	
Average renter household size	Number of people in renter households divided by the number of renter households	.08	ACS
Share of Black people	Share of all individuals that identify as African American/Black and do not identify as Hispanic or Latino	.54	ACS
Share of Asian people	Share of all individuals that identify as Asian and do not identify as Hispanic or Latino	-.09	ACS
Share of Latine people	Share of all individuals that identify as Hispanic or Latino, regardless of race	.01	ACS
Share of Indigenous, Pacific Islander, and multiracial people	Share of all individuals that identify as American Indian or Alaskan Native, Pacific Islander, or multiracial and do not identify as Hispanic or Latino	.00	ACS

Sources: Indicators in the final ERAP Index 2.0 are sourced from 5-year 2017–2021 American Community Survey (ACS) estimates (US Census Bureau 2022) and 2015–2019 Comprehensive Housing Affordability Strategy (CHAS) data (HUD 2022c). Correlations are calculated using index data sourced from 5-year 2014–2018 American Community Survey (ACS) estimates (US Census Bureau 2019) and 2014–2018 Comprehensive Housing Affordability Strategy (CHAS) data (HUD 2021) in relation to 2018 Eviction Lab data (Gromis et al. 2022).
Notes: Correlations reflect the association between each indicator/subindex and eviction-filing rates at the national level.

Model Development

Our overarching goal in updating the index was to produce an empirically and qualitatively informed tool that would support communities in prioritizing emergency rental assistance. To quantitatively design the index, we needed an outcome measure against which we could model the index and the subindices. We took counts of eviction filings at the tract level, available from the Princeton University Eviction Lab (Gromis et al. 2022), and standardized them by tract-level population estimates to produce eviction-filing rates. We modeled candidate indicators and, subsequently, the subindices against these eviction-filing rates.

To select and weight indicators to create the composite index, we needed multiple selection criteria, including measuring the relationships between candidate indicators and neighborhood-level risk for homelessness; prioritizing indicators that would be updated consistently, so that we could keep the index tied to close-to-real-time housing assistance needs into the future; and selectively omitting indicators to achieve a more parsimonious final index (see box 4) that would be interpretable and meaningful.

BOX 4

Model Parsimony

"Model parsimony" refers to the concept of balancing the complexity and accuracy of a model, where a simpler model is preferred to a more complex model if both are similarly accurate. A parsimonious model makes the index easier to understand and ensures that each indicator included in the index has theoretical and/or empirical grounding. We wanted the index to accurately map the need for rental assistance with as few predictor variables as possible.

SELECTING CANDIDATE INDEX INDICATORS

Our process for selecting indicators for the ERAP Index 2.0 began with the indicators contained in the ERAP Index 1.0. Correlations between ERAP Index 1.0 subindex scores and eviction-filing rates showed that the COVID-19 Impact Subindex was not strongly correlated with eviction-filing rates in any states. Additionally, one of the two indicators that made up the Covid-19 Impact Subindex, "share of low-income jobs lost to COVID-19," was obtained from an Urban-developed tool that was discontinued as of August 2021. Due to these factors, we decided not to include either of the indicators from the COVID-19 Impact Subindex in the ERAP Index 2.0.

Another source of candidate indicators was feedback from users of the original version of the index. Users noted that the original index often highlighted university-adjacent neighborhoods as high-priority geographies, and that geographies with significant subsidized housing were often ranked as lower-priorities than expected. To consider whether we might adjust for these features in the revised index, we created a measure of the number of assisted housing units per tract using HUD's Picture of Subsidized Households dataset (HUD 2022d) and created a measure of the share of university-enrolled adults using tract-level American Community Survey Data.

We also conducted a literature review to identify additional relevant indicators. One limitation was that much of the prior research on predictors of homelessness had focused on geographies larger than the census tract (e.g., at the county or Continuum of Care levels; see, for example, Hanratty 2017 and Nisar et al. 2019), and that measures from this literature do not necessarily translate to census tract-level analyses. Nonetheless, we attempted to evaluate all indicators that were consistently mentioned in the literature and for which we could obtain reliable, census tract-level data. Some of the candidate indicators considered included measures of educational attainment, measures of income distribution such as the Gini coefficient, and a measure of receipt of public assistance. The full list of candidate indicators we evaluated is provided in Appendix A table A1.

EVALUATING CANDIDATE INDEX INDICATORS

To obtain a final list of indicators for the ERAP Index 2.0, we sought to prioritize indicator inclusion along a number of factors, including the magnitude of influence and statistical significance the indicator had in quantitative models, theoretical relevance and background in the literature, interpretability, and relevance to users and decision-makers, among others. An overarching concern was to ensure that our indicators adequately captured how systems of racism and inequity shape existing need for housing assistance.

BOX 5

Race and Ethnicity Indicators

As a result of historic and contemporary systemic racism, there are significant differences between racial and ethnic groups in terms of the rates at which they experience evictions (Hepburn et al. 2020), homelessness (HUD 2022b), and housing cost burden (JCHS 2020), among other dimensions of housing instability.

In the ERAP Index 1.0, we created a single indicator reflecting the share of all households of color in each census tract. This approach had a number of advantages, including that this single measure was easier to interpret than multiple, more detailed measures, and that by combining multiple measures reflecting more specific racial and ethnic groups—some of which accounted for very small shares of the population in many tracts—we were able to create a combined measure that had lower uncertainty relating to sampling. Conversely, this approach was unable to capture the meaningful differences in housing assistance need between racial and ethnic groups.

In the ERAP Index 2.0, we have opted to include multiple race- and ethnicity-related measures, including the shares of: (1) Black, non-Latine; (2) Latine, any race; (3) Asian, non-Latine; and (4) Indigenous, non-Latine, Pacific Islander, non-Latine, and people identifying as multiracial and non-Latine. We feel that this is an important disaggregation of the data that better captures some of the nuance between race and ethnicity and need for emergency housing assistance. However, this approach remains limited, primarily due to challenges with sampling error (Spielman et al. 2014). Due to the small sample sizes for some racial and ethnic groups across many census tracts, estimates for these populations often had very large margins of error. To balance the advantages of disaggregating racial and ethnic groups with the disadvantages of relying on highly uncertain estimates for some groups, we chose to combine all people identifying as Latine, regardless of their race, into a single measure reflecting the share of Latine people of any race. Similarly, we grouped Indigenous (American Indian and Native Alaskan) non-Latine people, Pacific Islander non-Latine people, and people identifying as multiracial and non-Latine into a single measure.

While no approach to capturing racial and ethnic groups at the census tract level is without limitations, we feel that this approach reflects important variation between groups while recognizing the limitations of sample estimates from the American Community Survey. As users apply the ERAP Index 2.0 within their communities, they may be able to incorporate local data and other community-specific knowledge that can further aid in more accurately and justly distributing housing assistance resources.

To check that each indicator reflected a distinct aspect of risk for eviction, we ran multicollinearity tests to evaluate the Variance Inflation Factor (VIF) for each of our indicators using the *car* (Companion to Applied Regression) R package (Fox and Weisberg 2019).[13] Variables with high VIF scores were iteratively removed until all remaining indicators' VIF scores were fairly low (all final index indicators had VIF scores of less than three, while during initial modeling, some candidate indicators had VIF scores of more than 50). We also examined the correlations between each of our candidate indicators and eviction-filing rates (see table 1 for correlations of selected indicators).

We then used statistical modeling to confirm that the indicators we selected from the literature were also important drivers of eviction-filing rates in the data. We implemented two types of statistical models commonly used in the supervised machine learning literature: lasso regression and random forest regression. The lasso regression model is closely related to the standard linear regression model, the key difference being that it penalizes complexity by setting a subset of regression coefficients equal to zero. For this reason, it is commonly used for variable selection, where any variables of lesser significance are eliminated from the final model. The random forest model is a more complex and flexible model which generally achieves higher predictive accuracy than both linear and lasso regressions. Random forests comprise a large number of decision trees, each of which consist of splits of the variable space into branches (e.g., one such split could be "share of Black individuals > 30 percent" and "share of Black individuals < 30 percent") until similar census tracts are grouped into leaves; tracts within the same leaf are then predicted to have the same eviction-filing rates. Although in this context we were less interested in predicting eviction-filing rates than in understanding their key drivers, we were still able to evaluate which variables were most important during the splitting process in leading to leaves that are "pure" (i.e., that contain census tracts with similar eviction-filing rates).

DESIGNING SUBINDICES

To construct the ERAP Index 2.0, we assigned indicators to one of three subindices—Housing, Income, or Household Characteristics—based on treatment of the indicators in the literature and our own exploratory findings from correlations and regression models. To estimate the weights of each subindex, we used a weighted quantile sums (WQS) regression model, which we implemented using the gWQS R package (Renzetti et al. 2022).

WQS regression was originally developed for environmental mixtures analysis, in which there can be many correlated variables such as chemical exposures that form natural groups (or in our case, subindices) in influencing some outcome of interest (Carrico et al. 2015). WQS regression estimates a single score known as a weighted quantile sum, optimizing for maximum correlation between the resulting index scores and the outcome variable (in our case, eviction-filing rates). WQS regression also allows for control variables that are not considered part of a subindex.

We computed each subindex score by taking a simple average of the z-score of the indicators in that subindex.[14] Then, we estimated a weighted quantile sum, which can be decomposed into its underlying weights for each subindex. We calculated the composite index score by multiplying each subindex score by its corresponding weight and adding these products together. We included a flag for urban or rural status—derived from Rural-Urban Commuting Area codes and documentation from the Health Resources & Services Administration[15]—as a control variable, which allows us to separate the confounding effect that geographic factors may have on eviction filings.

GROUND-TRUTHING

We used ground-truthing as a strategy to check and validate our approach and findings with local experts. We conducted three ground-truthing discussions with Continuum of Care leads in three communities (Richmond, Virginia; Austin; and San Francisco) that worked with or were familiar with rental assistance programs, evictions, and community demographics.

In each of our conversations, we provided an overview of the tool, described the tool updates and the goals of the updated tool, and shared information about the new subindices and indicators. After describing the overall tool, we provided maps tailored to each community for the overarching index and each of the three subindices. Using these maps as a guide, we asked attendees to share their thoughts and feedback on the indices in relation to their experiences with and knowledge of renter households in the area (e.g., related to incomes, demographics, and household composition) as well as what they knew about geographic trends in rental assistance use.

In general, practitioners shared that they thought both the subindices and the overall indices aligned with what they knew about their communities. One community noted that although they had designed their own similar maps and measures using both national- and local-level data, they thought that the ERAP Index 2.0 was more reflective of the current community need because their map used older data. Attendees also noted that the maps, specifically the Income Subindex, accurately reflected the tracts in which there were high numbers of units of public housing and subsequently lower levels of cost-burdened rental households. Other feedback, which aligned with the original ERAP Index 1.0 ground-truthing sessions, was that tracts near large universities were given a higher priority within the index than practitioners perceived their levels of housing insecurity to be. (Student populations that live off-campus can have substantial impacts on estimates of poverty rates and other sociodemographic characteristics; US Census Bureau 2013, US Census Bureau 2018). However, some also noted that they felt the index scores were reflective of communities near community colleges, whose students may be more likely to experience housing insecurity (The Hope Center for College, Community, and Justice 2021).

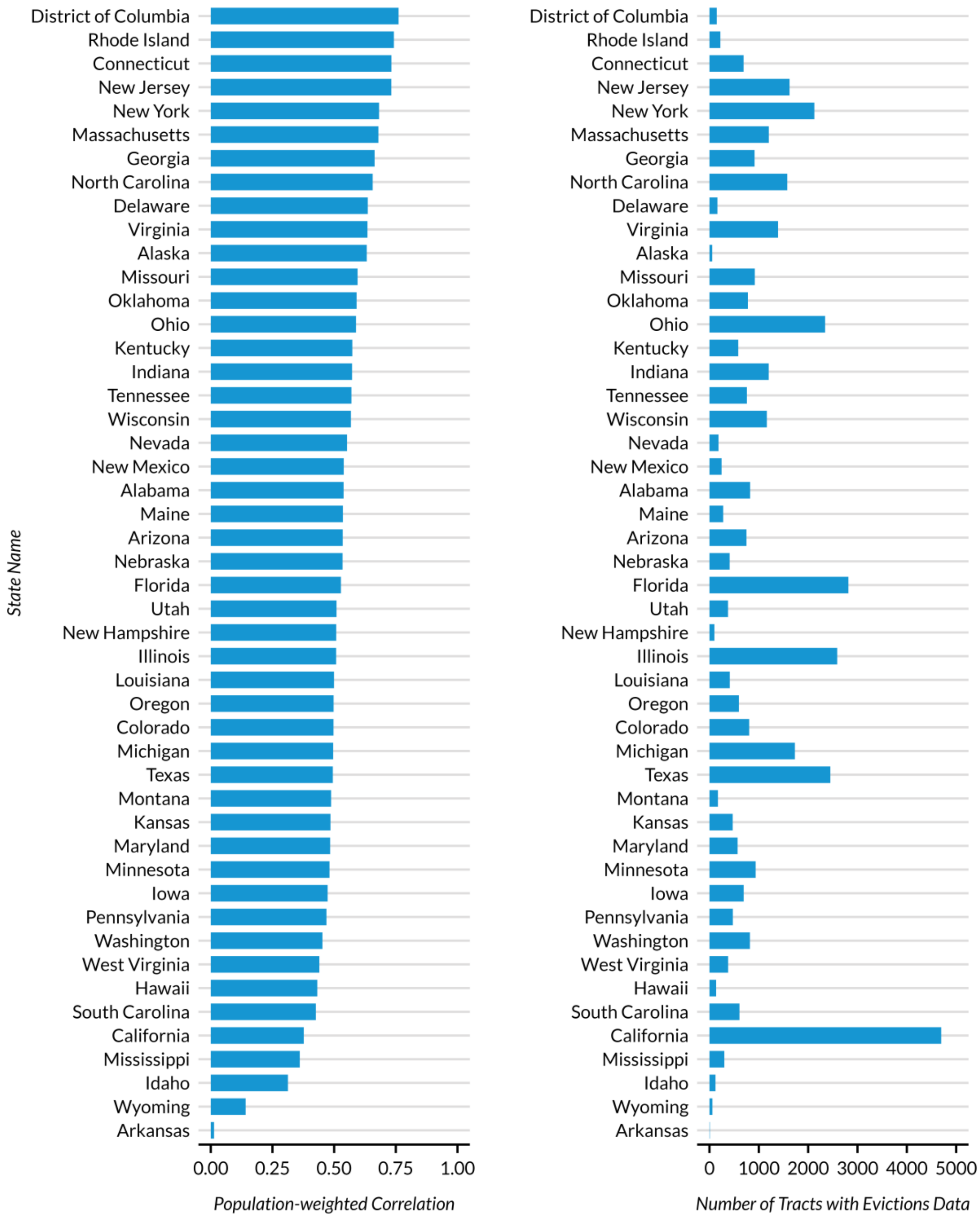
Index Characteristics

Our final index indicators, organized by subindex, are presented in table 1. This arrangement of indicators and subindices, with corresponding WQS-derived weights, produces a total index score that has a correlation with eviction-filing rates at the census tract level of .47. The Housing, Income, and Household Characteristics subindices have correlations with eviction-filing rates of .46, .27, and .4, respectively.

Figure 1 highlights state-level correlations between the total index and eviction-filing rates, with more than half of all states having population-weighted correlations greater than .5 (median = .53; mean = .53). Notably, California—which accounts for a plurality (11 percent) of all tracts in the US—has a lower-than-average population-weighted correlation (.38) between eviction-filing rates and the total index, which pulls down the overarching correlation across all states.

FIGURE 1

Population-weighted Index Correlations and Tract Counts by State



URBAN INSTITUTE

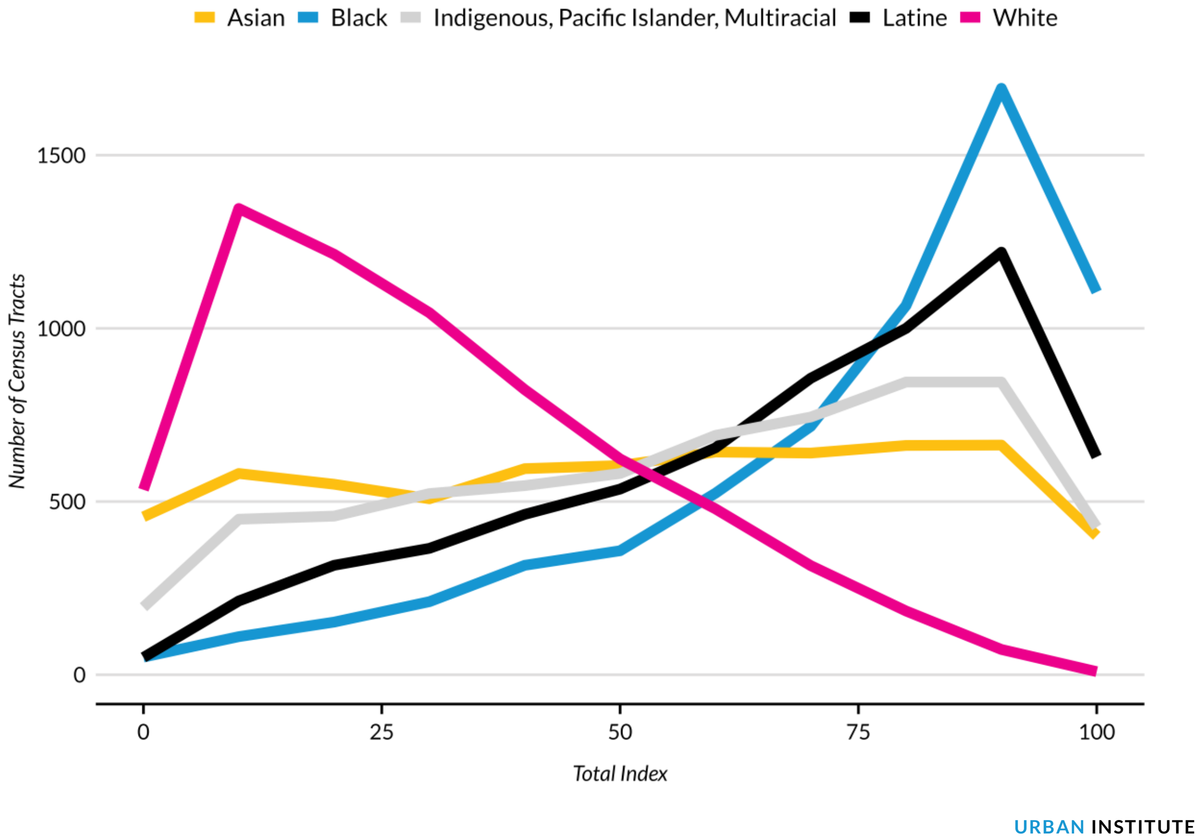
Source: Urban Institute analyses of ERAP Index 2.0 data and Eviction Lab data (Gromis et al. 2022).

While variation in index correlations across states shows that the ERAP Index 2.0 is less closely associated with eviction-filing rates in some states than others, the index—which relied on literature reviews and discussions with local practitioners and subject matter experts in addition to quantitative modeling—was designed to be robust to possible "noise" in eviction-filing rates. For example, state and local policies can affect eviction-filing rates by defining processes (such as costs, timing, and criteria) for filing evictions and receiving an actual eviction judgment. However, some of these differences may influence eviction-filing rates without substantively affecting actual eviction judgments. By selecting indicators that we believe to be related to actual risk for homelessness and underlying need for emergency rental assistance—in addition to being tied to eviction-filing rates quantitatively—we hope that, even in states with lower population-weighted correlations with the index, the index is still an accurate and useful tool for informing housing assistance resource prioritization.

Both the ERAP Index 1.0 and 2.0 were explicitly designed to advance housing justice, including improving housing conditions for racial and ethnic groups that currently experience disproportionate rates of homelessness, eviction, and housing instability. Figure 2 shows the distribution of ERAP Index 2.0 scores across the census tracts that contain the top 10 percent of values for each race and ethnicity indicator in the index.[16] Notably, the top deciles of tracts for Black and Latine residents frequently have very high index scores—reflecting that these tracts are higher priority for emergency rental assistance resources—but rarely have the lowest index scores. Conversely, the top decile of tracts for White, non-Latine residents typically have low index scores—below 50—and almost none of these tracts have index scores near 100.

FIGURE 2

Distribution of Index Scores among the Top Decile of Tracts by Share of Each Race/Ethnicity Group



Source: Urban Institute analyses of ERAP Index 2.0 data.
Notes: For each racial or ethnic group indicator (White, non-Latine is not an indicator in the index, but we include it here for comparative purposes), we plot the tracts that fall into the top decile (by share of residents) for each group. These tracts are not exclusive; some tracts fall into the top decile for multiple indicators.

Limitations and Opportunities

The ERAP Index 2.0 has several important limitations relating to both the data sources used in the index and the methodological choices and assumptions we made in constructing the index. These limitations also point to important opportunities for strengthening the index and the provision of housing assistance.

Eviction filings are an imperfect proxy for need for rental assistance and these data have important quality limitations. The Eviction Lab's evictions dataset contains the most comprehensive national-level information on evictions, but it does not perfectly capture renters at risk of housing instability or homelessness. These data cover a substantial share (75 percent)—but not the entirety—of tracts in the US, and the data we use measure eviction *filings*, yet only a subset of renters who have an eviction filed against them are actually forced to leave their homes. These data also omit informal evictions that were not carried out through the court systems, which may be up to 5.5 times more common than formal evictions (Gromis and Desmond 2015).

Eviction filings present several data quality concerns. One is that court-reported eviction-filing counts don't equal counts that are calculated by aggregating individual eviction-filing records. Another is that some jurisdictions did not report subsets of eviction filings. These data quality concerns represent another important limitation of accurately measuring the need for emergency rental assistance. Another challenge with the evictions data were outlier eviction-filing rates. Maryland, in particular, had exceedingly high filing rates across most tracts in the state (a known phenomenon due to state eviction law),[17] and other states also had some tracts with unusually high filing rates.

To address outliers and the possible distortions they would create in modeling the data, we winsorized filing rates at the 95 percent level (see Appendix A figure A1). We also chose to include index indicators based on the literature, even when these indicators were not necessarily significant predictors in our models (see table 1 for indicator-level correlations with eviction-filing rates), in an effort to make the index more robust to data-accuracy limitations described above.

Data sources lag behind real-time conditions. To develop subindex weights, we use the most recent tract-level evictions data from 2018, along with the most recent indicator data available: 2014–2018 5-year American Community Survey (ACS) data and the 2014–2018 US Department of Housing and Urban Development's Comprehensive Housing Affordability Strategy (CHAS) data. However, the indicator data reflected in the index are from the most recently available datasets: 2017–2021 5-year ACS data and 2015–2019 CHAS data.

We employ older data in establishing subindex weights based on the hypothesis that indicator data from the same year as the outcome data are more likely to accurately model the relationship between our indicators and eviction-filing rates. However, we believe that the underlying relationship between our indicators and eviction-filing rates is likely to remain fairly stable over time. To evaluate this hypothesis, we compared the correlations between 2018-based indicator data and 2018 eviction-filing rates to the correlations between the most recent indicator data (2017–2021 5-year data for ACS-derived indicators and 2015–2019 CHAS data) and 2018 eviction-filing rates, using the same subindex weights—those calculated using 2018 indicator data and 2018 eviction-filing rates. We find that the difference in correlations is marginal (see Appendix A table A2): an index comprising 2018 indicator data has a correlation coefficient of .47 with 2018 eviction filings, while an index comprising the most recent indicator data has a correlation coefficient of .44. Our team will update indicator data in the online tool and on GitHub on an annual basis and will reassess the relationship between the ERAP Index and newer evictions data as it becomes available.

Some of the data are subject to accuracy or uncertainty issues. Any tract-level analysis using ACS data suffers from uncertainty due to sampling error because the survey reaches only a subset of Americans. This uncertainty is reflected in the margin of error provided alongside each ACS estimate. Because the census tract is such a granular unit of geography, we are able to provide index estimates at the neighborhood level, but this also means that those estimates are based on fewer people and thus are inherently more uncertain.

Many states also have higher or lower eviction-filing rates than expected due to idiosyncratic legal and policy dynamics. For example, California seals many cases ending in eviction from the general public, while New York only places judgments in the public record if the plaintiff pays to have them there (Desmond et al. 2018). To limit the influence of very large outlier eviction-filing rates, we winsorized these data at the 95 percent level (see Appendix A figure A1 for a distribution of eviction-filing rates nationally).

Omitted variables may have some importance in determining risk of housing instability or homelessness. We chose to omit certain indicators that were lightly associated with eviction-filing rates in order to maximize the interpretability of the index, and we opted against including interaction terms for the same reason. We also explored controlling for legal and policy variables that may affect the relatively higher or lower eviction-filing rates seen in some states (e.g., Maryland has high rates because the eviction process begins with a court filing, rather than an out-of-court tenant notice); however, we decided against this to ensure that the index remains feasible to update over time. Finally, there were many variables that we did not evaluate, either because we did not have reliable data sources for those variables or because we believed they were unlikely to be strongly related to eviction-filing rates.

The updated ERAP Index 2.0 is one input to informing communities' decisions about prioritizing housing assistance resources and should be coupled with other sources of knowledge. We believe the ERAP Index is a useful measure of relative need for emergency rental assistance and other forms of housing support. There are also many other important sources of knowledge that can inform resource prioritization decisions, including local sources of quantitative data, input from residents with lived experiences of housing instability and homelessness, and the knowledge of local practitioners who work in the affordable housing space. It's our hope that the ERAP Index validates and strengthens the conclusions reached when relying on these other sources of knowledge, and that, given its geographic comprehensiveness, the granularity at which the index is defined (at the census tract level), and the relatively current vintage of the data sources informing the index, the tool can help to fill in gaps in existing understandings of housing-assistance need.

Conclusion

Targeting rental-assistance resources to households most at risk of housing instability is crucial both for advancing equity and ensuring those resources have maximum impact. Updating the ERAP Index to enhance its methodological rigor and improve its digital interface allows communities to more accurately and easily target resources. The ERAP Index 2.0 benefits from indicators that are grounded theoretically, empirically, and in community feedback. These indicators reflect the post-pandemic context that households face today and are weighted using a statistical approach that aligns them with eviction-filing rates. Urban will maintain and update the ERAP Index with new releases of data on an annual basis so that the index can serve as an evergreen, open-source asset on which communities can rely for current and future planning.

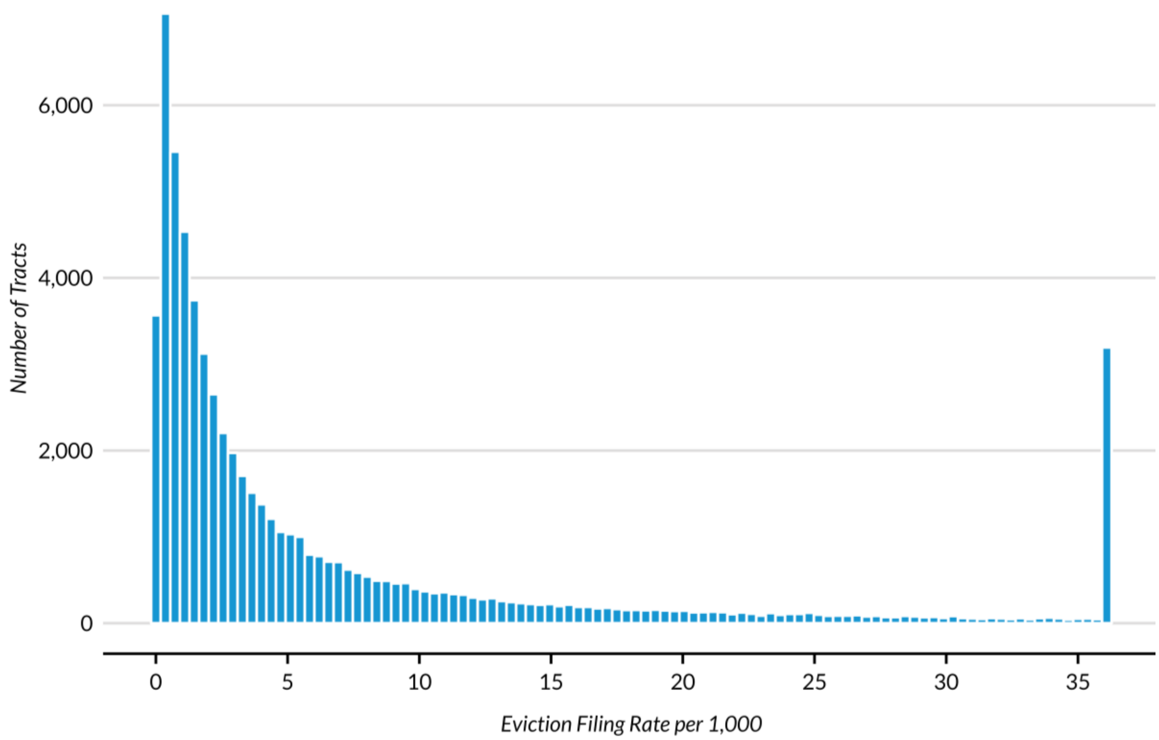
Appendix A: Supplemental Documentation

The figures, tables, and descriptions provided in this appendix offer additional detail about the data and modeling used to inform development of the ERAP Index 2.0. The project GitHub repository offers more detailed documentation of the analytic process used to create the ERAP Index 2.0. [18]

FIGURE A1

Distribution of Eviction-Filing Rates

Winsorization capped outlier eviction-filing rates, resulting in the peak just above 35 filings per 1,000



URBAN INSTITUTE

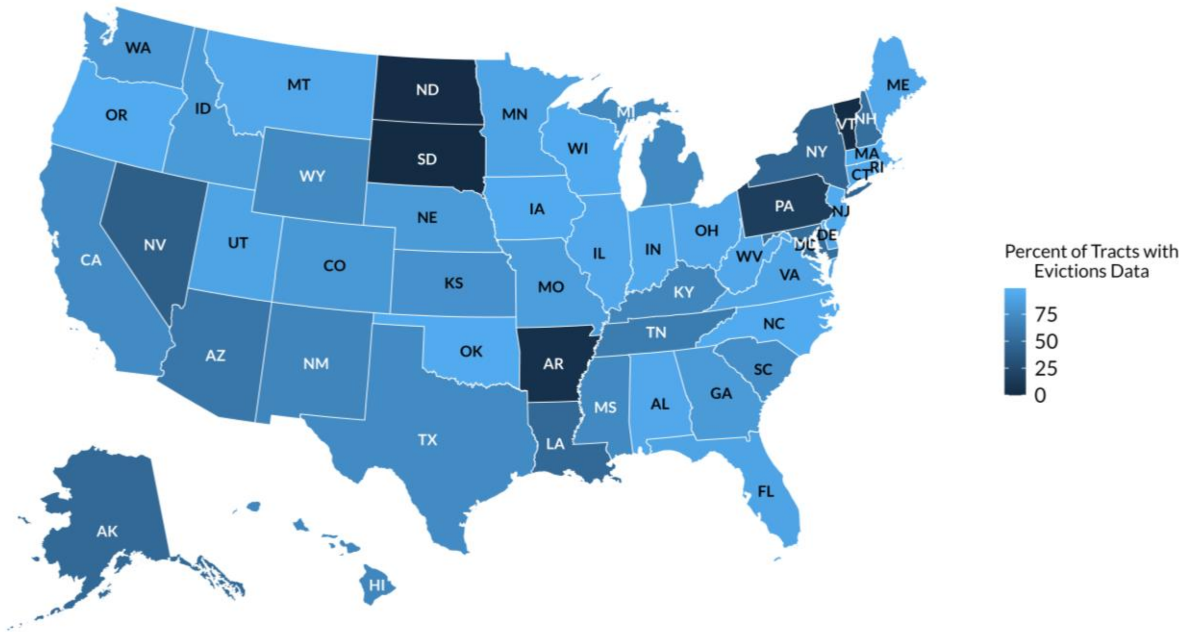
Source: Urban Institute analyses of Eviction Lab data (Gromis et al. 2022).

Notes: We winsorized values above the 95th percentile nationally for eviction-filing rates in order to reduce the influence of outliers, which in some cases appeared to reflect state or local policies about eviction-filing processes (e.g., some states make the process of filing for an eviction easier than others) more so than underlying risk for eviction and need for emergency rental assistance.

FIGURE A2

Evictions Data Coverage by State

Eviction-filing data were available for 75 percent of tracts nationally, though state-level coverage varied.



URBAN INSTITUTE

Source: Urban Institute analyses of Eviction Lab data (Gromis et al. 2022).

TABLE A1

ERAP Index 2.0 Candidate Indicators

The full set of indicators that were evaluated for inclusion in the final index, with included indicators set in bold

Indicator	Data source
Median monthly housing cost	**ACS**
Share of renter-occupied units	**ACS**
Share of renter-occupied units in multiunit buildings	**ACS**
Average renter household size	**ACS**
Share of overcrowded renter households	ACS
Share of renters with household sizes over five	ACS
Share of Black individuals	**ACS**
Share of Asian individuals	**ACS**
Share of Latine individuals	**ACS**
Share of Indigenous individuals	ACS
Share of Pacific Islander individuals	ACS
Share of multiracial individuals	ACS
Share of Indigenous, Pacific Islander, and multiracial people	**ACS**

Indicator	Data source
Share of people of color	ACS
Share of cost-burdened renter households	**ACS**
Share of extremely low-income renter households	**CHAS**
Share of people born outside the United States	ACS
Population density	ACS
Share of unemployed people	ACS
Share of college students	ACS
Share of people with a high school degree or GED or less education	ACS
Gini coefficient	ACS
Mean household income, bottom quintile	ACS
Share of people in poverty	ACS
Share of households receiving public assistance	ACS
Share of people who live in project-based subsidized units	Picture of Subsidized Households

Sources: Urban Institute analysis based on available data from the 5-year 2017–2021 American Community Survey (US Census Bureau 2022); 2015–2019 Comprehensive Housing Affordability Strategy (HUD 2022c); and 2021 Picture of Subsidized Households data (HUD 2022d).
Notes: ACS = 5-year 2017–2021 American Community Survey estimates, CHAS = 2015–2019 Comprehensive Housing Affordability Strategy (CHAS) data, Picture of Subsidized Households = 2021 Picture of Subsidized Households data

TABLE A2

Comparing Index Correlations with Eviction-Filing Rates

Index	Correlation (2018 indicators)	Correlation (2021 indicators)
Total Index	**.47**	**.44**
Housing Subindex	.46	.43
Income Subindex	.27	.25
Household Demographics Subindex	.40	.38

Source: Urban Institute analyses of ERAP Index 2.0 data and Eviction Lab data (Gromis et al. 2022).
Notes: Both the indices constructed using 2018 and 2021 data rely on the same subindex weights (calculated using 2018 data). The difference in correlation scores reflects the differences in the values of the indicators comprising each subindex.

The Weighted Quantile Sums Regression Framework

Weighted quantile sums regression is a supervised model in which a single score, the *weighted quantile sum*, is estimated to summarize the overall effect of the "mixture" of indicators on the outcome variable. After creating our three subindices, we convert the score for each subindex into deciles. Carrico et al. 2015 explain that converting continuous scores into quantile values mitigates the effect of extreme values on the resulting subindex weights.

After converting scores to decile values, an overall weighted quantile sum (WQS) is estimated through bootstrap sampling, based on the following equation:

$$WQS = \sum_{i=1}^{3} w_i \, q_i$$

where w_i is the bootstrap-estimated weight for each of the three subindices, and q_i is each tract's decile value for that subindex (i.e., q_i takes on a value from 1 to 10). The weights are constrained to be between zero and one and sum to one.

From here, the WQS regression equation is:

$$y = \beta_0 + \beta_1 WQS + \beta_2 Rural$$

where y is a tract's eviction-filing rate and *Rural* is a control variable for urban/rural status of a census tract. After estimating this regression equation, we can extract the weights computed for each subindex and multiply them by each subindex score to derive a final index score for each census tract.

Notes

[1] An archived version of the original ERAP Index 1.0 feature is available at https://www.urban.org/data-tools/where-prioritize-emergency-rental-assistance-keep-renters-their-homes. The data for the original ERAP Index 1.0 is available on GitHub at https://github.com/UrbanInstitute/covid-rental-risk-index.

[2] "Emergency Rental Priority Index 2.0," Urban Institute, July 2023, https://www.urban.org/data-tools/mapping-neighborhoods-highest-risk-housing-instability-and-homelessness.

[3] While every neighborhood in the country is ranked (excluding a few neighborhoods that have no extremely low-income renters), the rankings are relative to other neighborhoods in the same state. This helps states and other levels of government identify the highest-priority neighborhoods relative to the jurisdictions in which they operate.

[4] See Samantha Batko, Andrea Bell, Joanne Karchmer, and Monique King-Viehland, 2021, "What Can We Learn from Communities about Equitably Providing Emergency Rental Assistance?" Urban Institute, May 25, 2021, https://www.urban.org/events/what-can-we-learn-communities-about-equitably-providing-emergency-rental-assistance.

[5] Steven Brown, "The COVID-19 Crisis Continues to Have Uneven Economic Impact by Race and Ethnicity," *Urban Wire* (blog), Urban Institute, July 1, 2023, https://www.urban.org/urban-wire/covid-19-crisis-continues-have-uneven-economic-impact-race-and-ethnicity.

[6] Graham MacDonald, Christopher Davis, Ajjit Narayanan, Vivian Sihan Zheng, and Yipeng Su, "Where Low-Income Jobs are Being Lost to COVID-19," Urban Institute, August 6, 2021. https://www.urban.org/data-tools/where-low-income-jobs-are-being-lost-covid-19.

[7] Urban Institute, "Housing Justice Hub," Accessed June 21, 2023, https://www.urban.org/projects/housing-justice-hub.

[8] Sue Popkin, "Disability Justice Isn't Possible without Housing Justice," *Urban Wire* (blog), Urban Institute, March 1, 2023, https://www.urban.org/urban-wire/disability-justice-isnt-possible-without-housing-justice.

[9] David C. Blount, Katharine Elder, Samantha Fu, Kaela Girod, Jessica Perez, and Bill Pitkin, "Pursuing Housing Justice: Interventions for Impact", May 2023, https://www.urban.org/apps/pursuing-housing-justice-interventions-impact.

[10] Will Curran-Groome, Judah Axelrod, Brendan Chen, Lynden Bond, and Samantha Batko, "Emergency Rental Assistance Priority (ERAP) Index 2.0 GitHub Repository," accessed July 6, 2023, https://github.com/UrbanInstitute/emergency-rental-assistance-priority-index.

[11] "The Eviction Lab," Eviction Lab, accessed May 22, 2023, https://evictionlab.org/.

[12] For limitations associated with collecting and analyzing eviction judgment data, see Ashley Gromis, Ian Fellows, James R. Hendrickson, Lavar Edmonds, Lillian Leung, Adam Porton, and Matthew Desmond, "Supplementary Information: Estimating Eviction Prevalence across the United States," Section 7, Princeton University Eviction Lab, 2022, https://evictionlab.org/docs/Eviction_Lab_Methodology_Report_2022.pdf

[13] For the ERAP Index data reflected on the online feature and available in Urban's data catalogue, the measure of extremely low-income renters, which was sourced from HUD's Comprehensive Housing Affordability Strategy (CHAS) data, was reported based on 2010-based census tract boundaries, whereas all other indicators were sourced from American Community Survey (ACS) estimates, which were reported based on 2020-based census tract boundaries. To align the data, we attributed estimates from 2010 to 2020 census tract boundaries based on the areal overlap between tracts of different vintages.

[14] Because WQS assumes that all indicators affect the outcome variable in only one direction, either positively or negatively, we took two indicators that were negatively correlated with evictions in the data and multiplied them by −1: average renter household size and median monthly housing cost. After this process, as the value of each subindex increases, we would also expect eviction-filings rates to increase.

[15] Health Resources & Services Administration, "Defining Rural," March 2022, https://www.hrsa.gov/rural-health/about-us/what-is-rural

[16] Note that White, non-Latine is not an indicator in the ERAP Index, but we include it here for comparative purposes.

[17] Refer to Gromis et al. (2022), Section 5.3, for a discussion of Maryland eviction records.

[18] Will Curran-Groome, Judah Axelrod, Brendan Chen, Lynden Bond, and Samantha Batko, "Emergency Rental Assistance Priority (ERAP) Index 2.0 GitHub Repository," accessed July 6, 2023, https://github.com/UrbanInstitute/emergency-rental-assistance-priority-index.

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