



Assessing Vulnerability Indicators and Race/Ethnicity

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Disclaimer

The views expressed herein are those of the author and not necessarily those of the University of California, Los Angeles. The authors alone are responsible for the content of this report.

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Abstract

This study assesses four vulnerability indicators that are being considered by public agencies as policy tools to select the most-at-risk neighborhoods for interventions. These indicators can play a role in prioritizing the provision of pandemic resources and services; consequently, they have implications for how many people of color and minority neighborhoods are served. The study compares three vulnerability indicators developed prior to COVID-19 and one developed in response to the pandemic. Two sets of assessments are conducted. The first calculates the degree of concordance between pairs of indicators, that is, how frequently they identify the same tracts as being disadvantaged. The analysis finds that low rates of commonality (approximately less than half of all designated tracts); therefore, the choice of indicator inherently translates into a significant variation in the tracts classified as being eligible or ineligible for prioritization. The second set of assessments examines the differences among the indicators by comparing the racial composition of the residents in designated high-vulnerability tracts, and by comparing the relative number of minority neighborhoods included in high-vulnerability tracts. The analyses find substantial differences among the indicators in population compositions and proportion of minority neighborhoods included. The findings can help ameliorate a policy dilemma. Despite the reality that African Americans and Hispanics have suffered disproportionately from COVID-19, the 1996 Proposition 209 prohibits the state from explicitly using race as a factor in the provision and distribution of pandemic relief and coronavirus vaccines. The study's findings provide insights into which of the four vulnerability indicators can serve as a reasonable proxy, one that captures an important underlying mechanism producing systemic racial inequality. By several criteria, among the indicators that do not explicitly include race/ethnicity as an input, the indicator based on pre-existing health conditions (medical vulnerabilities) performs best in including African Americans. A final recommendation is that public agencies should develop and construct new pandemic-oriented indicators to help guide policies beyond racial equity.

Introduction

This study assesses four vulnerability indicators that are being used as policy tools to select the most-at-risk neighborhoods for prioritized interventions. Without timely and geographically precise data on COVID-19 infections and the factors that determine the rate of infection, public agencies have turned to pre-pandemic vulnerability indicators that measure socioeconomic and other types of vulnerabilities. The underlying assumption is that these indicators are highly correlated with disparities in COVID-19 outcomes, thus are useful proxies to identify at-risk neighborhoods. The indicators can play a role in prioritizing the provision of pandemic resources and services. For example, both National Academies of Science, Engineering, and Medicine (NASEM), and the Center for Disease Control and Prevention (CDC) have recommended the use of two pre-existing indicators to identify the most-at-risk places to allocate a proportion of the vaccines,^{1,2} a practice that has been adopted by many states.³

This study compares three pre-pandemic indicators and a more recently developed indicator based on pre-existing health conditions. The analysis focuses on the numbers of people of color residing in designated high-vulnerability neighborhoods, and the relative number of minority neighborhoods that fall into the high-vulnerability areas. Race/ethnicity is an important factor because Latinos, and Pacific Islanders are disproportionately more likely to be infected by COVID-19, and African Americans, Latinos and Pacific Islanders are more likely to die from an infection.⁴ While Asian Americans have lower rates, there is evidence that some Asian ethnic subgroups also bear a disproportionate share of negative COVID-19 outcomes.⁵ Race is also important because people of color encounter multiple dimensions of inequality that are only partially reflected in the indicators. For example, none of the indicators include an input variable that directly measures systematic differences and disparities in policing.

The assessment utilizes a policy-oriented exercise that simulates what would be the outcomes if an indicator is used to identify the most vulnerable neighborhoods. By comparing the hypothetical results for the four indicators, the policy-based exercise provides insights into which neighborhoods and populations would be classified as at high-risk and consequently prioritized for programmatic action. The findings show noticeable differences in the groups and places designated as being vulnerable, thus the choice of which indicator to use has highly consequential implications in terms of who is served and who is not along racial lines.

Indicators and Method

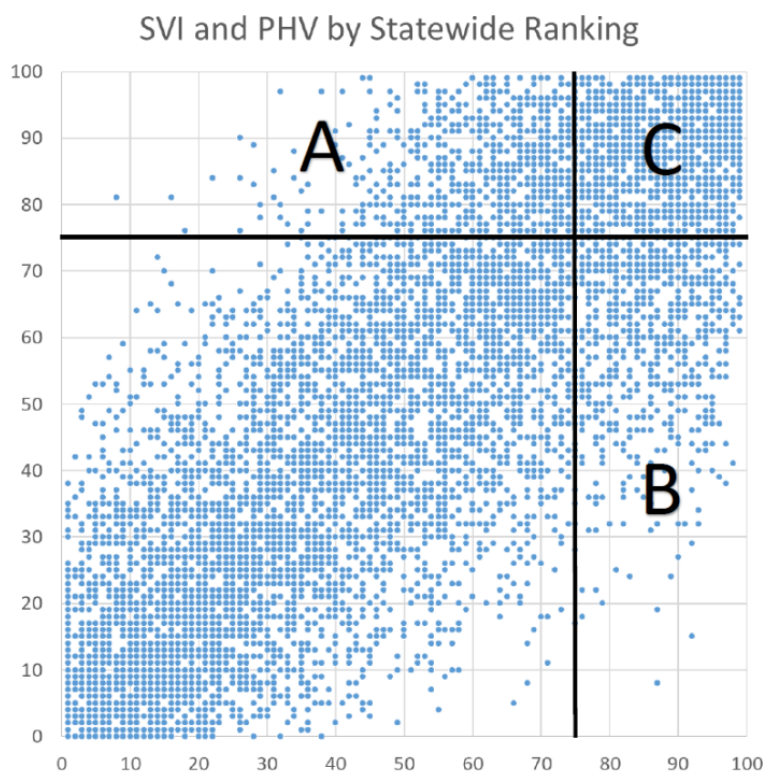
This study uses three pre-pandemic indicators at the census tract level. The social vulnerability index (SVI) was created by the CDC to identify vulnerable areas for disaster planning and response.⁶ The indicator uses 15 ACS variables organized into four dimensions: socioeconomic status, household composition, minority status and language, and housing type and transportation. This study uses the most recent CDC version of the SVI, 2018.⁷ The second national indicator is the Area Deprivation Index (ADI), which initially developed by the Health Resources & Services Administration, and subsequently refined by Dr. Amy Kind and her research team.⁸ ADI uses ACS data related to income, education, employment, and housing quality, and designed to inform health delivery and policy. ADI block-group level data are aggregated to tracts using population weights. The SVI and ADI are the two indicators recommended by CDC and NASEM to identify vulnerable places. The Healthy Places Index (HPI) was developed by the Public Health Alliance of Southern California⁹ and designed to help policy makers target the most disadvantaged communities for interventions and resources. California has adopted the HPI as one of its policy indicators. The index uses 25 variables from eight sources (including ACS) and organized in eight domains: economy, education, healthcare access, housing, neighborhoods, clean environment, transportation, and social environment. The rankings are inverted so higher values denote greater vulnerability. Neither the HPI nor the ADI include race/ethnicity variables.

The study includes a newer indicator constructed specifically for the pandemic. The UCLA Pre-Existing Health Vulnerability (PHV) index captures the risks or severity of COVID-19 infection due to preexisting health conditions¹⁰ and is based on data from the California Health Interview Survey (CHIS)¹¹. The input data for the PHV are small area estimates at the tract level modeled from CHIS data. PHV is a composite of six variables: diabetes, obesity, heart disease, overall health status, mental health and food insecurity. Each variable is ranked, and the variables are then summed at the tract level. The majority of the tracts are estimated directly from CHIS data, the values for other tracts are estimated with predictive regression models using data from ACS and CalEnvironScreen¹². The regression model also incorporates information on PHV from nearby tracts is also used when available.

For the state as a whole, the indicators (ranked as percentiles) are highly correlated with each other, with unweighted r-values ranging from 0.69 (ADI and SVI) to 0.88 (HPI and SVI), and the population weighted correlations range is very similar from 0.70 (ADI and SVI) to 0.88 (HPI and SVI). These results are not surprising since all four indicators include ACS data, in some cases the same input variables. The correlations based on percentile rankings, however, do not provide sufficient information about the indicators' performance as a policy instrument that defines which neighborhoods are eligible and ineligible for assistance. The NASEM and CDC recommends, for example, that the most-at-risk places are those ranked in the top 25% in vulnerability. California also follows this practice, so for the simulation analyses, tracts are categorized as 1 if they are in the top quartile of the vulnerability ranking, else 0. We use two ranking procedures. The first is for all tracts in the state, which simulates how state agencies and statewide organizations might use the data. This can produce a disproportionately larger number of tracts in some regions relative to other regions. The second is separate ranking within each county (that is the top quartile within a given county), a procedure that county health departments might use.

Two sets of assessments are conducted. The first calculates the degree of concordance between pairs of indicators, that is, how frequently they identify the same set of tracts as being disadvantaged relative to tracts that are uniquely by just one indicator. The concordance rate is the number of tracts in common divided by tracts identified by either or both indicators. Figure 1 provides an example using the SVI (on the Y or vertical axis) and the PHV (on X or horizontal axis). The black lines within the graph represent the 75th percentile for each indicator. The tracts identified by SVI as being highly vulnerable are in areas “A” and “C”, and the tracts identified by PHV as being highly vulnerable are in areas “C” and “B”. The concordance rate is the tracts in “C” divided by the tracts in “A” plus “B” plus “C”. If there is extensive commonality in the way places are classified, then the policy choice of indicator is not critical. However, if there are significant differences, then the choice may matter. Empirically the former is the outcome; consequently, the indicators can potentially produce different results in terms of the populations and neighborhoods designated to receive priority because of high risk.

Figure 1: Distribution of Tracts by SVI and PHV Statewide Ranking



The second set of assessments examines the differences among the indicators by comparing the demographic outcomes. The first step is based on population composition by race. This is done by summing up the counts from the 2015-19 American Community Survey for the tracts designated as being highly vulnerable. For the tracts included in the study (which mostly excludes places with no population or with a disproportionately large number of persons in group quarters), non-Hispanic Whites comprise 37.2% of the total, Asian Americans comprise 14.5% of the total, African American comprise 5.8%, and Hispanics 39.0%. Given that African Americans and Hispanics are relatively more disadvantaged, then it is likely that they comprise a larger percent of the population in high vulnerability tracts.

The second step is calculating the probability that majority minority neighborhoods are classified as being vulnerable, using 2015-19 ACS data. Minority neighborhoods have disadvantages beyond those encountered at the individual level.¹³ Residents in these places face place-based forms of discrimination and unfair treatment by people, firms and institutions, and systematic barriers to regional opportunities. Operationalizing the designation is done by first identifying the tracts that are predominantly of one demographic group (African Americans, Asian Americans, Hispanic and non-Hispanic Whites).¹⁴ Among the 8,059 tracts included in the study, there are 2,937 tracts are majority non-Hispanic White, 373 tracts are majority Asian American, 66 are majority African American, and 2,522 Hispanic. The analysis determines the proportion of these majority tracts are designated as being highly vulnerable. Because there are a very large number of majority Hispanic tracts, the analysis also examines very poor majority Hispanic neighborhoods (defined as a majority Hispanic tract where persons below the federal poverty line comprise 30% or more of the total population).



Results

The two figures below summarize the concordance analysis. Figure 2 is based on designating the vulnerable neighborhoods by ranking for all tracts within the state. Because of regional differences in overall socioeconomic and other demographic characteristics, designated vulnerable tracts are not proportionately distributed among the regions. For example, 29% of all tracts are in Los Angeles County, while 12% of ADI vulnerable tracts, 40% of HPI vulnerable tracts, 32% of PHV vulnerable tracts and 40% of SVI vulnerable tracts are in the County. Concordance rates vary from a low of 37% (ADI and SVI) to a high of 61% (HPI and SVI). The average is 46%, meaning that there are more uniquely identified tracts than commonly identified ones; therefore, the choice of indicator inherently translates into a significant variation in the sets of tracts that are classified as being as being eligible or ineligible for prioritization.

Figure 2: Concordance Rates of Tracts Based on Statewide Vulnerability Rankings

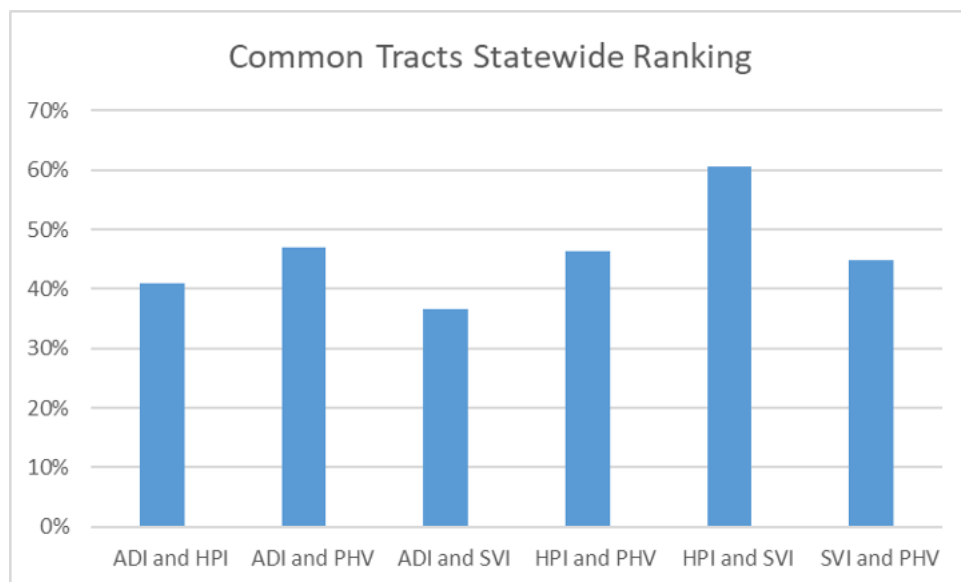
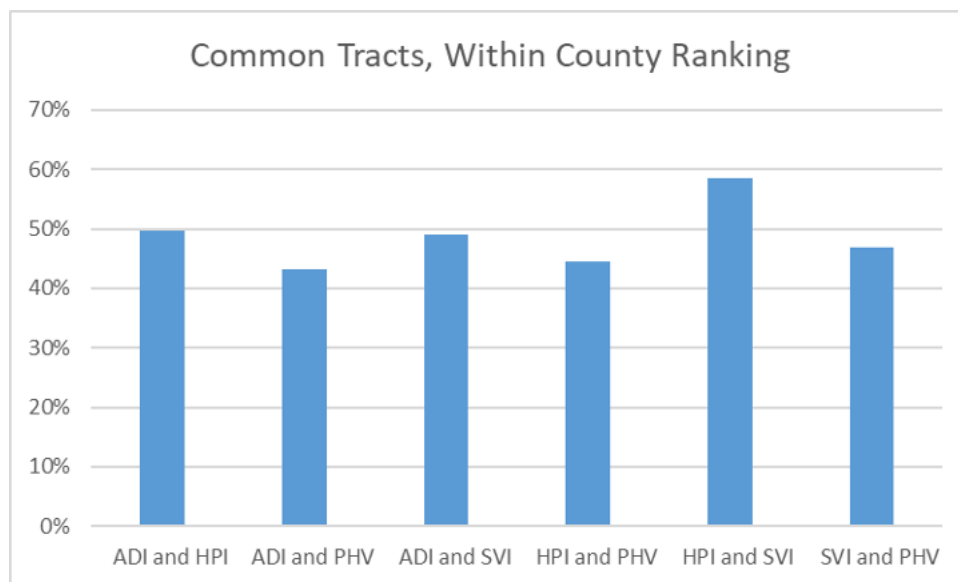


Figure 3 is based on designating the vulnerable neighborhoods by separate rankings within each county. This implicitly means that there are proportionally the same number of designated vulnerable tracts (the top quartile) in each county regardless of sizable differences in socioeconomic and other demographic characteristics. This can be seen in the case for affluent San Francisco County by comparing the designation by within county ranking and statewide ranking. By definition, approximately a quarter of San Francisco tracts are designated as being vulnerable (24% to 25%, depending on how tracts at the 25th percentile are classified). On the other hand, 1% or none of San Francisco tracts are designated as being vulnerable when using statewide ranking. Despite the differences when using within county rankings, the concordance rates are low, ranking from 43% (ADI and PHV) to a high of 59% (HPI and SVI), with an average of 49%. As with the previous analysis using statewide rankings, the results here also means that there are more uniquely identified tracts than commonly identified ones. The implication is the same: the choice of indicator inherently translates into a significant inconsistency in the tracts that are uniquely classified as eligible or ineligible for prioritization.

Figure 3: Concordance Rates of Tracts Based on Within County Vulnerability Rankings



The following two tables summarize the population analysis by race. Table 1 is based on designating the vulnerable neighborhoods by ranking for all tracts within the state. As expected, African Americans and Hispanics comprise a larger percent of the population in high vulnerability tracts because these two groups are relatively more disadvantaged. (For comparison, the following are the percentages for all tracts in the study: 27% for non-Hispanic Whites, 14% for Asian Americans, 6% for African American and 39% for Hispanics) There are, however, noticeable differences across indicators. Simulation with ADI produces the largest relative number of NH whites (about twice as much as SVI), and PHV produces the largest relative number of African Americans (over 1.2 times as much as ADI). The differences in percentages translate into significant differences in the absolute size of the populations. For example, there is a difference of 168 thousand African Americans in ADI vulnerable tracts and PHV vulnerable tracts, a substantial number.

Table 1: Policy Simulation Results Based on Statewide Rankings

	ADI	HPI	PHV	SVI
Percent of Population in Vulnerable Tracts				
Non-Hispanic White	30%	17%	19%	15%
Asian American	6%	8%	6%	9%
African American	7%	8%	9%	8%
Hispanic	54%	65%	63%	66%
Percent of Majority Tracts Included by Indicator				
Non-Hispanic White	17%	5%	5%	2%
Asian American	1%	7%	0%	11%
African American	9%	45%	61%	38%
Hispanic	41%	56%	56%	61%
Hispanic, High Poverty	71%	96%	79%	97%

The bottom panel in Table 1 reports the probability that majority minority neighborhoods are classified as being vulnerable. Relatively, there are few Asian American tracts in designated vulnerable tracts, due to an overall higher socioeconomic and health status¹⁵, although the findings do not reveal substantial differences among Asian ethnic groups. The ADI captures very few African American neighborhoods, while the PHV captures three-in-five African neighborhoods. The latter high rate is probably due to the multiple health problems in this population, including a high prevalence of pre-existing health conditions that increase vulnerability to COVID-19. The ADI captures the fewest Hispanic neighborhoods, while the SVI captures the most. Among the other three indicators, PHV captures fewer than HPI and SVI, perhaps due to the “Hispanic Epidemiological Paradox,” where this population has better health outcome relative to their low socioeconomic status.¹⁶

Table 2 is based on designating the vulnerable neighborhoods by separate ranking for tracts within each county. Many but not all of the results are similar to those based on statewide rankings. As expected, African Americans and Hispanics comprise a larger percent of the population in high vulnerability tracts because these two groups are relatively more disadvantaged. (Again, for comparison, the following are the percentages for all tracts in the study: 27% for non-Hispanic Whites, 14% for Asian Americans, 6% for African American and 39% for Hispanics.) Compared with the statewide analysis, the differences across indicators in the percentages for all four ethnoracial groups are smaller. For example, African Americans as a percent of the population in vulnerable places range from 8.5% for PHV to 8.0% for SVI based on county rankings. One notable outcome is that county-based rankings include more Asian Americans than statewide rankings.

Table 2: Policy Simulation Results Based on Within County Rankings

	ADI	HPI	PHV	SVI
Percent of Population in Vulnerable Tracts				
Non-Hispanic White	20%	19%	18%	18%
Asian American	11%	11%	9%	11%
African American	8%	8%	8%	8%
Hispanic	58%	60%	62%	60%
Percent of Majority Tracts Included by Indicator				
Non-Hispanic White	9%	7%	5%	5%
Asian American	19%	17%	12%	21%
African American	41%	44%	65%	33%
Hispanic	47%	49%	53%	52%
Hispanic, High Poverty	72%	84%	59%	87%

Conclusion

One of the underlying motivations for this study is addressing the politically contentious prohibition against race/ethnic-based policies to rectify past injustices by “leveling the playing field.” The 1996 Proposition 209 imposed severe restrictions on California, forbidding government and public institutions from using race/ethnicity (and other forms of social identities) in giving “preference” in the provision and distribution of goods and services.¹⁷ Californians revisited Proposition 209 in the November 2020 election, but the voters refused to overturn the prohibition. This does not mean, however, that racism cannot be acknowledged. Californians rejected the 2003 Proposition 54, what would have prohibited the collection of race/ethnic data. One of the strongest arguments against the initiative was the critical need for race/ethnic data to track and analyze health outcomes. The legal constraint creates a policy dilemma.¹⁸ It is possible to identify systematic and implicit racial and ethnic biases in California’s racial-neutral policy to prioritize neighborhoods high-impact by the pandemic, but it is not permissible to use race/ethnic-conscious policy instruments to rectify the flaw. The proposed solution is to utilize indirect measurements (indicators) based on underlying mechanisms that play major roles in generating racial and ethnic disparities.

The findings from the policy-oriented simulation findings provides some insight into what could be a good proxy to capture underlying racial disparities. The results show noticeable differences in the groups and places designated as being vulnerable; consequently, the choice has implications in terms of who is served and who is not along racial lines. ADI performs the worst in terms of capturing African American and Hispanic persons and neighborhoods. There are also noticeable differences among the other three indicators. PHV tends to capture more African American persons and neighborhoods, probably because this group are more likely to have pre-existing health conditions. HPI and SVI have many similar outcomes, probably due to having many common input data from the American Community Survey. Base on a strict interpretation of Proposition 209, the SVI indicator could be considered not a viable option because one of its input variables is based on race. Among the remaining three (ADI, HPI and PHV), which do not explicitly include race, the PHV is the most likely to be inclusive of people and neighborhoods of color.

The study’s limited assessment does not indicate which indicator is “best” by other criteria and for other policy goals beyond racial justice. An analytical better approach to evaluating the indicators’ usefulness is to examine how an indicator aligns with explicit policy objectives. For example, the PHV is more useful in identifying the neighborhoods that would be more adversely impacted by new waves of coronavirus infections because of more severe health and mortality outcomes. This means that inoculating residents in high PHV neighborhoods would be a desirable preventive action. The PHV, however, is not effective in directly identifying social and economic vulnerabilities. While the other three (ADI, HPI and SVI) include these types of risks, it is difficult to fully or simply understand their relative strengths and weaknesses without identifying the most relevant type and form of vulnerability. The three indicators’ strength is also their weakness. They include a very broad range of factors that enable them to rank generalized vulnerability, but this breadth also makes them difficult to interpret for specific risks (e.g., probability of spreading infection associated with the built environment, or communication and trust barriers to accepting vaccines). An alternative is developing and constructing new and customized indicators that are aligned to the specific vulnerability characteristics associated with the pandemic and policy goals.



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