Screening Method and Map for Evaluating Transportation Access Disparities and Other Built Environment-Related Determinants of Health

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Figures and Tables

Acronyms and Abbreviations

AASHTO	American Association of State and Highway Transportation Officials
AB	Assembly Bill
ACS	American Community Survey
AMI	Area Median Income
APR	Annual percentage rate
BEV	Battery electric vehicles
CalEPA	California Environmental Protection Agency
Caltrans	California Department of Transportation
CAP	California Bureau of Automotive Repair’s Customer Assistance Program
CARB	California Air Resources Board
CARS	Car Allowance Rebate System
CDPH	California Department of Public Health
CEC	California Energy Commission
CES 3.0	CalEnviroScreen 3.0
CHP	California Highway Patrol
CNK	Center for Neighborhood Knowledge
CNT	Center for Neighborhood Technology
COVID-19	Coronavirus disease 2019
CSA	Combined Statistical Area
CTC	California Transportation Commission
CTPP	Census Transportation Planning Products
CVMT	Commute vehicle miles traveled per worker
CVRP	Clean Vehicle Rebate Project
DI	Disability Insurance
DMV	California Department of Motor Vehicles
DOI	California Department of Insurance
DPR	California Department of Parks and Recreation
EFMP	Enhanced Fleet Modernization Program
EPA	US Environmental Protection Agency
ESRI	Environmental Systems Research Institute
FFIEC	Federal Financial Institutions Examination Council
FHA	Federal Housing Administration
FHWA	US Department of Transportation Federal Highway Administration
FICO	Fair Isaac Corporation
FTA	Federal Transit Administration
GHG	Greenhouse gas
GIS	Geographic Information System
GMAC	General Motors Acceptance Corporations
GPS	Global Positioning System
GTFS	General Transit Feed Specification
HCD	California Department of Housing and Community Development

HDM	Caltrans Highway Design Manual
HMDA	Home Mortgage Disclosure Act
HQTL	High-Quality Transit Location
HVMT	Household vehicle miles traveled
H+T Index	Housing and Transportation Index
LEHD	Longitudinal Employer-Household Dynamics
LEHD LODES	LEHD Origin-Destination Employee Statistics
LEP	Limited English Proficiency
MPOs	Metropolitan Planning Organizations
MSA	Metropolitan statistical areas
MUTCD	Manual on Uniform Traffic Control Devices
NACTO	National Association of City Transportation Officials
NH White	Non-Hispanic White
NTD	National Transit Database
OEHHA	California Office of Environmental Hazard Assessment
OSHPD	Office of Statewide Health Planning and Development
PEV	Plug-in Electric Vehicle
PHEV	Plug-in hybrid electric vehicles
PMT	Person miles traveled
PUMS	Public Use Microdata Sample
RTP/SCS	Regional Transportation Plan Sustainable Communities Strategy
SAS	Statistical Analysis System
SB	Senate Bill
SBBC	South Bay Bicycle Coalition
SCAG	Southern California Association of Governments
SGC	Strategic Growth Council
SLD	Smart Location Database
SoMa	South of Market
SWITRS	Statewide Integrated Traffic Records System
S&P	Standard & Poor
TIMS	Transportation Injury Mapping System
UCLA	University of California, Los Angeles
UI	Unemployment Insurance
USALEEP	US Small-area Life Expectancy Estimates Project
USPS	US Postal Service
WAC	Workplace Area Characteristics
VA	Veterans Affair
VMT	Vehicle miles traveled
ZCTA	ZIP code tabulation area

Glossary of Key Terms

The following provides a short description of key terms. More details can be found in the body of the report.

Access to High-Quality Transit Locations: Availability of nearby transit stops with high service level. This indicator defines a high-quality transit location as being within a quarter mile of transit stops with a high level of service during the morning commute. Planners generally accept the quarter mile as the distance a typical person is willing to walk to local transit service.

Automobile Insurance Premium: Average auto insurance premium in dollars for comparable coverage (same level of liability and similar driver and vehicle characteristics).

Availability of Bikeways: Availability of bikeways per population, weighted by class of bikeways.

Availability of Public-Parks: Availability of nearby public-park space measured as park area within and near a given census tract divided by the population within and near that tract.

Clean Vehicles: Vehicles that fully or partially use energy sources other than gasoline or diesel; “newer” clean vehicles include vehicles with model years between 2013 and 2017; “older” clean vehicles include vehicles with model years 2012 and earlier.

Clunkers Vehicles: Vehicles with a model year of 1997 or earlier.

CVMT: Estimated average annual commute vehicle miles traveled per worker.

HVMT: Estimated average annual vehicle miles traveled per household.

Job Access: Accessibility to employment opportunities estimated as number of jobs inversely weighted by distance.

Job Density: Jobs divided by a neighborhood’s geographic area.

Jobs–Housing Fit: Number of low-wage jobs relative to number of affordable rental housing units.

Lending Barriers: The proportion of mortgage loans with high interest rates serves as a proxy for auto lending barriers. Higher-priced loans are those with interest rates above the prevailing rate for the typical borrower. These loans often reflect riskier or subprime loans. For this project, we consider mortgage loans designated as “higher-priced loans” as subprime loans.

Neighborhood: For this project, the geographic extent of a neighborhood is equivalent to the census tract. The two terms are used interchangeably throughout this report.

Neighborhood Change: Difference in socioeconomic and housing characteristics between two time points.

Relative Neighborhood Income: A census tract’s median household income as a percent of the region’s median income.

Traffic Collision per Roadways: Estimated number of reported collisions per lane-weighted roadways.

Transportation networks: An infrastructure system that facilitates the movement of people and goods (e.g., roads, transit routes, sidewalks).

Abstract

This report documents the UCLA Center for Neighborhood Knowledge's development of a statewide database and data/mapping portal that displays census-tract level variables and indicators that the existing literature and previous research have documented as being associated with the causes, characteristics, and consequences of transportation access disparity.[1] The project covers vehicle ownership, public transit, active transportation, and transportation networks. The information is designed for decision makers, public agencies, and community groups that are working to address systematic transportation access-related inequities, including their root causes and outcomes.

The project's major objectives are: (1) support CARB's equity-related work through the use and compilation of new and innovative data, and (2) make that information accessible to other stakeholders working to ensure that lower income populations and neighborhoods benefit from the state's climate change policies and have their transportation needs met to facilitate access, public health, economic, and quality-of-life improvements.

The project's distributional analysis found and quantified that lower income neighborhoods experience several challenges: greater barriers to vehicle ownership, disproportionately fewer "clean vehicles" (defined as vehicles that fully or partially use energy sources other than gasoline or diesel) and more "clunkers" (defined as vehicles aged 20 years and older), more limited ability to travel (as illustrated by less access to private vehicles and lower vehicle miles traveled), and less access to infrastructure that supports active transportation. The other major finding is a significant diversity in transportation characteristics among lower income neighborhoods - such as differences in access to public transit, bikeways and economic opportunities.

The diversity of transportation characteristics indicate that California has a complex and highly heterogeneous neighborhood system, and a need to go beyond a simple "one-size" approach to promoting equitable sustainable development. Practical solutions to address transportation access disparities and their root causes and outcomes should be customized to the particular needs and opportunities of each place.

[1] To access the data/mapping portal visit:
https://experience.arcgis.com/template/9c13f35df3904dcb80530d0df49bdf9e

Executive Summary

Background: This report documents the development and construction of a statewide database, data/mapping portal[2], and screening tool to highlight indicators that the literature and previous research have documented as being associated with the causes, characteristics, and consequences of transportation disparities. The database contains census tract–level variables and indicators that were informed by and prioritized with the help of an Advisory Committee that included planning and health experts, academics and researchers, and community organizations. The project generates information relevant to California's equity work and its efforts to address climate change per Assembly Bill (AB) 32, Senate Bill (SB) 375, SB 535, SB 350, and SB 150. The project covers disparities in private vehicle ownership, public transit, active transportation, and transportation networks. The project provides critical information for decision makers, public agencies, and community groups addressing systematic inequality in transportation and related issues (e.g., sustainable community strategies, prioritizing neighborhoods for investments).

Objectives: The project's major objectives are to supports CARB's equity work by developing new and innovative data related to transportation inequities and making that information available to stakeholders working to ensure that lower income communities and neighborhoods benefit from the state's climate change policies.

The project had six major tasks to fulfill the project's objectives:

- Task 1 involved engagement with stakeholders using the Advisory Committee to solicit input and review preliminary findings to ensure that the final products are relevant and useful.
- Task 2 identified and prioritized indicators that were technically feasible, within the project's resources to collect, and consistent with input from the Advisory Committee.
- Task 3 centered on the construction of a transportation disparity database, using recent available data from multiple sources, and utilizing existing and new analytical techniques.
- Task 4 developed a data/mapping portal that can identify neighborhood-level transportation disparities, needs, and investment opportunities, particularly for the most economically disadvantaged communities.
- Task 5 focused on developing a sophisticated but accessible web-based information, visualization, and mapping portal.
- Task 6 documented the project and produced guidelines and a guidebook for users.

Methods and Indicator Construction: The transportation disparity database contains 40 indicators that can be sorted into two categories: (1) preexisting indicators (27 in total) and (2) newly constructed indicators (13 in total). The set of preexisting indicators includes four that were previously developed by UCLA Center for Neighborhood Knowledge (CNK) for a project funded by CARB and Caltrans[3] and 23 from other sources, which were evaluated to determine relevancy for inclusion. To construct the 13 new indicators that fall into the second category, CNK followed five steps:

- Step 1: Access and assemble data from multiple sources: readily available public data (e.g., from the U.S. Census Bureau), specialized data from public agencies (e.g., clean and clunker vehicles), and data from other nonpublic entities (e.g., insurance premiums).

[2] To access the data/mapping portal visit:
https://experience.arcgis.com/template/9c13f35df3904dcb80530d0df49bdf9e

[33] See Ong, P. M., Pech, C., Cheng, A., & Gonzalez, S. R. (2018). Developing Statewide Sustainable-Communities Strategies Monitoring System for Jobs, Housing, and Commutes (Caltrans Agreement No. 65A0636). UCLA Center for Neighborhood Knowledge.

- Step 2: Assess potential input data for quality, timeliness, precision and accuracy, and consistency.
- Step 3: Use spatial tools to construct metrics (e.g., the availability of nearby parks to neighborhood residents).
- Step 4: Evaluate newly constructed metrics by comparing them to similar preexisting ones.
- Step 5: Rank the metrics where appropriate.

Results and Findings: A key objective and outcome of this project was the creation of the transportation disparity database and its accompanying data/mapping portal. In constructing this database, the researchers conducted various assessments of the data to determine the most appropriate method for reporting indicator values in the database and data/mapping portal. For many of the constructed indicators, the research team determined that it was most appropriate to report indicators as decile rankings because they perform reasonably well to capture *relative* positions of census tracts, but the underlying numerical value is imprecise and can be misleading. For example, average vehicle miles traveled per household uses a mix of data sources, including data from California Bureau of Automotive Repair, which is collected every other year and biased to older vehicles, and CARB-DMV, which collects a stock of vehicles by age. For this reason, average vehicle miles per household is reported in deciles in the database and in quintiles in the mapping tool (quintiles are easier shade for visual representation). The contents of Chapter 2: Indicator Construction in this report makes clear reporting/display method in the database and mapping tool.

The project conducted a distributional analysis to determine patterns of transportation disparities across neighborhoods (census tracts; the two terms are used interchangeably). This was done by comparing lower income neighborhoods with more affluent ones, which are defined by a tract's median household income relative to the regional average. The analysis found and quantified that low-income neighborhoods experience several challenges: more barriers to vehicle ownership, disproportionately fewer clean vehicles and more clunkers, more limited ability to travel (less access to private vehicles and lower VMT), and less access to infrastructure supporting active transportation. Differences for the other indicators (e.g., neighborhood change, job–housing fit, job density) also show systematic inequalities. The other major finding is a significant diversity in transportation characteristics among lower income neighborhoods (and higher income ones). For example, while most lower income neighborhoods are public park poor (consequently, lower ability to engage in walking and other activities because of a relative lack of availability to green space), some are not (albeit disproportionately fewer in number). Not all lower income neighborhoods are identical in terms of their transportation challenges and opportunities. California's complex and highly heterogeneous neighborhood system means that equity policy should go beyond a simple "one-size" approach to promoting equitable and just sustainable development.

Conclusion/Recommendations: The project's database and distributional analysis provide critical information that CARB, other state and local governments, regional agencies, and stakeholders can utilize in their efforts to redress systematic transportation disparities. However, the real-world impacts of this project will depend on actively using, analyzing, and updating and refining the information to inform the development and modification of equity policies, programs, and actions. There are four major recommendations.

1. The first recommendation is to promote greater usage. CARB should actively promote the data system, conduct workshops for stakeholders, and regularly publish reports that include examples of how the information can be used, research based on the data, and updates to the data system.
2. The second recommendation is to conduct additional analyses and research that build upon this work and other past research and projects to improve the lived experience of people in lower income communities and communities of color. This recommended future work can be included in the proposed CARB publications. This includes conducting similar distributional analysis using the definition of "disadvantaged communities" identified by the California Environmental Protection

Agency (CalEPA) and "low-income communities" as defined in Assembly Bill 1550. Equally important is supporting research on the determinants and consequences of transportation inequality. This will provide insights into how best to eliminate the root (systemic) causes of transportation inequality, and into prioritizing interventions to maximize "downstream" cobenefits (e.g., improving health).

3. The third recommendation is to continuously update and refine indicators, and the web-based data and mapping portal based on the latest available information. This is particularly important given recent events. The COVID-19 pandemic has upended people's lives and livelihood, and there are likely to be long-term impacts and changes that will transform and exacerbate the neighborhood-level causes, characteristics, and consequences of transportation disparities.
4. The last recommendation is to explicitly address racial disparities transportation. While Proposition 209 limits the use of race in allocating funds and services, it does not prohibit conducting analyses to understand how unequal access to transportation and transportation-related resources marginalize people of color. CARB and other state agencies should assemble a panel of experts on racial, social, and economic inequality to develop a research agenda that can explicitly assess and improve institutional practices regarding equity within these organizations. The long-term outcome of such a research agenda can produce insights that identify the social and economic mechanisms that generate inequality and enable the state to develop policies and programs to address those unfair processes.

Chapter 1 Introduction

This report details the process undertaken by the UCLA Center for Neighborhood Knowledge to develop a statewide transportation disparity database, data/mapping portal, and screening tool. (Screening is done through a filtering process in the data/mapping portal that enables users to select tracts based on their specific neighborhood characteristics.)[4] The database contains variables and indicators that the existing literature and previous research have documented as being associated with the causes, characteristics, and consequences of transportation disparities. This report also provides details on the new indicators constructed by the project, information regarding how these indicators differ across neighborhoods by economic status (relative Area Median Income, or AMI), and information on how to access and utilize the data.

The project supports and builds upon California's efforts to implement the Global Warming Solutions Act of 2006 (also known as Assembly Bill or AB 32) and to do so in a way that equitably benefits all Californians, especially those living in disadvantaged and low-income communities. The specific AB 32-related laws and policies that this project builds from and supports include:

- Senate Bill (SB) 375, which requires that the California Air Resources Board (CARB) set regional GHG reduction targets related to long-range regional and transportation planning and that each metropolitan planning organization (MPO) adopt a regional "sustainable communities strategy" describing how the regional target will be met.
- SB 350, which required CARB to develop and publish a study on barriers for low-income customers to zero-emission and near-zero-emission transportation options, including those in disadvantaged communities, as well as recommendations on how to increase access to zero-emission and near-zero-emission transportation options to low-income customers, including those in disadvantaged communities. This study was published in 2017 and contained many recommendations that CARB and other agencies are now pursuing.
- SB 150, which tasked CARB with issuing a report every four years analyzing the progress made under SB 375. The report must assess progress made toward meeting the regional SB 375 greenhouse gas emissions reduction targets, include data-supported metrics for strategies utilized to meet the targets, and include a discussion of best practices and challenges faced by MPOs in meeting the targets, including the effect of state policies and funding.

The project also contributes to the state's commitment to ensure that all communities, including disadvantaged populations and neighborhoods, will benefit from its climate change policies and related policies.[5] The project's final products will contribute to CARB and other organizations' ability to fulfill these climate change mandates.

1.1 Background and Process

The project was designed to contribute to CARB's equity work and equity work underway at other agencies and stakeholder organizations in four key ways. First, the project covers four main forms of transportation-related disparities: private vehicle ownership, access to public transit, access to infrastructure that support active transportation (bikeways, parks), and transportation networks (an infrastructure system that facilitates the movement of people and goods [e.g., roads, transit routes, sidewalks]). Second, the products will assist efforts to reduce these disparities by addressing their root causes, offsetting deficits in

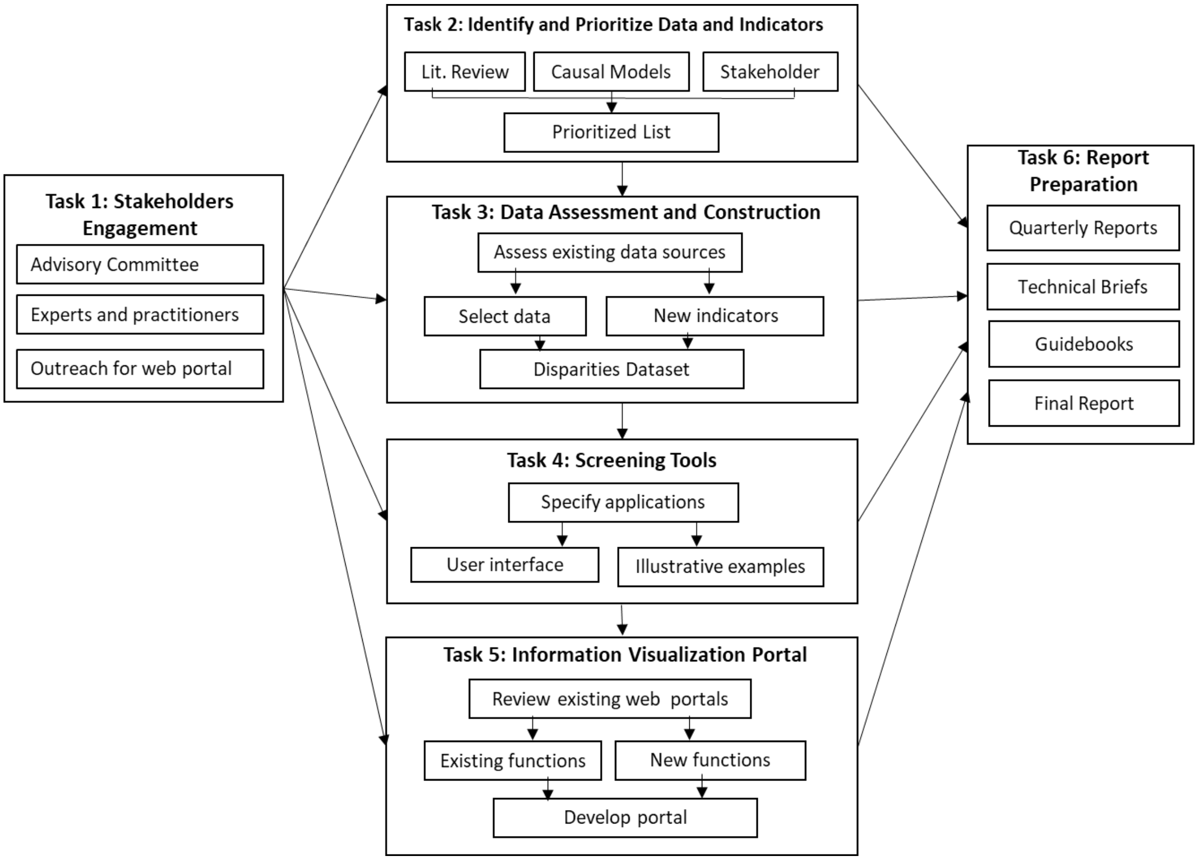
[4] The final scope of work is not identical to that in the original proposal because of agreed upon changes as a result of priorities identified by CARB and the Advisory Committee during the project.

[5] California's climate change policies includes the previously cited legislation in addition to SB 535 and AB 617.

transportation resources and thereby ameliorating downstream outcomes. Third, the products will be useful to a wide range of users addressing various elements of transportation disparities: state agencies (e.g., CARB, Caltrans, Strategic Growth Council, Office of Planning and Research, Department of Housing and Community Development), regional and local jurisdictions, community and nonprofit groups (particularly those involved in environmental justice), and funders (e.g., major foundations supporting place-based strategies and solutions). The products are intended to be helpful to sophisticated professionals (e.g., those using large-scale regional economic, land-use, and transportation models) as well as nontechnical individuals (e.g., neighborhood leaders). In addition, the project includes some information related to employment and health. Lastly, the project includes neighborhood effects, particularly as they relate to neighborhood change in terms of housing and socioeconomic characteristics.

This project has six major components, or tasks, as shown in Figure 1-1. The first three tasks established the foundation of this research. Task 1 focused on engaging stakeholders through the involvement of an Advisory Committee to ensure that the project's plans, activities, and products were well vetted by and ultimately useful to key constituencies. This Advisory Committee included planning and health experts, academics and researchers, and community organizations, and the research team solicited their input in all stages of the project. Task 2 focused on identifying and prioritizing data and indicators using multiple sources. Prioritization is very important because it is critical to focus the project's resources to collect and construct information most consistent with a causal understanding of transportation disparity. It is also important to prioritize based on what is most appropriate for policies and stakeholders. The Advisory Committee played a crucial role in prioritizing which indicators should be included in our products. Task 3 focused on the construction of a transportation disparity database, combining information from existing sources with new information where needed. The objective was to produce a database characterized by high-quality inputs, sound methods for constructing indicators, and consistency with outcomes. External experts and practitioners were consulted to vet data sources and construction methods for appropriateness and accuracy.

Figure 1-1. Overview of Project's Major Components



The next three tasks integrated the indicators and populated these data into the data/mapping portal. Task 4 developed a screening tool (filtering) that can identify neighborhood-level transportation disparities, needs, and investment opportunities, particularly for the lowest income communities. The objective was to promote better selection and matching of neighborhoods to the particulars of policies, plans, and investments. Task 5 focused on the development of a data/mapping portal, which helps users visualize the geographic patterns through interactive maps. The objective was to provide a high level of accessibility to those agencies and organizations that can address transportation disparities. Task 6 focused on documenting the project, producing guidelines that can enhance the usability of the project's products, and leaving a record that can contribute to future development.

The project directly contributes to CARB's equity work and aligns with SB 535 requirements, which require that California Environmental Protection Agency (CalEPA) "identify disadvantaged communities for investment opportunities" and that "administering agencies should maximize benefits for disadvantaged communities." This project is not meant to redefine or substitute for CalEPA's designation of "disadvantaged neighborhoods." The project provides additional information that can be useful to refine policies and programs as it relates to CARB and CalEPA's equity work. The project's final products will contribute to the ability of CARB and other organizations to fulfill these mandates. These products will serve potential stakeholders working on related policies, plans, and programs, and will enhance the effectiveness, reach, and sustainability of transportation-related investments, interventions, and other efforts to improve employment, educational, and health outcomes. The project will help inform investments pursuant to SB 535.

1.2 Assessing the Data, Indicators, and Measures

Given the range of what is directly and indirectly related to transportation and health disparities, there is a wide spectrum of possible dimensions to measure and include in our statewide transportation disparity database and data/mapping portal. Additionally, there are a variety of methods for measuring and tracking four major transportation disparities: private vehicle ownership, public transit, active transportation, and transportation networks. Because time and resources are limited, development of our products are based on prioritized metrics identified through input from an Advisory Committee, other stakeholders, and CARB.

The indicators identified and included in our database and data/mapping portal will highlight disparities in root causes, transportation resources, quality of transportation resources, access to opportunities with available transportation resources, and neighborhood changes across California. The data and indicators will augment and complement other databases used by CARB and other agencies, thus increasing their ability to pinpoint specific transportation-related needs and monitor and evaluate progress in addressing these needs.

Data collection, assessment, and construction have many alternatives and trade-offs associated with certain data sources and methods. In our process of constructing the indicators for our statewide database of indicators and variables, data/mapping portal, we found a wide range of data quality (e.g., timing in reporting, errors, inconsistencies), which can impact the quality of our constructed indicators (e.g., errors in data that trickle down into erroneous results). In addition, there were issues with potentially incompatible application of existing formulas and parameters toward the construction of accessibility measures that can be especially problematic when scaling up to larger levels (e.g., going from census tracts to ZIP code tabulation areas). Some of the data and indicators used by this project also have similar issues and limitations. To minimize any data problems and methodological shortcomings, we corrected when possible and tested alternative approaches.

In each indicator construction chapter, we detailed the data source, data coverage, accuracy, and consistency with other data sources. Doing so provides us with confidence in the validity of our indicators and results. Through this process, we identified gaps and addressed issues in the data prior to indicator construction. As a result, some of our indicators represent the most complete database available, based on our knowledge of the field and a review of related studies.

The statewide database includes a total of 40 indicators of which 17 are CNK-constructed indicators. Of the 17, 13 are newly constructed for this project and 4 were adopted and/or refined from a previous project conducted by the researchers for CARB and Caltrans[6]. The remaining 23 indicators are from other sources (e.g., ACS, CalEnviroScreen 3.0, EPA, OSHPD, USALEEP). Table 1-1 list all 40 indicators included in the database.

We use the following categories to group indicators: (1) “Transportation” refers to vehicle-related characteristics; (2) “Accessibility” refers to spatial access to opportunities and amenities; (3) “Housing” refers to the characteristics of the housing stock and inhabitants; (4) “Socio-Demo-Economic” refers to social, demographic, and economic characteristics of the population; and (5) “Health” refers to the health-related characteristics of the population or neighborhood. Some indicators may fall into more than one category but the assignment is based on what we consider to be the primary classification.

[6] See Ong, P. M., Pech, C., Cheng, A., & Gonzalez, S. R. (2018). Developing Statewide Sustainable-Communities Strategies Monitoring System for Jobs, Housing, and Commutes (Caltrans Agreement No. 65A0636). UCLA Center for Neighborhood Knowledge.

Table 1-1. Indicators in the Transportation Disparity Database

Indicator	Category	Source
Indicators Constructed by CNK		
Auto Insurance Premium	Transportation	UCLA CNK
Lending Barriers	Transportation	UCLA CNK
“Newer” Clean Vehicles	Transportation	UCLA CNK
“Older” Clean Vehicles	Transportation	UCLA CNK
“Clunker” Vehicles	Transportation	UCLA CNK
VMT per Household	Transportation	UCLA CNK
Commute VMT Per Worker	Transportation	UCLA CNK
Accessibility to Employment Opportunities	Accessibility	Caltrans (65A0636)/UCLA CNK
Availability of Public Park Space per Population	Accessibility	UCLA CNK
Availability of Weighted Bikeways per Population	Accessibility	UCLA CNK
Traffic Collisions per Weighted Roadways	Health	UCLA CNK
Neighborhood Change, Housing Variables	Housing	UCLA CNK
Neighborhood Change, Socioeconomic Variables	Socio-Demo-Econ	UCLA CNK
Neighborhood Income Relative to Regional AMI	Socio-Demo-Econ	UCLA CNK
Job Density	Socio-Demo-Econ	Caltrans (65A0636)/UCLA CNK
Jobs–Housing Fit	Accessibility	Caltrans (65A0636)/UCLA CNK
Access to High-Quality Transit Locations	Accessibility	Caltrans (65A0636)/UCLA CNK
Indicators Constructed by Other Sources		
% Bike for Job Commute	Transportation	ACS
% Carpooled for Job Commute	Transportation	ACS
% Drove Alone for Job Commute	Transportation	ACS
% Households Paying 30–49% of Income Toward Housing Costs	Housing	ACS
% Households Paying 50% or More of Income Toward Housing Costs	Housing	ACS
% Households with No Vehicle	Transportation	ACS
% No Health Insurance	Health	ACS
% Poverty	Socio-Demo-Econ	ACS
% Public Transportation for Job Commute	Transportation	ACS
% Renter-Occupied Households	Housing	ACS
% Walk for Job Commute	Transportation	ACS
% with Medicaid Health Insurance Only	Health	ACS
Average Travel Time to Work (Minutes)	Transportation	ACS
Housing Unit Density	Housing	ACS

Indicator	Category	Source
Largest Ethnoracial Group	Socio-Demo-Econ	ACS
Median Household Income	Socio-Demo-Econ	ACS
Population Density	Socio-Demo-Econ	ACS
Vehicles Per Household	Transportation	ACS
Asthma Prevalence	Health	CalEnviroScreen 3.0
Cardiovascular Disease	Health	CalEnviroScreen 3.0
Walkability Index	Health	EPA (Version 2.0)
Primary Care Shortage Areas	Health	OSHPD
Life Expectancy at Birth	Health	USALEEP

The remainder of this report is organized by analytic tasks, as follows:

- Chapter 2 details each CNK-constructed indicator. Each indicator includes a brief background discussion, followed by discussion of the data source, construction method, its consistency with other similar indicators, and results illustrated through charts and maps.
- Chapter 3 provides one way of examining how transportation disparities vary across neighborhoods in California by conducting a distributional analysis of each indicator across CNK's area median income (AMI)–based neighborhoods.
- The final chapter, Chapter 4, summarizes our research efforts, outlines our major conclusions, and offers recommendations for future expanded research.

Chapter 2 Indicator Construction

This chapter details the development of the transportation disparity database and construction of indicators. The chapter contains three sections. The first, "Approach," provides a brief overview of our approach to constructing the indicators. The subsequent section discusses the assessment of input data and the criteria used to determine how the indicators are reported (e.g., decile rankings). The third section provides detailed discussion of how each of the new CNK indicators were constructed.

2.1 Approach

The transportation disparity database contains two types of indicators. The first includes those previously developed by CNK prior to this project and preexisting ones from other sources, which were evaluated to determine which are relevant for inclusion. The second type of indicators includes new ones constructed by the project. The latter effort involved five steps.

1. The first was to access and assemble data from multiple sources: readily available public data (e.g., from the U.S. Census Bureau), specialized data from public agencies (e.g., clean and clunker vehicles), and data from other nonpublic entities (e.g., insurance premiums).
2. Step two assessed potential input data for quality, timeliness, precision and accuracy, and consistency.
3. Step three used spatial tools to construct metrics (e.g., the availability of nearby parks to neighborhood residents).
4. Step four evaluated those newly constructed metrics by comparing them to similar preexisting ones (where possible).
5. Step five ranked the metrics where appropriate.

The transportation disparity database includes a total of 40 indicators: 17 CNK-constructed indicators, 4 of which were either adopted entirely or updated (with more current data) from a previous research project funded by CARB and Caltrans[7], and 23 indicators from other sources. These include indicators constructed by CNK using the American Community Survey (ACS) that did not require much altering and indicators not constructed by CNK but obtained from other sources (e.g., CalEnviroScreen 3.0).

In this chapter, we detail the construction of the 13 new indicators constructed specifically for this project and provide descriptions and a summary of the construction method for the 4 indicators adopted entirely or updated from the previous CARB and Caltrans-funded project. Descriptions of the remaining 23 indicators can be found in Appendix D.

For each of the 13 newly CNK-constructed indicators, the following outline is used to describe their construction: 1) brief background; 2) an overview of the data used to construct the indicator; 3) construction method; 4) an assessment of indicator; 5) maps of the indicator; and 6) a list of references.

2.2 Assessing Input Data and Criteria for Reporting

Because some of the indicators are constructed by mixing inputs of varying quality and precision, they are reported as rankings only. The following factors are used to determine the quality and reporting of the CNK-constructed indicators. Construction of the indicators requires a considerable amount of data and

[7] See Ong, P. M., Pech, C., Cheng, A., & Gonzalez, S. R. (2018). Developing Statewide Sustainable-Communities Strategies Monitoring System for Jobs, Housing, and Commutes (Caltrans Agreement No. 65A0636). UCLA Center for Neighborhood Knowledge.

calculation. Data for each indicator varied in the following key dimensions: ***precision***, "***data sources***," ***sample size***, ***biases***, ***methodological complexity***, ***geographic coverage***, and ***geographic resolution***.

- **Precision**
  - What is the relative size of standard error or coefficient of variance within a tract or other small reporting geographies?
- **Data Sources**
  - Was the indicator constructed by mixing two or more different data sources? (Data sources may not be completely consistent with each other.)
- **Sample Size**
  - How many records were captured in the data?
- **Biases**
  - Are there biases in the underlying data? Is the sample representative of the primary population of interest, or does it capture only a nonrandom subset of the population of interest?
- **Methodological Complexity**
  - Did the indicator construction result in multiple imputations, transformation, estimates, and weights? Do the calculations result in extreme nonlinear values and/or extreme outliers?
- **Geographic Coverage**
  - Are data available for all of California?
- **Geographic Resolution**
  - Are data available at the census tract level (unit of analysis) or estimated using spatial allocation of original data into tracts?
- **Reporting Method in Final Dataset**
  - Based on an assessment of the key dimensions above, a decision was made on how to report the final indicators (e.g. decile rankings, numerical values).

Table 2-1 summarizes our assessment of the input data based on the key criteria and requirements discussed in the preceding text. We find considerable heterogeneity in the quality of the information. There are considerable differences in geographic resolution (e.g., automobile insurance premiums are by ZIP code, while ACS data are in ZCTAs and tract), sample size (e.g., five-year ACS is based on a sample of about 12 percent of the households, while BAR data covers about half of older vehicles), and completeness (e.g., data from the Home Mortgage Disclosure Act, or HMDA, includes all loan applications, while the parks data does not include all open public spaces). Some input data also have other limitations, such as underreporting (e.g., traffic collisions), and inconsistency in reporting by different agencies (e.g., bikeways). It should also be noted that there is a general lack of timeliness for most input data, which is unavoidable because of the time required for agencies to collect, assemble, review, and release information. Because of the data limitations, users should use the indicators with caution. We partially address the data limitations through minimizing reporting false precision, which is discussed after Table 2-1.

The assessments are used to determine how the indicators are reported, either as deciles or as numerical values. Some indicators are reported as decile ranking because they perform reasonably well to capture relative positions of tracts but the underlying numerical value can be misleading. For example, average vehicle miles traveled per household uses a mix of data sources, including data from California Bureau of Automotive Repair, which is collected every other year and biased to older vehicles, and CARB-DMV, which collects a stock of vehicles by age.

There are some indicators where the observations cannot be evenly distributed into deciles because there is at least one cluster of observations with the same value and that comprises more than a tenth (10 percent) of the total. This often happens at either (top or bottom) end ranges or both. For example, more than a tenth of the tracts in California are places where no residents are within a quarter mile of a high-quality-transit location; consequently, the lowest category has more than a tenth of the observations. The availability of the bikeways-to-population indicator is another example; more than a tenth of tracts have no availability of bikeways infrastructure. In some rare cases, this phenomenon (clustering of large numbers of observations greater than a tenth of all tracts) can also happen with values away from the two extremes. When this type of clustering occurs, users should be careful in interpreting the distribution because it is impossible to create equal deciles. (For example, users should not state a census tract is in the top tenth if that ranking has more than a tenth of the observation.)

The reporting matrix is only applicable to 13 indicators that CNK constructed for this project. Indicators that are not constructed by CNK are explained in Appendix D: Other Indicators and have their values reported as-is (numerical values) in the transportation disparity database. These include indicators from American Community Survey (ACS), CalEnviroScreen (CES) 3.0, U.S. Environmental Protection Agency (EPA), and U.S. Small-Area Life Expectancy Estimates Project (USALEEP).

Table 2-1. Indicator Reporting Matrix

Indicator	Precision	Data Sources	Sample Size	Biases	Methodological Complexity	Geographic Coverage	Geographic Resolution	Reporting Method in Final Dataset
Auto Insurance Premium	Assumed to be relatively fair to good: based on insurer reporting to survey	Constructed using a combination of two different data on insurance premiums: CA DOI and ProPublica	DOI data covers all ZIP codes in California; some ZIP codes were missing from the ProPublica dataset and number of reporting units per ZIP code not large	ProPublica not weighted by insured share of market; DOI basic coverage does not account for spatial variation in vehicle and driver composition	Some tracts required regression model and spatial autocorrelation to fill in missing data	DOI covers all of California. ProPublica is missing a few ZIP codes.	ZIP code spatial allocation of census blocks to ZIP code and then blocks to tracts	Decile
Lending Barrier (proportion of mortgage loans with high interest rates serves as a proxy for auto lending barrier)	Proxy is moderately correlated with auto lending barrier; precision is low	One source: HMDA as reported by Consumer Financial Protection Bureau	Not based on sampling; number of observations varies across tracts because of ownership and transaction rates	Relies on mortgages with an APR higher than the average prime offer rate as a proxy for auto lending barrier	Simple calculation of rates using observed HMDA accounts	Covers all of California	Census tracts	Decile
Clean Vehicles ("newer" and "older") as Share of Total Vehicle Stock	Assumed to be relatively high: administrative, recording of vehicle model, vintage and fuel type is	One source: DMV as tabulated by CARB	Not based on sampling; large number of observations based on administrative data	Vehicle counts may include business vehicles	Simple calculation of rates using observed DMV data	Covers all of California	Block group (aggregated to census tracts)	Decile

Indicator	Precision	Data Sources	Sample Size	Biases	Methodological Complexity	Geographic Coverage	Geographic Resolution	Reporting Method in Final Dataset
	most likely to be correct							
Clunker Vehicles as a Share of Total Vehicle Stock	Assumed to be relatively high: administrative, recording of vehicle model, vintage and fuel type is most likely to be correct	One source: DMV as tabulated by CARB	Not based on sampling; large number of observations based on administrative data	"Clunkers" are defined by age rather than operating condition; vehicle counts may include business vehicles; unregistered vehicles not counted	Simple calculation of rates using observed DMV data	Covers all of California	Block group (aggregated to census tracts)	Decile
VMT Per Household	Assumed to be relatively fair: average VMT report for vehicles grouped into multiyear categories	Mixing BAR, DMV, and ACS data	Based on high sampling of vehicles captured by BAR; DMV not based on sampling but complete administrative file; ACS based on fair size sample of households (approximately more than 12%).	VMT data based on BAR data, not all vehicles are required to go in for smog check, primarily captures older vehicles	Multiple and cumulative imputations and estimates	Covers all of California	Census tracts	Decile
Commute VMT per Worker	Assumed to be relatively fair to good:	Mixing LEHD commute flows and ACS means	Not based on sampling for worker trips in	Does not include workers outside	Multiple and cumulative	Covers all of California	Census tracts	Decile

Indicator	Precision	Data Sources	Sample Size	Biases	Methodological Complexity	Geographic Coverage	Geographic Resolution	Reporting Method in Final Dataset
	uses census tract centroids to estimate travel distances, and uses HERE network distance for only one specific period	of transportation data	LEHD, but on administrative records; ACS based on fair size sample of workers (approximately more than 12%).	of the Unemployment Insurance and Disability Insurance programs	imputations and estimates			
Availability of Public Park Space per Population.	Unknown precision: not all public spaces are accounted	Mixing Dept. of Parks and Rec. with ACS	Not based on sampling; large number of observations based on administrative shapefiles	Certain types of public spaces are not likely to be included	Generated using tract and surrounding buffer area, some park space can be in more than one tract	Covers all of California. No prevailing standard on walkable buffer size surrounding tract.	Park area	Decile
Availability of Weighted Bikeways per Population	Unknown precision: incomplete and inconsistent data collection by local jurisdiction	Mixing bikeway and ACS	Not based on sampling; observations based on administrative shapefiles	Inconsistent in assignment of bikeway classification	Weights were created for different classifications of bikeways. Weights may be imprecise.	Does not cover all of California. Includes most MPOs and some local jurisdiction. No prevailing	Line, spatial join to census tracts	Ranking to account for clustering at the bottom

Indicator	Precision	Data Sources	Sample Size	Biases	Methodological Complexity	Geographic Coverage	Geographic Resolution	Reporting Method in Final Dataset
						standard on walkable buffer size surrounding tract.		
Traffic Collisions per Weighted Roadways	Unknown precision: unknown number of collisions that go under reported	Mixing separate collision and street network data	Not based on sampling; large number of observations based on administrative data	Selection of surrounding buffer size may not be correct; does not capture all collisions (e.g., less severe collisions)	Generated using surrounding buffer; some collisions can be in more than one tract. No prevailing standard of weighting of roadway classifications. Weights may be imprecise.	Covers all of California	Point (location of collisions); geocoding may not be precise for some collisions; some collisions are not geocoded	Decile
Neighborhood Change (socioeconomic & housing) (composite score)	Assumed to be relatively fair	Mixing two 5-year ACS aggregated statistical data	Relies on ACS data that is based on a sample (approximately 12% of population)	May be affected by short-term business cycle	Indicator constructed using principal component analysis	Covers all of California	Census tracts	Decile
Neighborhood Income Relative to Regional AMI ratio	Assumed to be relatively fair	Mixing reported aggregated ACS statistics and microlevel ACS PUMS data	Relies on ACS data that is based on a sample (approximately 12% of population)	May be affected by short-term business cycle	Indicator based on relation to regional AMI	Covers all of California	Census tracts	Ratio

Indicator	Precision	Data Sources	Sample Size	Biases	Methodological Complexity	Geographic Coverage	Geographic Resolution	Reporting Method in Final Dataset
Access to Employment Opportunities (index score capturing job opportunities accessible from a tract)	Assumed to be relatively high	Mixing jobs data from LEHD LODES and travel time and distance from HERE street network	Jobs data not based on sampling; large number of observations based on administrative data	Jobs data does not include workers outside of the UI/DI programs. May be affected by the short-term business cycle.	Complex involving the use of street network with travel times, and estimating parameters for different decay functions	Covers all of California	Census blocks for jobs aggregated into Census tracts	Decile
Access to High-Quality Transit Location (proportion of population within ½ mile of HQTL)	Assumed to be relatively high for locations with sufficient data	Mixing GTFS datasets compiled from various transit agencies and U.S. Census Bureau block level data.	Transit schedules not based on sampling; fair number of location-specific information base on available schedule.	Does not include many smaller transit agencies.	Moderately complex involving spatial area estimates	Does not cover all of California. Includes only those transit agencies that report transit data in GTFS format at the time of research.	Point location of transit stop, census blocks for population	Ranking to account for clustering at the bottom
Jobs–Housing Fit (ratio of low-wage jobs relative to the availability of nearby affordable rental housing	Assumed to be relatively fair	Mixing aggregated ACS, CTPP statistical data	Relies on data that is based on a sample (approximately 12% of population)	May be affected by the short-term business cycle.	Moderately complex involving multiple imputations, data matching and allocations.	Covers all of California	Census tracts	Decile

Indicator	Precision	Data Sources	Sample Size	Biases	Methodological Complexity	Geographic Coverage	Geographic Resolution	Reporting Method in Final Dataset
Job Density (jobs per square mile)	Assumed to be relatively high	Mixing LEHD LODES for jobs data and land area from the U.S. Census Bureau	Jobs data not based on sampling; large number of observations based on administrative data	Does not include workers outside of the UI/DI programs. May be affected by the short-term business cycle.	Simple calculation of density using observed data	Covers all of California	Census blocks aggregated into Census tracts	Decile

Note: Criteria can be overlapping. For example, precision is a function of sample size and underlying population variance

2.3 Indicators

This section provides a detailed discussion of the construction of the 13 new CNK indicators developed for this project and the four indicators constructed by the researchers for a previous project sponsored by CARB and Caltrans. Each subsection includes information on the relevant literature, input data sources, construction methods, assessment of consistency, and results. The section also includes maps of the indicators along with brief descriptions of the broad and general spatial patterns for the state, the Bay Area, and Los Angeles. Analyzing and explaining the patterns is beyond the scope of the project, but the overview is consistent with previous research that shows geographic differences and disparities in transportation characteristics are associated with social and economic inequality. Users can find additional details for specific neighborhoods by consulting the data/mapping portal, which is discussed in Appendix E.

2.3.1 Auto Insurance Premiums

This subsection describes the approach to constructing the auto insurance premium indicator.

Table 2-2. Summary Table for Auto Insurance Premium Indicator

Key Indicator Information		
Units	Average auto insurance premium in dollars	
Category in Mapping Tool	Transportation	
Display Method in Mapping Tool	Decile (visualized in quintiles)	
Precision	Fair to good, based on insurer reporting to survey	
Methodological Complexity	Some tracts required regression model and spatial autocorrelation to fill in missing data	
Geographic Resolution	ZIP code; spatial allocation of census blocks to ZIP code and then blocks to tracts	
Key Information about Data Sources Used to Construct Indicator		
Data Sources Used to Construct	ProPublica (original sources: Quadrant Information Services, S&P Global, Inc.)	California Department of Insurance (DOI)
Sample Size	1,816 ZIP codes	All ZIP codes with sufficient information, and based on where insured vehicles are garaged.
Biases	Not weighted by insured share of market	Basic coverage does not account for spatial variation in vehicle and driver composition
Geographical Unit	ZIP code (converted to ZCTAs)	ZIP code (converted to ZCTAs)
Geographic Coverage	Missing a few ZIP codes	Covers all of California

Data Vintage	2007-2011	2014-2016
Other Important Notes (if applicable)	For more information on ProPublica's study method and data, see Angwin et al., 2017.	Data represent DOI's estimate on average premium for basic coverage as required by law.

Background

Auto insurance premiums are another barrier to vehicle ownership rates. The differences in average insurance costs across states have large and negative impacts on car ownership rates (Raphael & Rice, 2002). Insurance rates impact an individual's ability to register a vehicle (California) and maintain ownership (e.g., insurance payments). Insurance premiums are based on the type and level of insurance coverage as well as the driver's actuary-based risk summarized by their past driving record, current age, and estimated future miles driven (Ong & Gonzalez, 2019).

Insurance rates are also based on an individual's ZIP code creating spatial disparities. This is true for residents in rural areas who have lower rates compared to residents in urban areas, after accounting for individual factors (Ong & Gonzalez, 2019). Area-based price setting is also present within urban areas, where insurance premiums can vary by a factor of two depending on where an individual lives (Ong & Gonzalez, 2019). Actuary-based risk price setting is a reasonable practice in a market economy, but there may be less legitimate reasons for area-based setting given historical evidence of redlining for automobile and home insurance (Center for Economic Justice, 1997; Marshall, 1940; Squires, 2003; Squires and Chadwick, 2006). The auto insurance industry denies any racial discrimination, claiming that any differences in insurance premiums across geography or individuals is due to actuary risk. However, a study found that premiums were higher in low-income and minority neighborhoods, after accounting for the factors that the insurance industry claims determine premiums and their disparities (Ong & Stoll, 2007). A multistate study by the Consumer Federation of American and ProPublica confirmed these results showing widespread use of nondriving factors (e.g., socioeconomic characteristics and credit scores) to set premiums, unfairly discriminating against low- and moderate-income good drivers (Angwin et al., 2017; Feltner and Heller, 2015; Larson et al., 2017).

Data Source

The data on insurance premium by ZIP code come from two sources: ProPublica and California Department of Insurance (DOI).

ProPublica

The data generated from ProPublica are based on their study of racial disparities by neighborhoods in automobile premiums. The data report the average premium paid (from multiple insurers) holding constant vehicle type, coverage, and driving history. ProPublica obtained the data from two commercial data providers, Quadrant Information Services and S&P Global Inc. For California, they received data for 1,816 ZIP codes for the number of cars insured and payouts by the state's insurers from 2007 through 2011. For more information see ProPublica's report and methodology, see Angwin et al., 2017.

California Department of Insurance
The second data on automobile insurance premiums come from the California Department of Insurance, specifically the DOI's estimate on average premium for basic coverage as required by law.[8] Basic level coverage is a better measure of the cost of insuring a vehicle for the same amount of coverage in different geographic areas. By just examining the overall observed average premium (regardless of coverage type), one would find that ZIP codes in wealthier areas would have higher premiums than ZIP codes in lower wealth areas. This reflects the value of the vehicles being insured. People with a more expensive vehicle would insure it for a higher limit/amount of coverage than an average car (i.e., someone with a Maserati will want to insure their vehicle for a higher limit than someone driving a Honda Accord).[9] As such, to create a more balanced comparison, we focus on premiums limited to policies at the basic level of coverage. The data on basic coverage come from the DOI's Survey on Auto Liability (SAL)[10] and represents three years of data: 2014, 2015, and 2016. Data are provided for all ZIP codes in California where insured vehicles are garaged.[11]

Construction Method

Constructing the average auto insurance premium at the census tract level involved multiple steps that can largely be divided into three major parts. The first involves spatially assigning census blocks to ZIP codes to derive the five-digit ZIP code information for each block. This is done using ArcGIS. Second, we merged the block-level data to the insurance premium dataset, containing estimated average insurance premium from ProPublica and DOI by ZIP code. Finally, we estimated the average insurance premium for each census tract using a combination of the average premium listed in ProPublica and DOI. The three major steps are detailed in the following text.

Step 1 – Assigning Census Blocks to ZIP Codes

All census blocks in California were spatially assigned to a ZIP code using ArcGIS. This process is needed to identify the corresponding ZIP code in which a census block is located. The spatial assignment is done by using the centroid of the block, meaning that if the block centroid falls into a ZIP code then that block is assigned that five-digit ZIP code. Census blocks are the smallest geographic unit for which the Census Bureau collects and tabulates census information. Their small size makes them the ideal geographic unit for spatial allocation. Two different GIS shapefiles were used in this process. The first is the Census Block shapefile from Census Tigerline (2018 vintage) and the second is the U.S. Postal Service (USPS) Zip code shapefile derived from ESRI (shapefile updated as of 6/18/19).

Step 2 – Merging Census Block Data to Zip Code–Level Data on Insurance Premium

The census block data, with the assigned five-digit ZIP code information, is merged with the auto insurance premium dataset by the five-digit ZIP code. The insurance premium dataset includes data on the average insurance premium, individually from ProPublica and DOI, for each ZIP code.

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[8] By law, California drivers must have the following minimum coverage: $15,000 for injury/death to one person, $30,000 for injury/death to more than one person, and $5,000 for damage to property. https://www.dmv.ca.gov/portal/dmv/detail/pubs/brochures/fast_facts/ffvr18 (Accessed November 19, 2019)

[9] The observed average premium can be affected by several factors. Three main rating factors used by insurance companies to set rates are annual mileage, driving history (i.e., number of tickets/collisions), and driving experience (i.e., years licenses). Geographic differences in these factors contribute to variance in average premiums across codes. The DOI does not have access to averages of these values at the ZIP code level, but they also would likely explain much of the variance in average premiums across ZIP codes.

[10] DOI also has data from the Auto Premium Survey, which provides the most consistent comparison across geographies because the driver and vehicle profiles are kept constant. Unfortunately, survey data are available for only 270 ZIP codes. While the sample is geographically diverse, it represents only about 10 percent of all ZIP codes in California.

[11] A small minority of the ZIP codes are PO boxes rather than garaging addresses.

Step 3 – Estimating Average Insurance Premium by Census Tract

The census block information is summarized up to the census tract for each type of insurance premium, ProPublica and DOI, weighted by the total number of occupied housing units in each census block. (Every Census Block has a unique 15-digit Federal Information Processing System [FIPS] code and embedded within the block FIPS code is the census tract FIPS code). Data on the total counts of occupied housing units for the block comes from the 2010 Decennial Census. This step generates two separate measures of average auto insurance premium for each census tract, one using ProPublica estimates and the second from the DOI. Ideally, the preferred weight is total counts of vehicles but the Census Bureau does not report this information at the block level nor does the project have access to this information at the census block level.

The final auto insurance premium measure is calculated using a combination of both the reported tract level insurance premium estimates for ProPublica and DOI. The following formula is used to calculate the average auto insurance premium for the census tract by combining the average premium for both ProPublica and DOI:

$$Average\ Premium_i = \frac{(DOI_i / \underline{DOI}) + (PP_i / \underline{PP})}{2}$$

DOI is the Department of Insurance's average insurance premium for census tract i
$\underline{DOI}$ is the Department of Insurance's average insurance premium for all census tracts in California
PP is ProPublica's average insurance premium for census tract i
$\underline{PP}$ is ProPublica's average insurance premium for all census tracts in California

Of the 8,057 tracts in California, 99 percent were estimated based on observed ZIP code–level data (using a combination of both DOI and ProPublica estimates); less than 1 percent (seven tracts) did not have ProPublica data and therefore estimated using a combination of DOI estimates and ProPublica estimates for surrounding/nearby tracts. The remaining tracts (50) do not have insurance premium estimates due to insufficient data (these tracts have no occupied housing units).

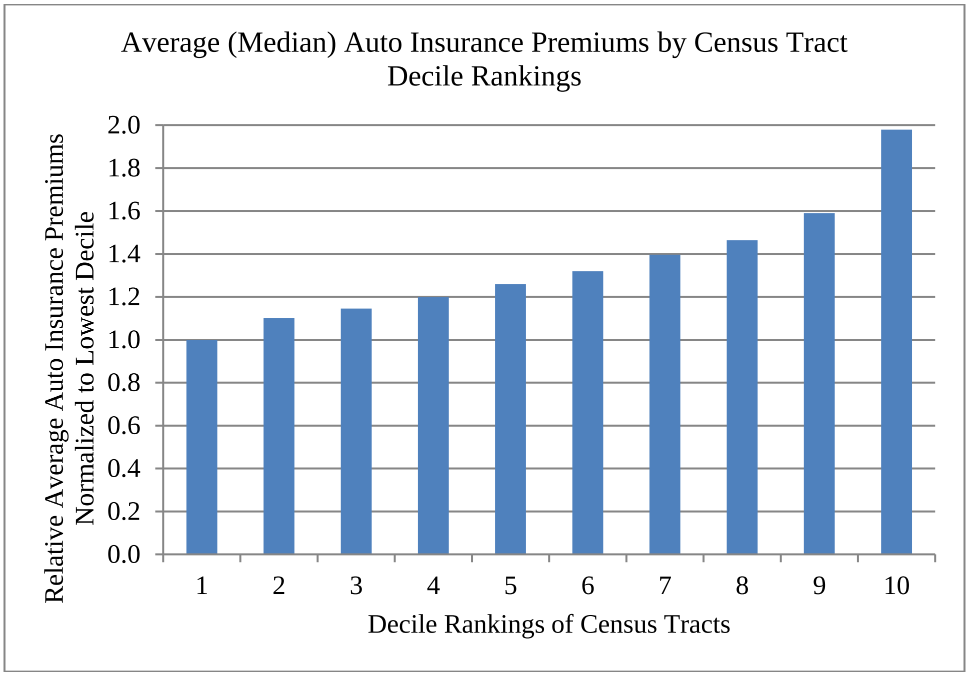
Assessment of Consistency

As part of our assessment, we compared the average premiums from ProPublica and DOI to each other at the ZIP code level. Doing the assessment at the ZIP code level, the geographic unit that the information is originally reported, rather than tracts, minimizes any possible biases or errors that may occur when allocating the information to census blocks. The average premium for ProPublica and DOI are highly correlated with a correlation value (r) of 0.92.

Results

California census tracts are divided into deciles according to each tract's automobile insurance premiums. Each decile category represents roughly 10 percent of the census tracts in California. Figure 2-1 compares the average (median) values of automobile insurance premiums in each decile category normalized by the lowest decile. A value greater than 1 indicates that auto insurance premiums for that decile is higher than the lowest decile category by that value. For example, the median premium in the highest area is twice as expensive as the median premiums in the lowest area.

Figure 2-1. Average (Median) Insurance Premiums by Census Tract Decile Rankings



Maps

The following maps display the distribution auto insurance premiums.

California

Statewide, the majority of California geographically has low insurance premiums (see Figure 2-2). Throughout most counties, the entire county area falls in the lowest quintiles for average vehicle insurance premium. This is especially true on the central coast and in Northern California. However, there are a few areas in which average vehicle insurance premiums are quite high in comparison to the rest of the state. Average vehicle insurance premiums are high in the Greater Los Angeles area, including not only Los Angeles County but the western parts of San Bernardino, Riverside, and Orange counties and the eastern part of Ventura County as well. The Bay Area and Sacramento also have high insurance premiums, though not as high as those in Los Angeles. These patterns are consistent in terms of where most of the population reside. Insurance premiums are generally higher in places where traffic collisions are more frequent and likely. Therefore, one would expect to see higher average vehicle insurance premiums in more densely populated and urbanized areas.

Bay Area

In the Bay Area, insurance premium correlates with urbanization (see Figure 2-3). The high and highest average vehicle insurance premiums are found in San Francisco and East Bay. The highest insurance premiums are found in San Francisco's low-income neighborhood of Bayview-Hunters Point, and in the low-income sections of Oakland. Outside of these highly urban areas, insurance premiums are lower, such as in the hills of Oakland, suburban sections of the Peninsula, and Marin County, which tend to be moderate to high-income areas.

Los Angeles

As an area with the highest average vehicle insurance premium, there is little variation in Los Angeles when it comes to insurance premiums (see Figure 2-4). The majority of the region, including downtown, South Central, the Westside, and the San Fernando Valley rank in the highest quintile for insurance premiums. Besides a few pockets in the southern part of LA County that rank in the moderate quintile, the majority of the area ranks either high or highest for average vehicle insurance premiums statewide.

Figure 2-2. Map of Average Auto Insurance Premium, all of California

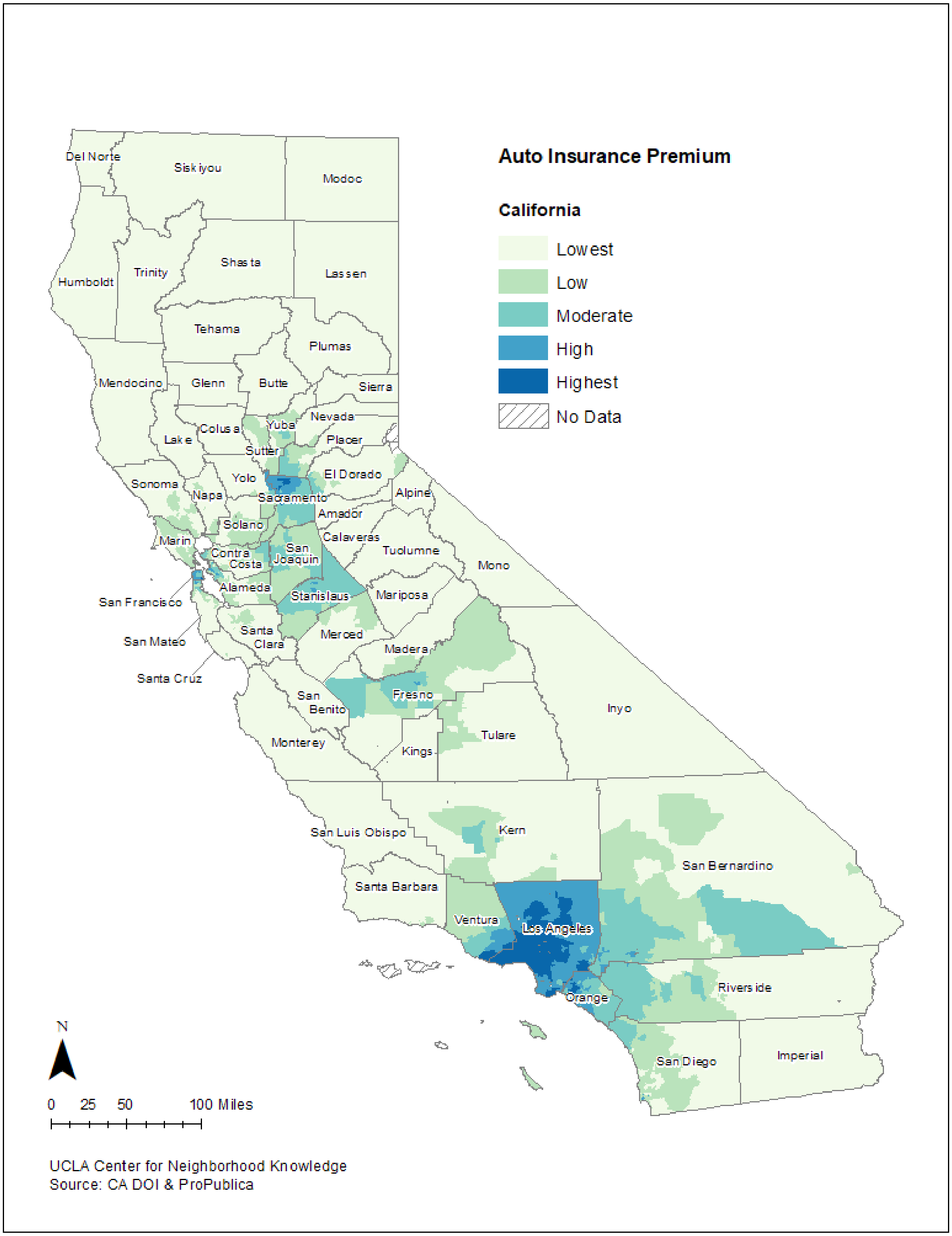


Figure 2-3. Map of Average Auto Insurance Premium, San Francisco Area

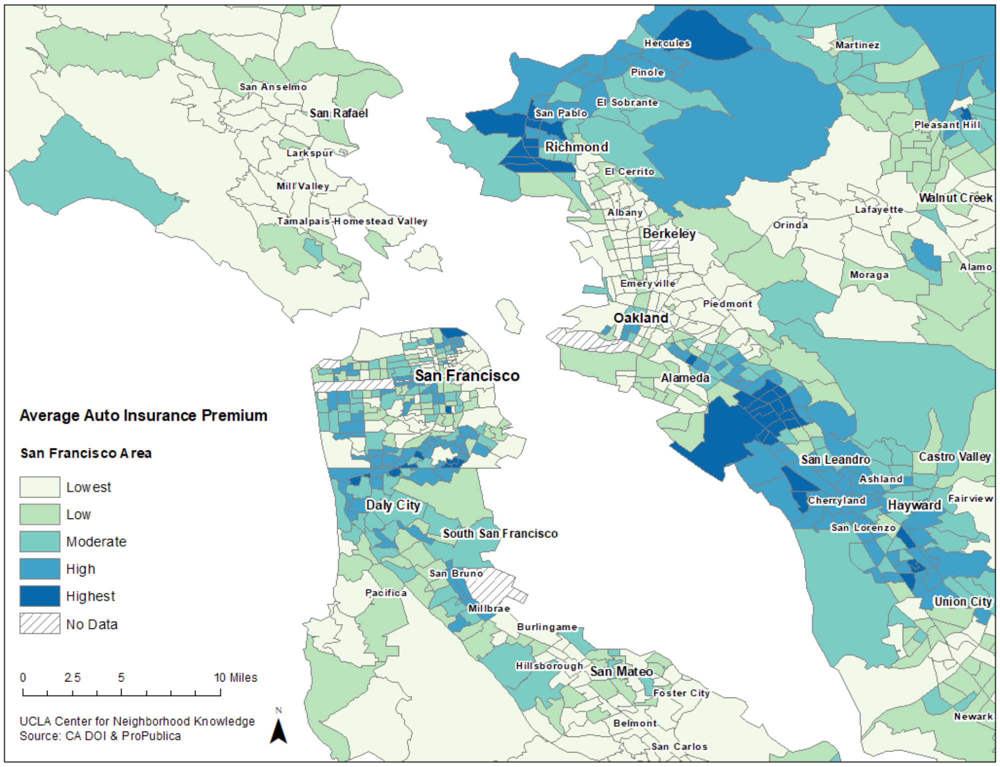
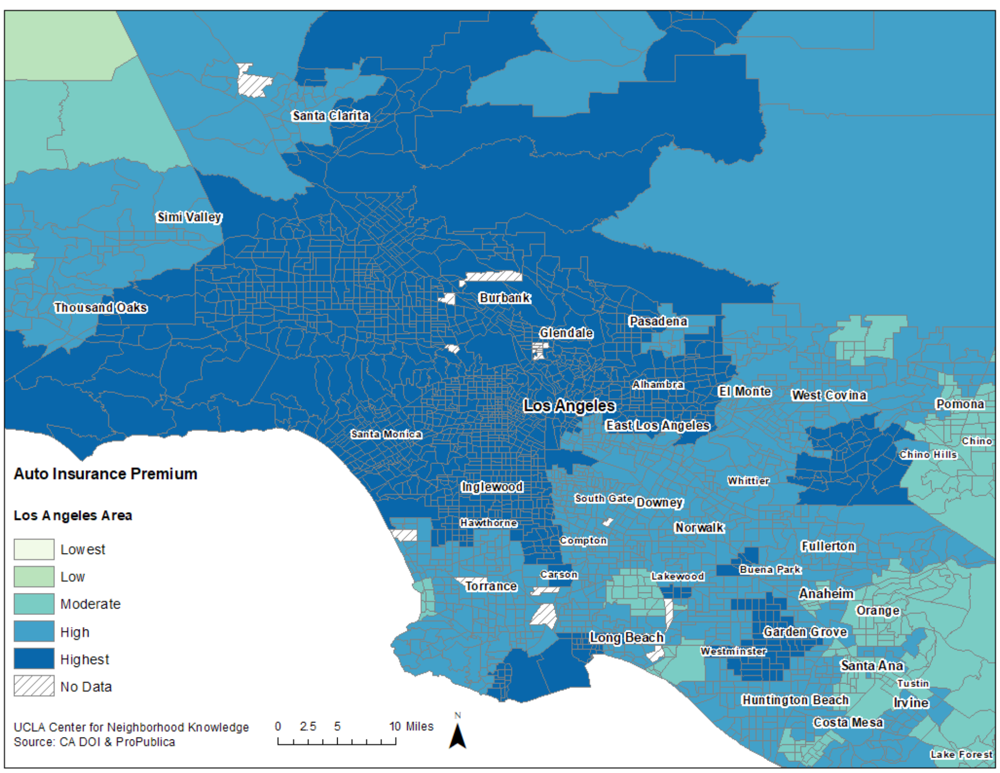


Figure 2-4. Map of Average Auto Insurance Premium, Los Angeles Area



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2.3.2 Lending Barriers

This subsection describes the approach to constructing an indicator on barriers to borrowing based on what is commonly referred to as "higher-priced mortgage loan". A higher-priced mortgage loan is one with an APR higher than the average primer offer rate. This serves as a proxy for a major obstacle to vehicle ownership: high automobile lending rates. This proxy is used because mortgage rates and vehicle loan rates are correlated.

Table 2-3. Lending Barrier Indicator Summary Table

Key Indicator Information	
Units	Lending Barriers (proportion of higher-priced mortgage loans serves as a proxy for auto lending barrier)
Category in Mapping Tool	Transportation
Display Method in Mapping Tool	Decile (visualized in quintiles)
Precision	Proxy at the place level (e.g. cities) is moderately correlated with auto lending barrier; precision is low and uncertain about relationship at the tract level
Methodological Complexity	Simple calculation of rates using observed HMDA accounts; use the estimated model to impute the hypothetical higher-priced mortgage rate for census tracts that do not have adequate HMDA data
Geographic Resolution	Census tract
Key Information about Data Sources Used to Construct Indicator	
Data Sources Used to Construct	Home Mortgage Disclosure Act data from the Consumer Financial Protection Bureau
Sample Size	Not based on sampling; number of observations varies across tracts because of ownership and transaction rates
Biases	Relies on higher-priced mortgages as a proxy for auto lending barrier
Geographical Unit	Census tract
Geographic Coverage	Covers all of California tracts (8,057 tracts; 97% based on observed data, 2% imputed, 1% not estimated due to insufficient data)
Data Vintage	2012-2017
Other Important Notes (if applicable)	N/A.

Background

Empirical research has shown that lending practices impact the rate of vehicle ownership. Some neighborhoods that experience higher loan interest rates, also have lower rates of vehicle ownership after accounting for other factors (Ong & Gonzalez, 2019). Minorities in particular face higher rates. Cohen

(2003) found that 1.5 million loans by General Motors Acceptance Corporations (GMAC) charged ethnic minorities higher interest rates for new car loans, which were not justified by the higher credit risks of applicants. These results were consistent with our analysis of Charles, Hurst, and Stephens (2008) on the Survey of Consumer Finances, which identified differential racial treatment in the interest rates paid on auto loans based on the type of finance institution used.

Lending terms are related to credit score: the lower the credit score, the higher the interest rate. Auto loan rates are also determined by applicants' credit scores. Applicants with high credit scores (760+) are considered prime loan applicants and will have auto loan interest rates as low as 3 percent (Wamala, n.d.). Those with low credit scores (<580) are considered subprime loan applicants and will pay auto loan rates 5–10 times higher than prime applicants, especially for used cars or longer-term loans (Wamala, n.d.). Excellent credit profiles typically pay interest rates below 60-month average of 4.21 percent and the median credit score for consumers who obtain auto loans is 711 (Wamala, n.d.).

Moreover, average credit scores vary systematically across neighborhoods. Credit scores and location are correlated, but there are other factors related to location that have a greater impact on average credit scores by ZIP code (Cesare, 2017). Lower income neighborhoods experience a higher concentration of predatory lenders compared to higher income neighborhoods, which drive down the credit score of that location (Cesare, 2017). Low credit scores are also reflected by the proportion of low-income households in the neighborhood. Credit scores can also be used as a tool to measure health, having a larger effect size than other socioeconomic position markers (Knapp & Dean, 2018). For example, it represents the financial history that influences an individual's ability to access financial and nonfinancial resources related to health. A standard deviation increase in credit score is associated with a 26 percent greater odds of better self-reported health (Knapp & Dean, 2018).

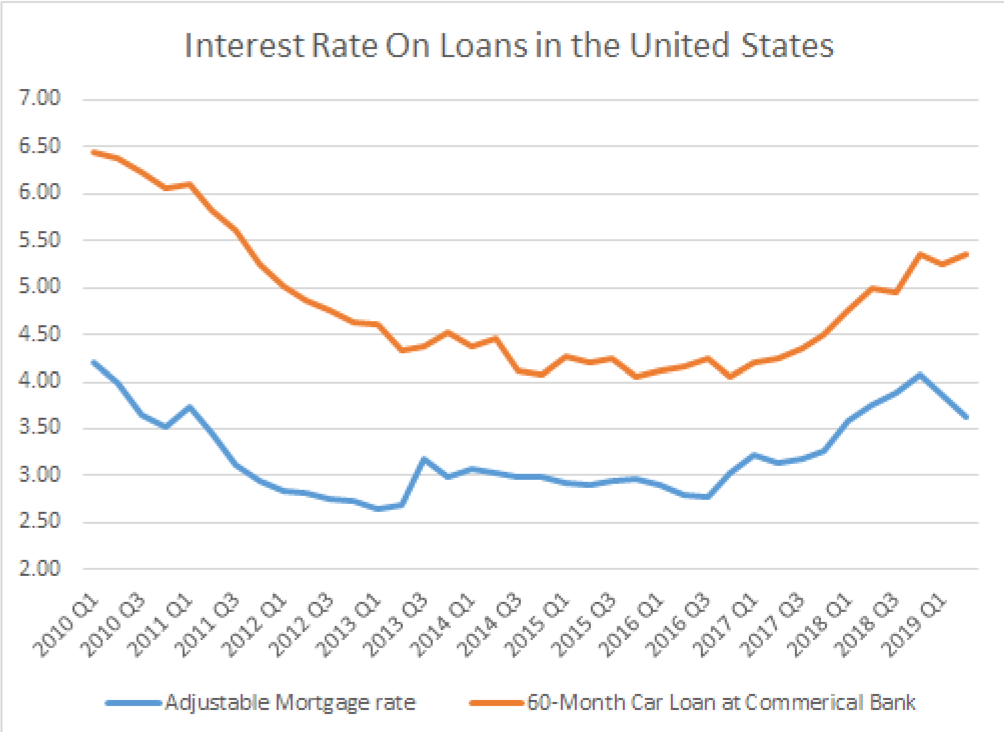
Data Source

Unfortunately, we do not have data on automobile loans for small geographies because this data is not readily available. Related measures such as credit scores are available, but are extremely expensive.[12] Therefore, this project developed a proxy of mortgage loans classified as "higher-priced" loans for the lending barrier indicator.

As shown in Figure 2-5, the graph of the 30-Year Fixed Rate Mortgage Average and the 60-month Car Loan at Commercial Bank rate, the markets of lending and borrowing are moderately correlated (r = 0.71). The two interest rates are related to one's credit scores.

[12] Experian, one of the major credit bureaus that provide VantageScore by ZIP code, was contacted for a quote for average credit score at the ZIP+4 level for California. The quoted price was $20,000 for one period. The contact was made in May 2019. Experian does not readily offer census tract level data, but the ZIP+4 would have provided enough geographic resolution to reasonably allocate to census tracts.

Figure 2-5. Interest Rates on Auto and Mortgage Loans



Source: Board of Governors of the Federal Reserve System (see https://www.federalreserve.gov/releases/g19/HIST/cc_hist_tc_levels.html. Accessed on November 10, 2019) (Car Loan) and Federal Reserve Bank of St. Louis (see https://fred.stlouisfed.org/series/MORTGAGE30US#0. Accessed on November 10, 2019) (Mortgage).

We used census tract–level data from the Home Mortgage Disclosure Act (HMDA) to construct a measure related to lending practices: the proportion of originated loans that are "higher-priced". This served as proxies for lending barriers. Ideally, we would like to include information on credit scores (e.g., FICO score, VantageScore) for each census tract because lenders use it to determine the interest rate individuals get on a loan, but acquiring this information, particularly for a small geography, is costly as previously mentioned.

HMDA was enacted by Congress in 1975 and was designed by the Federal Reserve Board to collect information on mortgage lending patterns. HMDA is managed by the Federal Financial Institutions Examination Council (FFIEC). The Home Mortgage Disclosure Act requires many lending institutions to report and disclose loan-level information about mortgages to the public. This data can be used to determine whether financial institutions are serving the housing needs of their communities, and in identifying possible discriminatory lending patterns.

HMDA offers information about the loan, including loan purpose (e.g., home purchase, refinancing), type (e.g., conventional, FHA-insured, VA), and amount; the property's location (census tract is the smallest geographic unit reported) and property type (e.g., one to four-family, multifamily), and whether or not a loan application was denied and if so, reasons for denial. Additionally, HMDA also includes information about the applicant or borrower, such as race/ethnicity, sex, and household income.

HMDA does not report interest rates but does indicate whether a loan is a "higher-priced" mortgage loan. A higher-priced loan is defined as a mortgage with an annual percentage rate (APR) that exceeds the average prime offer rate by 1.5 percentage points. Mortgage loans that are designated as “higher-priced” often reflect riskier or subprime borrowers. For this project, we consider mortgage loans designated as “higher-priced loans” as subprime loans.

The project uses six years of HMDA data, from 2012 to 2017. The 2012 HMDA data represents the first year where HMDA loan information are reported using 2010 census tract; and 2017 HMDA is the most recent data available during the time of this project.

Construction Method

First, we retrieved HMDA data from 2012 to 2017 from the Consumer Financial Protection Bureau.[13] We restricted our sample to include mortgages for:

- First lien
- Owner-occupied as a principal dwelling unit
- 1–4 family homes, excluding manufactured and multifamily housing
- Home purchase loan
- Originated loans

From this sample, we identified loans at the tract level that HMDA designated as “higher price” mortgage loans. We included tracts, based on direct observation, that have at least 10 originated loans. One limitation to this approach is that tracts that do not meet this criterion are excluded and they generally tend to represent tracts that have few homeowners or few mortgage transactions. These neighborhoods primarily consist of renters and low-income households. To ensure that we capture these neighborhoods, we opted to estimate the subprime rates for these neighborhoods without direct observations.

For neighborhoods or census tracts without originated loans or have less than 10, we imputed the subprime rate using a regression model based on neighborhoods with adequate observations. The model is predictive and not a causal model. A predictive model should have the ability to predict future outcomes, and a quantitative predictive model uses a set of observed or anticipated indicators (variables) that influence the projected results. We do not necessarily require knowing causal relationships because correlated indicators may be sufficient to forecast the outcome.

The dependent variable in the predictive model is the percent of subprime mortgage loans. The model accounts for population density, socioeconomic (poverty), demographic (race and ethnicity), housing (renters), transportation (vehicles per person), and fixed regional effects (county where census tract is located). Based on previous experience of analyzing spatial patterns we chose the independent variables and assessed their correlation with the subprime rates. We kept the variables that were statistically significant with subprime rates. We estimated the model for census tracts or neighborhoods with at least 10 originated mortgage loans. The model performed reasonably well with an adjusted r-squared of 0.68.

We use the estimated model to impute the hypothetical subprime rate for census tracts that do not have adequate HMDA data. We then assessed whether this pattern of estimates seems reasonable by comparing it to the surrounding census tracts. The assessment shows the patterns are consistent with nearby neighborhoods. We were not able to impute for all missing tracts because those tracts did not have enough information related to the model. Of the 8,057 tracts in California, 97 percent were observed (having at least 10 originated loans), 2 percent were imputed (with less than 10 originated loans), and 1 percent were not estimated due to insufficient data (no population or missing values for independent variables).

[13] See https://www.consumerfinance.gov/data-research/hmda/historic-data/ for more information. Accessed on December 31, 2019.

Assessment of Consistency

As part of our assessment of the lending barrier indicator (using subprime mortgage loans as a proxy), we compared the relationship between percent of subprime loans against reported average credit scores for 100 to 600 cities in California (see Brown [2017] for more info on average credit scores reported for cities). The percentage of subprime loans, reported at the census tract level, was assigned to their respective cities using Geocorr Crosswalk (Missouri Census Data Center, n.d.)[14] to get an estimate of supreme loans at the city level. This resulted in the total mortgage loans and the percent subprime loans for each city.

Table 2-4 shows the correlation between average credit score and our measure of subprime loans for cities in California. The table includes three different scenarios to test for the robustness of the results. The first scenario is a correlation of average credit scores and subprime loans with no restriction. The second captures only those cities with at least 100 mortgage loans reported (setting a minimum sample size). The third test is for those cities with at least 100 reported mortgage loans and with less than 5,000 housing units. The restriction on the number of housing units of less than 5,000 may possibly capture smaller cities. Unlike larger cities, which tend to be heterogeneous and containing significant diversity of neighborhoods, smaller cities tend to be more socioeconomically homogenous. Overall, subprime loans are negatively correlated with average credit scores (at least a correlation coefficient [r value] of –0.70). The negative relationship means that the lower the cities' average credit score, the higher the proportion of subprime mortgage loans or vice versa. The assessment indicates that subprime loans and credit scores are moderately correlated and using subprime loans as a proxy for lending barriers is likely sufficient in trying to understand the lending barriers faced by different neighborhoods, particularly given the lack of available data on auto loans and credit scores at the tract level.

Table 2-4. Correlations between Mortgage Subprime Loans and Average Credit Scores for Cities

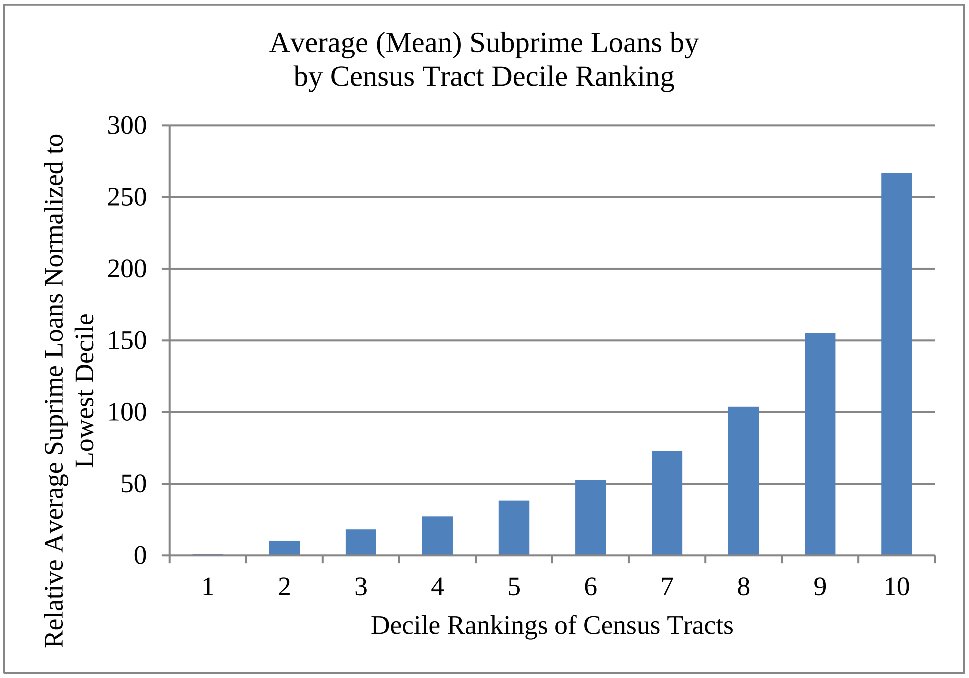
Scenario	Coefficient	Significance	n
No Restrictions	–0.7238	<.0001	641
With at least 100 loans	–0.7844	<.0001	534
With at least 100 loans and < 5,000 housing units	–0.7764	<.0001	196

Results

California census tracts are divided into deciles according to each tract's average (mean) subprime rate. Each decile category represents roughly 10 percent of the census tracts in California. Figure 2-6 compares the average subprime rate in each decile category normalized by the lowest decile. A value greater than 1 indicates that the share of subprime loans for that decile is higher than the lowest decile category by that value. For example, the average subprime rate in the highest area (highest decile) is more than 260 times more than in the lowest area (lowest decile).

[14] Geocorr is a tool developed by the Missouri Census Data Center. It shows the relationship between different geographic coverage for the United States. It allows users to allocate one geography to another geography, in our case, putting census tracts into cities.

Figure 2-6. Average (Mean) Subprime Rate by Census Tract Decile Rankings



Maps

The following maps displays the distribution of subprime loans, our proxy for lending barriers.

California
Much of the Central Valley as well as the northeastern and southeastern corners of the state are among the moderate to highest areas for subprime loans. One outlier is Inyo County. Most of the areas in San Bernardino County, Lassen County, and Plumas County have the highest percentage of subprime loans. The coastal regions and major urban areas tend to be on the lower end for subprime loans (see Figure 2-7).

Bay Area
Parts of San Francisco, Daly City, Richmond, Oakland, and Hayward have a much higher proportion of borrowers encountering lending barriers. However, other parts of the urbanized areas are less likely to experience subprime lending, such in and around Berkeley. The more suburban places and the outer edges of the Bay Area (e.g., Sonoma County and Santa Clara County) are among the areas with the lowest subprime loans (see Figure 2-8).

Los Angeles
In LA County, much of the urban core, and South LA in particular, has the highest probability of experiencing lending barriers. East LA and parts of the San Fernando Valley also have high incidences of subprime lending. These areas are comprised of more lower income residents. The areas with the lowest probability of encountering lending barriers are located on the Westside and along the coastal cities like Santa Monica, El Segundo, and Redondo Beach. Residents in these areas are high income who may not have taken out these riskier mortgage loans (see Figure 2-9).

Figure 2-7. Map of Lending Barriers, all of California

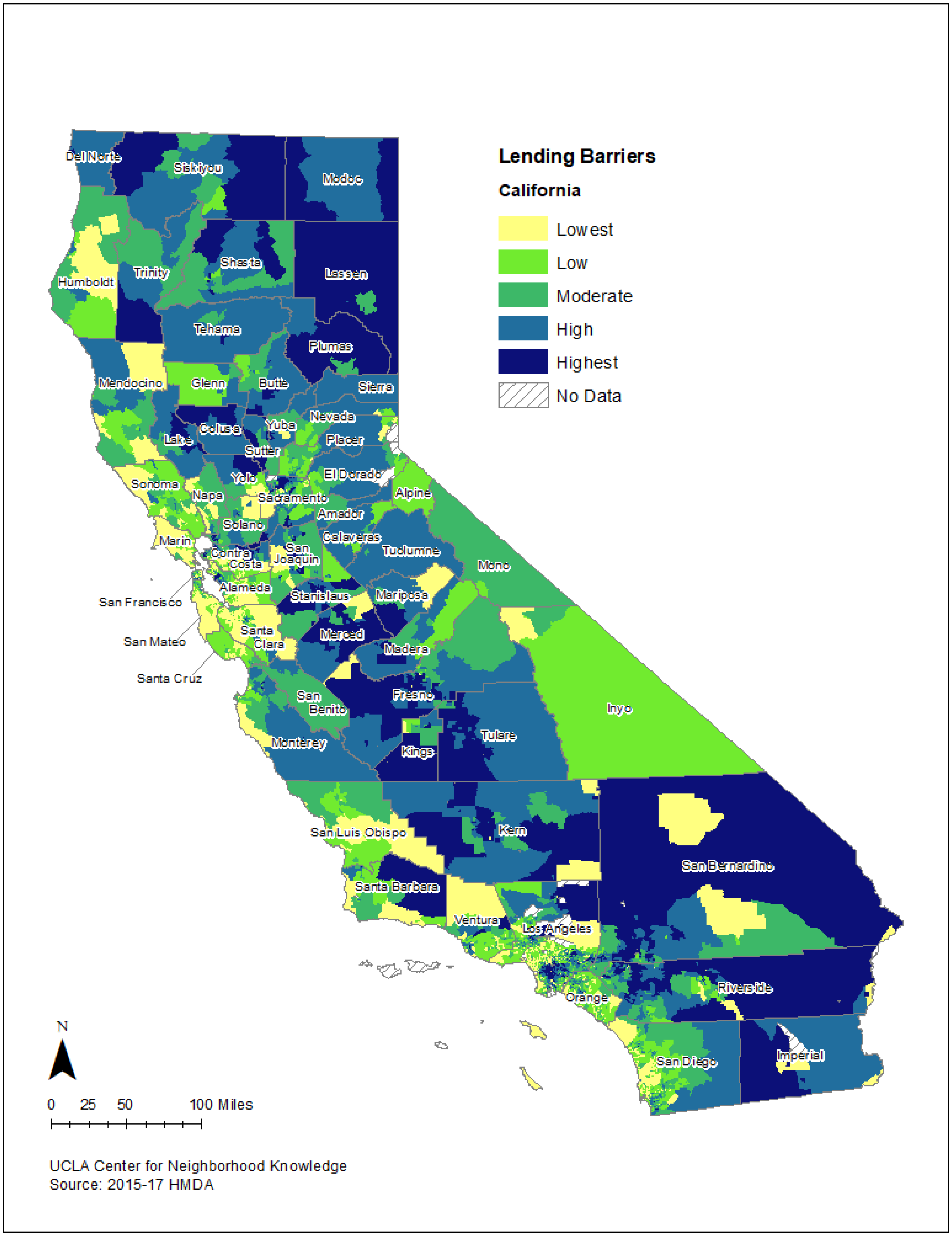


Figure 2-8. Map of Lending Barriers, San Francisco Area

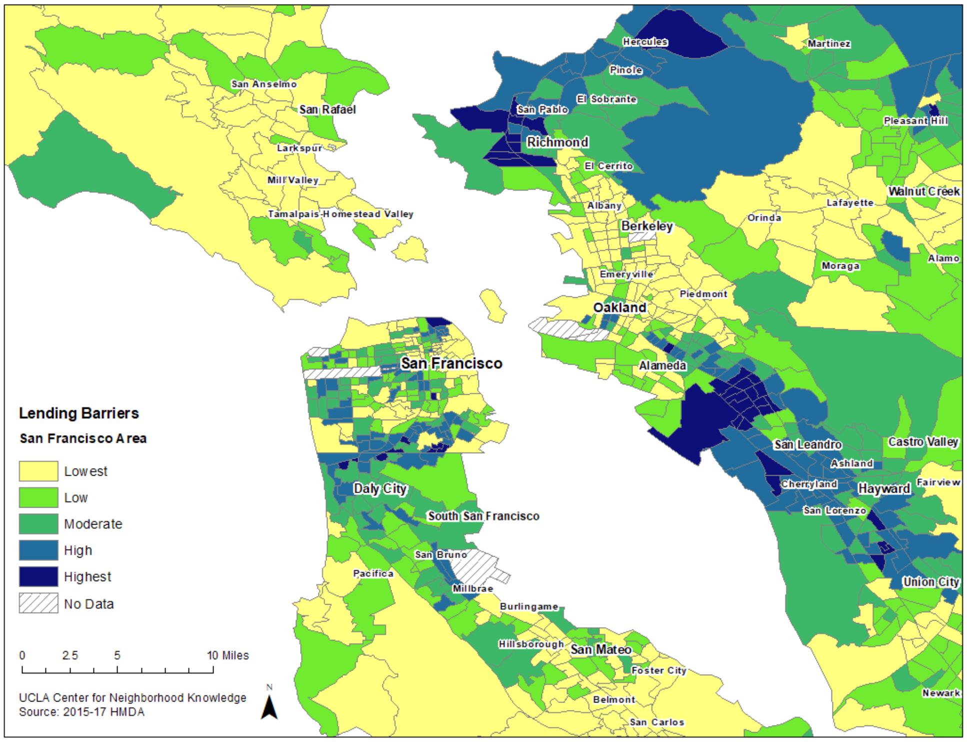
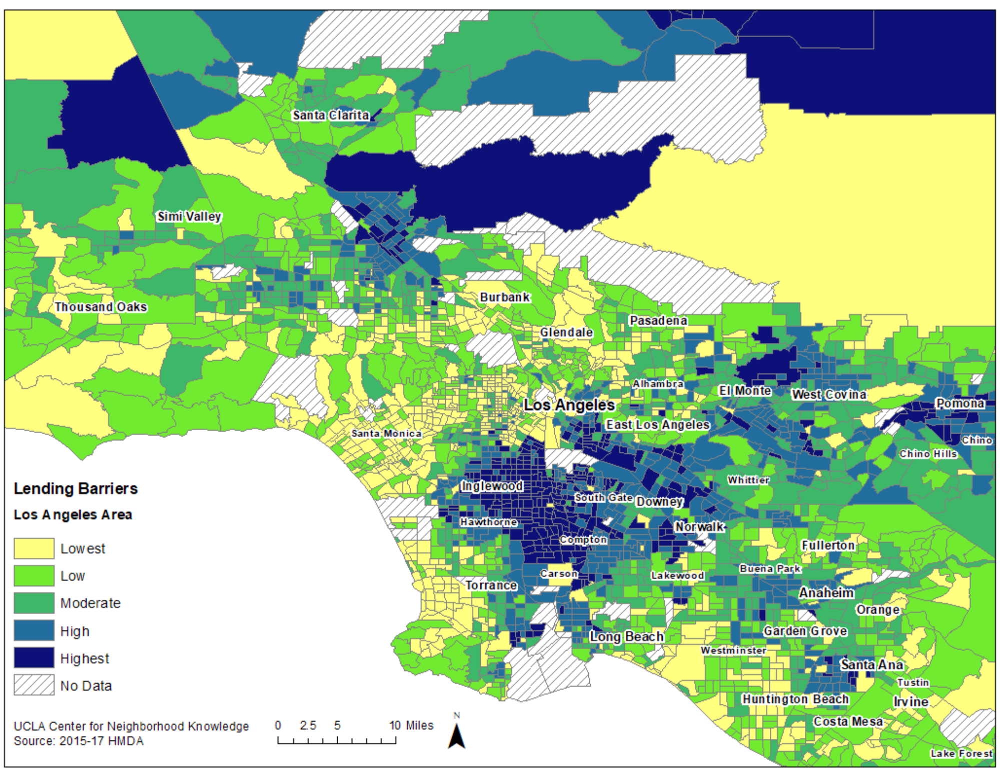


Figure 2-9. Map of Lending Barriers, Los Angeles Area



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2.3.3 Clean and Clunker Vehicles

The following subsection discusses the construction of the share of "clean" vehicles and "clunker" vehicles as a share of all vehicles.

Table 2-5. Summary Table for Clean Vehicle Indicator

Key Indicator Information	
Units	Clean vehicles as a share of total vehicle stock
Category in Mapping Tool	Transportation
Display Method in Mapping Tool	Decile (visualized in quintiles)
Precision	Assumed to be relatively high: administrative, recording of vehicle model, vintage and fuel type is most likely to be correct
Methodological Complexity	Simple calculation of rates using observed DMV data
Geographic Resolution	Block group (aggregated to census tracts)
Key Information about Data Sources Used to Construct Indicator	
Data Sources Used to Construct	Department of Motor Vehicles fleet database provided by the California Air Resources Board
Sample Size	Not based on sampling; large number of observations based on administrative data
Biases	Vehicle counts may include business vehicles
Geographical Unit	Census tract
Geographic Coverage	Covers all of California
Data Vintage	2017
Other Important Notes (if applicable)	Clean vehicles include: Battery electric vehicle, plug-in hybrid-electric vehicle, and hybrid electric vehicle. The project includes two measures of clean vehicles: "Newer" clean vehicles are defined as vehicles with model years between 2013 and 2017 (last five years of data); and "Older" clean vehicles are defined as vehicles with model years 2012 and earlier.

Table 2-6. Summary Table for Clunker Vehicle Indicator

Key Indicator Information	
Units	Clunker vehicles as a share of total vehicle stock
Category in Mapping Tool	Transportation
Display Method in Mapping Tool	Decile (visualized in quintiles)
Precision	Assumed to be relatively high: administrative, recording of vehicle model, vintage and fuel type is most likely to be correct
Methodological Complexity	Simple calculation of rates using observed DMV data

Geographic Resolution	Block group (aggregated to census tracts)
Key Information about Data Sources Used to Construct Indicator	
Data Sources Used to Construct	Department of Motor Vehicles fleet database provided by the California Air Resources Board
Sample Size	Not based on sampling; large number of observations based on administrative data
Biases	"Clunkers" are defined by age rather than operating condition; vehicle counts may include business vehicles; unregistered vehicles not counted
Geographical Unit	Census tract
Geographic Coverage	Covers all of California
Data Vintage	2017
Other Important Notes (if applicable)	Clunkers include vehicles aged 20 years or older; for this project, this include vehicles with model year 1997 or earlier.

Background

Vehicle and transportation fuels are a large source of carbon emissions in California. While there have been strides in improving air quality, the greater Los Angeles region and San Joaquin Valley are classified as "extreme" ozone nonattainment areas by the U.S. Environmental Protection Agency because they do not meet the health-based air quality standards (CARB, n.d.). Older cars unable to pass emissions tests represent only 10–15 percent of all vehicles in California but are responsible for more than half of the smog generated by passenger vehicles (Wheeler et al., 2014). Many of the households that own these older cars are low income and located in car-dependent areas like the San Joaquin Valley. There are current efforts incentivizing car owners to give up their inefficient, high-polluting "clunker" vehicles to purchase clean vehicles. Zero-emission vehicles, or clean vehicles, include battery electric vehicles (BEV), plug-in hybrid electric vehicles (PHEV), and hybrid electric vehicles (HEV). These vehicles have ultra-low smog-forming and GHG pollutants and are, therefore, essential in achieving long-term emission reduction goals. However, these vehicles are not without environmental issues—for example, battery disposal continues to be a significant environmental challenge.

Societal Benefits

Mitigating local and global emissions is the primary societal benefit of clean vehicle operation. At the household level, evidence on the total direct cost of ownership vis-à-vis conventional vehicle is mixed. In the absence of subsidies (or further taxes on the externalities introduced by conventional vehicle operation), clean vehicles remain more expensive than conventional gasoline vehicles due to the higher purchase price (Breetz & Salon, 2018). In the presence of subsidies, however, households may be able to break even within the time frame of vehicle ownership (Palmer et al., 2018). This is especially true in the context of heavily subsidized used clean vehicle purchases. Once the vehicle is purchased, the most obvious benefit is savings on the cost of gasoline, which some recent research suggests may have been underestimated (Sheldon and Dua, 2018b).

At the community level, the largest positive impact is from lower (or no, depending on the vehicle) pollution exposure from the transversal operation of clean vehicles in disadvantaged neighborhoods. Most of the focus with clean vehicles has been on global GHG reductions, however, so little quantification on this issue at the local level is available. As Reiter and Kockelman (2016) succinctly summarize, vehicle cold starts account for up to 80 percent of some mobile-source air pollutants, but electrification of vehicles removes cold-start emissions. Accordingly, increasing numbers of electric vehicles in disadvantaged neighborhoods would yield substantial local air-quality benefits, but levels of vehicle penetration are likely not yet high enough to measure this empirically in most disadvantaged communities.

Presence of Vehicles in Disadvantaged Neighborhoods

The literature generally finds that clean vehicles[15] are less likely to be purchased[16] and owned by disadvantaged households (DeShazo et al., 2017) and thus less likely to be used in disadvantaged neighborhoods (Rubin & St. Louis, 2016). At the same time, lower-income households have not consistently been shown to have less strong preferences for clean vehicles (Egbue & Long, 2012) per se, rather they face higher constraints in terms of liquidity and credit (Pierce et al., 2019). Used plug-in electric vehicle (PEV) owners also tend to be lower income than new PEV owners, corresponding with the established trend that higher-income households generally purchase newer and smaller vehicles (Bhat et al., 2009; Choo & Mokhtarian, 2004; Tal et al., 2017). Lower-income households also tend to purchase hybrids to BEVs or PHEVs within the clean vehicle sphere (Pierce et al., 2019; Tal et al., 2017).

Incentive/Subsidy Policies and Programs

There have been several incentive/subsidy policies and programs offered to promote the purchase of clean vehicles for disadvantaged households. An income tax credit (currently up to $7,500) has been offered at the federal level since 2009 for the purchase of clean vehicles, although this incentive is now lower for the most popular clean vehicles. The California-specific Clean Vehicle Rebate Project (CVRP) and more recently the Enhanced Fleet Modernization Program (EFMP) offer enhanced buy down incentives for clean vehicle purchase when households retire an older vehicle. These state programs do not offer anything to low-income households without a vehicle. An additional state incentive initially offered carpool lane stickers to all households who purchased clean vehicles, which significantly induced demand (Sheldon & DeShazo, 2017), but such policies are now being curtailed. Additionally, most if not all of these programs offer less incentive for the purchase of a used versus new vehicle, and some do not offer any incentive if the vehicle purchased was used. DeShazo (2016) summarizes the contours of many of these and similar programs nationally.

Cash for Clunkers

Inspiration for vehicle retirement and replacement programs came from the well-documented cost-ineffective emission benefits of national pure vehicle retirement Car Allowance Rebate System program, popularly called “cash for clunkers.” CARS was a two-month national program, from July to August 2009, which induced the retirement of more than 700,000 vehicles by offering a $3,500–$4,500 incentive (Gayer & Parker, 2013; Li et al., 2013; Mian & Sufi, 2009). CARS had no income requirements or tiers for different incentive levels. Evidence from the consumer expenditure survey suggests that participants’ income is higher than consumers who purchased a new or used vehicle, but lower than consumers who purchased a new vehicle outside of the CARS program over the same period (Gayer & Parker, 2013).

The ongoing current pure vehicle retirement incentive offered by the California Bureau of Automotive Repair’s Customer Assistance Program (CAP) sought to improve the state’s air quality by reducing vehicle emissions. For older unwanted vehicles that failed their last Smog Check Test, low-income customers were eligible to receive $1,500, as opposed to $1,000 for others (California Bureau of Automotive Repair, n.d.). To the best of our knowledge, no evaluation of this program with respect to distributional aspects has ever been published.

[15] Defined of cleanliness: battery electric vehicles, plug-in hybrid electric vehicles and hybrid electric vehicles.

[16] Low-income households, when given the opportunity, do not tend to lease vehicles.

Data Source

Clean and clunker vehicle data was obtained from the Department of Motor Vehicles (DMV) fleet database provided by the California Air Resources Board (CARB) for 2017. Data include vehicles registered to an individual, eliminating vehicles owned by corporations, such as car rental companies. Data is provided at the census block group level and aggregated into census tracts.

Clean vehicles include the following fuel types: Battery electric vehicle (BEV), plug-in hybrid-electric vehicle (PHEV), and hybrid electric vehicle (HEV). "Newer" clean vehicles are defined as vehicles with model years between 2013 and 2017 (last five years of data). "Older" clean vehicles are defined as vehicles with model years 2012 and earlier. "Clunker" vehicles include all vehicles that are more than 20 years old based on the model year.[17] Given the year of the fleet database available for this project, vehicles with a model year of 1997 or earlier are designated as "clunkers". It is important to note that this is a proxy for "clunkers." Using this age cutoff might capture vehicles that are considered vintage or classic that are used for collection and there is no way to separate out vehicles used as collectibles in the dataset.

Construction Method

"Newer" Clean Vehicles as a Share of Total Vehicle Stock
This indicator was constructed by dividing the count of "newer" clean vehicles by the total vehicle stock from DMV data.

"Older" Clean Vehicles as a Share of Total Vehicle Stock
This indicator was constructed by dividing the count of "older" clean vehicles by the total vehicle stock from DMV data.

"Clunker" Vehicles as a Share of Total Vehicle Stock
This indicator was constructed by dividing the count of "clunker" vehicles by the total vehicle stock from DMV data.

Assessment of Consistency

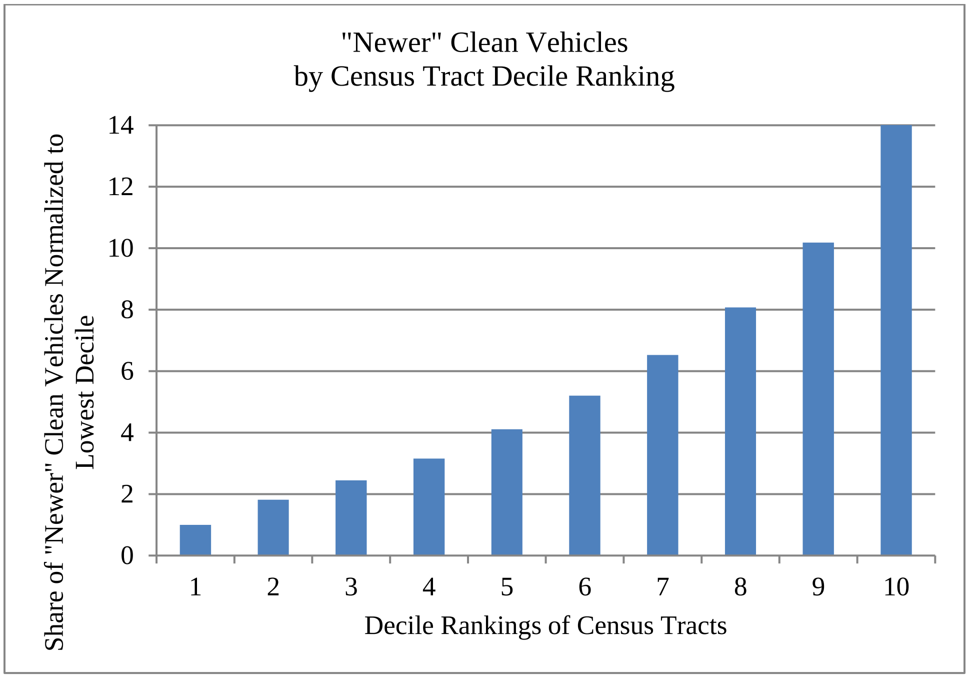
The DMV data received was assessed against the vehicles available data from 2013–17 5-year ACS and the two are highly correlated with a correlation value (r) of 0.918. The DMV data included all registered vehicles in 2017, their fuel type, and age. The fuel type information was used to classify clean vehicle counts. The age information was used to classify which vehicles were "newer" clean, "older" clean, and "clunkers." ACS data is self-reported, may count vehicles that are not registered, and does not provide vehicle fuel type or age. Therefore, we are only able to assess overall total counts.

Results

"Newer" Clean Vehicles
California census tracts are divided into deciles according to each tract's share of "newer" clean vehicles. Each decile category represents roughly 10 percent of the census tracts in California. Figure 2-10 compares the share of "new" clean vehicles in each decile category normalized by the lowest decile. A value greater than one indicates that the share of "newer" clean vehicles for that decile is higher than the lowest decile category by that value. For example, the median "newer" clean vehicles share in the highest decile area is 14 times as great as in the lowest area.

[17] This vehicle age cutoff is based on input from CARB.

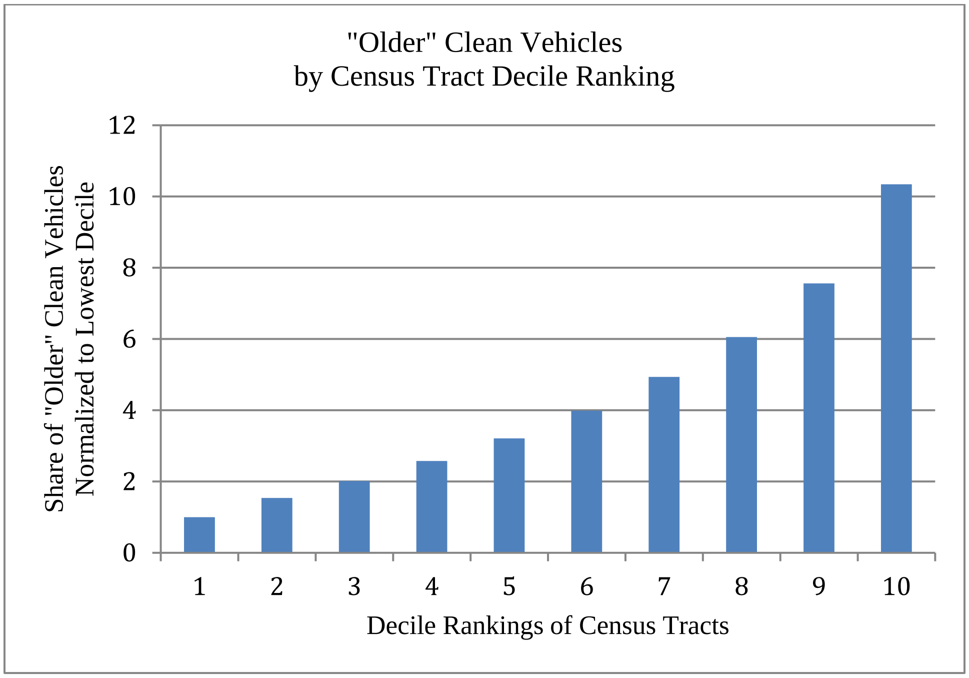
Figure 2-10. “Newer” Clean Vehicles by Census Tract Decile Rankings



“Older” Clean Vehicles

California census tracts are divided into deciles according to each tract’s share of “older” clean vehicles. Each decile category represents roughly 10 percent of the census tracts in California. Figure 2-11 shows the share of “older” clean vehicles in each decile category normalized by the lowest decile. A value greater than 1 indicates that the share of “old” clean vehicles for that decile is higher than the lowest decile category by that value. For example, the median “older” clean vehicles share in the highest decile area is more than 10 times as great as in the lowest area. This indicates a slight increase in the geographic dispersion of older clean vehicles compared to newer clean vehicles.

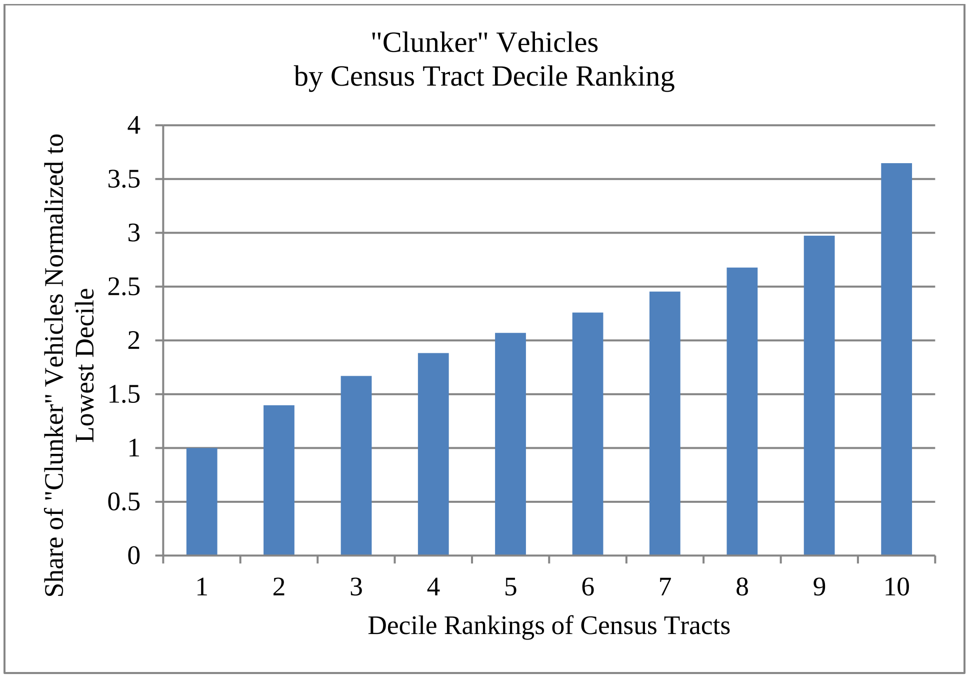
Figure 2-11. “Older” Clean Vehicles by Census Tract Decile Rankings



Clunker Vehicles

California census tracts are divided into deciles according to each tract’s share of clunker vehicles. Each decile category represents roughly 10 percent of the census tracts in California. Figure 2-12 compares the share of clunker vehicles in each decile category normalized by the lowest decile. A value greater than 1 indicates that the share of clunker vehicles for that decile is higher than the lowest decile category by that value. For example, the median clunker vehicles share in the highest decile area is more than 3.5 times as great as in the lowest area. The distribution of clean vehicles in California census tracts is negatively correlated with clunker vehicles.

Figure 2-12. “Clunker” Vehicles by Census Tract Decile Rankings



Maps

The following maps displays the distribution of clean (“newer” and “older”) vehicles.

“Newer” Clean Vehicles as Share of Total Vehicle Stock

<u>California</u>
Newer clean vehicles in California are concentrated in neighborhoods along the coastal areas, specifically in the Bay Area coastal counties and sections of Los Angeles. The Bay Area has the highest relative number of clean vehicles as a share of their vehicle stock. Central Valley and eastern counties in California have the lowest share of these vehicles (see Figure 2-13).

<u>Los Angeles</u>
Newer clean vehicles in LA County are concentrated on the Westside and the coastal neighborhoods. There is also a high percentage of these vehicles in pockets of neighborhoods in Glendale and Pasadena. Neighborhoods in South LA, East LA, and the San Fernando Valley have among the lowest share of “new” clean vehicles. This distribution follows the pattern of household income with higher income areas having a higher share of newer clean vehicles and low-income areas having a lower share (see Figure 2-14).

<u>Bay Area</u>
A majority of the Bay Area neighborhoods have a high share of newer clean vehicles relative to other neighborhoods in the state. The areas with a relatively lower share are located in Oakland and Richmond (see Figure 2-15).

Figure 2-13. Map of “Newer” Clean Vehicles, all of California

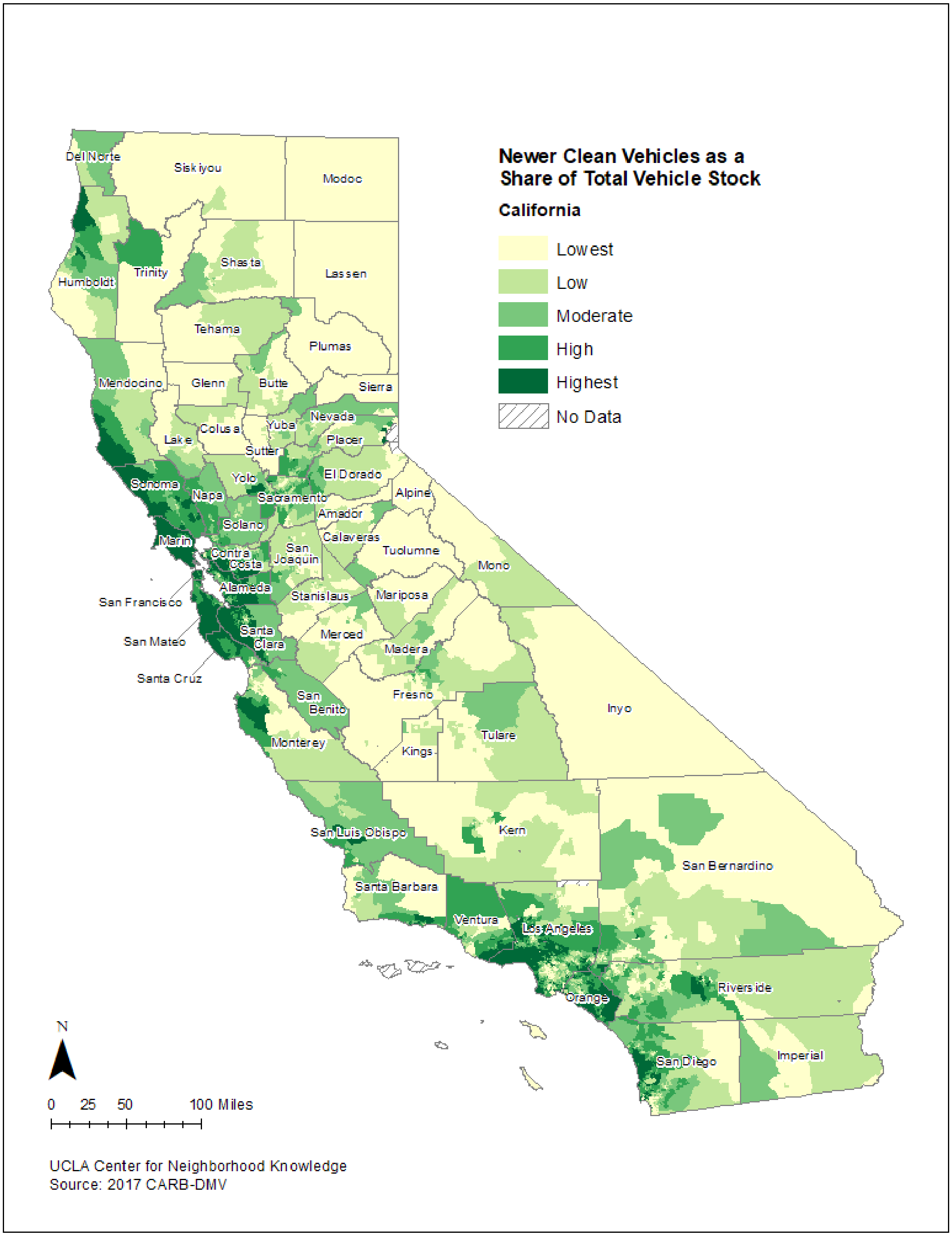


Figure 2-14. Map of "Newer" Clean Vehicles as a Share of Total Vehicle Stock, San Francisco Area

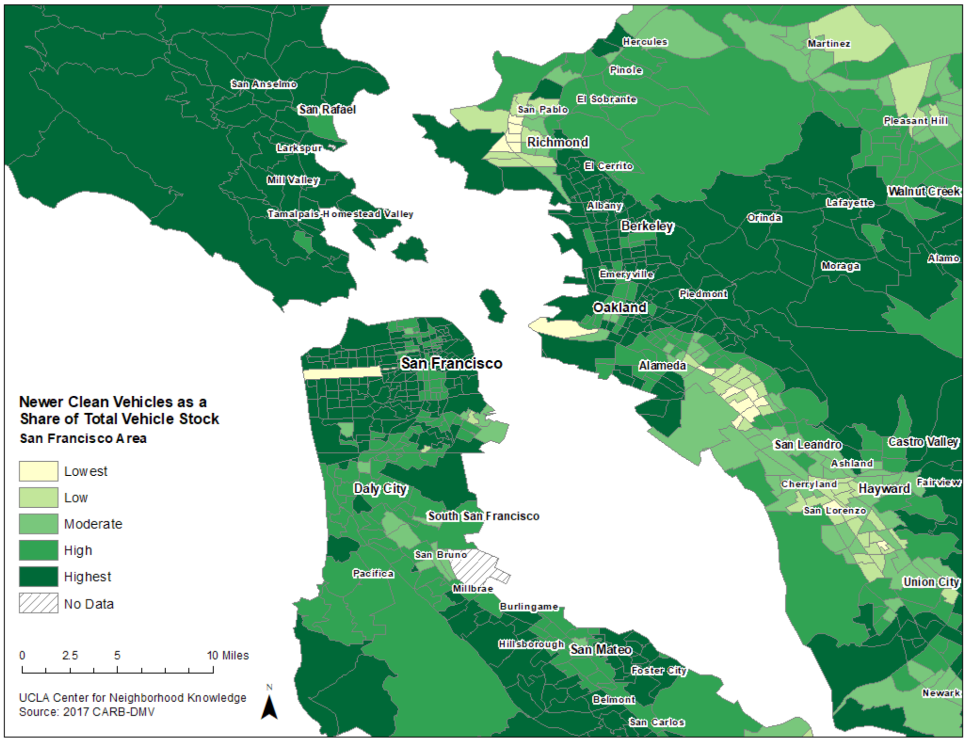
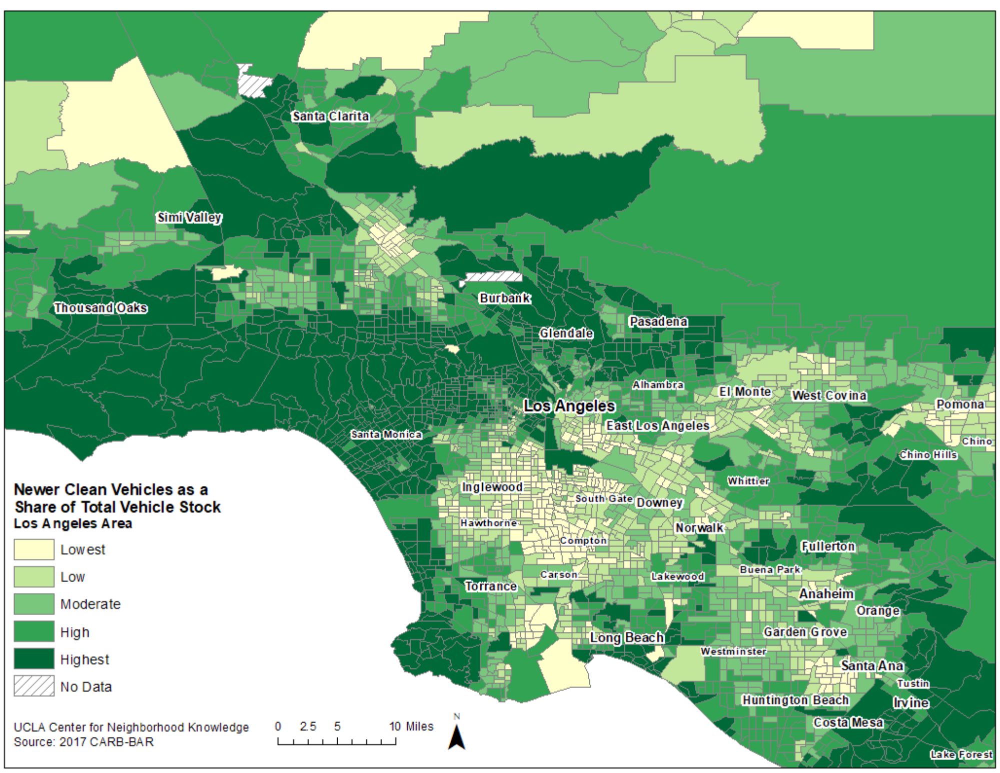


Figure 2-15. Map of "Newer" Clean Vehicles as a Share of Total Vehicle Stock, Los Angeles Area



"Older" Clean Vehicles as Share of Total Vehicle Stock

California

The spatial distribution of "older" clean vehicles (as a share of the vehicle stock) is similar to that of "newer" clean vehicles across the state. The share of "older" clean vehicles in California's total vehicle stock is concentrated along the coastal neighborhoods. The Bay Area again has among the highest share of clean vehicles in the state. The Central Valley and most counties in the eastern part of California have a relatively low share of "older" clean vehicles (see Figure 2-16).

Bay Area

Once again, a majority of the Bay Area neighborhoods have a high share of older clean vehicles compared with other neighborhoods in the state. The areas with a relatively lower share are located in Oakland and Richmond (see Figure 2-17).

Los Angeles

This map is similar to the distribution of "newer" clean vehicles in LA County. There is a stark difference between LA County neighborhoods with a high share of clean vehicles and those who do not. The Westside and coastal areas have the highest share of clean vehicles. South and East LA and the San Fernando Valley have the lower share of older clean vehicles. This map reflects the income distribution of LA County residents with high-income areas that have a high share of older clean vehicles (see Figure 2-18).

Figure 2-16. Map of “Older” Clean Vehicles as a Share of Total Vehicle Stock, all of California

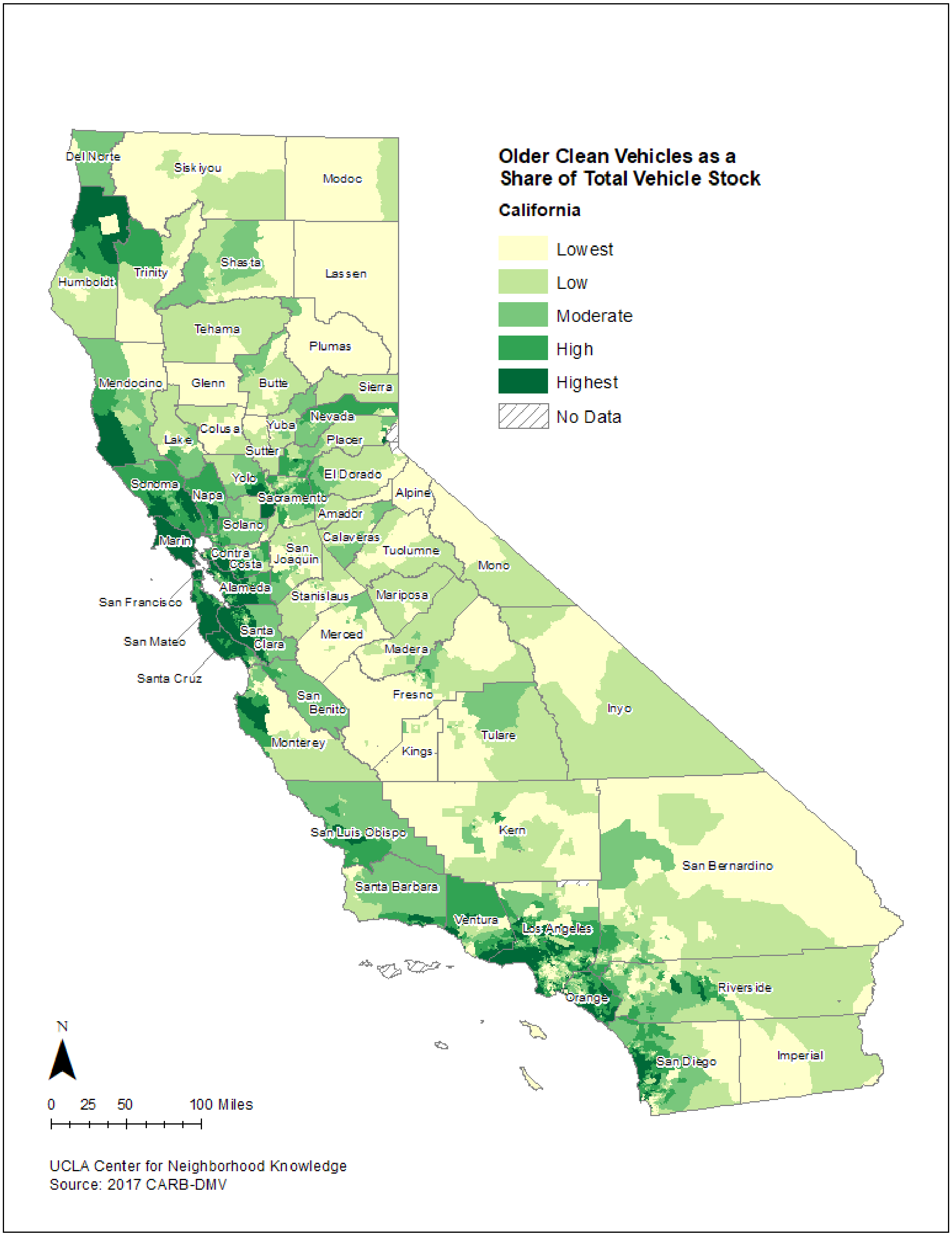


Figure 2-17. Map of "Older" Clean Vehicles as a Share of Total Vehicle Stock, San Francisco Area

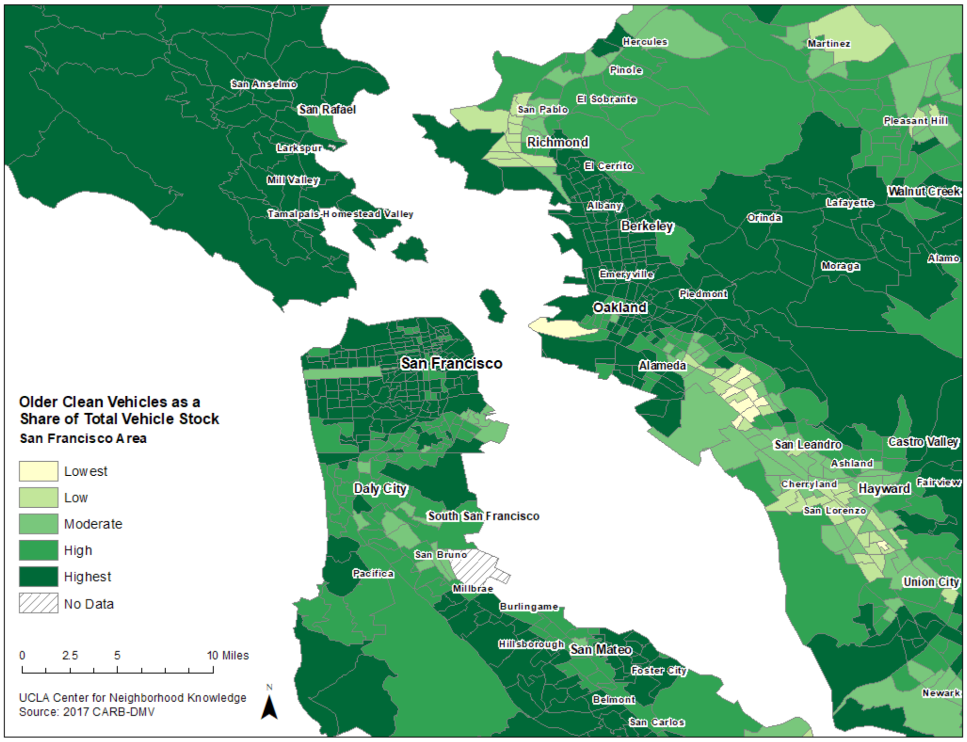
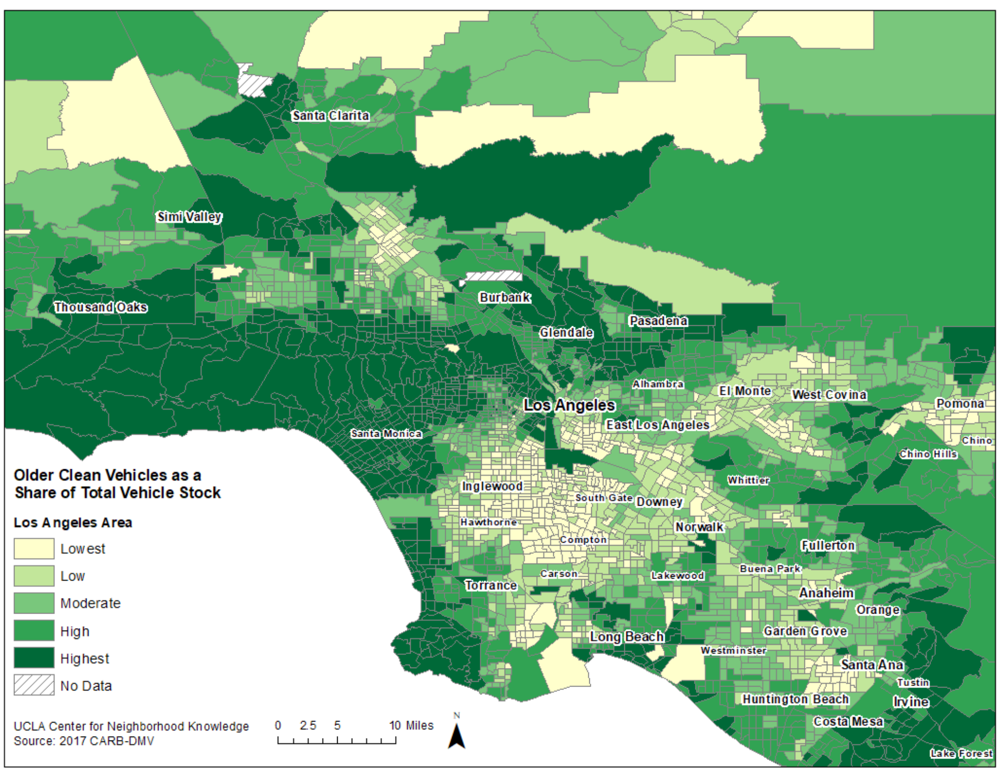


Figure 2-18. Map of "Older" Clean Vehicles as a Share of Total Vehicle Stock, Los Angeles Area



“Clunker” Vehicles as Share of Total Vehicle Stock

The following maps display the distribution of “clunker” vehicles.

California
The majority of the less populated counties in northern and central California are dominated by clunker vehicles (as a share of the vehicle stock). The more populated counties, like Los Angeles, Orange, those in the Bay Area, and Sacramento have lower share of clunker vehicles when compared to other parts counties in the state, but there are neighborhood variations within these areas (see Figure 2-19).

Bay Area
“Clunker” vehicle ownership is also correlated with income in the Bay Area. Affluent areas including much of San Francisco and the Peninsula do not have high “clunker” vehicle ownership. The lower-income parts of San Francisco, such as Bay View–Hunters Point, the East Bay including Oakland, and Richmond, have considerably more “clunker” vehicle ownership. There is also high “clunker” vehicle ownership in the more rural areas in coastal Marin County. Given that Marin County also has a high share of “newer” and “older" clean vehicles, the high share of “clunker” vehicles might be attributed to collectibles or classic/vintage cars (see
Figure 2-20).

Los Angeles
In Los Angeles, “clunker” vehicle concentration is largely correlated with income. Low-income areas like South Central Los Angeles, Boyle Heights, and Wilmington all have greater ownership of clunker vehicles compared to their affluent counterparts. For example, there is very low “clunker” vehicle ownership in the high-income areas of the Westside, the Santa Monica Mountains, and Palos Verdes (see Figure 2-21).

Figure 2-19. Map of “Clunker” Vehicles as a Share of Total Vehicle Stock, all of California

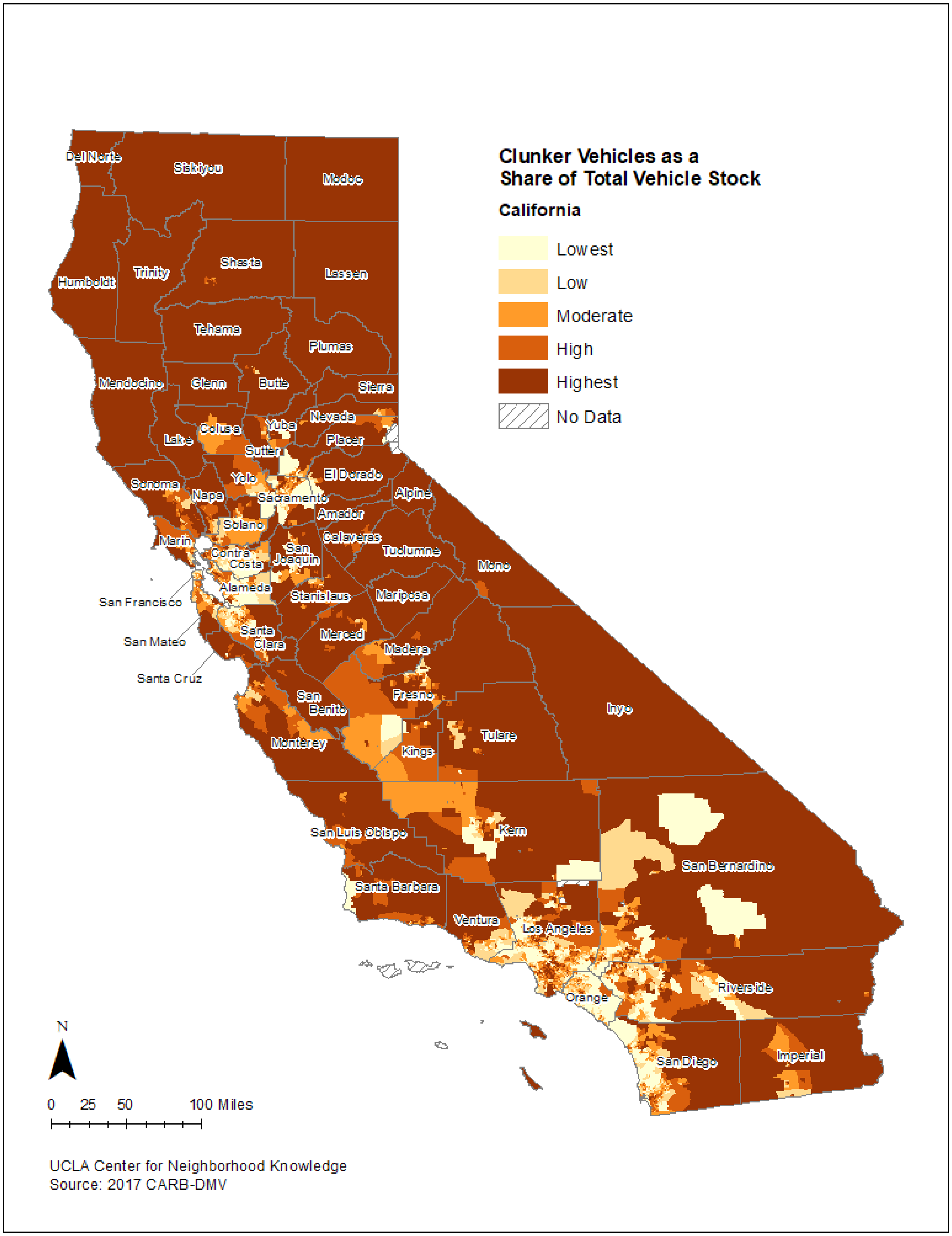


Figure 2-20. Map of "Clunker" Vehicles as a Share of Total Vehicle Stock, San Francisco Area

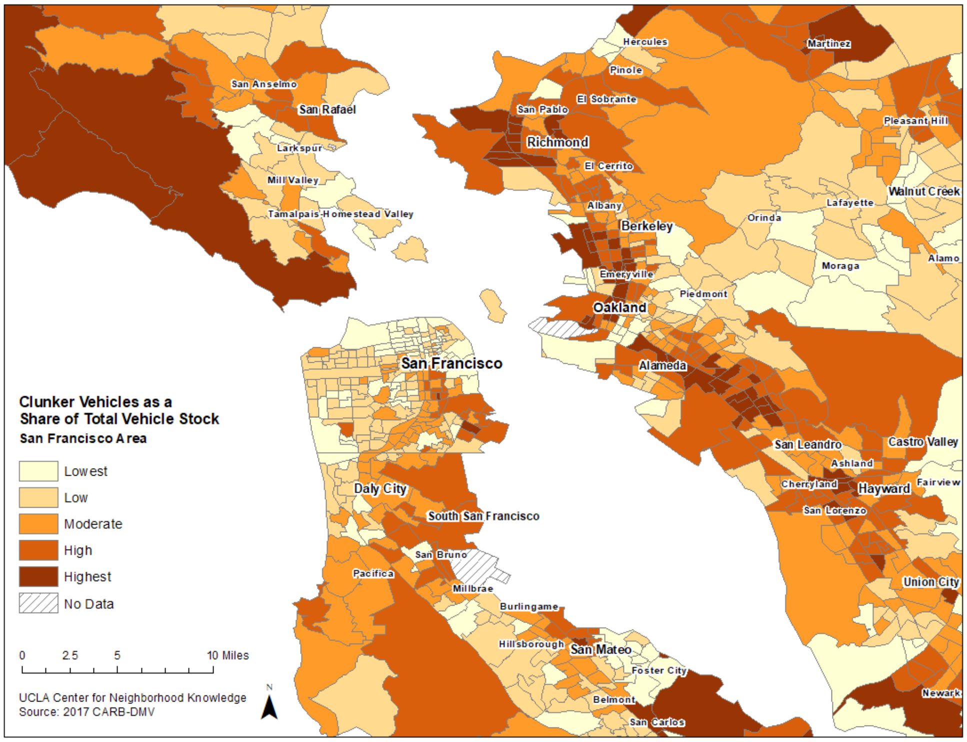
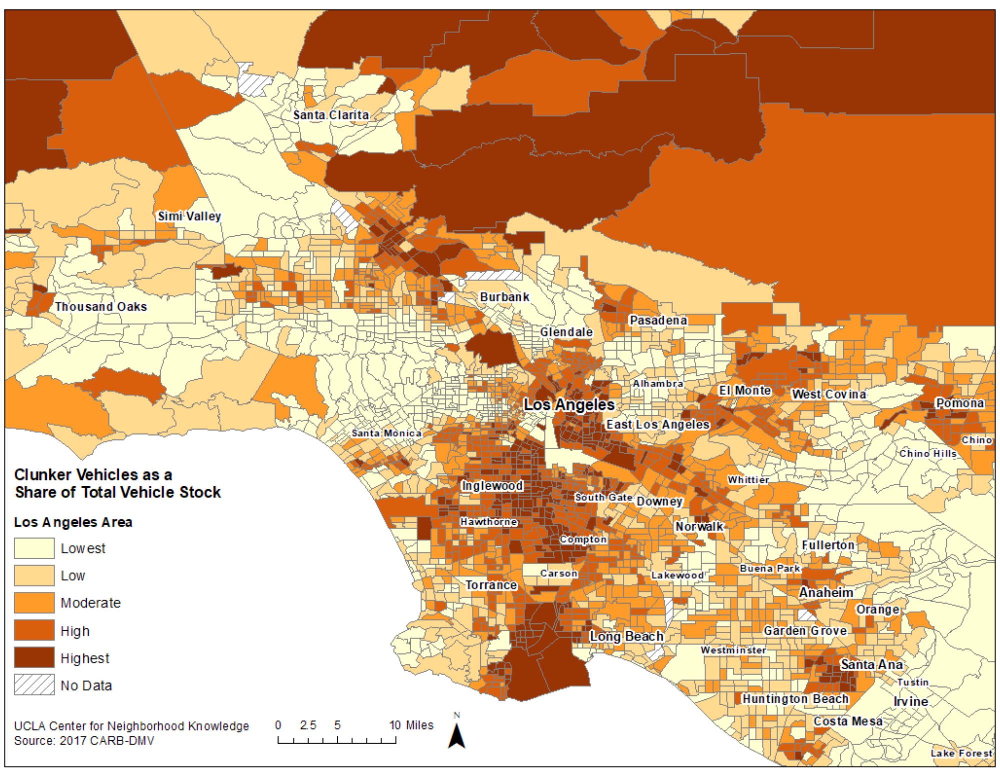


Figure 2-21. Map of "Clunker" Vehicles as a Share of Total Vehicle Stock, Los Angeles Area



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2.3.4 Vehicle Miles Traveled (Household, Commute)

This subsection details the construction of two measures of vehicle miles traveled (VMT): vehicle miles traveled per household (HVMT) and commute vehicle miles traveled per worker (CVMT).

Table 2-7. VMT per Household Indicator Summary Table

Key Indicator Information	
Units	VMT per Household
Category in Mapping Tool	Transportation
Display Method in Mapping Tool	Decile (visualized in quintiles)
Precision	Assumed to be relatively fair: average VMT report for vehicles grouped into multiyear categories
Methodological Complexity	Simple calculation of rates using observed DMV data
Geographic Resolution	Census tract
Key Information about Data Sources Used to Construct Indicator	
Data Sources Used to Construct	BAR, DMV, and ACS data
Sample Size	Based on high sampling of vehicles captured by BAR; DMV not based on sampling but complete administrative file; ACS based on fair size sample of households (approximately more than 12%).
Biases	VMT estimates based on BAR data, not all vehicles are required to go in for smog check, primarily captures older vehicles
Geographical Unit	Census tract
Geographic Coverage	Covers all of California
Data Vintage	2016 and 2017 odometer readings for BAR data; 2017 for registered vehicles from DMV, and 2013-17 5-year ACS
Other Important Notes (if applicable)	VMT estimates based on BAR information and provided by CARB. CARB’s VMT estimates were reweighted to reflect the overall composition of the vehicle fleet based on DMV data for 2017 (as provided by CARB).

Table 2-8. Commute VMT per Work Indicator Summary Table

Key Indicator Information	
Units	Commute VMT per Worker
Category in Mapping Tool	Transportation
Display Method in Mapping Tool	Decile (visualized in quintiles)
Precision	Assumed to be relatively fair to good: uses census tract centroids to estimate travel distances, and uses HERE network distance for only one specific period

Key Indicator Information	
Methodological Complexity	Multiple and cumulative imputations and estimates
Geographic Resolution	Census tract
Key Information about Data Sources Used to Construct Indicator	
Data Sources Used to Construct	LEHD and ACS
Sample Size	Not based on sampling for worker trips in LEHD, but on administrative records; ACS based on fair size sample of workers (approximately more than 12%).
Biases	Does not include workers outside of the Unemployment Insurance and Disability Insurance programs
Geographical Unit	Census tract
Geographic Coverage	Covers all of California
Data Vintage	2015 LEHD and 2013-17 5-year ACS
Other Important Notes (if applicable)	N/A.

Background

In the United States, about 30 percent of greenhouse gas (GHG) emissions stem from transportation sources (U.S. Environmental Protection Agency, 2015). According to the California GHG Emission Inventory, this number is even higher in California with the transportation sector making up about 40 percent of GHG emissions in 2017 (California Air Resources Board, 2019). Of transportation-related GHG emissions, about 70 percent come from passenger vehicles. Given the link between automobile use and GHG emissions, there is a need to reduce VMT to lower emissions, protect the environment, and improve public health. VMT is a convenient proxy to estimate fluctuations in GHG output.

As a proxy for transportation-related GHG emissions, VMT can show the impacts of vehicle travel on air quality and community health. Decreasing the use of passenger vehicles and increasing the use of active transportation can reduce VMT, improve air quality, and promote physical activity (Centers for Disease Control and Prevention, 2011). In regard to physical activity, increasing the walkability of a community can reduce VMT and is correlated to increased time spent being physically active through travel (Frank et al., 2006). The length of time an individual spends in the car is associated with an increased risk for obesity (Frank et al., 2004). GHG emissions can also worsen respiratory and cardiovascular health. Air pollutants, such as PM2.5, ozone (which is formed in the atmosphere from emissions), nitrogen dioxide, and diesel exhaust, can trigger symptoms among those who have asthma (CalEnviroScreen 3.0 Report). Proximity to congested roadways is associated with adverse health impacts, the strongest association is with asthma (Kim et al., 2004; McConnell et al., 2006), and others including asthma onset in children, impaired lung function, and increased heart disease (CARB, 2012; HEI, 2010).

Data Source

VMT per household (HVMT) measures a household's amount of travel for their vehicles in a given period. This indicator does not capture VMT for specific types of trips, such as home–work commutes, but it can provide insight on a household's general travel patterns. Although VMT does not capture miles traveled using other transportation modes, California residents have a strong dependence on personal vehicles as their primary mode of transportation.

VMT data are from CARB's smog check data from BAR. Data are from 2016 and 2017 odometer readings, grouped by vehicle model years, and reported at the census tract level. VMT is based on the odometer reading during a smog check. All gasoline-powered vehicles, hybrid vehicles, and alternative-fuel vehicles that are model 1976 and newer require a smog check. However, vehicles that are eight model years and newer do not need a biennial inspection and vehicles that are four model years and newer do not need a change-of-ownership inspection. Diesel-powered vehicles that are 1998 and newer with a gross vehicle weight rating of 14,000 pounds and less require a smog check. Currently, motorcycles and electric-powered vehicles are exempt from the Smog Check Program.

In addition to vehicle type, the Smog Check Program may require a different inspection depending on the program area. California is divided into three program areas according to their air quality: Enhanced Areas, Basic Areas, and Change of Ownership Areas. In general, all areas of the state require smog check certifications when a specified model-year vehicle changes ownership or is registered in California for the first time.

1. *Enhanced Areas* are areas in California that do not meet federal or state air-quality standards for ozone and carbon monoxide. In addition to the change-of-ownership and initial registration inspection requirements, a biennial smog check is required.
2. *Basic Areas* are less polluted relative to Enhanced Areas and require biennial inspections. Specified model-year vehicles require a biennial smog check during their registration renewal with DMV.
3. *Change of Ownership Areas* are more rural areas that only require smog check certification when the vehicle changes ownership (except gasoline vehicles four or less model-years-old) or was initially registered in California. Vehicles within specified model years registered in these areas require a smog check only during change of ownership or initial California registration.

These VMT data are an objective reading of odometers, rather than self-reported data. However, it does not capture VMT for newer cars, motorcycles, or electric-powered vehicles; does not consider miles traveled on other modes of transportation; and does not specify the trip type (e.g., work commute, personal trips).

CARB's VMT estimates based on BAR information were reweighted to reflect the overall composition of the vehicle fleet based on DMV data for 2017 (as provided by CARB). The DMV provides CARB with access to motor vehicle registration data for usage to "better characterize the motor vehicle fleet and support development and implementation of air quality regulations".[18]

The American Community Survey (ACS) variables used in our indicator construction were vehicles available, household counts, and means of transportation to work. Vehicles available counts the number of passenger cars, vans, and pickup or panel trucks kept at a home for the use of household members. Household counts measured the number of households in a particular geography level (e.g., census tract). Means of transportation to work reports commutes by car, truck, or van ("drive alone" or "carpool"), public transportation, motorcycle, bicycle, and walking. We specifically focused on commute estimates for personal vehicles (e.g., drove alone, carpooled with two persons, carpooled with three persons).

[18] Air Resources Board DMV Registration Data Confidentiality Agreement.

In addition to ACS, we utilized the 2015 Longitudinal Employer-Household Dynamics (LEHD) data on commute flows (for all jobs) that looks at where workers are coming from (residential tract) and where they are going for work (job-site tract) combined with street network distances generated through HERE.[19]

Construction Method

Vehicle Miles Traveled per Household

This measure includes HVMT and incorporates all types of travel. VMT was constructed using a combination of CARB's VMT estimates based on BAR information, counts of registered vehicles from DMV and ACS vehicle and household counts. The following steps estimated annual HVMT.

Step 1 - Estimating Average VMT Per Vehicle in a Census Tract Using CARB's VMT Estimates Based on BAR Data and Registered Vehicle Counts from DMV

The VMT data provided by CARB are broken down into three categories by vintage of vehicle: less than 10 years old, between 10–20 years old, and more than 20 years old. CARB's VMT estimates based on BAR information were reweighted to reflect the overall composition of the vehicle fleet based on DMV data. The following formula calculates the average VMT per vehicle for each tract:

$$Avg_{VMT_{Veh}} = \frac{(count_1 * vmt_1 + count_2 * vmt_2 + count_3 * vmt_3)}{(count_1 + count_2 + count_3)}$$

Avg_VMT_Veh is Average VMT per vehicles
$Count_1$ is number of vehicles less than 10 years
$Count_2$ is number of vehicles between 10–20 years
$Count_3$ is number of vehicles greater than 20 years
VMT_1 is estimated VMT for vehicles less than 10 years
VMT_2 is estimated VMT for vehicles between 10–20 years
VMT_3 is estimated VMT for vehicles greater than 20 years

Step 2 - Calculate Vehicle Per Household from 2013-17 ACS

$$Veh_{HH} = \frac{Veh}{HH}$$

Veh_{HH} is number of vehicles per household in a census tract
Veh is number of reported vehicles in a census tract
HH is number of households in a census tract

Step 3 - Estimate Average HVMT in a Census Tract

$$VMT_{HH} = Avg_{VMT_{Veh}} * Veh_{HH}$$

VMT_{HH} is VMT per household
Avg_VMT_Veh is average VMT per vehicles
Veh_{HH} is number of vehicles per household in a census tract

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[19] For additional details about HERE Street Network and the assessments of distances generated through HERE, see Ong et al. (2018a).

Commute Vehicle Miles Traveled per Worker
Commute vehicle miles traveled (CVMT) per worker in a tract represents the average (mean) distance a worker drives to work by vehicle. CVMT is constructed using a combination of two datasets. The first is constructing person miles traveled (PMT) for commute and converting this measure to commute by vehicle. The second is obtaining Means of Transportation to Work data from 2013–17 5-year ACS.

Step 1 - Estimate Person Miles Traveled

Average (mean) PMT to work site is a measure of the typical commute of a worker at that place of residence to their work site. It is constructed using the 2015 LEHD data on commute flows (where one lives and works) combined with distances generated through HERE street network. The average (mean) commute for these workers is calculated by multiplying the network distance between residential tract and job-site tract and dividing it by the number of workers in the residential tract. For a full description of these two datasets and their construction see the PI's Caltrans and CARB report on developing indicators related to measuring sustainable communities' strategies (Ong et al., 2018a; Ong et al., 2018b).

The data on commute flows from LEHD does not directly translate into VMT because it depends on the worker's mode of transportation. For example, PMT would equal CVMT if the worker drove alone; however, some workers carpool and therefore each worker generates less VMT because they share the vehicle. One would have to adjust for the composition by mode of transportation. This is done in the next step using data on Means of Transportation to Work from the American Community Survey.

Step 2 - Calculate the Means of Transportation to Work for Select Modes

The ACS Means of Transportation to Work reports commutes by car, truck, or van ("drive alone" or "carpool"), public transportation, motorcycle, bicycle, and walking. We specifically focused on commute estimates for personal vehicles (e.g., drove alone, carpooled with two persons, carpooled with three persons). To do so, we modified the carpool measure to account for the number of passengers in a carpool. In this case, we are assuming that all passengers are workers.

The final CVMT measure is calculated as follows:

$$CVMT_{Worker} = PMT * \frac{(Alone + \frac{Pool_2}{2} + \frac{Pool_3}{3} + \frac{Pool_4}{4} + \frac{Pool_5}{5.5} + \frac{Pool_7}{8})}{Commuters}$$

CVMT_Worker is commute VMT per worker
PMT is person miles traveled
Alone is number of workers driving alone to work
$Pool_2$ is number of workers in a 2-person carpool
$Pool_3$ is number of workers in a 3-person carpool
$Pool_4$ is number of workers in a 4-person carpool
$Pool_5$ is number of workers in a 5- or 6-person carpool
$Pool_7$ is number of workers in a 7- or more person carpool
Commuters is number of workers that commute by personal vehicle
Carpool estimates are adjusted to account for differences in number of commuters per vehicle.

Assessment of Consistency

We compared our VMT estimates against the Center for Neighborhood Technology (CNT) Housing + Transportation (H+T) Index. Our HVMT and CVMT measures are based on more direct California specific data, which CNT simulates using parameters estimated with non-California data (e.g., Chicago and St. Louis metro areas).

CNT's H+T Index is simulated using parameters estimated from non-Californian data and were not highly correlated with estimates based on observed information. According to their H+T Index methodology, the dependent variable of auto use measures data on the amount that households drive and the vehicles miles traveled (VMT) per automobile (Center for Neighborhood Technology, 2017). They have three measures of VMT with each varying on the "type of household." A "regional typical household" assumes the household has a regional area median income, regional average household size, and regional average number of commuters per household ("Glossary of Terms," n.d.). Second, the "regional moderate household" assumes the household has an income that is 80 percent of the regional area median income, regional average household size, and regional average number of commuters per household ("Glossary of Terms," n.d.). Lastly, the "national typical household" assumes the household has a national median household income, national average household size, and national average of commuters per household ("Glossary of Terms," n.d.).

Data for their auto use variable uses odometer readings from 2010 to 2012 for Chicago and St. Louis metro areas in the state of Illinois. These data represent a diverse set of areas in Chicago and St. Louis and were used to calibrate the model. In addition, these data were first geographically identified with ZIP codes and then assigned to census block groups. This is important to note given the H+T Index uses Chicago and St. Louis to simulate VMT estimates for states across the country.

When we assessed our HVMT measure against CNT's various VMT measures, it was moderately correlated across each of the household types (see Table 2-9). For example, our HVMT measure assessed against their VMT for the regional typical household measure was moderately correlated (0.71, which explains about half of the total variance). Even after restricting outliers with HVMT <50,000, our HVMT measure did not have a strong correlation.

Table 2-9. Correlation Table of VMT Measures

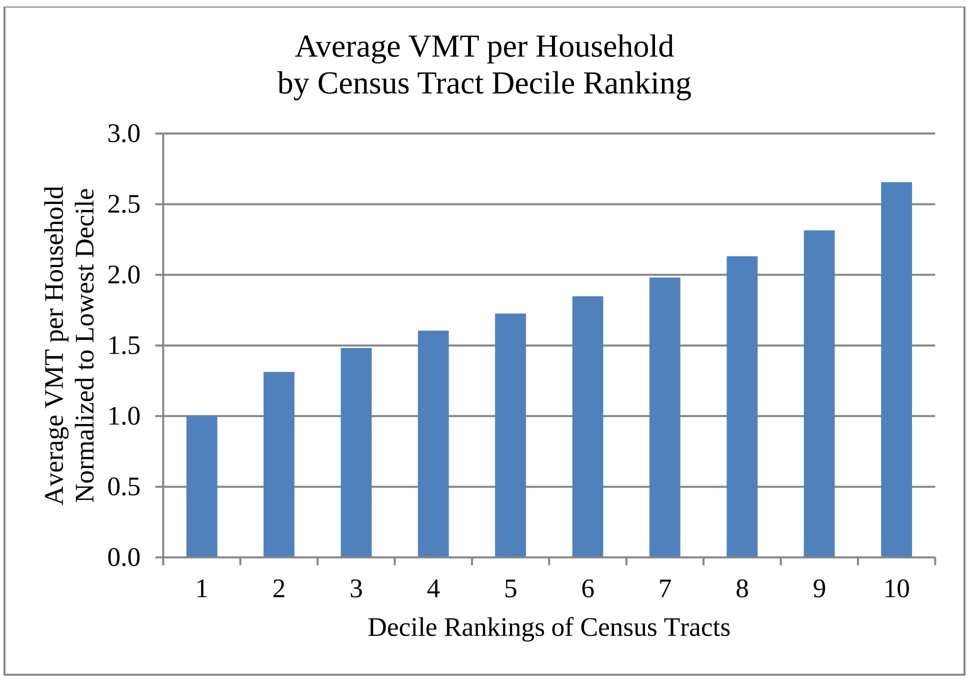
Pearson Correlation Coefficients Prob > |r| under H0: Rho=0 Number of Observations				
	CNT_vmt_per_hh_80ami	**CNT_vmt_per_hh_ami**	**CNT_vmt_per_hh_nmi**	**CNK_hvmt**
CNT_vmt_per_hh_80ami*	**1**	**0.99831**	**0.98412**	**0.70522**
		<.0001	<.0001	<.0001
	7984	7984	7984	7877
CNT_vmt_per_hh_ami**	**0.99831**	**1**	**0.9843**	**0.69814**
	<.0001		<.0001	<.0001
	7984	7984	7984	7877
CNT_vmt_per_hh_nmi***	**0.98412**	**0.9843**	**1**	**0.67259**
	<.0001	<.0001		<.0001
	7984	7984	7984	7877
CNK_hvmt****	**0.70522**	**0.69814**	**0.67259**	**1**
	<.0001	<.0001	<.0001	

	7877	7877	7877	7877
* CNT's VMT measure for a regional moderate household. ** CNT's VMT measure for a regional typical household. *** CNT's VMT measure for a national typical household. **** CNK's VMT measure for an average household.				

Results

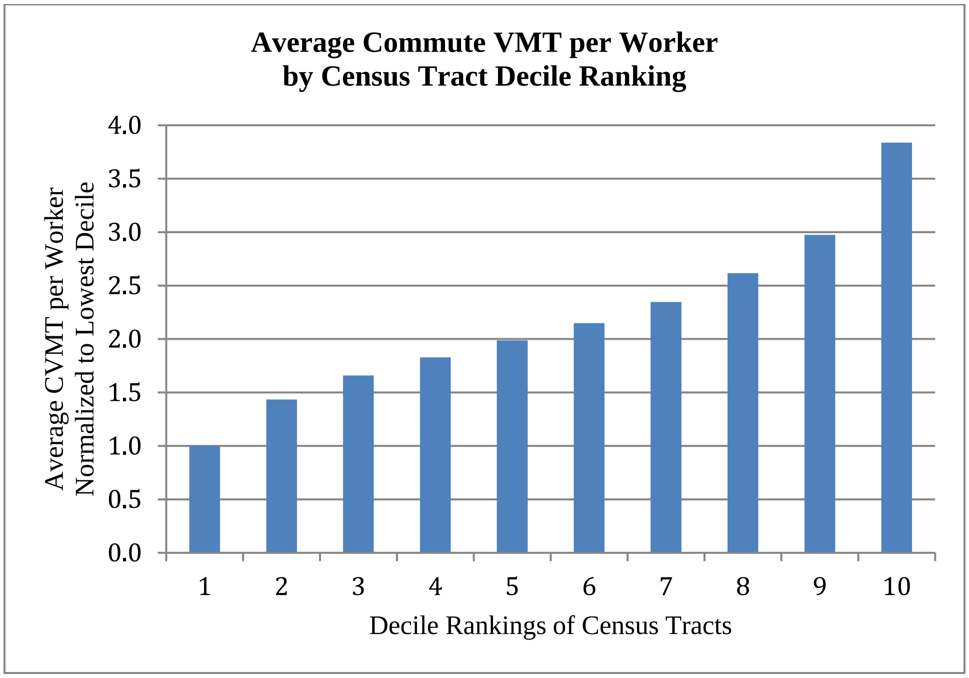
Average Vehicle Miles Traveled Per Household
California census tracts are divided into deciles according to each tract's average HVMT. Each decile category represents roughly 10 percent of the census tracts in California. Figure 2-22 compares average HVMT in each decile category normalized by the lowest decile. A value greater than one indicates that the average HVMT for that decile is higher than the lowest decile category by that value. For example, the median HVMT in the highest area is more than 2.5 times as great as in the lowest area.

Figure 2-22. Average Vehicle Miles Traveled Per Household by Census Tract Decile Rankings



Commute Vehicle Miles Traveled Per Worker
California census tracts are divided into deciles according to each tract's average CVMT. Each decile category represents roughly 10 percent of the census tracts in California. Figure 2-23 compares average CVMT per worker in each decile category normalized by the lowest decile. A value greater than 1 indicates that the average CVMT per worker for that decile is higher than the lowest decile category by that value. For example, the median CVMT per worker in the highest area is nearly four times as great as in the lowest area.

Figure 2-23. Average Commute Vehicle Miles Traveled Per Worker by Census Tract Decile Rankings



Maps

The following maps displays the distribution of average VMT per household.

California
Households with a high VMT are concentrated in less dense areas, the census tracts surrounding urban cores like the Bay Area and LA County. Also, most of the areas in the Central Valley are among the highest average VMT per household in the state. This may be due to the fact that housing, jobs, and serves are more dispersed, thus requiring more travel. This appears to be particularly true for areas that are agricultural or rural, where residents drive long distances to travel to nearby cities (see Figure 2-24).

Bay Area
Unlike LA County, the Bay Area has significantly fewer areas with a high average HVMT. Areas like San Francisco, Berkeley, and Oakland are walkable and have substantial public transit with high frequencies. This may encourage residents not to take their personal vehicles—if they do have one. Areas on the outskirts of the Bay Area have a higher average HVMT. These areas may not have immediate access to public transit or may be more spaced out than the denser urban core (see Figure 2-25).

Los Angeles
In LA County, the areas with the highest average HVMT are in Southeast LA, the Gateway Cities, the San Fernando Valley, Santa Clarita, and the Antelope Valley (Palmdale, Lancaster). Some of these areas are suburban or highly residential, which would require residents to travel longer distances to do daily activities (see Figure 2-26).

Figure 2-24. Map of Average VMT Per Household, all of California

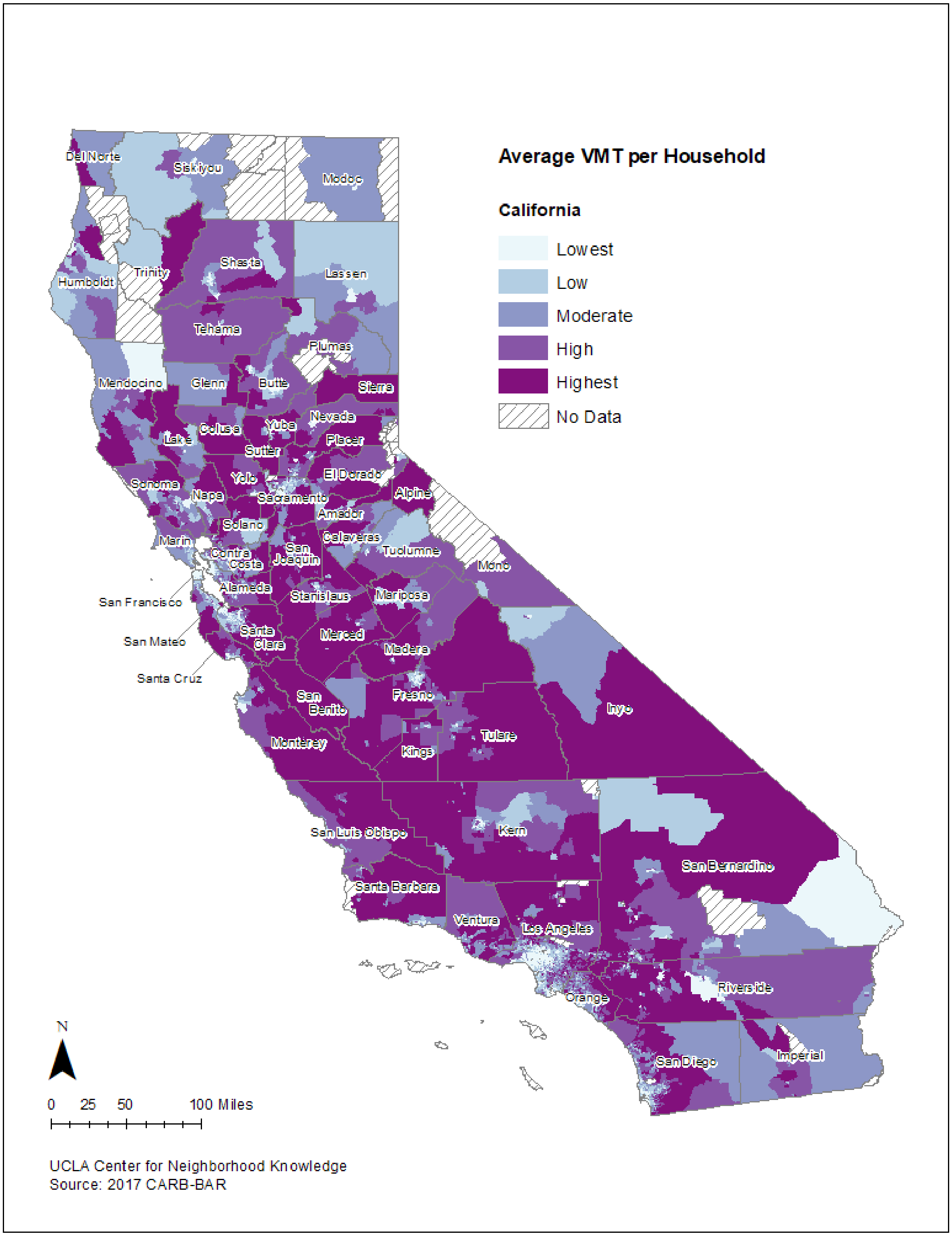


Figure 2-25. Map of Average VMT Per Household, San Francisco Area

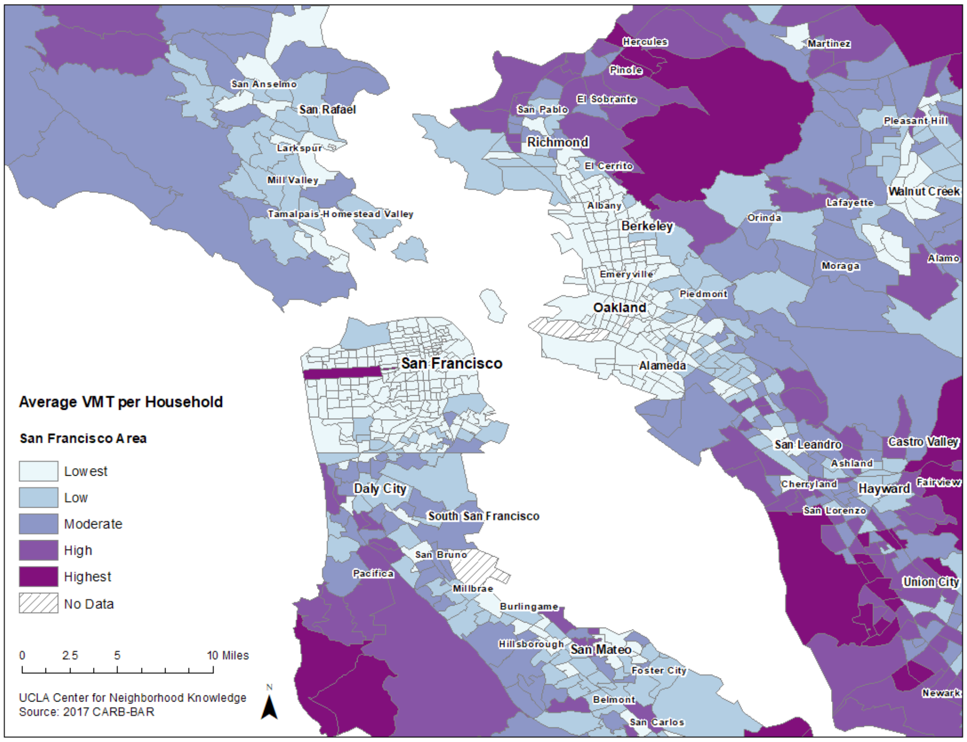
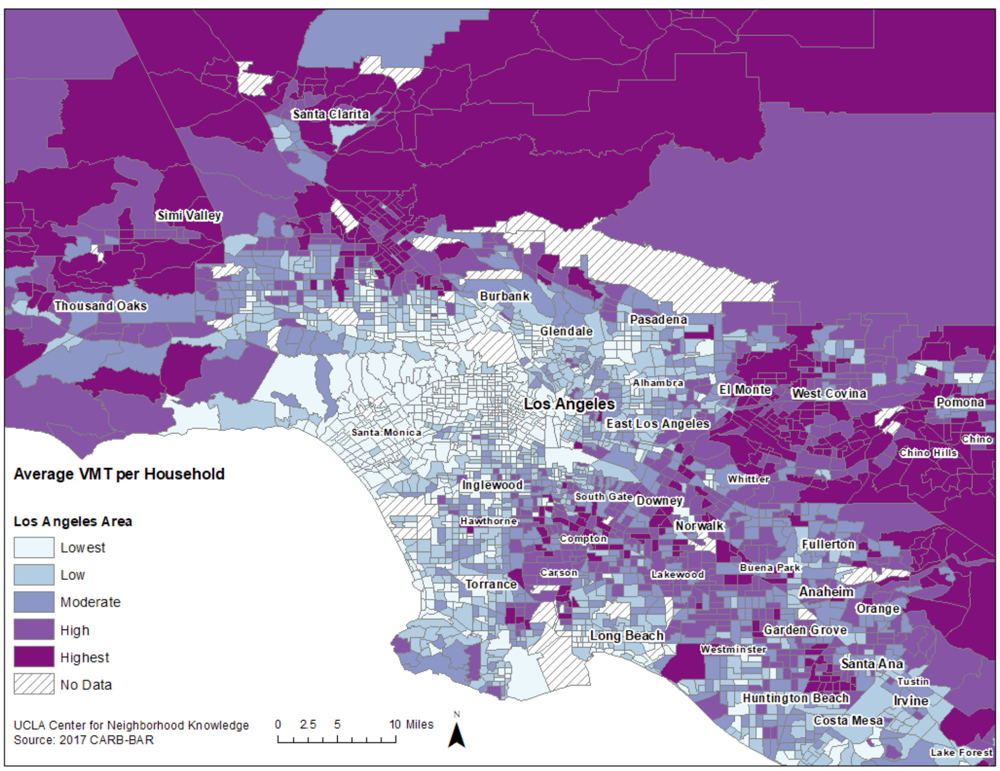


Figure 2-26. Map of Average VMT Per Household, Los Angeles Area



The following maps displays the distribution of average commute VMT per worker.

California

There are visible geographical differences in CVMT. In rural agricultural-based counties, we tend to see higher CVMT largely because employment opportunities and other activities centers are more geographically disbursed. Unlike the average HVMT, a majority of California workers, with exception to those in urban cities, have a high average CVMT. This may be due to the fact that many live in the suburbs and exurbs and drive into areas of employment centers in the urban cores for work (see Figure 2-27).

Bay Area

There is a similar, negative correlation in the Bay Area. In the heavily commercial and urban areas, there are low average commute VMT. Areas where this is especially true include all of San Francisco and Oakland. Radiating out from this commercial center, commute VMT increases gradually. Commute VMT is moderate east of Oakland and in Marin County. Further down the western side of the Peninsula, CVMT creeps into the high to highest range (see Figure 2-28).

Los Angeles

In LA County, the neighborhoods with the highest average CVMT are in located in areas further away from job centers. Some of these areas are suburban or highly residential, which would require residents to travel longer distances to work. These include, for example, Santa Clarita and the northern parts of LA County (see Figure 2-29).

Figure 2-27. Map of Average Commute VMT Per Worker, all of California

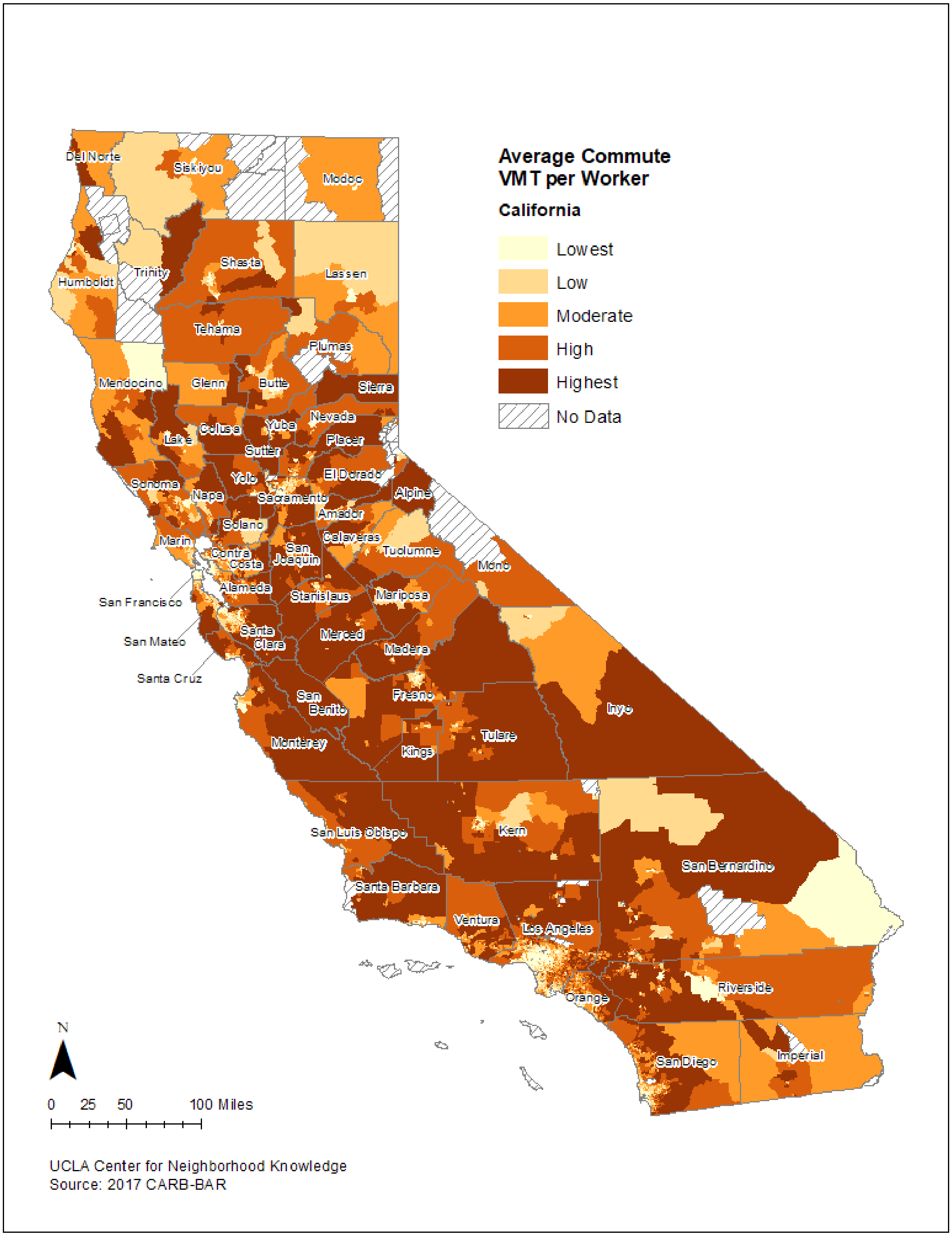


Figure 2-28. Map of Average Commute VMT Per Worker, San Francisco Area

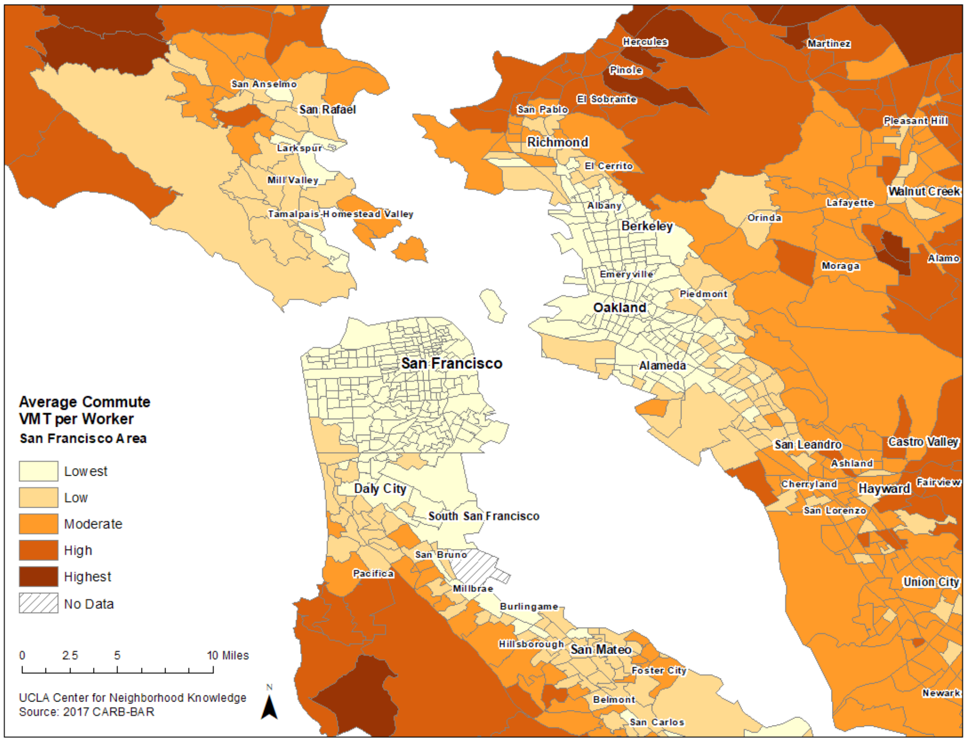
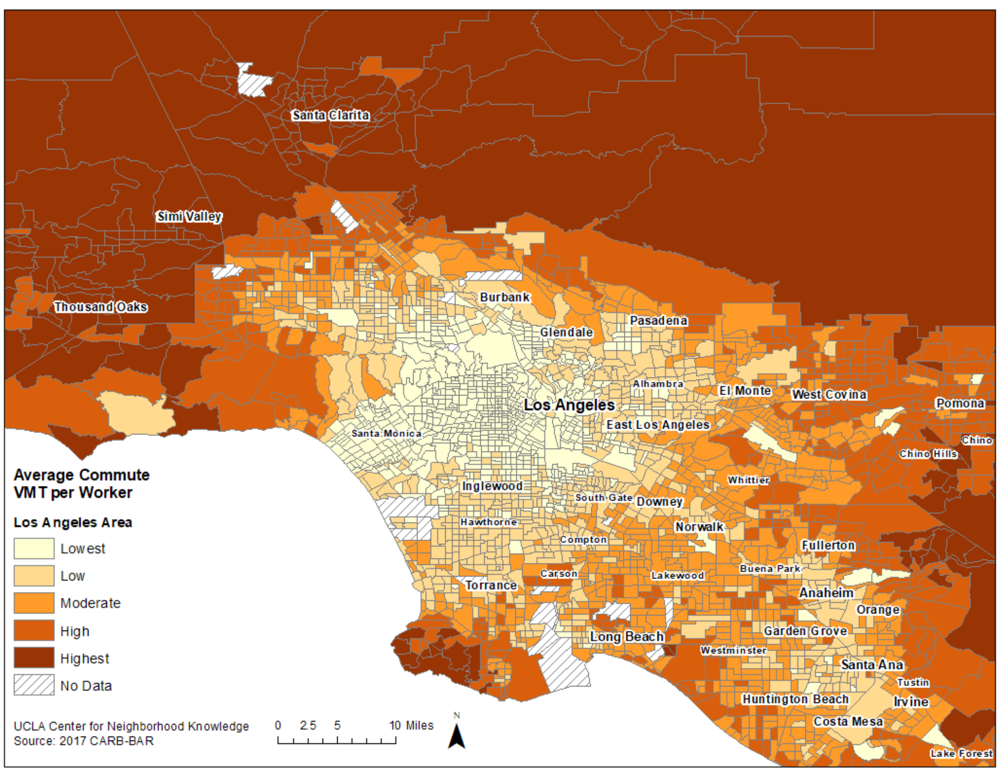


Figure 2-29. Map of Average Commute VMT Per Worker, Los Angeles Area



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2.3.5 Availability of Public Park Space

This subsection reports the construction of the park availability indicator that measures the availability of public park space per population.[20]

Table 2-10. Availability of Parks Indicator Summary Table

Key Indicator Information	
Units	Availability of Public Park Space per Population
Category in Mapping Tool	Accessibility
Display Method in Mapping Tool	Decile (visualized in quintiles)
Precision	Unknown precision: not all public spaces are accounted
Methodological Complexity	Generated using tract and surrounding buffer area, some park space can be in more than one tract
Geographic Resolution	Park area
Key Information about Data Sources Used to Construct Indicator	
Data Sources Used to Construct	CA. Department of Parks and Recreation's park access tool
Sample Size	Not based on sampling; large number of observations based on administrative shapefiles
Biases	Certain types of public spaces are not likely to be included
Geographical Unit	Census tract
Geographic Coverage	Covers all of California. No prevailing standard on walkable buffer size surrounding tract.
Data Vintage	2015
Other Important Notes (if applicable)	N/A.

<u>Background</u>

Park usage can be predicted by its proximity to the community in addition to its size and design characteristics (Giles-Corti & Donovan, 2002). Although theoretically a person can use a park or public open space, its design can influence one's perception of actual safety and provide cues for active or passive behavior. Parks can increase a neighborhood's walkability and bikeway availability if it has the appropriate infrastructure. In California, more than 25 percent of California Household Travel Survey respondents reported that the greatest barrier to walking was having "no place interesting to go" (McGuckin, 2012). Thus, it would seem likely that increased proximity to desirable places (shopping, restaurants, parks, etc.) would motivate individuals to make more walking trips. This assumption is supported by many scholars who find a relationship between walking trip frequency, population density, and destination proximity (Handy et al., 2006; Kim & Susilo, 2013; McGuckin, 2012; Saelens & Handy, 2008). These factors are likely interrelated: proximity to destinations increases with density and vice versa.

[20] It is important to note the difference between park availability and park access because the two are often used interchangeably. Park availability measures the amount of open space available to a population in and around a tract, whereas park access measures the proportion of population that is within a half-mile buffer around the park.

Parks and open spaces often provide opportunities for safe physical activity and provide important mental health benefits as well. Exercise facilities, including parks are associated with vigorous physical activity in both adults and children (Sallis et al., 1997; Sallis et al., 1998), which can decrease heart disease, diabetes, and high blood pressure (Bedimo-Rung et al., 2005). Park-based leisure can improve moods, reduce perceived stress, and improve an individual's sense of wellness (Bedimo-Rung et al., 2005; Orsega-Smith et al., 2004).

Data Source

CNK's park availability indicator modifies the California Department of Parks and Recreation's park access tool (PPK) that uses neighborhood-level park access and demographic information from 2015. The tool measures park access using two standard methods: (1) living within a half mile of a park and (2) ratio of park acres per one thousand residents (CA Department of Parks and Recreation, n.d.). The CNK indicator will address the limitations of the second method: park area to population.

Construction Method

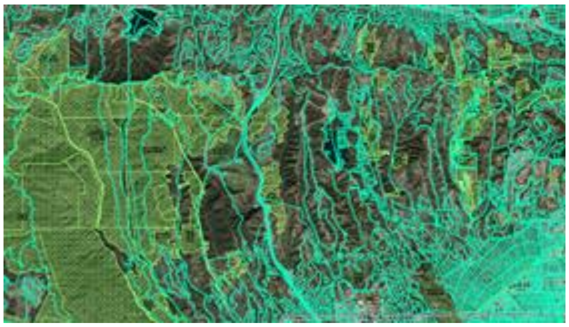
The park area per population method of the Department of Parks and Recreation's park access tool had two limitations. One limitation is that it did not account for parks directly adjacent to a tract rather than within the tract. Tracts are often defined by streets and sometimes a single park can make up its own tract leaving adjacent tracts apparently without park access. For example, in Figure 2-30, DPR's park access tool would show Park A is available to the population within the census tract designated by a black boundary. However, Parks B and C, which are adjacent but outside of the tract boundaries, would be considered unavailable to the population. To address this limitation, we used a quarter-mile buffer to capture adjacent areas.

The second limitation is that the size of tracts may be too large to be considered walkable, leaving park areas not as easily reachable by people within the tract. For example, someone living on the opposite side of the tract may not be within walking distance of Park A, which is within the same tract. To address this limitation, census block groups (a geography smaller than tracts) were averaged to generate a tract-level value.

A quarter-mile buffer was created around each block group and intersected with adjacent blocks, resulting in a block group plus neighboring blocks. The DPR's population and park area data was also summed up and assigned to its corresponding block group. Then, a tract value was calculated by using a weighted average of the values generated for the block groups (based on block group buffers) and weighted by the population within the block groups (not inclusive of buffers). While the DPR's method shows that tracts directly adjacent to park tracts have little access to green spaces because the green spaces are not within the tract, adding a buffer shows that tracts adjacent to park tracts also have access to green spaces.

Figure 2-30. Park Access and Tract Borders

Figure 2-31. Block Shapes in Less Dense Areas



Block shapes may be less helpful outside of dense urban areas (see Figure 2-31) but are used because of the available census data by those geographies. The specific implementation used may capture areas larger than what may be considered walkable. The use of block centroids within a certain distance of the original tract or proportional allocation-based area should be considered in future research.

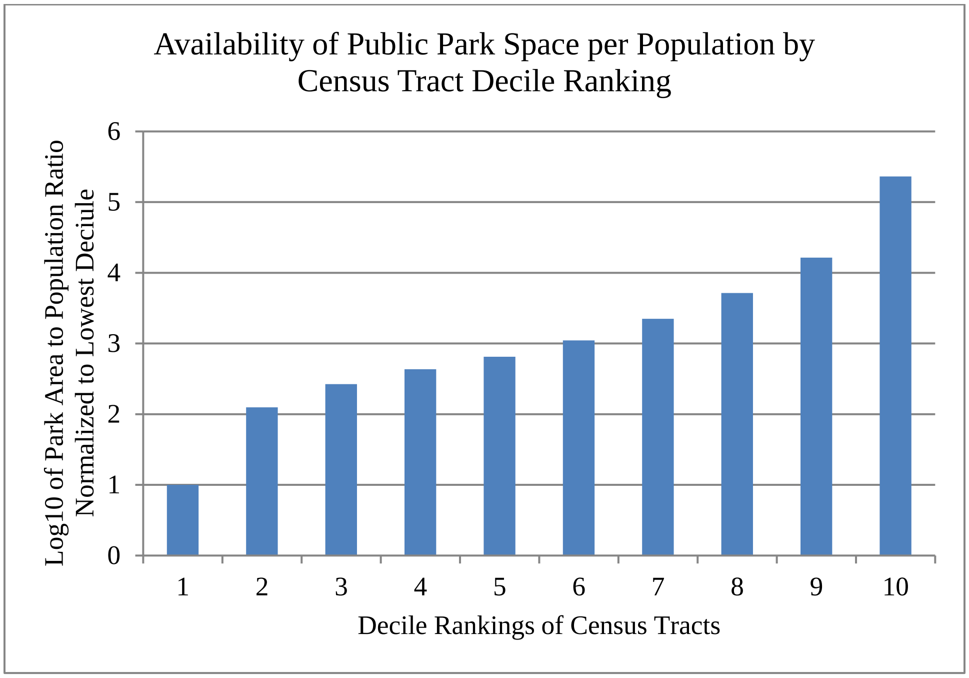
Assessment of Consistency

Appendix A shows examples of how park access differs between Golden Gate Park in San Francisco, and Balboa Lake and Rancho Park in Los Angeles in terms of the DPR's Park Access tool and CNK methodology. Shading is based on quintiles, with the darkest area having the highest green area-to-person ratio. Bright green hatch-marked areas are public green spaces.

Results

California census tracts are divided into deciles according to each tract's public park space availability per population. Each decile category represents roughly 10 percent of the census tracts in California. Given that the measure of space is very nonlinear and has large relative differences between each decile, the indicator was transformed. Figure 2-32 compares the log10 (log of ratio with base 10) of park area to population ratio in each decile category normalized by the lowest decile. A value greater than 1 indicates that public park space availability per population for that decile is higher than the lowest decile category by that value. Each unit is equal to a tenfold increase in median value of public park space availability. For example, the lowest decile has only a tenth of available space as the second lowest decile.

Figure 2-32. Availability of Public Parks per Population by Census Tract Decile Ranking



Maps

The following maps displays the distribution of park availability per population.

California
There is high availability of parks in less dense and rural areas across the state. However, urban areas lack parks, and this is particularly true for the dense neighborhoods in Los Angeles, Orange, and southwest San Bernardino counties. Pockets of neighborhoods in the Central Valley also lacks parks relative to the rest of the state (see Figure 2-33).

Bay Area
A similar trend is found in the Bay Area, where park availability is strongly correlated with population density and income. Communities in the wealthy, less populated areas of Marin County and the Santa Cruz Mountains have high park availability. There is also high availability in the eastern parts of Contra Costa and Alameda counties. Areas with low park availability often fall along major freeways, especially along I-880 in the East Bay and US-101 up the Peninsula. Downtown San Francisco and the urban parts of Oakland and Berkley have the lowest park availability of the Bay Area (see Figure 2-34).

Los Angeles
Park availability is highly correlated with urbanization and population density in LA. There is very little park availability in the highly populated parts of the San Fernando Valley, Downtown, and South Central Los Angeles. Availability increases in the less densely populated areas around the Santa Monica Mountains and the San Gabriel Valley. Some parts of LA have pockets of high park availability and these largely occur in high-income areas. For example, the Westside and Palos Verdes have higher availability of parks (see Figure 2-35).

Figure 2-33. Map of Availability of Public Park Space per Population, all of California

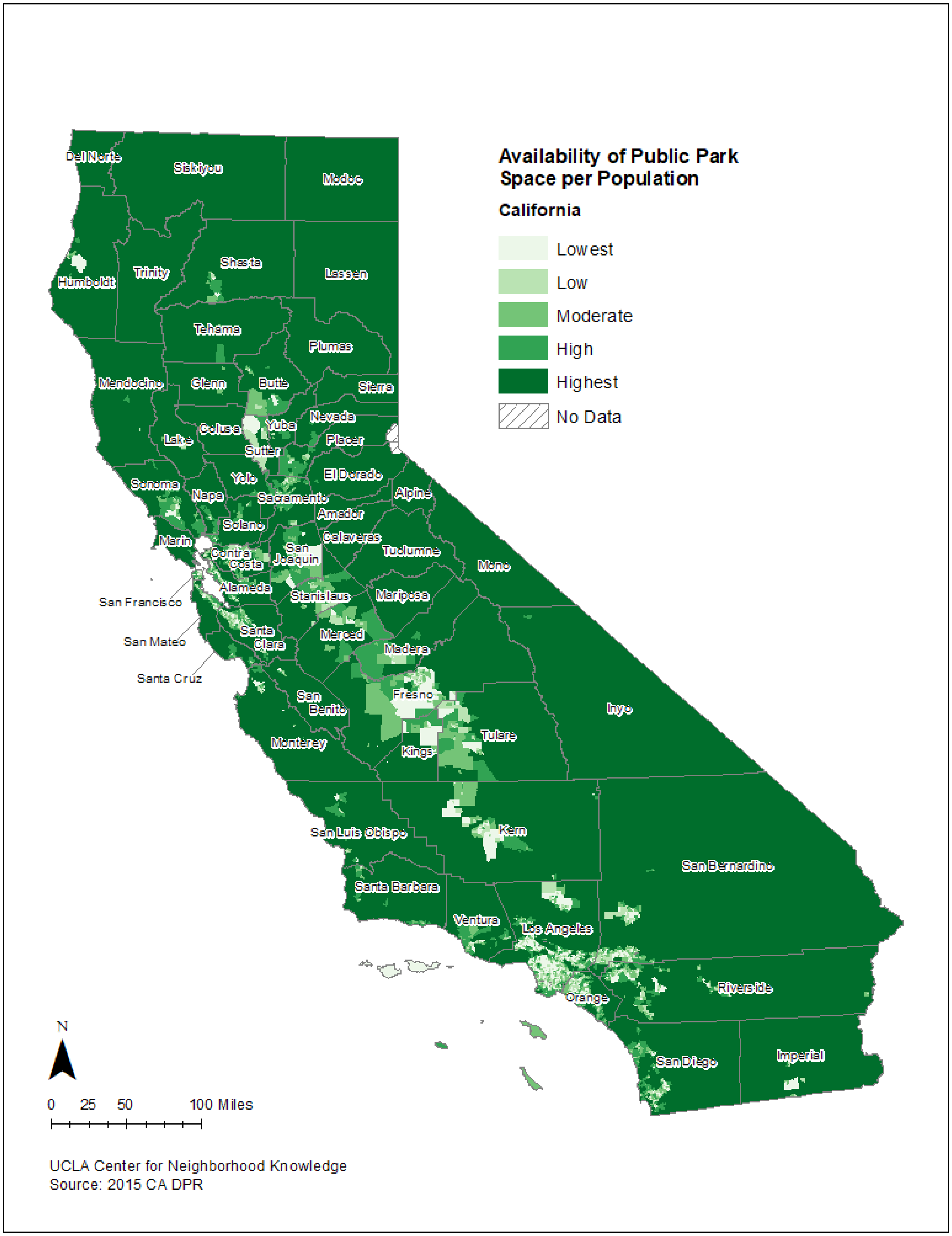


Figure 2-34. Map of Availability of Public Park Space per Population, San Francisco Area

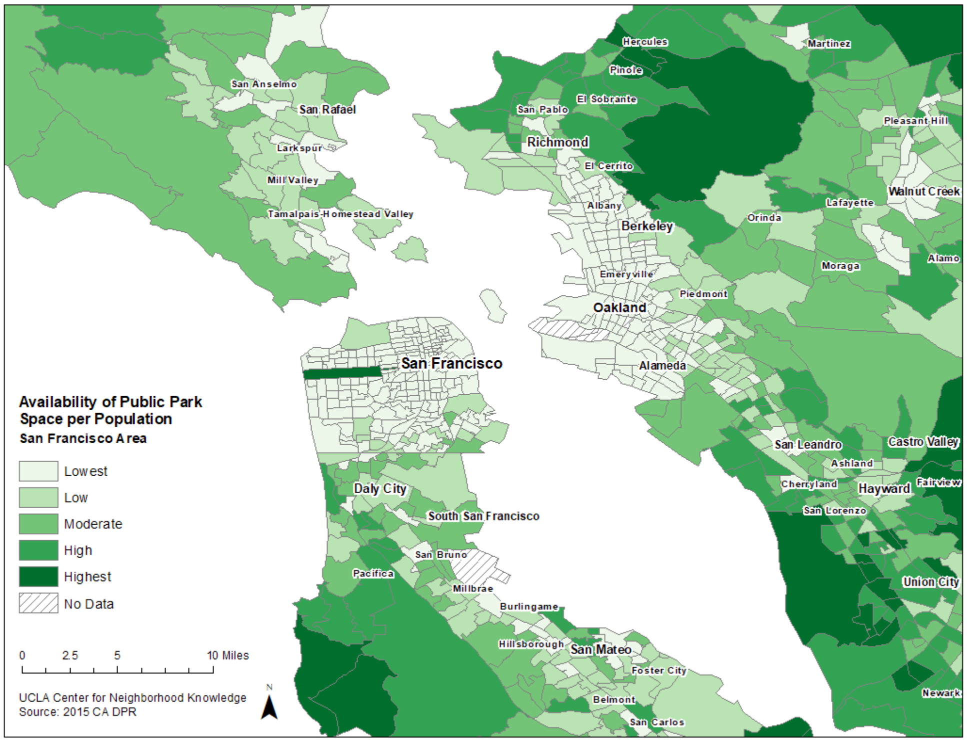
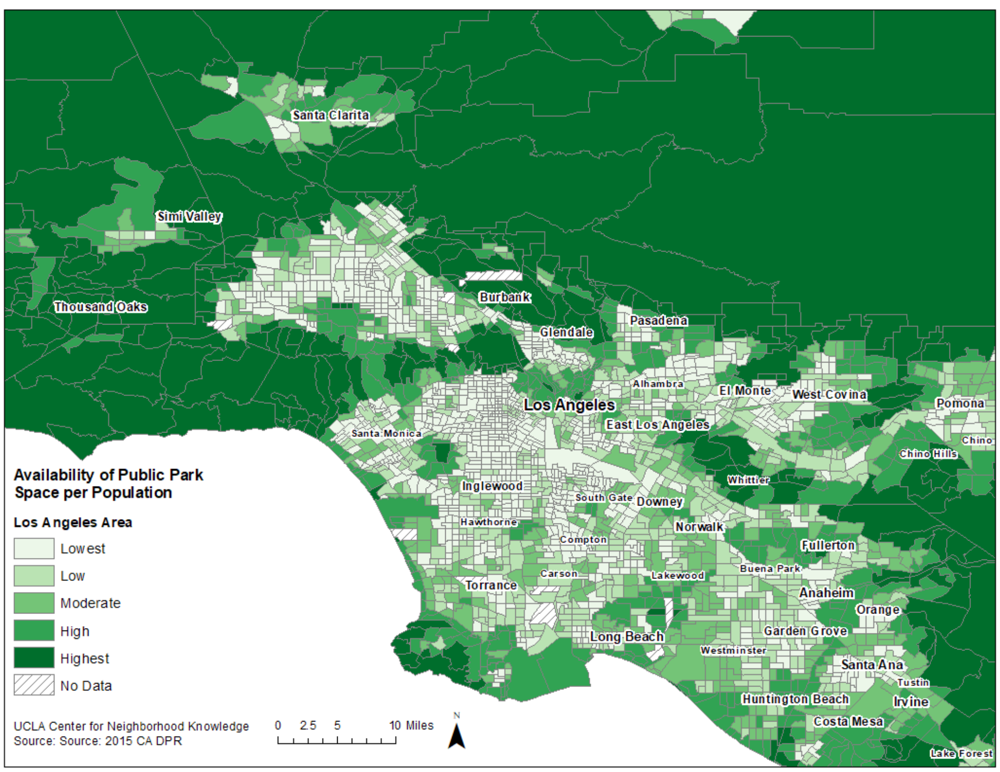


Figure 2-35. Map of Availability of Public Park Space per Population, Los Angeles Area



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2.3.6 Availability of Bikeways

This subsection reports the construction of the availability of weighted bikeways per population indicator.

Table 2-11. Availability of Bikeways Indicator Summary Table

Key Indicator Information	
Units	Availability of Weighted Bikeways per Population
Category in Mapping Tool	Accessibility
Display Method in Mapping Tool	Ranking to account for clustering at the bottom (see "Other Important Notes")
Precision	Unknown precision: incomplete and inconsistent data collection by local jurisdiction
Methodological Complexity	Weights were created for different classifications of bikeways. Weights may be imprecise.
Geographic Resolution	Line, spatial join to census tracts
Key Information about Data Sources Used to Construct Indicator	
Data Sources Used to Construct	Metropolitan Planning Organizations and counties in California
Sample Size	Not based on sampling; observations based on administrative shapefiles.
Biases	Inconsistent in assignment of bikeway classification
Geographical Unit	Census tract
Geographic Coverage	Does not cover all of California. Includes most MPOs and some local jurisdiction. No prevailing standard on walkable buffer size surrounding tract.
Data Vintage	Vary by source; ranges from 2014–18
Other Important Notes (if applicable)	Unlike previous indicators, the bikeway availability indicator cannot be evenly distributed into deciles because the very bottom range of availability (least available) has a cluster of census tracts that comprises more than 10 percent of total. Because of this clustering, we create a separate category for these tracts (no availability of bikeways) and then redistribute the remaining tracts (with bikeway availability) evenly across the remaining nine categories.

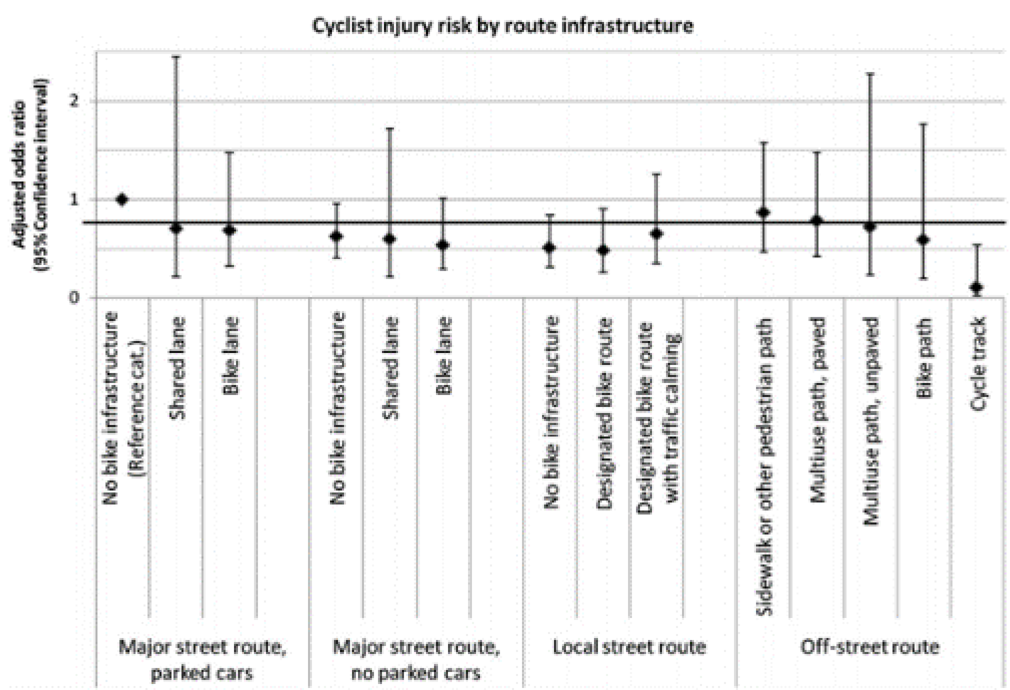
Background

The health benefits and risks of cycling are "complex, context dependent, and often under researched" (Götschi et al., 2016). On a societal level, cycling has indirect links to health by reducing air-quality pollution as it could replace trips by car. Cycling directly affects individual health by increasing physical activity, as many Americans do not meet their daily recommended amount of physical activity (Heath, 2019; Rutter et al., 2013). Estimates from a variety of studies demonstrate that cycling on a regular basis (for everyday commuting purposes) can decrease an individual's mortality risk between 10–28 percent, however, only 1 percent of California residents bike to work (Hamer & Chida, 2008; Oja et al., 1998;

American Community Survey, 2018). Additionally, cycling is linked to other indirect health benefits including weight control, mental health, emotional well-being, and happiness (De Hartog et al., 2010; Mueller et al., 2015). In fact, drawing from the American Time Use Survey, researchers find cyclists to be the happiest among all commuters, possibly because of its additional health benefits beyond physical health and happiness, but further research is necessary.

However, the benefits of cycling are offset by the risks from crash exposure. Cycling injury or fatality risk from a crash is more difficult to quantify because of data issues. Most cities do not keep track of injuries and fatalities at specific locations, making it difficult to combine crash occurrence with an appropriate denominator to properly assess risk. However, some researchers have looked at the relative crash risk with different types of bike infrastructure. As seen in the Figure 2-36, separated cycle tracks have the lowest injury risk of all infrastructure types (based on data from Teschke et al., 2012). In addition, cyclists may face higher exposure to air pollution, especially from motor vehicles, depending on traffic, topography, and other environmental conditions (De Hartog et al., 2010). However, direct evidence of the air pollution–related risks from cycling are relatively unstudied. According to Götschi et al. (2016) review, there are no studies that link cycling-related air pollution exposure and long-term negative health effects.

Figure 2-36. Cyclist Injury Risk by Route Infrastructure



Bikeway Design

Bikeway design is defined and codified in national and state engineering design guidelines that include references such as "A Policy on Geometric Design of Highways and Streets: The Green Book" produced by the American Association of State and Highway Transportation Officials (AASHTO) and the "Manual on Uniform Traffic Control Devices" (MUTCD) produced by the U.S. Department of Transportation Federal Highway Administration (FHWA). Both documents govern streets and highways design, as well as the devices that control traffic, signals, signs, and pavement markings. The MUTCD has the force of law. The Green Book sets standards on federally regulated roads but is advisory for urban streets (AASHTO, 2019).

In California, street design is dictated by the Caltrans Highway Design Manual (HDM) that outlines four distinct bikeway types (California Department of Transportation, 2018). Bikeway descriptions draw from the HDM, other related guidance documents from California, and the National Association of City Transportation Officials (NACTO) Urban Bikeway Design Guide. The NACTO guide was endorsed by the FHWA in 2013 and is largely taken as the best tool for urban cycling planning (NACTO, 2011). In some states, this four-tier classification is hierarchical (swapping the types in classes 2 and 4), but this is not the case for California.

Class I: Bike Path
Bicycle paths or sidepaths provide a completely separated travel experience for the exclusive use of people cycling and walking supporting both recreational and commuting opportunities. They restrict access from motorized vehicles and typically have minimal crossings with vehicles. Paths are most commonly found alongside waterways, former railroad corridors (e.g., rails to trails program), within school campuses, or within or between parks.

Class II: Bike Lane
Bicycle lanes are on-street facilities for one-way bike travel, typically demarked with white paint striping. Bike lanes are distinguished from bikeways in Class I or IV because it has no physical barrier that restricts encroachment of motorized traffic. The desirable width of a bike lane is 6’ wide, cyclists need at least 4’ of rideable space and the absolute minimum is 3’ wide.

Class III: Bike Routes
Bicycle routes are streets where bicyclists and vehicle traffic share right of way space. Bike routes do not have dedicated bike space and rather feature items like shared lane markings or “sharrows” and bike route signage indicating a shared lane environment between vehicles and cyclists. Many local streets with low traffic speeds and volumes are good candidates for bike routes because they already have the bones of a safe bicycling environment.

Class IV: Separated Bikeway
Separated bicycle facilities are the newest and fastest-growing bikeway type in the United States. Separated bikeways, or cycle tracks as they are known in European cities, are recognized as one of the most effective ways to make people of all ages and abilities feel comfortable cycling on urban streets. Class IV facilities are on-street facilities, compared to the off-street Class I facilities. Separated bikeways can be designed for one- or two-way traffic and can be physically separated from traffic in a number of different configurations.

Data Source

There is no single source for bikeway data for California. We were unsuccessful in downloading Google’s bikeway data and had difficulties with open source data from OpenStreetMap. Therefore, bikeway data was obtained in a GIS shapefile format from individual Metropolitan Planning Organizations (MPOs) and counties in California. Not every region in the state is within an MPO, such as far northern and eastern parts, and are therefore not included in this indicator analysis. Data was obtained for 17 out of the 18 MPOs in California (Appendix A). Out of a total of 58 counties in California, data covered 36 counties, which is about 96 percent of the state’s total population. We did not have data for the remaining 22 counties (Appendix A). One county had bikeway data but chose not to report it to us because it was not up to date.

Given the different sources, data had temporal and classification inconsistencies and the collection date determined by each MPO ranges from 2014–18. Some data included proposed bikeways, which we filtered out for this analysis.

Population count data were obtained from the 2010 Decennial Census at the block group level. Using the centroid of a smaller geographical unit provides a higher spatial resolution and can show the population proportion within each bikeway buffer, which will be explained more in detail in the next section.

Construction Method

Because bikeway shapefile data were not standardized, there were numerous inconsistencies in how each agency classified bikeways. Based on our literature review, there are four standard classifications of bikeways with each having their unique criteria. Some agencies had unusual classifications, so we used Google satellite imagery to determine the nature of these bikeways. We also reduced the number of classifications to achieve a level of consistency across the state (Table 2-12). For example, some data had a Class 4 category for bikeways. After a visual inspection using Google Satellite Imagery, we decided to reclassify Class 4 bikeways as Class 2 because of their similar characteristics. It was key to have uniform bike classifications across all MPOs because shapefiles were eventually merged together to run spatial analysis using ArcGIS.

Table 2-12. Bikeway Reclassifications

Examples of Bike Classes Provided	Reclassification Notes
Class I, Class II, Class III, Class IV	Reclassified Class IV to 2. Changed class values to numerical Class 1, 2, 3.
Existing 1, Existing 2, Existing 3	Changed class values to numerical Class 1, 2, 3.
1,2,3,4	Reclassified Class 4 to 2.
Connector	"Connector" is a shared road near Chico. Reclassified to Class 3.
Multiuse	"Multiuse" is a trail in park areas and around a river. Reclassified to Class 1.
Other	Other described as "Major Roads: Bikes Allowed." Reclassified to Class 3.

Bikeway Buffer

To measure weighted bikeway availability per population, we examined literature and consulted with bike experts and advocacy groups of previous methods. We obtained input on the adequate distance to use for a buffer around a bikeway representing the distance a person is willing to travel to bike on a designated bikeway.

We experimented with numerous buffer sizes based on input and decided to do a one-eighth-mile buffer for all bikeways in California.[21] Then we assigned census blocks to the buffer areas using the centroid of the block. Population counts for blocks that had a centroid inside the buffer were summed and aggregated to census tracts to determine the proportion of the population that had access to a bikeway within a one-

[21] We compared the bikeway maps using a one-half-, one-quarter-, and one-eighth-mile buffer. A one-half-mile buffer resulted in a large proportion of the population in high urban areas to have access to a bikeway. A one-quarter mile was also too extensive.

eighth mile. We are aware that there are nuances because some bikeways have certain points of entry for which we do not account for given limited time and resources.

Bikeway Density
Bike density was measured to consider differences between census tracts. Bike density is defined as the number of miles of bikeway in a given census tract. A 25-feet buffer was added around the census tract to account for bikeways that are near its border. Knowing how many miles of bikeways are in a neighborhood shows which neighborhoods have higher access.

Bikeway Weighted Value
In addition, each bike class has distinct qualifications and differ in the amount of investment of resources. A Class 1 bikeway is separate from a street and it is not shared with vehicles compared to a Class 3 bikeway that is a shared road with minimal signage. We believe on average Class 1 bikeways should be valued higher than the other classes because of its safety, cost, and environmental quality. Although the assigned values are debatable, the research team felt that weighing the classes in a 4:2:1 ratio, as indicated in Table 2-13, is appropriate and perhaps even conservative. Other researchers have suggested an even greater spread. After weighing each bike class, we added their lengths again, and then normalized by population count.

Table 2-13. Bike Class Weight Value

Bike Class	**Weight Value**
Class 1	4
Class 2	2
Class 3	1

Assessment of Consistency

To the best of our knowledge, census tract–level data of bikeway availability are not publicly available to which to assess our indicator. However, we conducted different analyses to ensure that our data and constructed indicator were relatively appropriate.

First, we compared the data shapefiles from the counties and MPOs against other sources like Google Maps and Open Street Maps to check for inconsistencies. For instance, we found different bikeways on UCLA campus on online platforms (e.g., Google Maps) and data from our MPO, Southern California Association of Governments (SCAG) (see Appendix A).

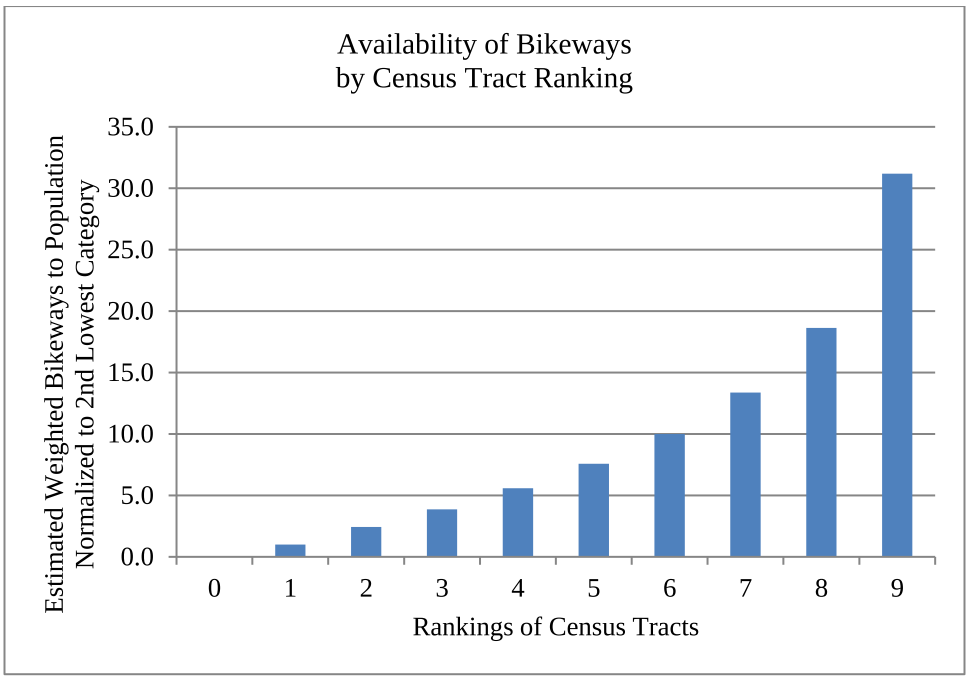
Next, we calculated the correlation between census data on commuting to work by bicycle and bikeway availability by tract level. After excluding counties with no bikeway data, we found that the two are positively correlated ($r = 0.136$). It is not a high correlation, which may be due to other factors that contribute to commuting to work by bike (e.g., income, distance to work).

Results

Unlike previous indicators, the bikeway availability indicator cannot be evenly distributed into deciles because the very bottom range of availability (least available) has a cluster of census tracts that comprises more than 10 percent of total tracts. In other words, more than a tenth of the tracts in California have no bikeways available to residents. Because of this clustering, we create a separate category for these tracts (no availability of bikeways) and then redistribute the remaining tracts (with bikeway availability) evenly across the remaining nine categories.

Figure 2-37 reports the adjustments made to reporting categories. There are three notable patterns. First, the availability gap is enormous, with approximately one-in-six census tracts completely devoid of any bikeways, absolute "bikeway deserts." The second pattern is an extreme concentration of bikeways in the very top category. This can be seen by comparing the estimated weighted bikeway to population ratio in each category normalized by the second lowest category (bin 1). A value greater than one indicates that the availability of bikeways for that category is higher than the second lowest category (bin 1) by that value. According to the parity index, the median bikeway availability in the highest category is more than 31 times as the second lowest. The final observation is that bikeways are extremely unevenly distributed even within the highest category, which can be seen in the relative size of the mean and median values. (Higher mean-to-median ratio indicates more uneven distribution or greater inequality.)

Figure 2-37. Availability of Bikeways by Census Tract Decile Rankings



Maps

The following maps displays the distribution of bikeways availability per population.

California

On the statewide scale, the data on the availability of bikeways is less complete and less consistent compared to other indicators. Information is missing for much of Northern California and the area directly east of the Bay Area. Despite the missing data, there are a few observable trends. Compared to the rest of the state, bikeway availability is relatively high in the Bay Area. There is high availability in Monterey, Merced, and Santa Barbara. In Los Angeles, availability is much more uneven (see Figure 2-38).

Bay Area
On the average, the Bay Area enjoys greater bikeway availability than Los Angeles. This is especially true along the coastal and shoreline areas within the Bay and along the ocean fronts. Marin County has particularly high levels of bikeway availability, and the western edge of the East Bay also has high bikeway availability. This is also true for the less dense areas in in the East Bay. Along the Peninsula, availability is high in and around Palo Alto and in the mountainous region. The greatest variation in bikeway availability in the Bay Area is in San Francisco, where areas near Golden Gate Park, the Marina, and Presidio have high bikeway availability. However, the downtown area (except along Market Street), Chinatown, parts of North Beach, and parts of the Mission lack availability (see Figure 2-39).

Los Angeles
In Los Angeles, bikeway availability is more prominent along coastal neighborhoods, corresponding with high-income areas. The Westside (including Santa Monica and Venice) have high bikeway availability. Bikeways are much scarcer in lower-income areas like East LA and South-Central LA. In less urbanized areas like the Santa Monica Mountains and Angeles Forest, there is limited bikeway availability probably due to lack of infrastructure, maintenance, and records (see Figure 2-40). These areas, however, have off-road bike trails that are not captured by the available data.

Figure 2-38. Map of Availability of Weighted Bikeway per Population, all of California

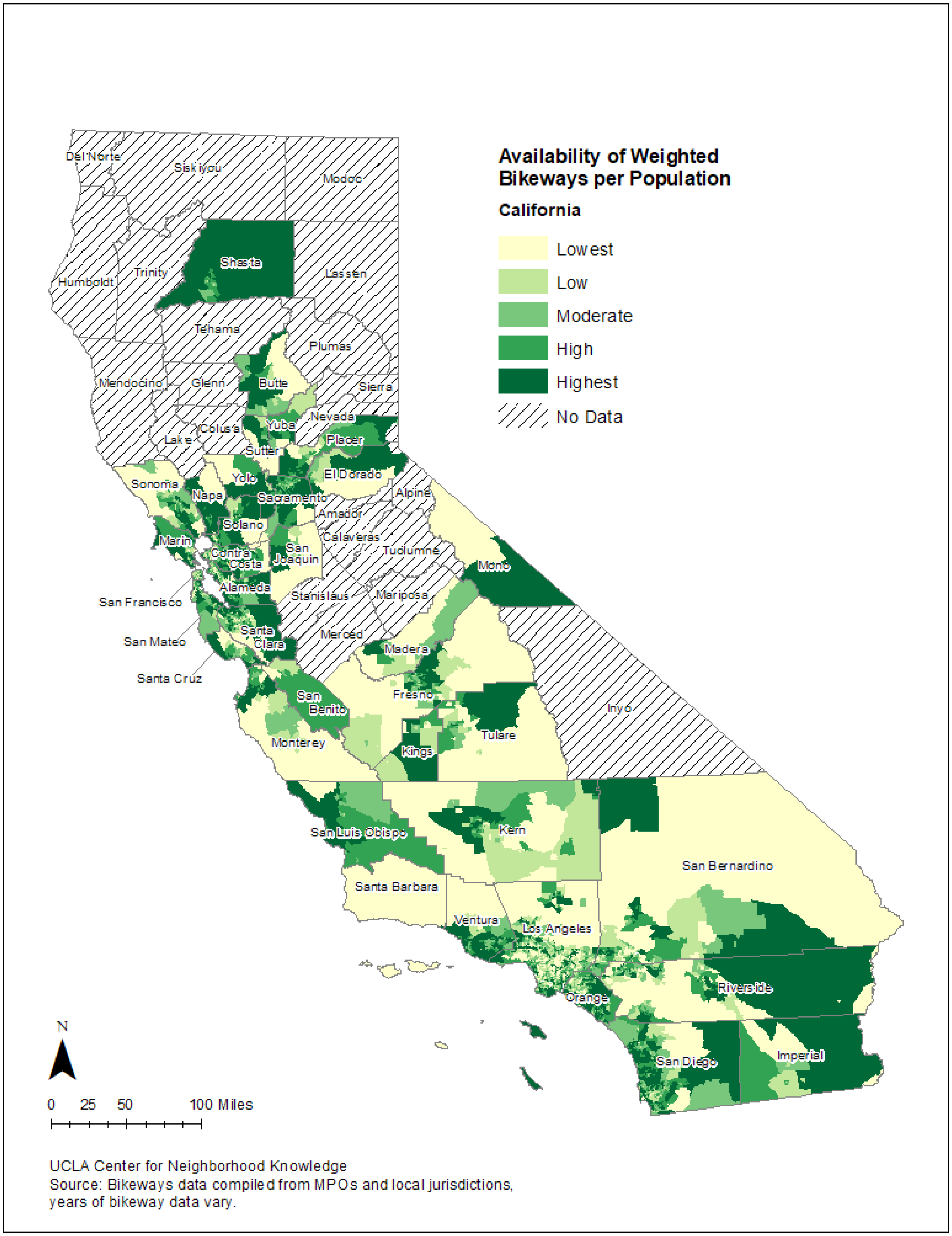


Figure 2-39. Map of Availability of Weighted Bikeway per Population, San Francisco Area

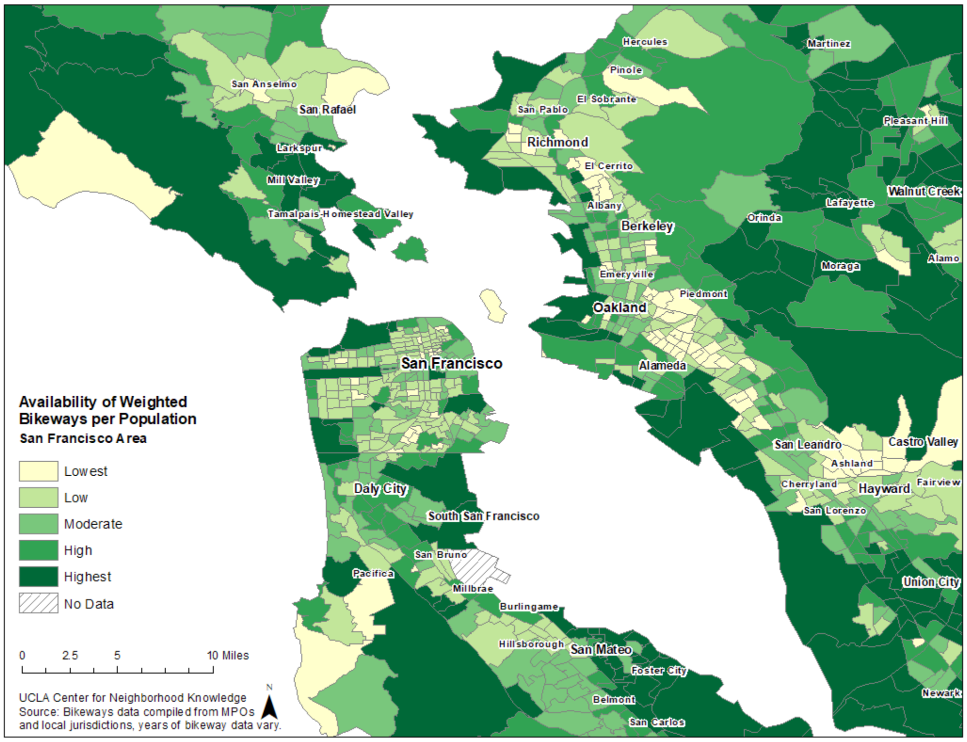
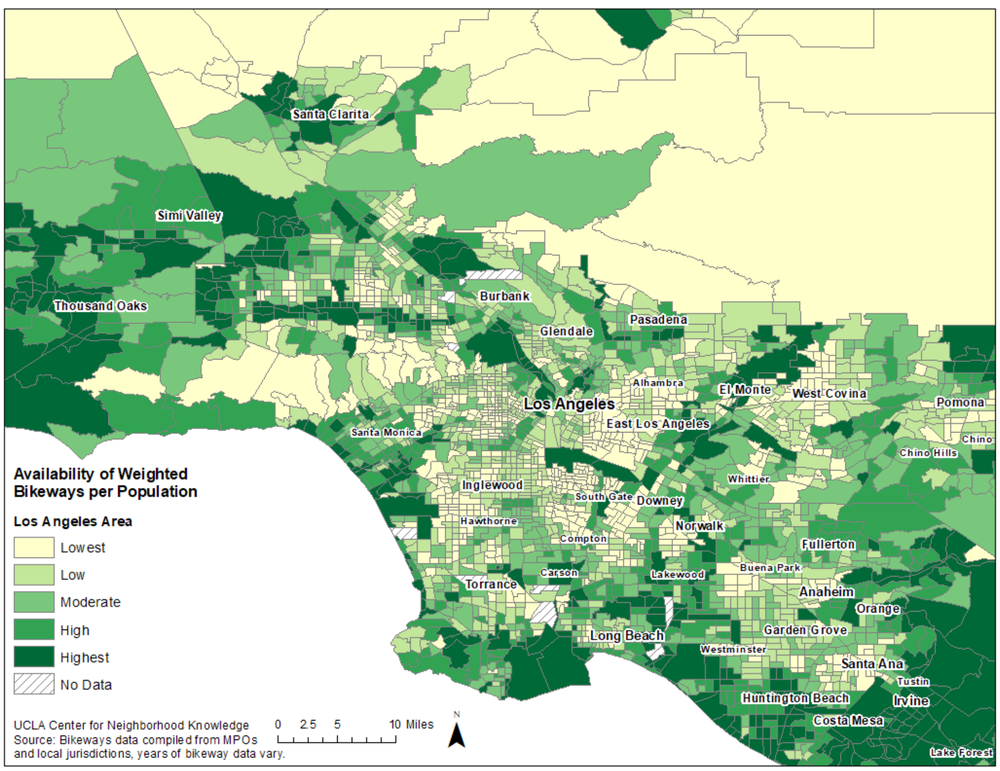


Figure 2-40. Map of Availability of Weighted Bikeway per Population, Los Angeles Area



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2.3.7 Traffic Collisions

This section details the construction of the traffic collisions per weighted roadways indicator.

Table 2-14. Traffic Collisions Indicator Summary Table

Key Indicator Information	
Units	Traffic Collisions per Weighted Roadways
Category in Mapping Tool	Health
Display Method in Mapping Tool	Decile (visualized in quintiles)
Precision	Unknown precision: unknown number of collisions that go under reported
Methodological Complexity	Generated using surrounding buffer; some collisions can be in more than one tract. No prevailing standard of weighting of roadway classifications. Weights may be imprecise.
Geographic Resolution	Point (location of collisions; aggregated to the census tract)
Key Information about Data Sources Used to Construct Indicator	
Data Sources Used to Construct	UC Berkeley's Transportation Injury Mapping System which obtains data from California Highway Patrol Statewide Integrated Traffic Records System
Sample Size	Not based on sampling; large number of observations based on administrative data
Biases	Selection of surrounding buffer size may not be correct; does not capture all collisions (e.g., less severe collisions)
Geographical Unit	Census tract
Geographic Coverage	Covers all of California
Data Vintage	Collisions that occurred between 1/1/2011 to 12/31/2015
Other Important Notes (if applicable)	Geocoding may not be precise for some collisions; some collisions are not geocoded in the dataset.

Background

The indicator can support better transportation, particularly Vision Zero, a widely adopted initiative to eliminate traffic fatalities and severe injuries through strategic decisions and action to promote safe mobility. Traffic collisions are the results of multiple factors. Roadway design and engineering, as well as the behaviors of road users, the type of user, and their perception of safety may influence the frequency, type, and severity of crashes. Road safety is important to everyday life and though road safety in the United States has improved over time, it remains a priority for government agencies, decision makers, and advocacy organizations alongside other goals of the transportation system, such as mobility, efficient movement of people and goods, and environmental quality concerns (U.S. Federal Highway Administration, 2017). Fatalities and injuries resulting from traffic collisions are an important public health concern as these incidents are largely preventable. For instance, fatalities from traffic collisions are the leading cause of unintentional death in the United States for the population aged 5–24, and the second leading cause of death for those over the age of 24 (National Center for Injury Prevention, 2019).

While no single indicator can capture the complexity of traffic collisions, the indicator should be consistent with some key concepts. According to the U.S. Federal Highway Administration (2017), road safety can be characterized as the ability to travel freely without injury or death, and is typically measured by the number, the rate, or severity of traffic incidents per unit of time. Commonly cited measures of safety are summarized in Table 2-15. The project's indicator is related to the first two metrics. The indicator can be best used to identify "hot spots" that can be prioritized for strategic investments and interventions. The indicator is a starting point for users who can assemble additional data based on their specific needs and goals. (See for example, the case study on bikeway planning in Appendix E.)

Table 2-15. Common Measures of Road Safety

Measure	**Description**	**Usefulness**
Crash frequency	Number of crashes occurring per year or other unit of time	General measure of exposure
Crash rate	Number of crashes normalized by a particular population or metric of exposure (e.g., per 100,000 people, VMT, licensed drivers)	General measure of exposure
Crash outcome	Measured by the types of injuries sustained to the people involved in the crash	Prioritize safety activities

Source: Adapted from U.S. Federal Highway Administration (2017, pp. 1.4–1.5)

<u>Data Source</u>

Collision data for the indicator come from UC Berkeley's Transportation Injury Mapping System (TIMS, 2019), which obtains data from California Highway Patrol (CHP) Statewide Integrated Traffic Records System (SWITRS).[22] The TIMS data allow geographic analysis of traffic collisions by applying a consistent geocoding methodology to the SWIRTS data. The data include information at the collision, party, and victim level that allows linking between the three. We utilized the collision level data, which includes information such as type of collision and severity, involvement of pedestrians and bicyclists, the date, time, and various geographical details as well as road, lighting, and weather conditions in which the incident occurred.

The SWITRS represents only a portion of all incidents that occur as the database consists only of collisions where a police response takes place and a report is taken in the field. Further, the SWIRTS is more likely to capture more serious incidents that require a police response; therefore, minor collisions are less likely to be reported. Other challenges include human error in reporting and lags times crashes being entered into the database. Despite these limitations, crash data from sources such as SWITRS are considered the most widely used and essential for road safety analysis (U.S. Federal Highway Administration, 2017).

[22] The indicator in this dataset should not be used to generate summary statistics.

Construction Method

We include all collisions that occurred between 1/1/2011 to 12/31/2015 and that contain information about the geographic location (with a latitude and longitude) of the collision, regardless of the road location type. Numbers reported may not meet the criteria for the Office of Traffic Safety Reports. We used the variables "point_x" and "point_y" in the dataset to identify the longitude and latitude, respectively. These coordinates are assigned by TIMS based on the street descriptions in the collision reports. If the "point_x" and "point_y" values have zero or missing values, we assign the location using GPS coordinates reported by the CHP, if available ("Latitude" and "Longitude" variables in TIMS dataset).[23] This approach captures 95 percent of collisions (see Table 2-16).

Table 2-16. Total Collision Counts

Source	Count
With TIMS latitude and longitude	775,799
Imputed with CHP GPS coordinates	13,842
Total in dataset (used for this project)	789,641
Total in TIMS	831,420

Deriving the collision metric required several steps. First, we created a census tract shapefile with a 200 feet floating buffer to allocate collisions to tracts. We used a buffer because collisions can occur on either side of a street. The buffer size was selected after assessing the location of collisions and widths of major streets.[24] We then divided the number of collisions by weighted street length. The street length measure is the sum of street lengths in a buffered tract weighted by the number of lanes in the buffered tract. The street lengths and number of lanes were derived in ArcGIS using the 2016 ESRI Streets line layer (Streets File Geodatabase Feature Class), which includes streets, highways, roads, ramps, and ferries.

Assessment of Consistency

We assessed the weighted street length against the EPA's Smart Location Database (SLD) street network measure. To find the total street network, we used the street network density variable (D3a) and multiplied by total block group area (AC_TOT) as described on page 20 of version 2.0 of the SLD user guide.[25] SLD data are at the census block group level. We aggregated block groups to a census tract, which could

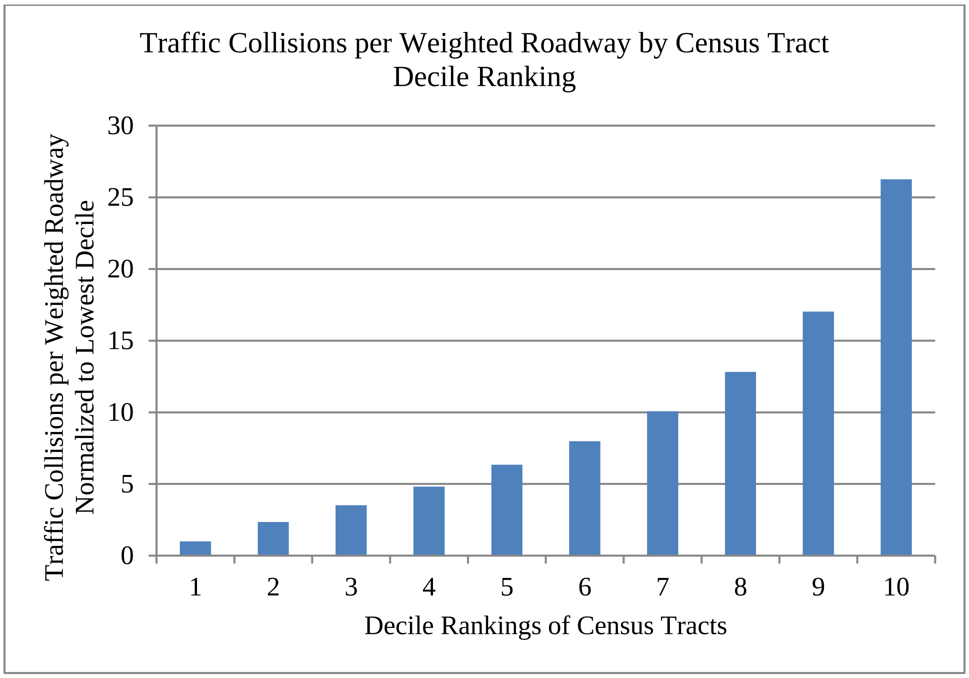
[23] TIMS support noted that CHP coordinates may not be accurately reported (e-mail communication November 5, 2019).
[24] An alternative approach is to create a buffer around a collision and then allocate to a tract. For instance, Pulugurtha and Sambhara (2011) use the average numbers of pedestrian crashes within 200 feet of a signalized intersection as the dependent variable to develop pedestrian crash estimation models for Charlotte, North Carolina. Researchers investigating the impact of the built environment of the severity of pedestrian and cyclist accidents in Montreal, Canada also used different buffer sizes around the site of the collision (50, 100, 150, 200, and 400 m) and found that the buffer in which the variable was most significant varied for each built environment indicator (Zahabi et al., 2011). We could not identify a study that used a buffer around a census tract. However, mathematically, creating a buffer around a census tract or around a collision should yield similar results.
[25] See Smart Location Database: Version 2.0 User Guide at https://www.epa.gov/sites/production/files/2014-03/documents/sld_userguide.pdf

introduce some double counting of streets at the edges block groups within a tract, compared the weighted street length and the SLD measure, and found them to be correlated, particularly in the urban areas, despite the difference data sources, periods of the street data, and types of streets included.

Results

California census tracts are divided into deciles according to each tract's traffic collision rates per roadway (latter weighted by number of lanes). Each decile category represents roughly 10 percent of the census tracts in California. Figure 2-41 compares traffic collision rates per weighted roadways in each decile category normalized by the lowest decile. A value greater than one indicates that the traffic collision rates per weighted roadway for that decile is higher than the lowest decile category by that value. For example, the median collision rate share in the highest area is more than 26 times as great as in the lowest area.

Figure 2-41. Traffic Collision Per Weighted Roadway by Census Tract Decile Rankings



Maps

The following maps displays the distribution of traffic collisions per weighted roadway.

California

On the state level, traffic collisions per weighted roadways are strongly correlated with population density. This makes sense given that more densely populated areas have more roadways. Major sites for collisions are concentrated in four major urban areas: San Francisco Bay Area, Sacramento, Los Angeles, and San Diego. Most of California have low levels of traffic collisions, especially in rural counties like those in Northern California and the central inland portion of the state. There are pockets of areas with higher collision rates in the Central Valley, but the majority of collisions occur in the main urban areas (see Figure 2-42).

Bay Area

Similar to Los Angeles, the Bay Area traffic collisions per weighted roadway are also concentrated in densely populated and commercial areas. For example, downtown and Chinatown San Francisco and urban Oakland, among the most densely populated areas of the Bay Area, have the greatest level of traffic collisions. Areas with fewer collisions are more suburban and exurban, less populated, and less commercial. These include Marin County, west Alameda County, and the area surrounding the Santa Cruz mountains on the Peninsula (see Figure 2-43).

Los Angeles

In Los Angeles, the amount of traffic collisions per weighted roadways strongly corresponds to commercial activity and population density. The busy and highly populated areas of downtown, South LA, and West LA have the highest amount of traffic collisions. The San Fernando Valley also has very high levels of traffic collisions. Radiating out from these highly populated, commercial centers, traffic collisions become less common. For example, Palos Verdes, an affluent area with low population density, has lower commercial activity and corresponding low levels of collisions (see Figure 2-44).

Figure 2-42. Map of Traffic Collisions Per Weighted Roadways, all of California

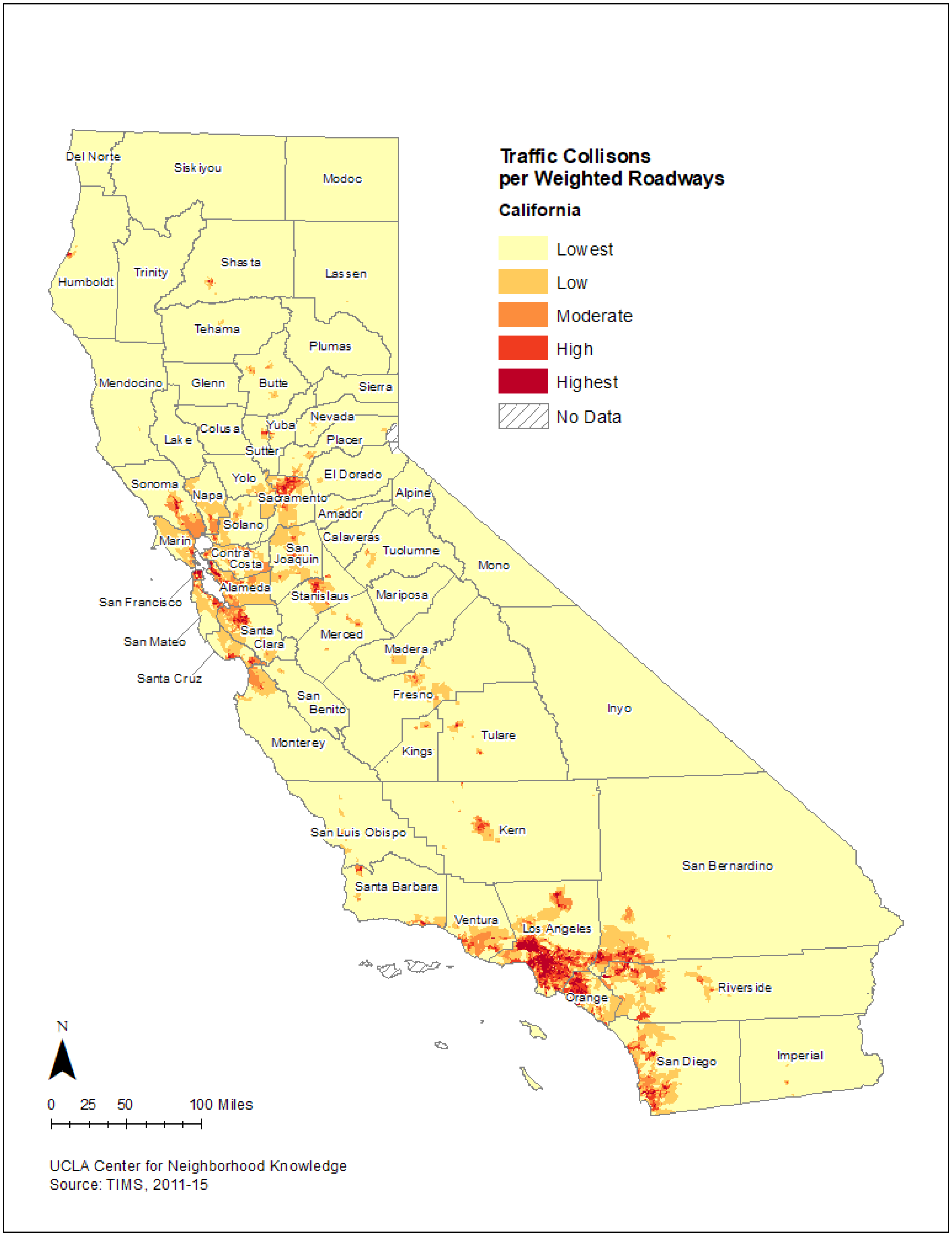


Figure 2-43. Map of Traffic Collisions Per Weighted Roadways, San Francisco Area

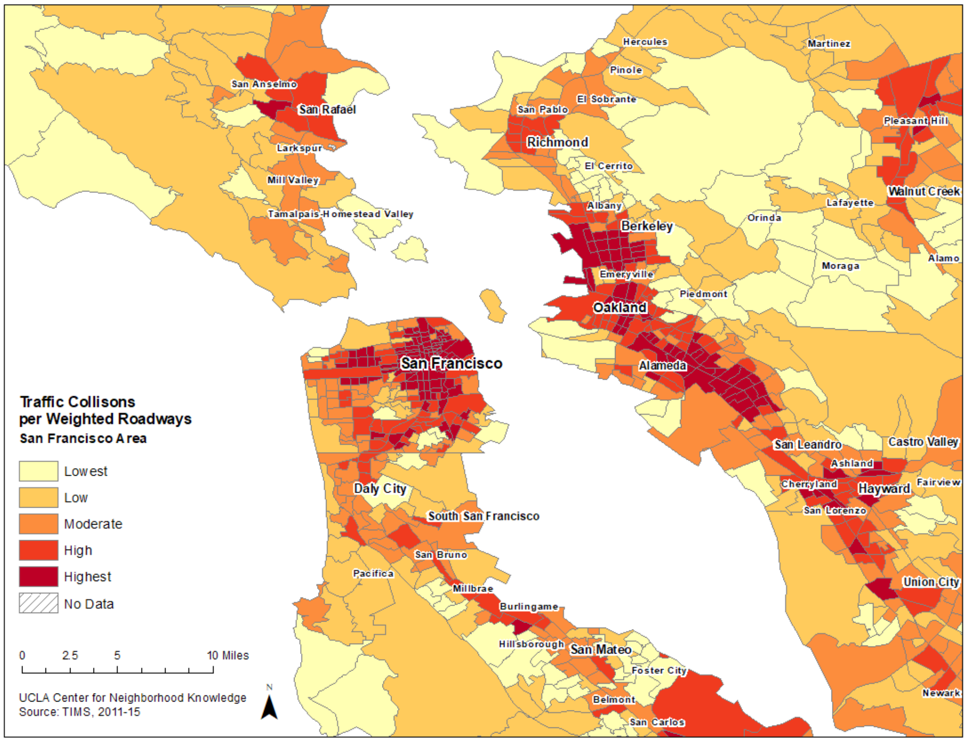
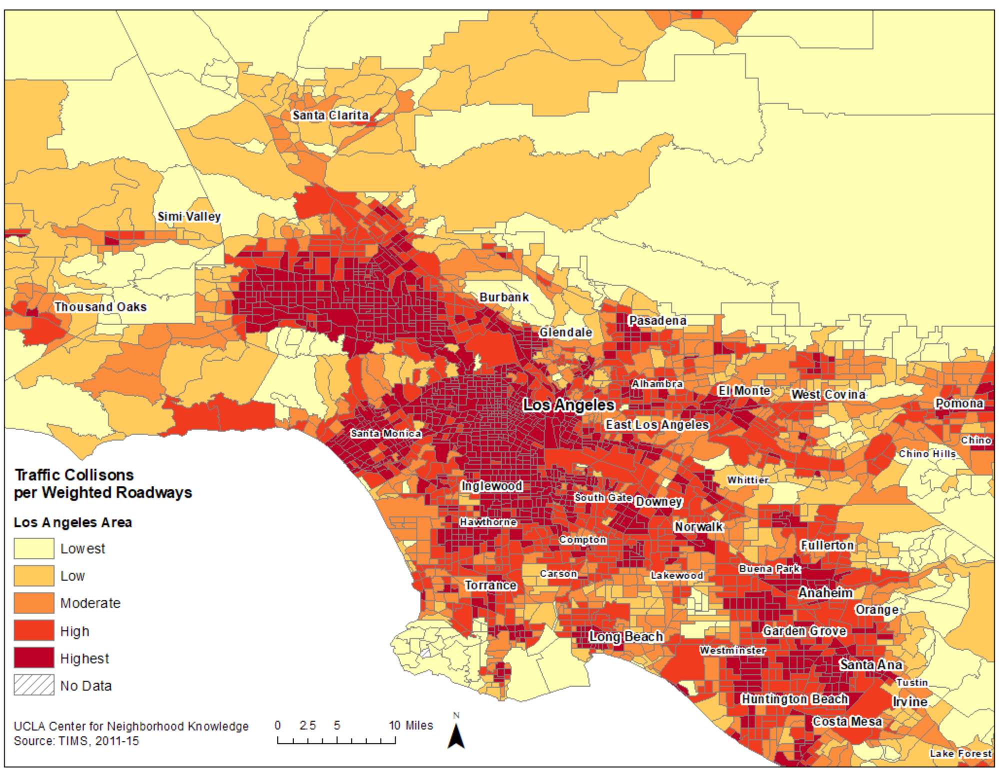


Figure 2-44. Map of Traffic Collisions Per Weighted Roadways, Los Angeles Area



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2.3.8 Neighborhood Change (Socioeconomic and Housing)

This subsection reports the construction of the neighborhood change indicator that looks at the transformation in the neighborhood's socioeconomic and housing market composition.

Table 2-17. Neighborhood Change Indicator Summary Table

Key Indicator Information	
Units	Neighborhood Change (socioeconomic & housing) (composite index produced by principal component)
Category in Mapping Tool	"Socio-Demo-Econ" (socioeconomic indicator) and "Housing" (housing market indicator)
Display Method in Mapping Tool	Decile (visualized in quintiles)
Precision	Assumed to be relatively fair
Methodological Complexity	Indicator constructed using principal component analysis
Geographic Resolution	Census tract
Key Information about Data Sources Used to Construct Indicator	
Data Sources Used to Construct	American Community Survey
Sample Size	Relies on ACS data that is based on a sample (approximately 12% of population)
Biases	May be affected by short-term business cycle
Geographical Unit	Census tract
Geographic Coverage	Covers all of California
Data Vintage	2007-11 and 2014-18 5-year averages
Other Important Notes (if applicable)	These indicators are intended to capture neighborhood changes in the socioeconomic and housing characteristics that can be considered or interpreted as potential indication of upscaling or gentrification.

Background

Neighborhoods constantly change as people move, infrastructure is built, and economic priorities change. This mobility can be seen in the relative number of households that moved into their home within the last two years, slightly more than a quarter for Californians.[26] Geographic movement allows many to change jobs, meet new family needs, and adjust to new circumstances and preferences. Unfortunately, not all neighborhood changes and residential relocations are voluntary, nor desirable. Some changes lead to greater investments and improved socioeconomic status for a neighborhood (also known as upscaling), but other changes have the opposite effects of disinvestment and declining socioeconomic status (also known as downscaling). One policy concern focuses on a particular form of disruptive upscaling, where development and investment patterns result in increased property values and the displacement of low-income households, a process called gentrification (Chapple et al., 2017). Public investments, including transportation

[26] Estimates derived by authors using the 2019 1-year ACS (Table: B25038)

investments, have played a role in stimulating this process, and the resulting neighborhood changes have complicated efforts to address poverty (Chapple et al., 2017; Katz, 2012). By its very nature, gentrification disproportionately hurts people of color, low-income households, and renters. While it is important to understand, acknowledge, and address the problems created by gentrification, it is equally important to understand the larger pattern of neighborhood change to inform policies, plans, and more equitable investments

The project's neighborhood change indicator is based partly on earlier efforts. Tools, such as the Los Angeles Indices of Neighborhood Change created by the Los Angeles Innovation Team, were created to help city programs reduce displacement in revitalizing areas of the city. They use six measures: percent change in low/high IRS filer ratio, change in percent of residents 25 years or older with bachelor's degrees or higher, change in percent of Non-Hispanic/Latino White residents, percent change in median household income, and percent change in average household size (Los Angeles Innovation Team, n.d.). In addition, the Urban Displacement Project was also created to conduct "community-centered, data-driven, and applied research toward more equitable and inclusive futures for cities" (Zuk & Chapple, 2015). Their research and tools seek to understand gentrification and displacement and also empower advocates and policy makers to achieve equitable development. Urban Displacement uses some of the same input variables as the Los Angeles Innovation Team. The project's approach is similar to these two examples but covers the entire state.

Data Source

This project's indicator on neighborhood change uses the 2007–11 and 2014–18 5-year ACS. The 2007–11 5-year ACS represents the starting point where changes are examined and the 2014–18 5-year ACS represents current neighborhood characteristics. The 2014–18 5-year ACS is the most current data available from the Bureau of Census during the time of this project. The choice of these two periods is dictated in part by the availability of ACS data reported for the same (post-2020) tract boundaries. It should be noted that the changes between the two periods capture both cyclical (short-term economic fluctuations) and secular (long-term structural trajectory) changes.

We construct two separate measures of neighborhood change. The first indicator focuses on changes in the neighborhoods' socioeconomic characteristics, while the second measure examines changes in the neighborhoods' housing market, particularly with a focus on the rental market. We focus on the rental market because members of the Advisory Committee expressed concerns about the impacts of neighborhood change on low-income communities, mainly of which are comprised of renter households.
Table 2-18 summarizes the key variables used in the neighborhood change indicators.

Table 2-18. List of Socioeconomic Characteristics and Housing Market Variables

Socioeconomic Characteristics	Housing Market
● Median household income ● Median earnings ● Percentage of adult population (25 years or older) with a bachelor's degree or higher	● Renter-occupied household ● Median gross rent ● Rent-burdened households (households paying more than 30 percent of their income for housing) ● New housing units (built within the last five years: 2013–18)

Although changes in socioeconomic characteristics and housing market do not represent gentrification per se, they can give a sense of changes in indicators related to gentrification in low-income neighborhoods. These variables were chosen because they are among the core variables discussed in the literature on neighborhood change (upscaling, downscaling) and gentrification; and also built on previous CARB research projects on gentrification (see Chapple et al., 2017). It is important to note that changes being captured by the neighborhood change indicators may represent recovery from the Great Recession. The 2007–11 ACS dataset covers data collected during the Great Recession period (2007–9).

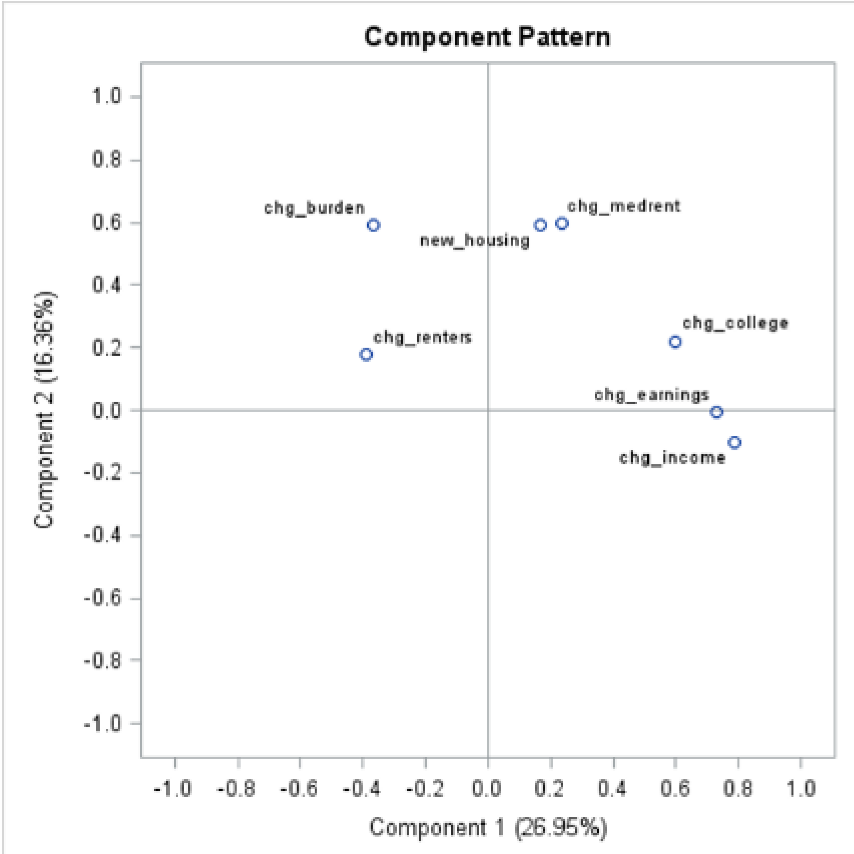
For the neighborhood change indicator on housing, we chose to focus on renter related variables (e.g., percent renter, median gross rent, and housing burden for renter households) rather than variables related to homeowners because the Advisory Committee and stakeholders expressed concerns about the impacts of neighborhood change, particularly gentrification, in low-income neighborhoods and many of the households in low neighborhoods are primarily renter households (e.g., on average, 60 percent of households designated by CalEPA as "Disadvantaged" are renter households, compared to the 40 percent average for nondisadvantaged neighborhoods). Additionally, renters on average are disproportionately lower income. Initially, variables related to homeowners such as "median home value," were included. However, we found that many neighborhoods or census tracts had "No Data" on "median home value" primarily due to the small number of homeowners in these neighborhoods, where estimates cannot be generated due to small sample size. Further assessment indicates that many of the neighborhoods with no values reported for median home value were primarily renter neighborhoods, many of which are low-income neighborhoods. To perform the principal component analysis, a census tract must not have missing values/data for any of the selected variables. By incorporating median home value as a variable in the model, many lower income neighborhoods with a higher share of renters are excluded because of the lack of data. Given this and the concerns expressed by members of the Advisory Committee to focus on the impacts of neighborhood change on low-income/renter neighborhoods, changes were made to include those variables related to rental housing. It is important to note that by including variables related to the rental market, some neighborhoods with a small number of renters (thereby having a small sample to generate information related to median gross rent for example) are excluded.

Construction Method

Principal component analysis (PCA) is used to construct the two neighborhood change indicators. The first PCA is performed on changes in the variables related socioeconomic characteristics of the neighborhood and the second on the variables related to the housing market.

Figure 2-45 displays the relationships between all seven variables. It shows the PCA loading plot for two principal components (component 1 and component 2). Changes in median household income, median earnings, and the share of the population with a college degree all have high loadings on component 1. Changes in median rent, proportion of renter-burdened households, and share of new housing units all exhibit high loadings on component 2.

Figure 2-45. Loadings for Principal Components 1 and 2



The principal components scores derived from the PCA allow for classification of census tracts based on their level of neighborhood change as it relates to socioeconomic and the housing market. Two principal components scores are generated: one for socioeconomic changes and the second for housing market changes. Higher socioeconomic PCA scores are associated with increasing income, earnings, and proportion of the population with a college degree. Likewise, higher housing PCA scores are associated with increases in median gross rent, renter-burdened households, and more construction of new housing.

The following charts (Figures 2-46 to 2-51) display the relationship between the change indicators and the PCA scores.

Figure 2-46. Socioeconomic Principal Component Scores and Changes in College Education

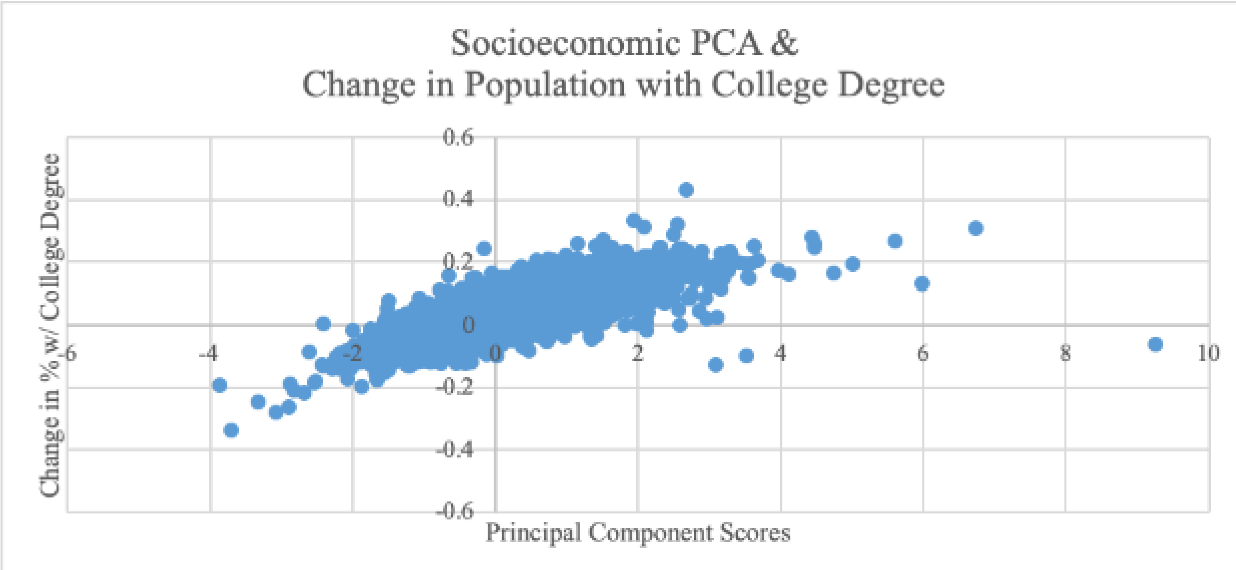


Figure 2-47. Socioeconomic Principal Component Scores and Changes in Median Household Income

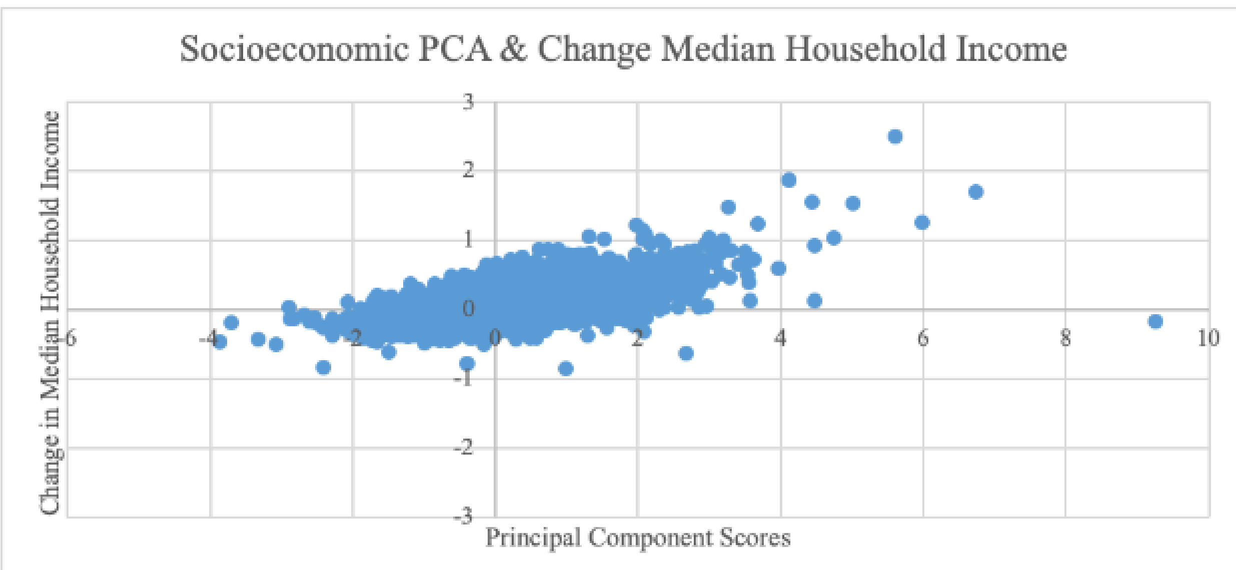


Figure 2-48. Socioeconomic Principal Component Scores and Changes in Median Earnings

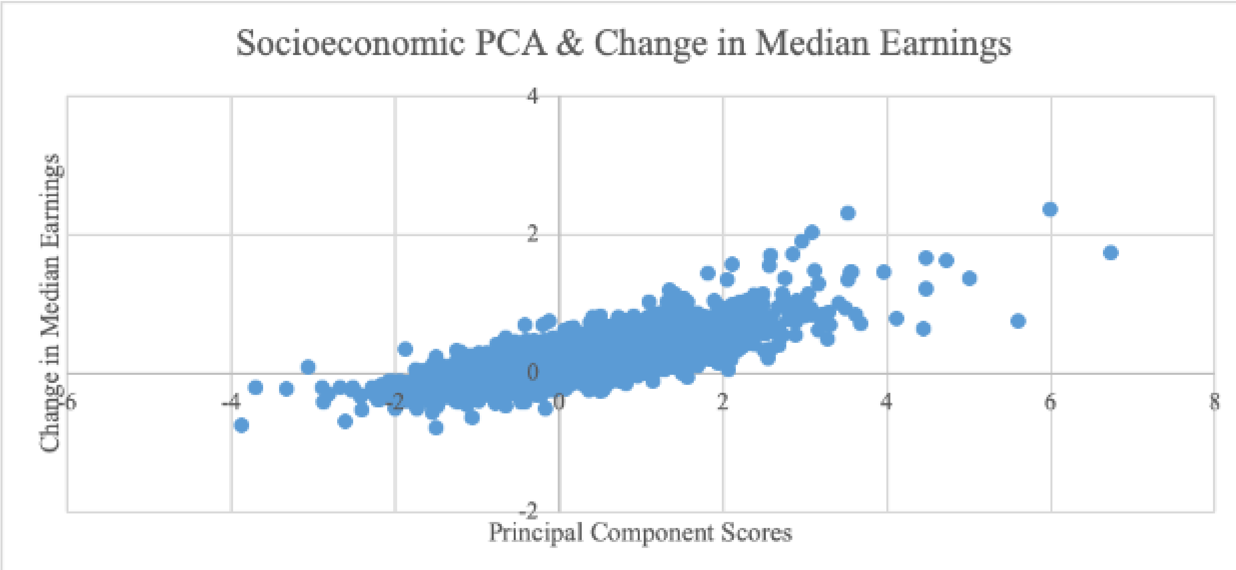


Figure 2-49. Housing Principal Component Scores and Changes in Median Gross Rent

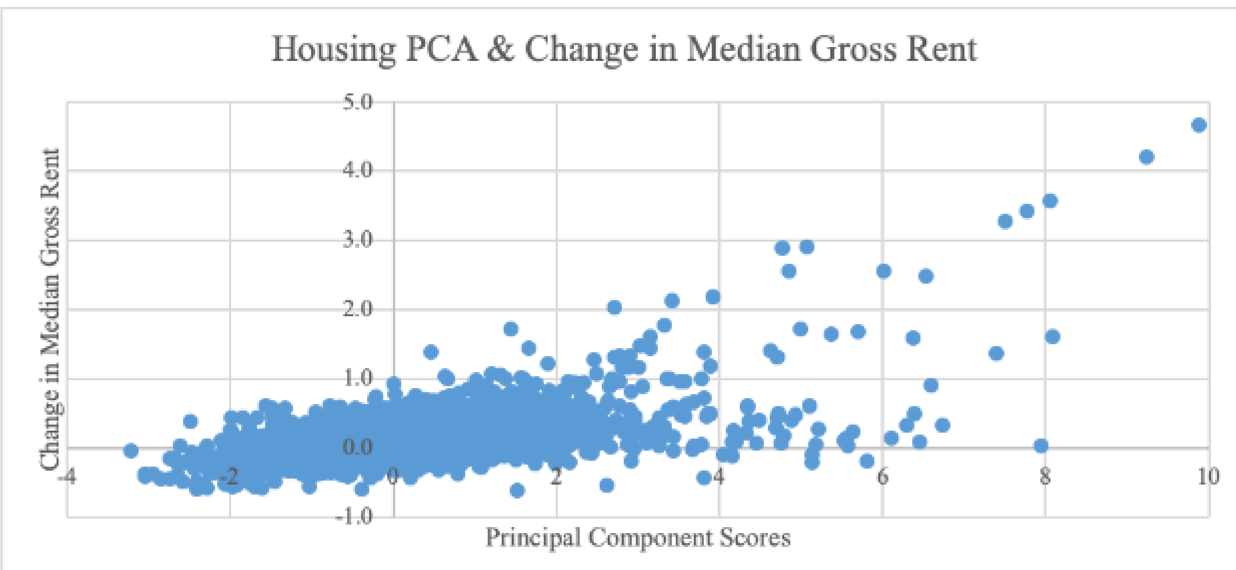


Figure 2-50. Housing Principal Component Scores and Changes in Rent-Burdened Households

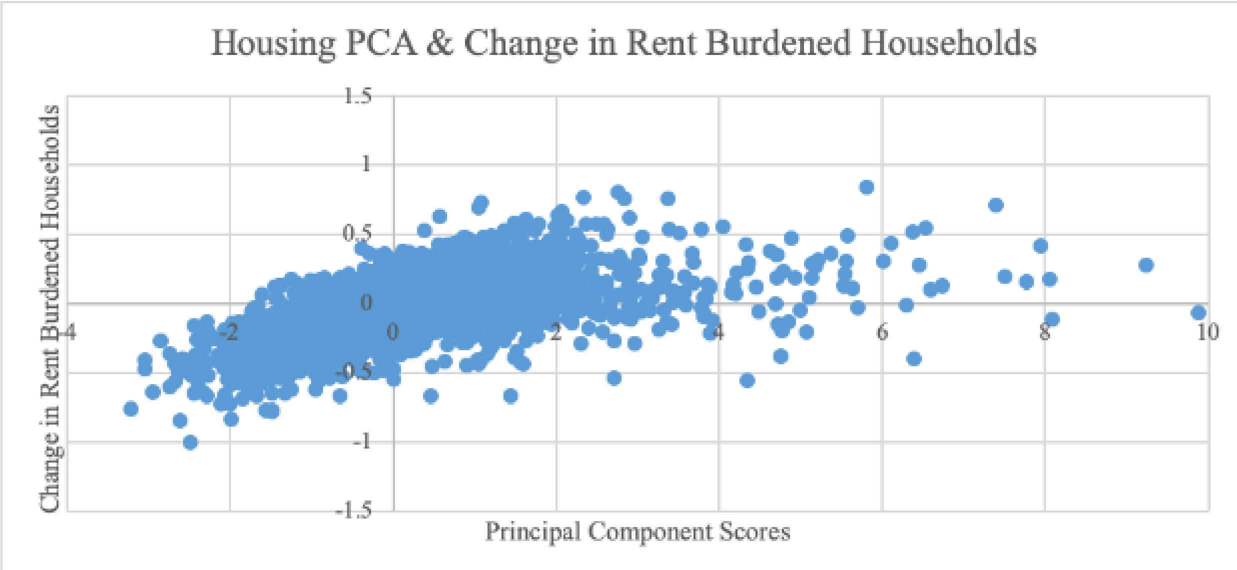
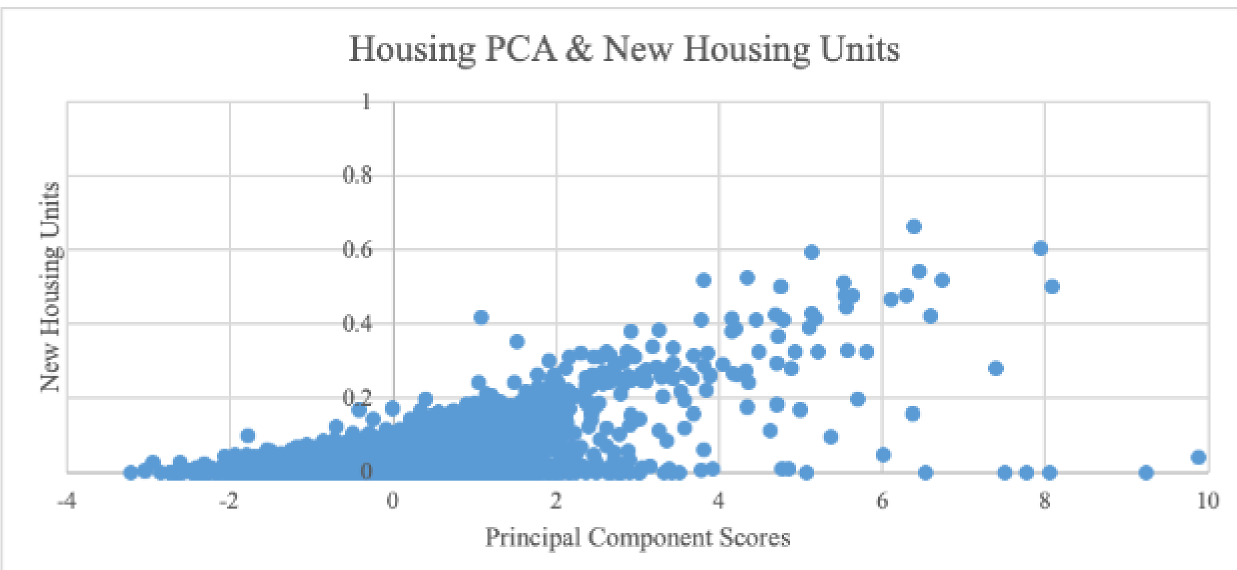


Figure 2-51. Housing Principal Component Scores and New Housing Units



Of the 8,012 census tracts in California with population, 99 percent (7,955) of tracts have socioeconomic PCA scores and 98 percent (7,866) have housing PCA scores. Census tracts with no PCA scores do not have sufficient data as they are missing data for at least one of the seven variables included in the analysis.

Assessment of Consistency

To the best of our knowledge and at least during the time of this project, there are no other statewide census tract–level indicators on neighborhood change available to which to assess our indicator. Existing indicators related to neighborhood change have largely focused on one type of change—mainly gentrification—and are only available for a number of regions in the state and may also be constructed using different methodology and data sources for different regions. This includes the gentrification index constructed for

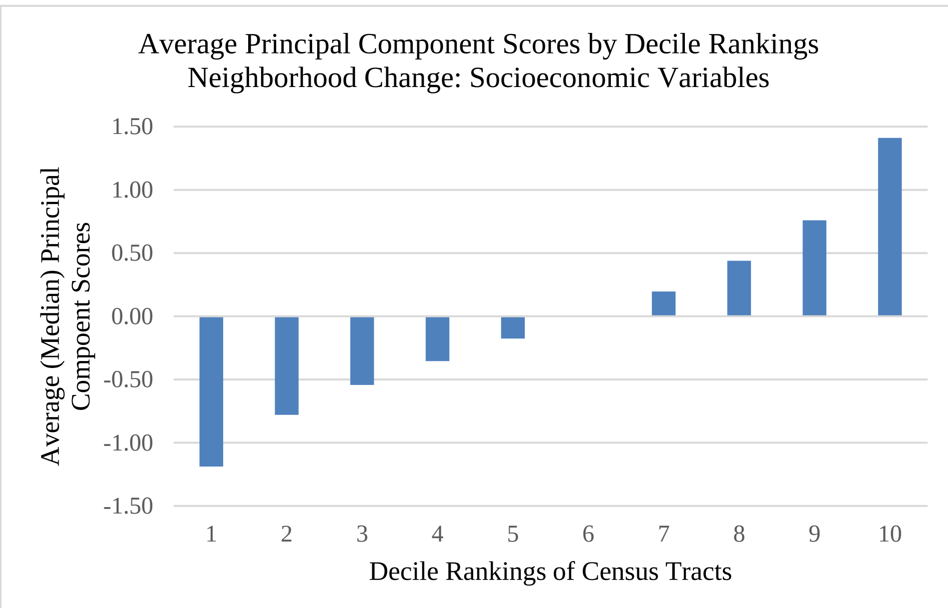
Los Angeles and the Bay Area by researchers of this project for an earlier CARB project. Given these factors, no assessment of these indicators against other neighborhood change indicators are conducted.

Results

California census tracts are divided into deciles based on each tract's neighborhood change score (calculated using principal component analysis) for changes in key socioeconomic variables and separately for housing market variables. Given the complexity of these indicators and the presence of positive and negative values, a parity index, similar to what was done for previous indicators, is not calculated.

Figure 2-52 compares the average (median) principal component scores in each decile category for changes in socioeconomic variables. A higher positive value indicates greater increases in income, earnings, and/or educational attainment. A higher negative value indicates greater decreases in income, earnings, and/or educational attainment. For example, the median neighborhood change score in the highest area (decile 10) is 1.41 compared to -1.19 in the lowest area (decile 1).

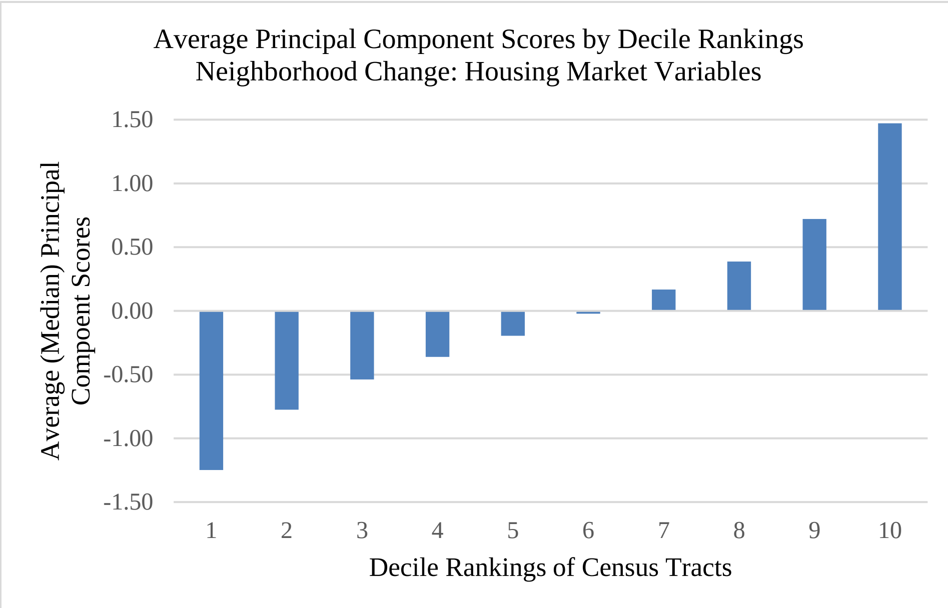
Figure 2-52. Average Principal Component Scores by Decile Rankings, Neighborhood Change: Socioeconomic Variables



Similarly, Figure 2-53 compares the average (median) principal component scores in each decile category for changes in housing market variables. A higher positive value indicates greater increases in renter-occupied household, gross rent, rent-burdened households and/or new housing units. A higher negative value indicates greater decreases along these key housing variables. For example, the median neighborhood change score in the highest area (decile 10) is 1.41 compared to -1.19 in the lowest area (decile 1).

For both indicators, the underlying values and rankings should be interpretative qualitatively (e.g., tract A with a higher decile ranking experienced more change than tract B with a lower decile ranking; or tract C with a decile ranking of 9 is among the tracts that experienced the most socioeconomic change). The quantitative score is ordinal, but should not necessarily be interpreted as interval values.

Figure 2-53. Average Principal Component Scores by Decile Rankings, Neighborhood Change: Housing Market Variables



Maps

The following maps display both of the neighborhood change indicators in low-income census tracts (where the median income is less than 60 percent of the regional AMI). We focus on these low-income neighborhoods because of the Advisory Committee's preference to focus on lower income places. Committee members also expressed an interest in whether the changes indicate possible gentrification. We can only speculate because determining gentrification would require considerably more analyses beyond the scope of the project. (For a detailed discussion on gentrification indices see Chapple et al., 2017.) The following maps provide an overview of the spatial patterns in socioeconomic and housing changes.

Socioeconomic Indicators

California

A majority of the low-income neighborhoods in California are concentrated in Los Angeles and the Bay Area, so our discussion focuses on those two regions. The exceptions are some exurb tracts, most noticeable along the outer edges of the urbanized areas of Southern California (see Figure 2-54). There is considerable variation among these places, which would require future analysis to determine if there are explainable systematic patterns.

Bay Area

In San Francisco, areas of SoMa (South of Market), the Tenderloin, and the Financial District are among the low-income areas that experienced noticeable changes. Parts of Oakland and Richmond are the areas that have changed the most in the East Bay (see Figure 2-55). Some of the changes indicator potential gentrification pressures.

Los Angeles

The low-income neighborhoods that experienced socioeconomic change are concentrated in the urban core, parts of the San Fernando Valley, East LA, and Long Beach area. Most of the census tracts in Downtown, East LA, and South LA went through greater socioeconomic changes than the other census tracts, and some of these changes are consistent with patterns associated with gentrification (see Figure 2-56)

Figure 2-54. Map of Neighborhood Change: Socioeconomic Variables, all of California

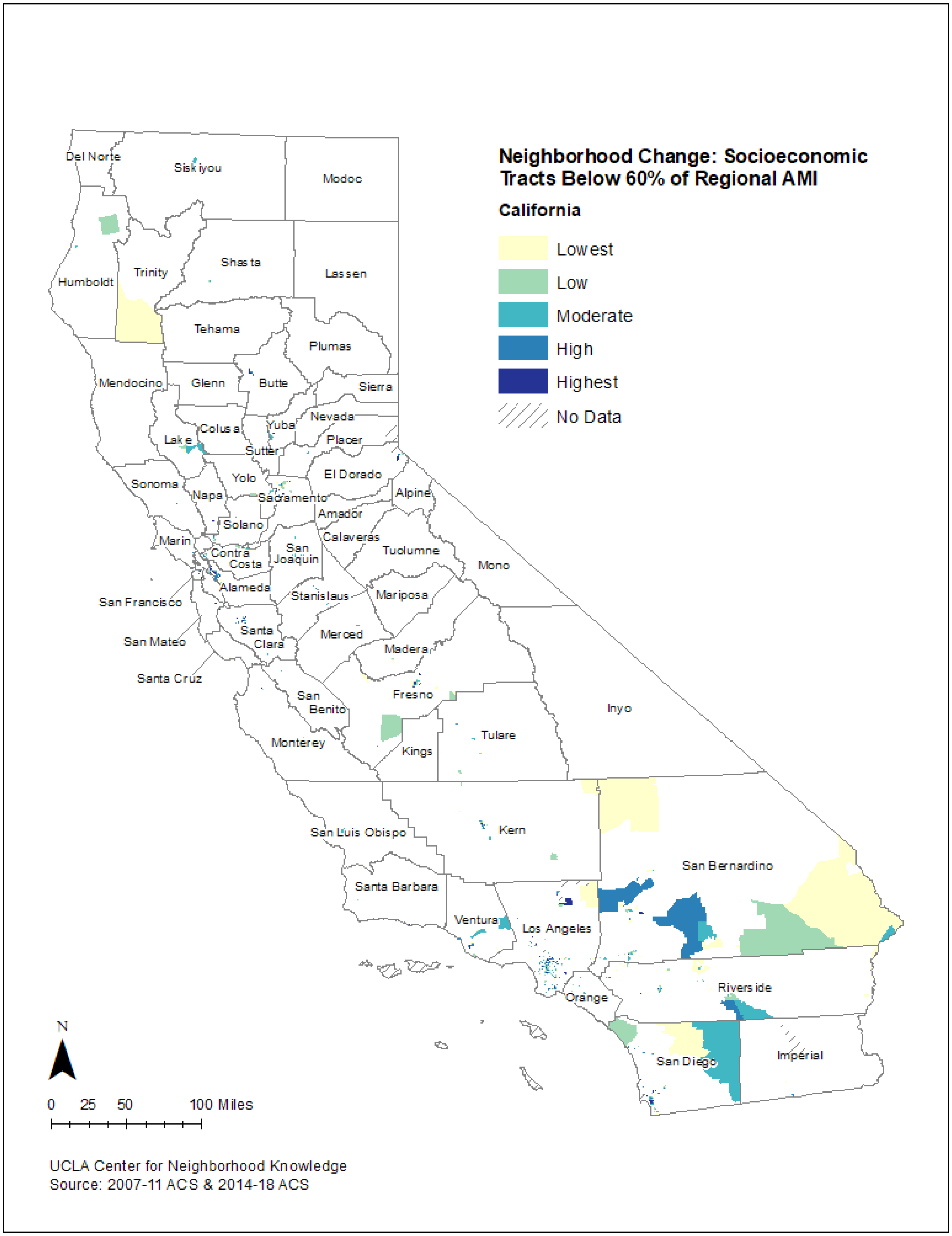


Figure 2-55. Map of Neighborhood Change: Socioeconomic Variables, San Francisco Area

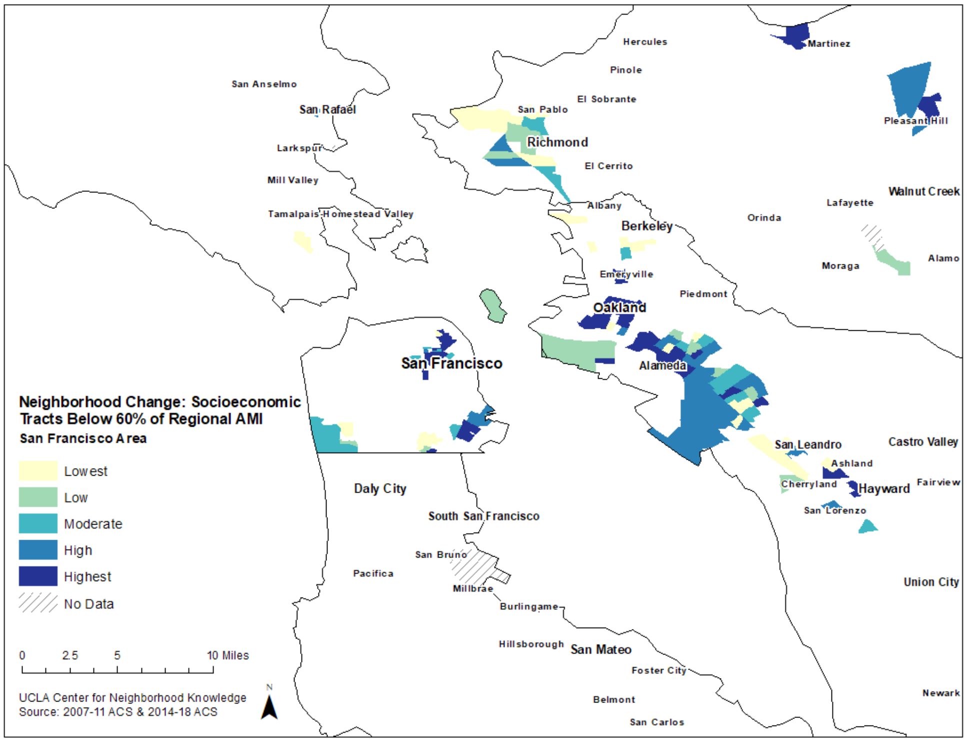
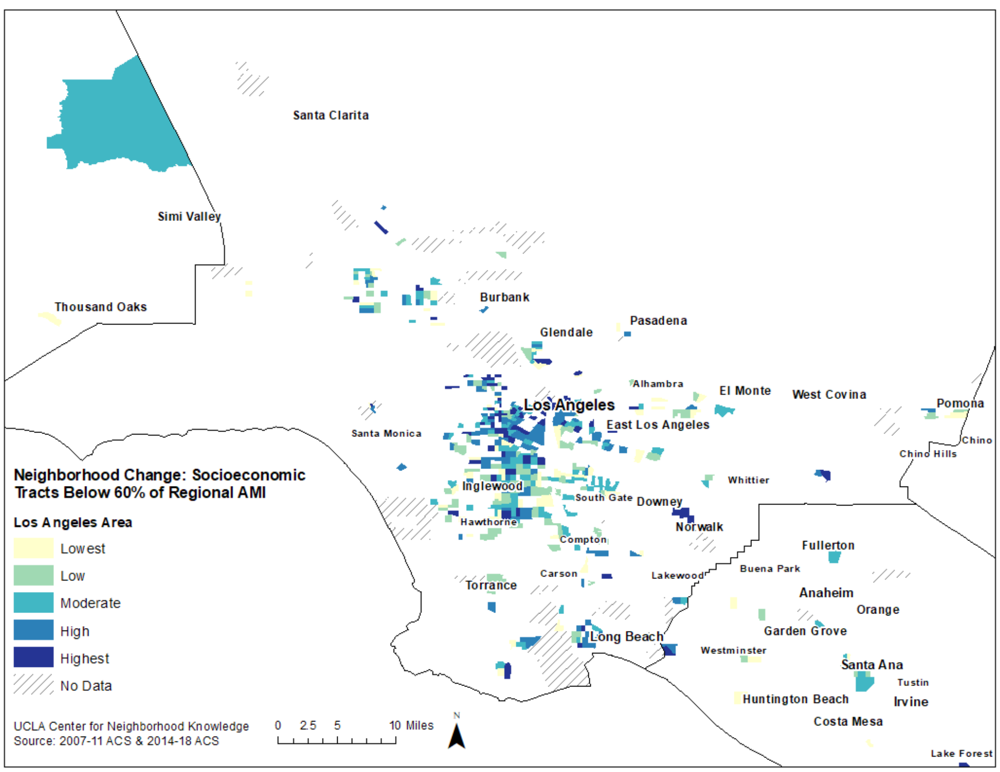


Figure 2-56. Map of Neighborhood Change: Socioeconomic Variables, Los Angeles Area



Housing Market Indicators

California
As noted earlier, a majority of the low-income neighborhoods in California are concentrated in Los Angeles and the Bay Area, so our discussion of changes in the housing market focuses on those two regions. Similar to the previous comments, some notable exceptions are exurb tracts, including those along the outer edges of the urbanized areas of Southern California (see Figure 2-57). There is considerable variation among these places, which should be examined in the future to determine if there are underlying factors and dynamics that generate the observed differences.

Los Angeles
Some of the areas that experienced a moderate to highest change in the housing market also had a similar level of change in socioeconomic characteristics. Census tracts directly below and above Downtown LA had the highest change in housing, but a moderate change in socioeconomic characteristics (see Figure 2-58). These changes may indicate some gentrification pressures.

Bay Area
The distribution of housing market changes in the Bay Area differs from the socioeconomic changes. Only some San Francisco census tracts experienced the highest level of change and they are somewhat more spread out, compared to those on the higher end for socioeconomic changes. Oakland, Richmond, and other parts of the East Bay experienced the highest change in the housing market in addition to socioeconomic characteristics (see Figure 2-59).

Figure 2-57. Map of Neighborhood Change: Housing Variables, all of California

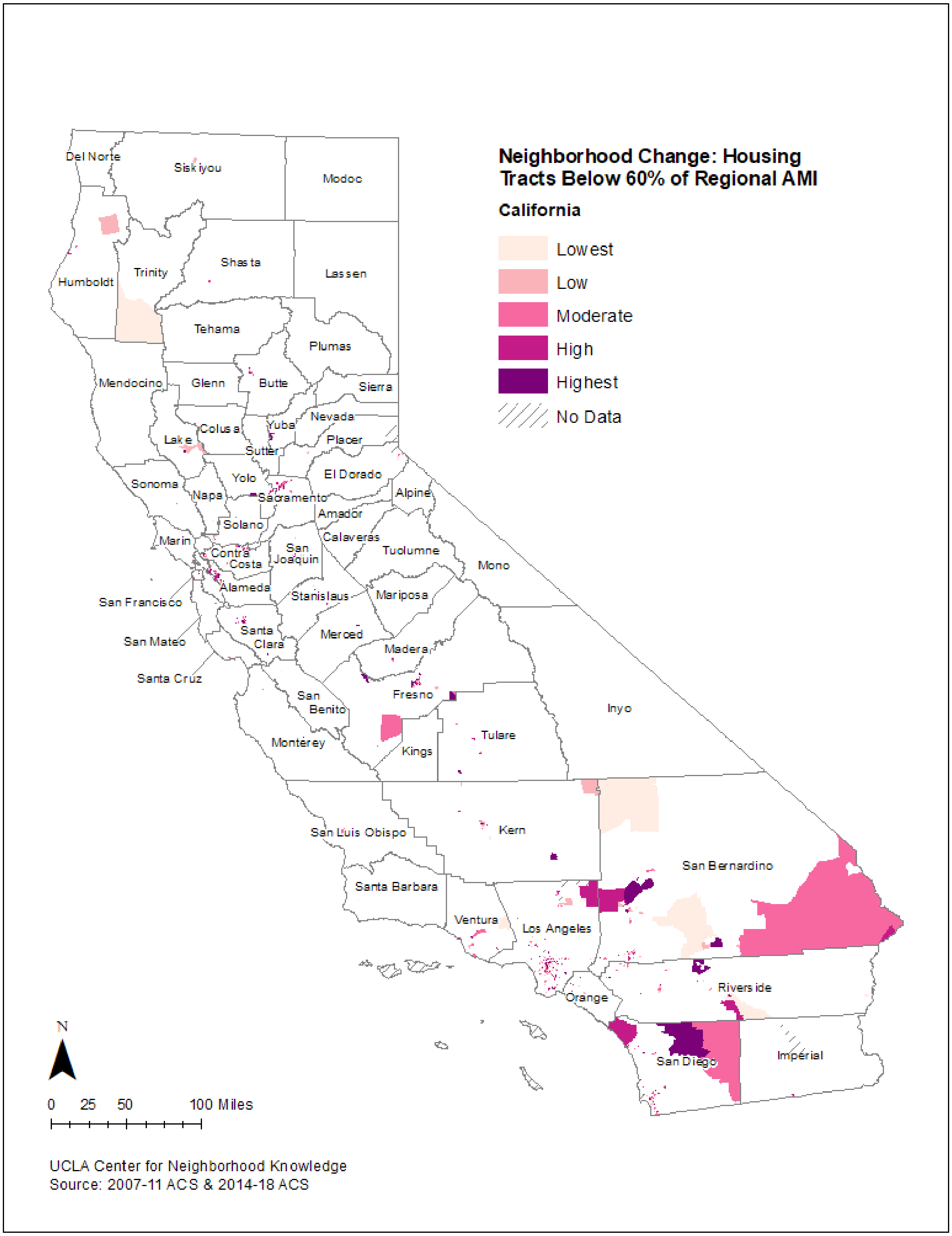


Figure 2-58. Map of Neighborhood Change: Housing Variables, San Francisco Area

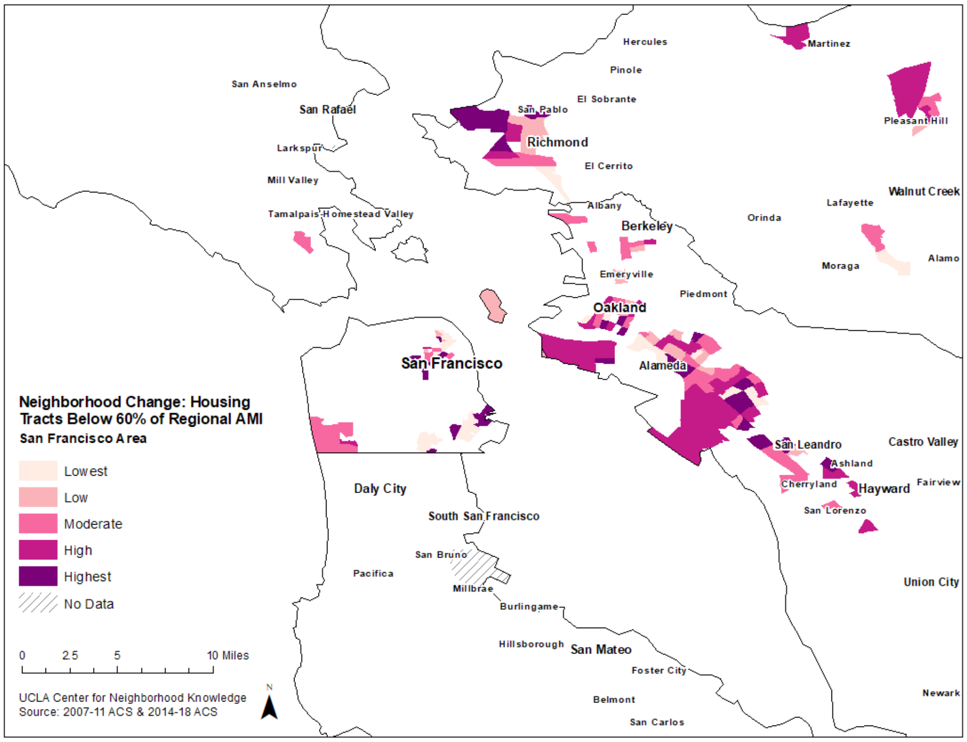
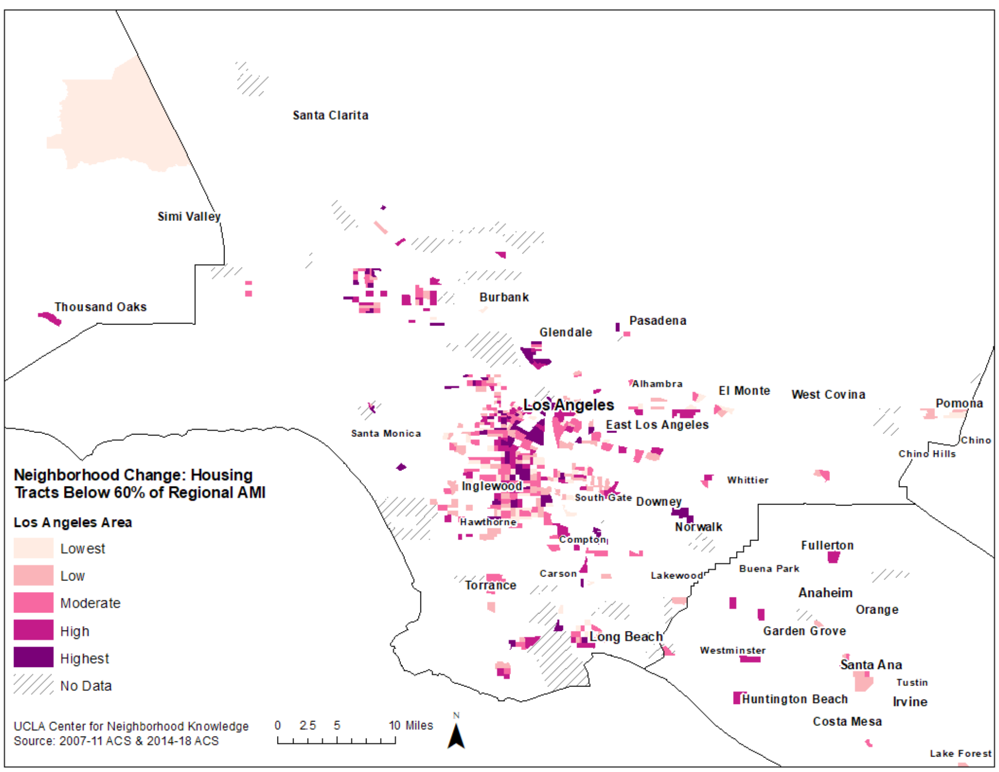


Figure 2-59. Map of Neighborhood Change: Housing Variables, Los Angeles Area



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2.3.9 Neighborhood Income Relative to Regional AMI

This section documents the construction of CNK's neighborhood income relative to regional AMI indicator, which is based on a neighborhood's median household income relative to a regionally adjusted area median income.

Table 2-19. Neighborhood Income Relative to Regional AMI Indicator Summary Table

Key Indicator Information	
Units	Neighborhood Income Relative to Regional AMI (Ratio)
Category in Mapping Tool	N/A (use for filtering)
Display Method in Mapping Tool	Categorical (ratio of tracts income relative to regional AMI)
Precision	Assumed to be relatively fair
Methodological Complexity	Indicator based on relation to regional AMI
Geographic Resolution	Census tracts
Key Information about Data Sources Used to Construct Indicator	
Data Sources Used to Construct	American Community Survey (tabulated and microdata)
Sample Size	Relies on ACS data that is based on a sample (approximately 12% of population)
Biases	May be affected by short-term business cycle
Geographical Unit	Census tract
Geographic Coverage	Covers all of California
Data Vintage	2013-17 5-year average
Other Important Notes (if applicable)	N/A.

Background

The state designates "disadvantaged communities" per Senate Bill 535 and "low-income communities" per AB 1550. The inclusion of the CNK indicator is not meant to replace the state's designation for either "disadvantaged" or "low-income" communities but is meant to supplement the two. We also use the CNK indicator for the project's analytical work in Chapter 3. We provide descriptions of each and include all three in the final database.

Disadvantaged communities are identified by the California Environmental Protection Agency as the top 25 percent most impacted census tracts in CalEnviroScreen 3.0, a screening and mapping tool used to help identify communities disproportionately burdened by multiple sources of pollution and with population characteristics that make them more sensitive to pollution. The final CalEnviroScreen score represents a composite of 20 different indicators relating to the environmental, health, and socioeconomic status of a neighborhood and its residents. In accordance with SB 535 (de Leon), CalEPA is responsible for identifying disadvantaged communities for Greenhouse Gas Reduction funding. As of February 2017, CalEPA designated disadvantaged communities as the 25 percent highest scoring census tracts in CalEnviroScreen 3.0, along with other areas with high amounts of pollution and low populations (CalEPA, 2017). It is important to note the term "disadvantaged communities" can potentially be misinterpreted as a description that focuses on deficits of these communities at the expense of their positive characteristics, strengths, and assets. This is not the intent of the project, which is designed to identify transportation and accessibility disparities.

Assembly Bill 1550 defines low-income communities as census tracts at or below 80 percent of the statewide median income or with median household incomes at or below the threshold demonstrated by the California Department of Housing and Community Development's (HCD) 2016 State Income Limits (CARB, 2017). Low-income communities based on the statewide median household income use $61,818 from the 2011–15 5-year ACS. Census tracts with a median household income at or below 80 percent of the statewide median household income ($49,545) are considered low income. AB 1550 low-income communities based on the HCD low-income limits refers to the "low" income threshold. HCD State Income Limits vary by household size for each county and have income threshold categories.

Data Source

Information on median household income for metropolitan areas is derived from the 2013–17 5-year ACS. We estimated the median household income for the entire residual area using the 2013–17 ACS PUMS.

Construction Method

For the project, we include an indicator that measures a neighborhood's income relative to regional AMI to identify the most economically disadvantaged neighborhoods. These neighborhoods are defined as census tracts with median household incomes less than 60 percent of the regional area median income. We use a 60 percent cutoff because this threshold captures the most economically disadvantaged neighborhoods. The project uses metropolitan statistical areas (MSAs) as the "region." The Census Bureau defines MSAs as the "county or counties (or equivalent entities) associated with at least one urbanized area of at least 50,000 population, plus adjacent counties having a high degree of social and economic integration with the core as measured through commuting ties." MSAs are considered a regional economy with their own housing cost and wage levels. Not all counties (and their census tracts) are part of a metropolitan area. For the purpose of CNK's indicator, counties that are not part of a metropolitan area are treated as a single (residual) geographic unit. There are 26 MSAs in California, which encompasses 37 counties, representing about 98 percent of California's population. The remaining 21 counties are not part of a MSA. Table 2-20 summarizes the median household income, 60 percent cutoff, and number of census tracts designated as low income for each region.

Each census tract was then assigned to its respective region (either MSA or residual) and compared the tract's median household income to the "regional" AMI. Due to differences in housing costs and distribution of low-wage workers throughout the state, this approach accounts for regional differences in income levels.

Table 2-20. Median Household Income by Metropolitan Statistical Area

Metropolitan Statistical Area	Median Household Income	60% of MHI	% Lowest Income Census Tracts	Total Census Tracts
Bakersfield	50,826	30,496	13%	147

Metropolitan Statistical Area	Median Household Income	60% of MHI	% Lowest Income Census Tracts	Total Census Tracts
Chico	46,516	27,910	12%	51
El Centro	44,779	26,867	10%	30
Fresno	48,730	29,238	19%	198
Hanford-Corcoran	49,742	29,845	0%	25
Los Angeles-Long Beach-Anaheim	65,331	39,199	16%	2,887
Madera	48,210	28,926	9%	23
Merced	46,338	27,803	6%	49
Modesto	54,260	32,556	9%	94
Napa	79,637	47,782	3%	40
Oxnard-Thousand Oaks-Ventura	81,972	49,183	11%	172
Redding	47,258	28,355	4%	48
Riverside-San Bernardino-Ontario	59,173	35,504	13%	817
Sacramento--Roseville--Arden-Arcade	64,407	38,644	13%	484
Salinas	63,249	37,949	5%	91
San Diego-Carlsbad	70,588	42,353	13%	621
San Francisco-Oakland-Hayward	92,714	55,628	14%	972
San Jose-Sunnyvale-Santa Clara	105,809	63,485	10%	383
San Luis Obispo-Paso Robles-Arroyo Grande	67,175	40,305	4%	52
Santa Cruz-Watsonville	73,663	44,198	4%	52
Santa Maria-Santa Barbara	68,023	40,814	7%	87
Santa Rosa	71,769	43,061	2%	99
Stockton-Lodi	57,813	34,688	17%	139
Vallejo-Fairfield	72,950	43,770	12%	94
Visalia-Porterville	44,871	26,923	8%	77

Metropolitan Statistical Area	Median Household Income	60% of MHI	% Lowest Income Census Tracts	Total Census Tracts
Yuba City	53,101	31,861	14%	35
Nonmetro Area	48,691	29,215	6%	199
Total			**13%**	**7,966**

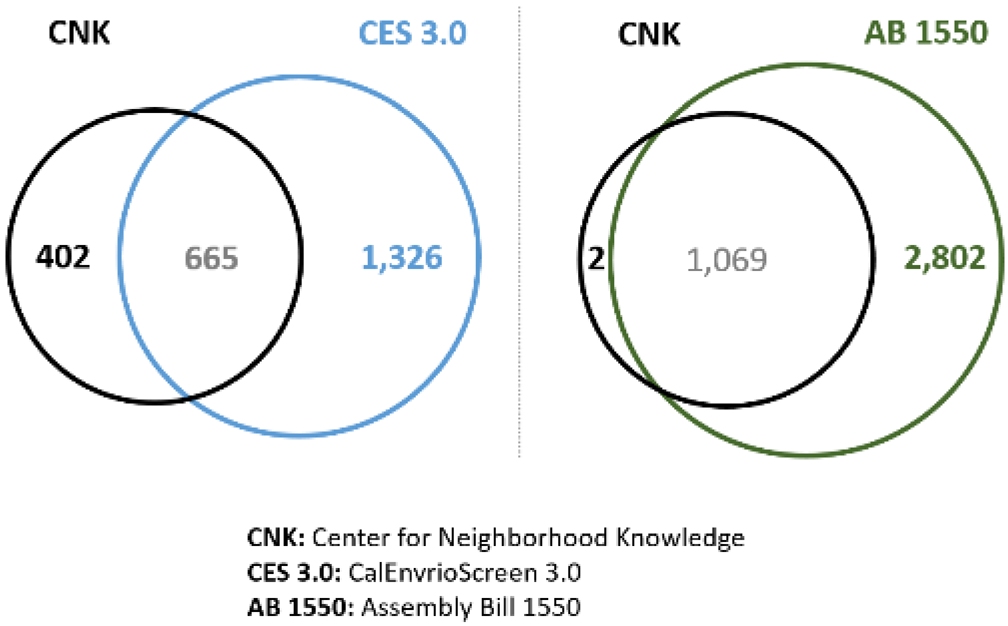
Source: 2013–17 5-year ACS.

We grouped tracts based on their median income relative to their region's average median income. We use the following four ranges: 0–60 percent (lowest income neighborhoods), 60–80 percent (low-income neighborhoods), 80–140 percent (middle-income neighborhoods), and 140 percent+ (high-income neighborhoods).

Assessment of Consistency

We compared our measure of lowest income neighborhoods with the two other definitions described earlier. Of all the census tracts in California, 25 percent are defined as "disadvantaged" by CES 3.0, 49 percent as "low-income" by AB 1550, and 13 percent "lowest income" (with AMI of less than 60 percent) by CNK. Figure 2-60 illustrates the overlap and differences. There is some overlap but the three are not all the same. Certain census tracts may be defined as disadvantaged under one definition but not another. This is particularly true when comparing CNK's definition to CES 3.0. This is not surprising given that CNK's measure only considers income while CES 3.0 includes other variables beyond income (e.g., environmental, health measures). Almost all CNK's lowest income neighborhoods are included under the definition used by AB 1550, though out of all three definitions, AB 1550 includes many more census tracts as disadvantaged (e.g., 49 percent of tracts in California).

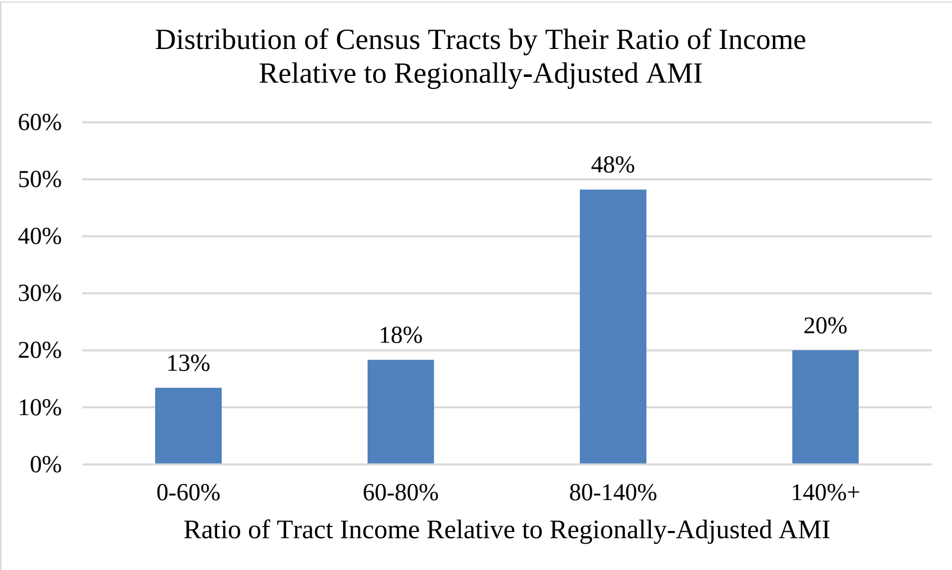
Figure 2-60. Relationship between CNK's Lowest Income Indicator and Measures of "Disadvantaged" and "Low-Income" Communities



Results

California census tracts are grouped into four categories based on their ratio of income relative to their region's average median income: 0–60 percent (lowest income neighborhoods), 60–80 percent (low-income neighborhoods), 80–140 percent (middle-income neighborhoods), and 140 percent+ (high-income neighborhoods). Figure 2-61 displays the distribution of CA census tracts by each of these four categories. Thirteen percent of California tracts fall into the lowest income category, followed by 18% in low-income, 48% in middle income and 20% in high-income neighborhoods.

Figure 2-61. Distribution of CA Census Tracts by Their Ratio of Income Relative to Regionally-Adjusted AMI



Maps

The following maps display the indicator on neighborhood income relative to regional AMI.

California
A majority of the lowest income neighborhoods in California are concentrated in the core of the more urbanized areas. The exception are some exurb tracts, most noticeable along the outer edges of the urbanized areas of Southern California. The coastal neighborhoods are among the areas with the highest income (see Figure 2-62).

Bay Area
In San Francisco, areas of Bay View, Tenderloin, along Market Street, and adjacent to San Francisco State University (students) are among the low-income areas. In the East Bay, the urban-poor corridor from West Oakland to Fruitvale, neighborhoods in and around Richmond, and the area around U.C. Berkeley (students) are also low income (see Figure 2-63).

Los Angeles
In LA County, much of the urban core, and South LA in particular, are among the lowest income. East LA and parts of the San Fernando Valley also have high incidences of economically disadvantaged residents. The more affluent neighborhoods are located on the Westside and along the coastal cities like Santa Monica, El Segundo, and Redondo Beach (see Figure 2-64).

Figure 2-62. Map of Neighborhood Income Relative to Regional AMI, all of California

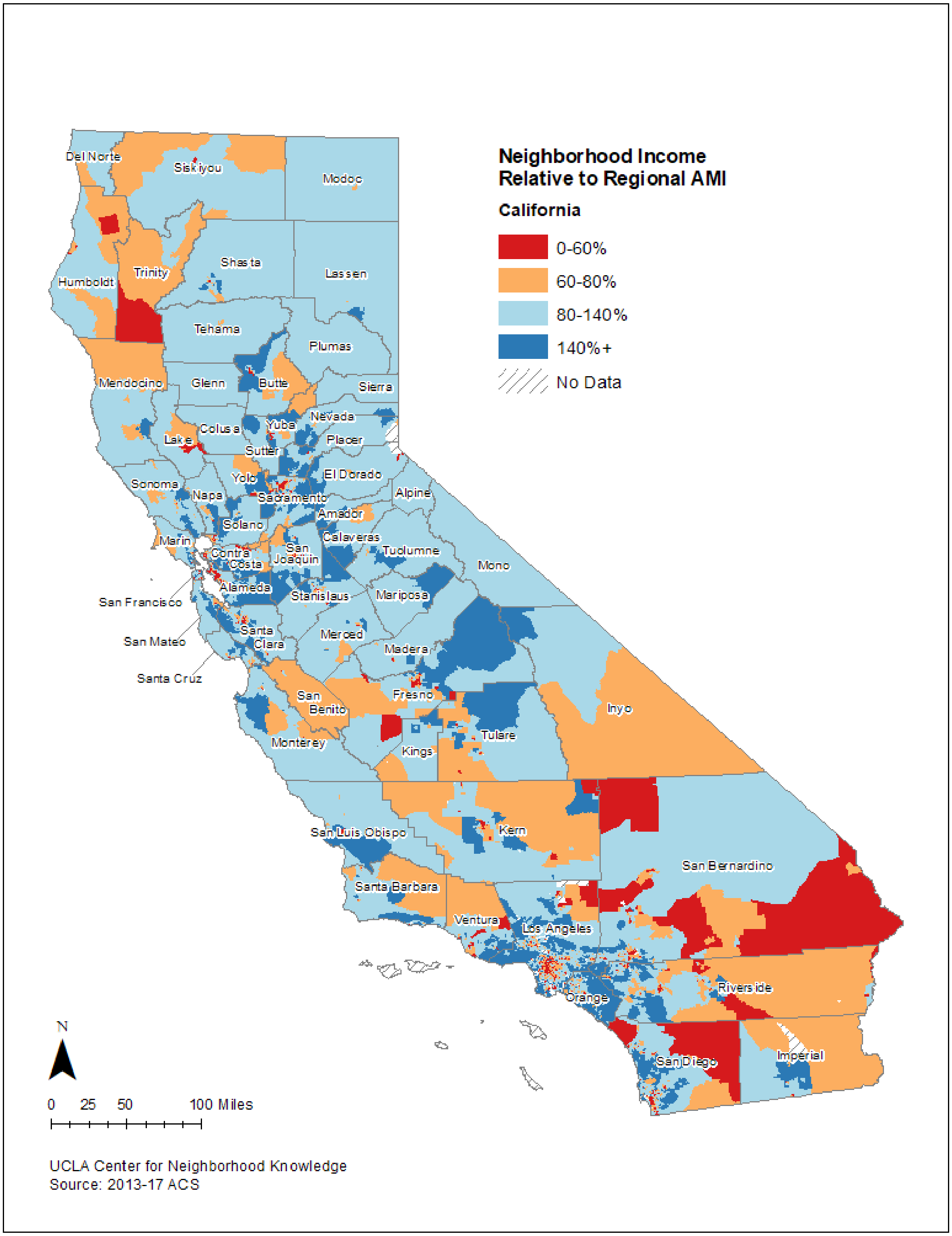


Figure 2-63. Map of Neighborhood Income Relative to Regional AMI, San Francisco Area

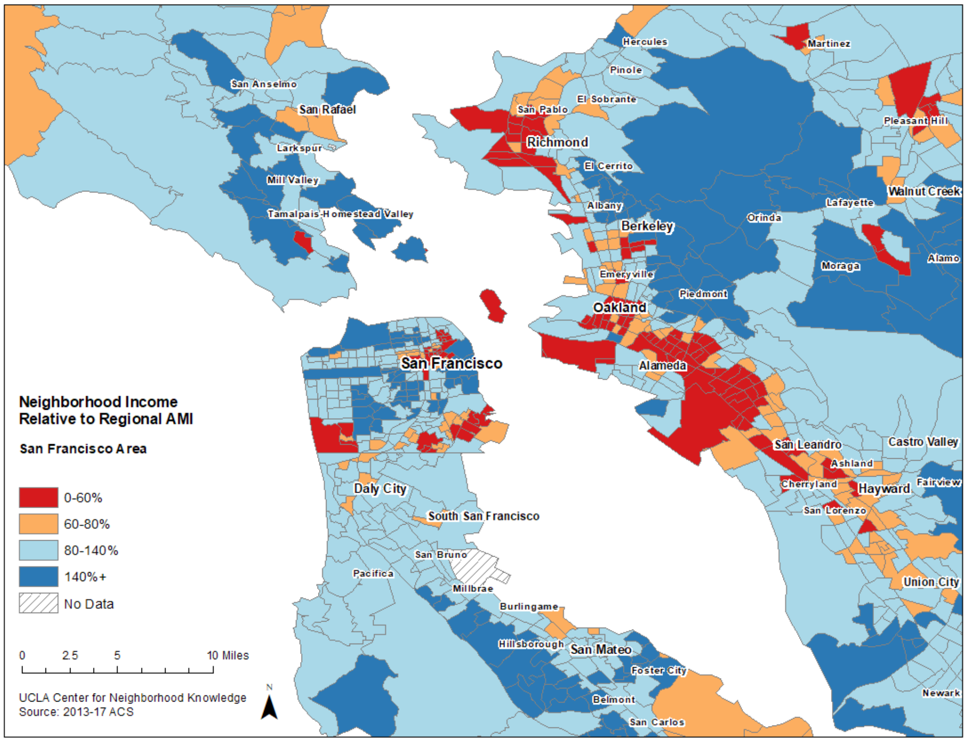
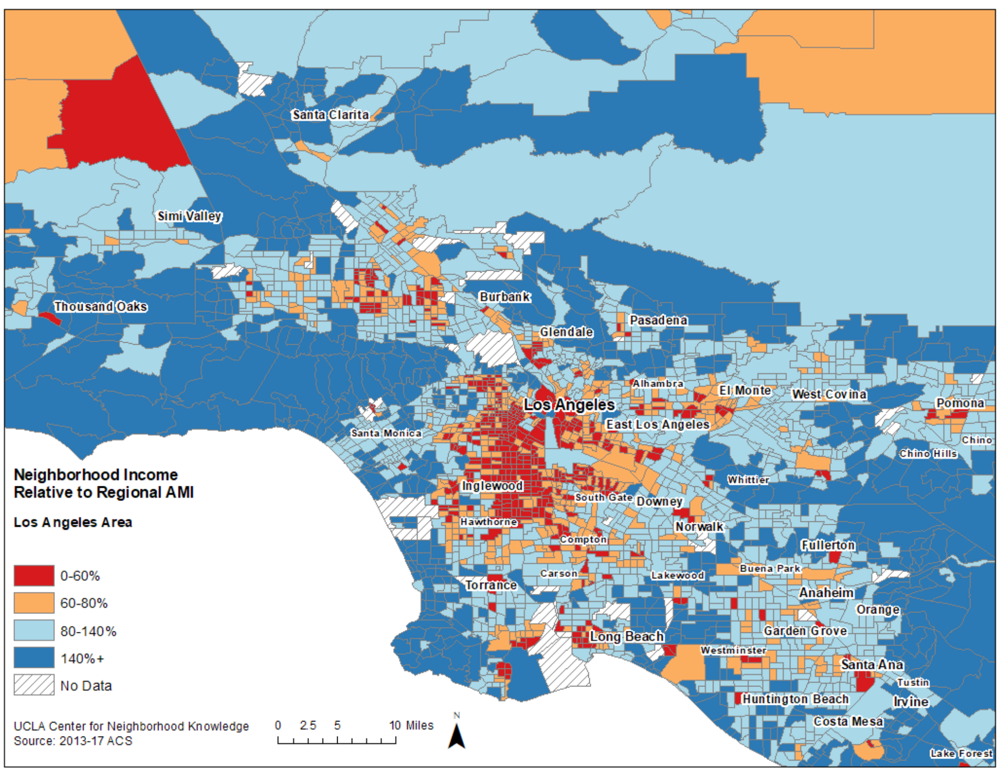


Figure 2-64. Map of Neighborhood Change: Socioeconomic Variables, Los Angeles Area



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2.3.10 Other CNK Indicators

This project on transportation disparities includes statewide indicators that were constructed for an earlier statewide project sponsored by CARB and Caltrans. That previous project developed neighborhood-level indicators for a Statewide Monitoring System to track progress toward achieving certain SB 375 goals across California. One of the legislation's goals is to promote better coordination of land-use, housing, and transportation planning with the goal of reducing vehicle miles traveled and greenhouse gas emissions. That project consisted of two phases. Phase I, funded by CARB, focused on developing indicators using Los Angeles County as a prototype. Phase II, funded by Caltrans, refined and developed additional indicators for all of California.[27]

The four indicators adopted from the earlier project include the following: access to employment opportunities, access to high-quality transit locations, jobs–housing fit, and job density. Some of these indicators were updated and/or refined for this project using more up to date data (e.g. this project updated access to jobs using more current data). Because these indicators are adopted from earlier projects, it may not include all of the components discussed for previous indicators constructed for this project. The intent is to provide brief descriptions of each of the four indicators and to summarize their construction method. For additional information about these indicators see previous CARB and Caltrans reports.[28] The following subsections summarizes the construction of the four indicators.

[27] To access Phase I report titled "Identifying, Evaluating, and Selecting Indicators and Data for Tracking Land Use and Transportation-Related Trends Related to SB 375 Goals" (CARB Agreement No. 15RD010) visit: https://ww2.arb.ca.gov/sites/default/files/classic/research/apr/past/15rd010.pdf.
To access Phase II report titled "Developing Statewide Sustainable-Communities Strategies Monitoring System for Jobs, Housing, and Commutes" (Caltrans Agreement No. 65A0636) visit: https://dot.ca.gov/-/media/dot-media/programs/research-innovation-system-information/documents/final-reports/ca18-2931-final-report-a11y.pdf
[28] See links to reports provided in the previous footnote.

2.3.11 Access to Employment Opportunities

This subsection documents the construction of the access to employment opportunities indicator (the terms “access to employment opportunities", “access to jobs”, and “job access” is used interchangeably in this report). This indicator measures the relative number of jobs within a region that are accessible by residential location.

Table 2-21. Summary Table for Access to Employment Opportunities Indicator

Key Indicator Information	
Units	Index score that captures job opportunities accessible from a tract
Category in Mapping Tool	Accessibility
Display Method in Mapping Tool	Decile (visualized in quintiles)
Precision	Assumed to be relatively high
Methodological Complexity	Complex involving the use of street network with travel times, and estimating parameters for different decay functions
Geographic Resolution	Census blocks for jobs aggregated into Census tracts
Key Information about Data Sources Used to Construct Indicator	
Data Sources Used to Construct	LEHD LODES (jobs) and HERE road network (distance and time)
Sample Size	Jobs data not based on sampling; large number of observations based on administrative data
Biases	Jobs data does not include workers outside of the UI/DI programs. May be affected by the short-term business cycle.
Geographical Unit	Census tract
Geographic Coverage	Covers all of California
Data Vintage	2017
Other Important Notes (if applicable)	The functional form used to calculate the final access to jobs measure is exponential decay with author estimated parameter

<u>Data Source</u>

Data on jobs come from the 2017 LEHD LODES database. Data on the road network come from HERE street network, and the information on times and distance are used to calculate the travel time between population-weighted tract centroids and jobs-weighted tract centroids.

The LEHD program combines “federal, state, and Census Bureau data on employers and employees” (U.S. Census Bureau LEHD, “About Us”, 2022). LODES data are collected by the US Census Bureau and reports data on the distribution of jobs by employment location, residential location, and the flows between home and work. It combines administrative data (unemployment insurance earnings data, the Quarterly Census of Employment and Wages data, and others) with census and survey data. These data are combined to “create statistics on employment, earnings, and job flows at detailed levels of geography and industry for different demographic groups” (U.S. Census Bureau LEHD “About Us”, 2022).

State LODES data covers approximately 95 percent of formal wage and salary jobs (Graham et al., 2014). LEHD does not limit its coverage to primary jobs, but does exclude data on a few specific classes of workers, including self-employed workers, informally employed persons, military personnel, and federal employees (Federal Employment, 2012).

LODES data has some documented shortcomings in instances of multiple worksite counts (Graham et al., 2014). These include instances where administrative addresses may be used in lieu of actual worksites or when multiple worksites are not reported as such. However, despite any shortcomings, LEHD/LODES data remains, for the purposes of this project, the most robust source of jobs data.

Construction Method

The access to employment opportunities indicator is calculated using an exponential decay method with a state-calibrated parameter. The main tasks in the construction of the access to jobs indicator includes the following: (1) data assembly, (2) estimating the decay parameters, and (3) calculating accessibility.

Assembling Data

Jobs data was downloaded for all census tracts in California from the 2017 LEHD LODES database.

Estimating Decay Parameters for California

Parameters were estimated for the exponential decay functional form. Other functional forms such as simple gravity and power decay with customized parameters were tested against commute patterns (average commute time and average commute distance) to determine the best-suited form for commute travel in California. The results showed the strongest relationship between the exponential decay form with author-calculated parameters and commute travel in California.[29]

The functional form used to calculate the final access to jobs measure is exponential decay with author estimated parameter:

$$e^{-b(t-11)} where\ b = \ 0.0395\ and\ t = time$$

Calculating Accessibility

The final jobs-accessibility indicator is an index score that captures all the job opportunities accessible by a tract, within a two-hour or 100-mile commute. We calculated the jobs accessibility indicator by, first, assembling 2017 job counts for each tract, using the LEHD dataset. The steps to calculating the indicator include assembling the data and attaching these to the origin-destination (OD) network. Each OD pair has an associated travel time between them. The job counts, the time measure, and a modifying parameter (to simulate the relative likelihood/attractiveness of driving to jobs at increasing distances) are the three numbers input into each of the functional forms to calculate accessibility. This calculation is conducted for each OD pair for every California tract. The accessibility indicator for each tract is a sum of all these calculations, by origin tract (i.e., all values for pairs with the same origin are added together). Excluded from the final indicator measure are all OD pairs with no jobs, and all pairs where travel between them was greater than two hours or 100 miles.[30]

[29] For more detailed discussion of the formulas tested and the methods used to estimate decay parameters, please see Phase I and II reports of the Statewide Monitoring System project. See links in previous footnote.
[30] Commutes of 100 miles or so and greater have been defined by many as an “extreme commute.” These are excluded from calculations.

Accessibility to employment opportunities is estimated as the number of jobs inversely weighted by the estimated time to cover the road network distance. For census tract i,

$$(\text{Job Access})_i = \text{SUM}(J_j/D_{i,j})$$
For census tracts j = 1 .. n

SUM is the summing function of elements within the parentheses, J is the number of jobs in tract j as reported by LEHD, and $D_{i,j}$ is the time-distance decay function described above.

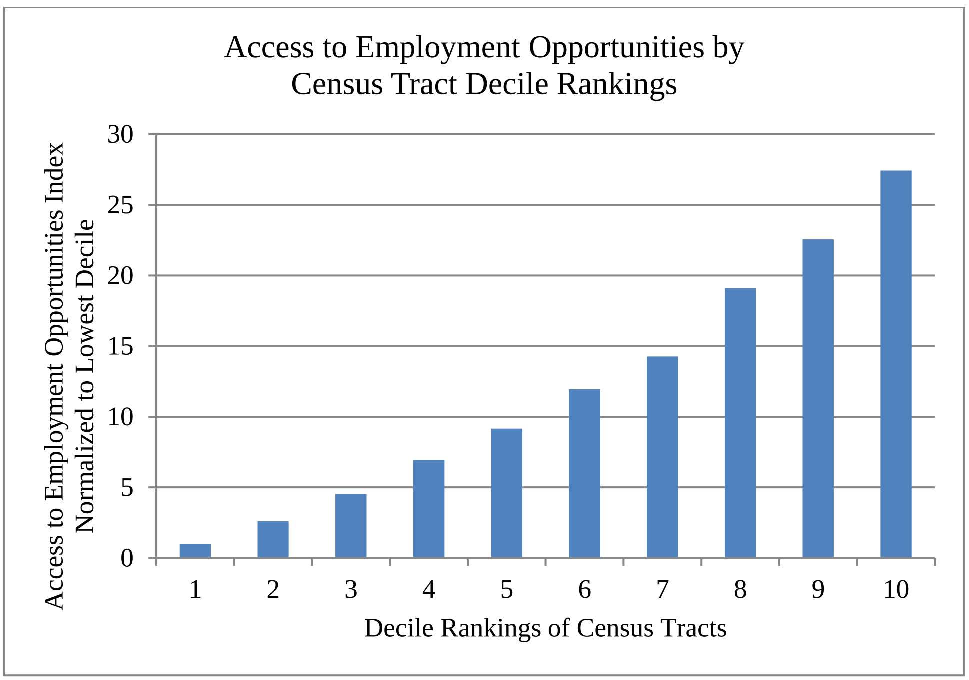
Construction Method

We compared our job-access indicator against job-access based on methods commonly used in the transportation field, such as the simple gravity model. We find that our job-access indicator is highly correlated with (highly consistent) with those alternatives.

Results

California census tracts are categorized into ordinal deciles according to each tract's calculated value of access to employment opportunities index. Each decile category represents roughly 10 percent of the census tracts in California. Figure 2-65 compares the median value of the access to jobs index in each decile category normalized by the lowest decile. A value greater than one indicates that the access to jobs index for that decile is higher than the lowest decile category by that value. For example, the value of the median job access index in the highest area is more than 27 times as great as in the lowest area, indicating the greatest access to jobs.

Figure 2-65. Access to Employment Opportunities by Census Tract Decile Rankings



Maps

The map displays the jobs accessibility indicator data by census tract. California census tracts are divided into five quintiles based on the tract's access to jobs estimate. Each quintile contains roughly 20 percent of all census tracts in the State.

California

In California, areas with the highest job accessibility are concentrated in and adjacent to the state's major metropolitan areas (e.g. Los Angeles and San Francisco Bay Area). This is due to the fact that jobs in urban areas are much more spatially concentrated than in non-urban and rural areas. (See Figure 2-66).

Bay Area

In the San Francisco area, neighborhoods with the highest job accessibility are concentrated around central business districts (e.g. the downtown areas of San Francisco and Oakland) and around other major employment centers (e.g. the sites for high tech firms). (See Figure 2-67)

Los Angeles

In the Los Angeles area, neighborhoods with the highest job accessibility are concentrated around central business districts (e.g. the downtown areas of Los Angeles and Orange county) and around other major employment centers (e.g. sites for firms in the entertainment industries). The areas with the least accessibility are in the suburban and exurban areas. (See Figure 2-68)

Figure 2-66. Map of Access to Employment Opportunities, all of California

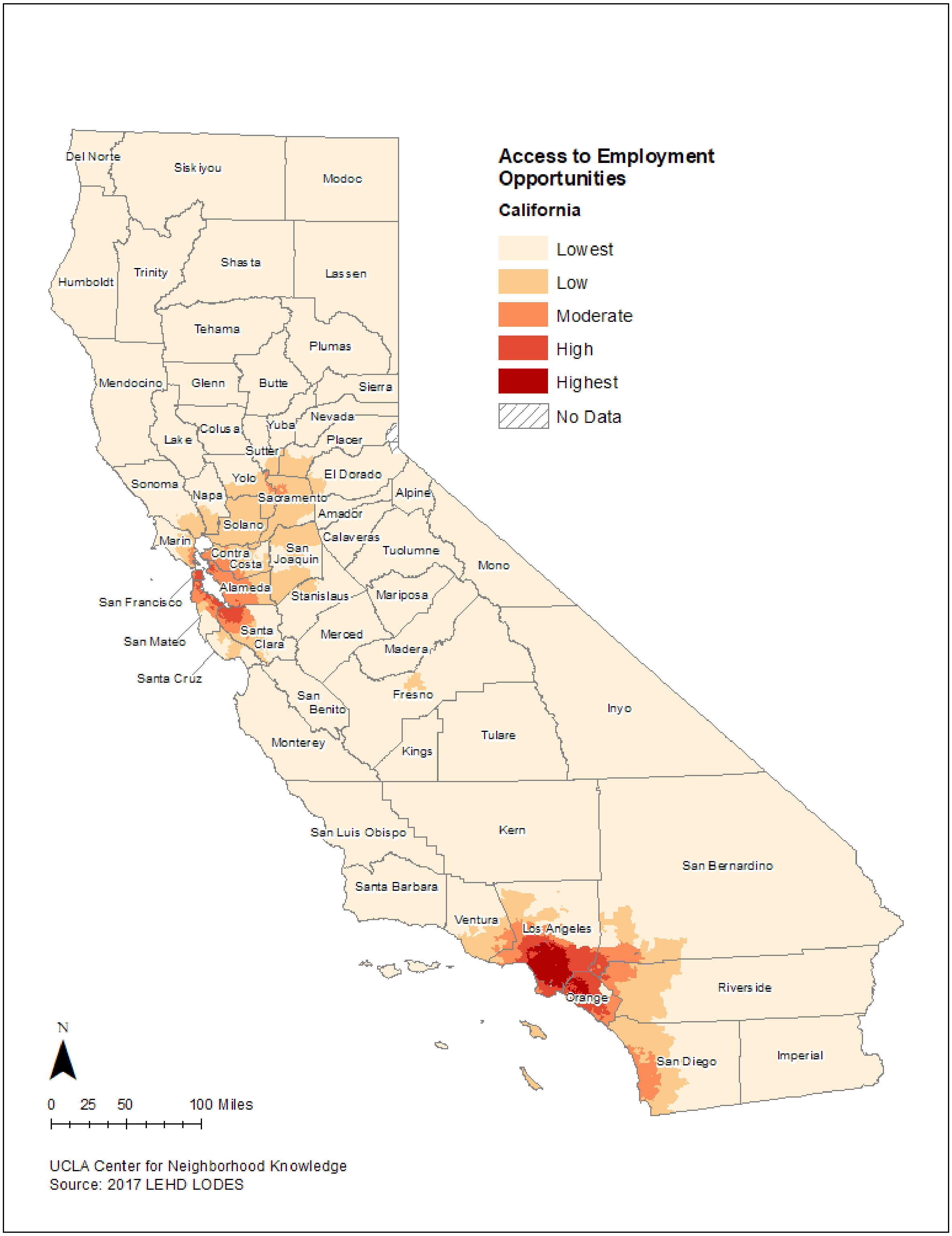


Figure 2-67. Map of Access to Employment Opportunities, San Francisco Area

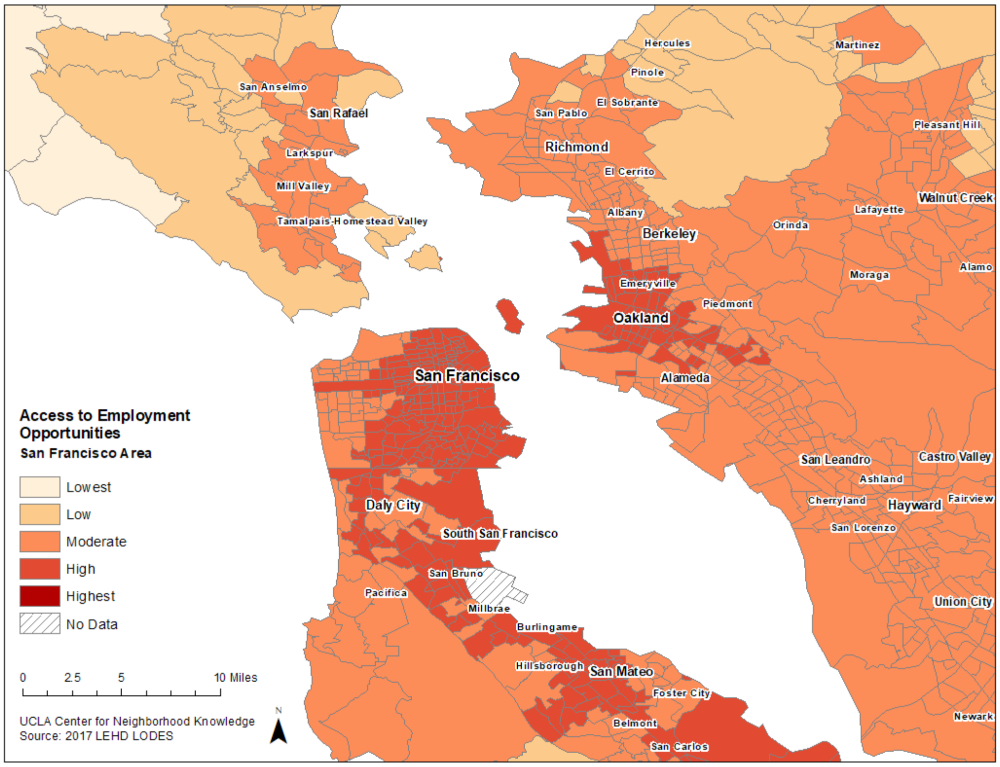
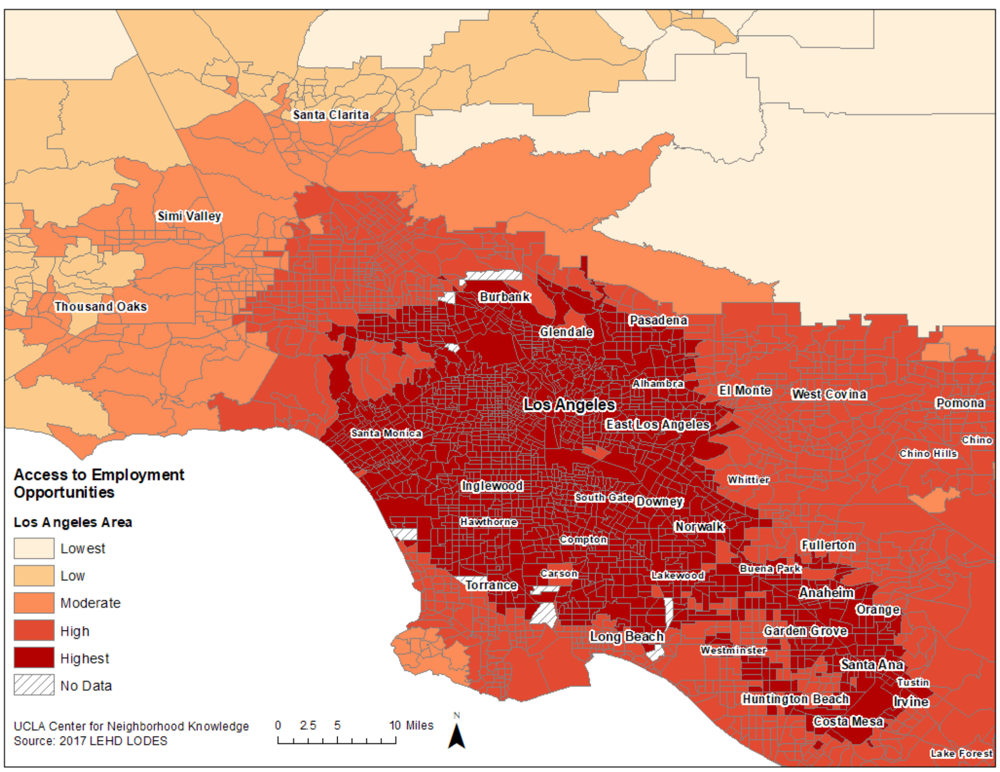


Figure 2-68. Map of Access to Employment Opportunities, Los Angeles Area



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http://lehd.ces.census.gov/. Accessed on January 1, 2022.

2.3.12 Access to High-Quality Transit Location

This subsection documents the construction of the access to high-quality transit locations indicator defined as being within a quarter-mile of transit stops with a high level of service during the morning commute. The indicator includes access to bus, rail, and ferry terminals.

Table 2-22. Summary Table for Access to HQTL Indicator

Key Indicator Information	
Units	Proportion of population in a tract that are within a half-mile catchment area from high-quality transit locations
Category in Mapping Tool	Accessibility
Display Method in Mapping Tool	Ranking to account for clustering at the bottom
Precision	Assumed to be relatively high for locations with sufficient data
Methodological Complexity	Moderately complex involving spatial area estimates.
Geographic Resolution	Point location of transit stop, census blocks for population
Key Information about Data Sources Used to Construct Indicator	
Data Sources Used to Construct	General Transit Feed Specification
Sample Size	Transit schedules are not based on sampling; fair number of location-specific information base on available schedules. GTFS feeds were gathered for 127 transit agencies in the state covering 52 out of 58 counties.
Biases	Does not include many smaller transit agencies.
Geographical Unit	Census tract
Geographic Coverage	Covers all of California
Data Vintage	2017
Other Important Notes (if applicable)	There is no one “go-to source” for transit data for California. GTFS data was gathered from multiple sources including open source and requests made directly to transit agencies. Some agencies do not report their transit data in GTFS format.

<u>Data Source</u>

The access to HQTLs was constructed using transit data from agencies that publish their transportation schedules in GTFS format. GTFS consists of a series of text files that provide information on transit stop locations, scheduled arrivals and departures, routes, and other relevant information such as transit fare. The main purpose behind agencies converting their transit data to GTFS format is to make available their schedules to users of Google Maps, BingMaps, and other trip-planning applications.[31]

[31] For additional details on GTFS and an assessment of the dataset, see Phase I report of the Statewide Monitoring System project - “Identifying, Evaluating, and Selecting Indicators and Data for Tracking Land Use and

GTFS data was gathered for California from multiple sources. The two primary sources are open data sources, Transitland and TransitFeeds, which collect and archive GTFS feeds and make available GTFS for download. These two sites do not always include the same agencies, thus requiring the use of both. GTFS was also acquired from a transit agency by directly contacting the agency (for those agencies that have GTFS but where the data is not available online). Overall, GTFS feeds were gathered for 127 transit agencies, covering 52 of the 58 counties in California and include both bus and rail.[32]

Our best estimate indicates that 54 percent of the agencies in California have open GTFS data. Of the agencies included in the Federal Transit Administration's (FTA) National Transit Database (NTD) (which does not include many small agencies), the 127 transit agencies included the compiled GTFS dataset and represent approximately 97 percent of the unlinked passenger trips traveled statewide.

The tasks involved in compiling a statewide GTFS database are complex and challenging, requiring a significant amount of time and resources to address. There are a number of major problems with GTFS that were identified for this project.

1. **Not all agencies produce GTFS**, particularly small agencies in both rural and urban areas.
2. **Not all GTFS feeds are on a single common data site** (as indicated, GTFS feeds were gathered from multiple sources).
3. **Because of differences in archiving, consistency in the vintage of data** (e.g., schedules do not cover the same dates across all transit feeds) depended on when data was uploaded and downloaded.
4. **Some existing GTFS feeds do not have complete subfiles** (e.g., the calendar file that is one of the required subfiles and that also helps indicate weekday and weekend schedules was missing for some of the GTFS feeds).
5. **Coding practices for GTFS vary among agencies.** While the GTFS standard defines a common format for transit agencies to publish their transit data including what information is required and what is optional, how agencies input this information differs from agency to agency. For example, the "stop_id" field, which is an ID that uniquely identifies a stop, station, or station entrance, is a required field, but agencies differ in how the information is input, with some using numeric values and some using character. The "stop_id" field is a unique ID that is used to merge across the various files in the GTFS including the "schedule" file; some agencies may have it in numeric format in one file but character in another file, causing the files to not merge because the variable "stop_id" is being read as both character and numeric.
6. **Poor documentation.** Other than the generic GTFS documentation provided by Google, which helps explain the types of files that comprise a GTFS transit feed and define the fields used in all those files, there is no publicly available documentation from individual transit agencies explaining the meaning behind some of their coding.
7. **Multiple schedules.** For many agencies, multiple schedules are included in the feeds, but no documentation is provided explaining the differences between these schedules and how to handle them. For the purpose of this project, one schedule should be selected to avoid double counting the frequency at a given transit location.
    a. Some agencies provide multiple schedules, one for weekdays and one for weekends. In this scenario, where there are only two types of schedules, the weekday schedule is selected over the weekend schedule.

Transportation-Related Trends Related to SB 375 Goals" (CARB Agreement No. 15RD010): https://ww2.arb.ca.gov/sites/default/files/classic/research/apr/past/15rd010.pdf.

[32] A list of these transit agencies can be found in Appendix A of Phase II report for the Statewide Monitoring System project - "Developing Statewide Sustainable-Communities Strategies Monitoring System for Jobs, Housing, and Commutes" (Caltrans Agreement No. 65A0636): https://dot.ca.gov/-/media/dot-media/programs/research-innovation-system-information/documents/final-reports/ca18-2931-final-report-a11y.pdf

b. There are occurrences where agencies include more than one weekday and weekend schedule. While the weekend schedule can easily be eliminated, identifying which weekday schedules to use from the GTFS feed oftentimes required more time to determine, especially without proper documentation. In some cases, the weekday schedules are duplicate records, with the same arrival and departure time and the same routes but with different service start and end dates. When these types of scenarios occur, the schedule with the most current start date of the two is selected.
c. Some agencies include separate schedules for services that operate year-round, seasonal schedules (e.g., summer and winter) and school days–only schedules. When these types of schedules are easily distinguishable, the year-round schedule is selected because it is the most consistent schedule throughout the year.
d. Oftentimes, it is difficult to determine what each schedule represents. The start and end service dates, for example, do not differ from one another and none of the files in the GTFS feed give any indication of how the schedules differ. In these cases, additional analysis was done to determine the differences across schedules. For example, each schedule was assessed against the routes file to see if there were any patterns that would give any clues on how the multiple schedules differ. At times, this process did provide some insights into how the schedules differ. For example, some schedules overlapped in the routes they cover but one might cover more routes than the other. Additional investigation included going directly to the agency's website to compare the GTFS to published schedules. In the end, the schedules selected for the access to transit measure is the best that the researchers can do given the resources, time, and limited documentation.

<u>Construction Method</u>

HQTLs. We define *HQTL* as the quarter-mile buffer around any one or more of the following locations:

1. Any existing transit rail station; or
2. A terminal served by a ferry system in major metropolitan areas; or
3. A location with bus service maintaining average headways of 15 minutes or less during morning peak commute; here defined as 6:30 to 8:30 AM on a given weekday.

Construction of the measure includes two key dimensions: a quarter-mile geographic catchment area and level of service (for bus only). *Level of service* is defined as the number of buses that go through the bus stop during the morning peak commute hours on a given weekday. Rail and ferry terminals that are within a quarter mile are automatically designated as a HQTL.
Transportation planners generally accept the quarter-mile distance, equivalent to about a five-minute walk, as the standard distance one is willing to walk to local transit service.

High-Quality Bus Location. A *bus location* is defined as the sum of all bus stops that are in close proximity to each other. Examples of this are the three unique stops displayed in Table 2-23 Each bus stop has slightly different longitude and latitude but is considered as the same location by street intersection (Hollywood and Western). Together, the location is a high-frequency transit location with a total frequency of 36 during the 6:30 to 8:30 AM peak period. To overcome the problem of agencies identifying stops differently (e.g., some agencies identify separate stops that are in close proximity to each other, such as being on opposite corners of an intersection, or different endpoints at a what most would consider a common stop), we merge all nearby stops when their locations are similar, that is, when their longitude and latitude rounded to three digits are identical (a difference of .001 is less than a fifteenth of a mile).

Table 2-23. Determining High-Quality Bus Location

stop_id	stop_name	Latitude	Longitude	Latitude Rounded	Longitude Rounded	Frequency 6:30–8:30 AM
1206	Hollywood/Western	34.10187	-118.30877	34.102	-118.309	0
2493	Hollywood/Western	34.10161	-118.30893	34.102	-118.309	19
11028	Hollywood/Western	34.10186	-118.30902	34.102	-118.309	17
All Stop	**Hollywood/Western HQTL**			**34.102**	**-118.309**	**36**

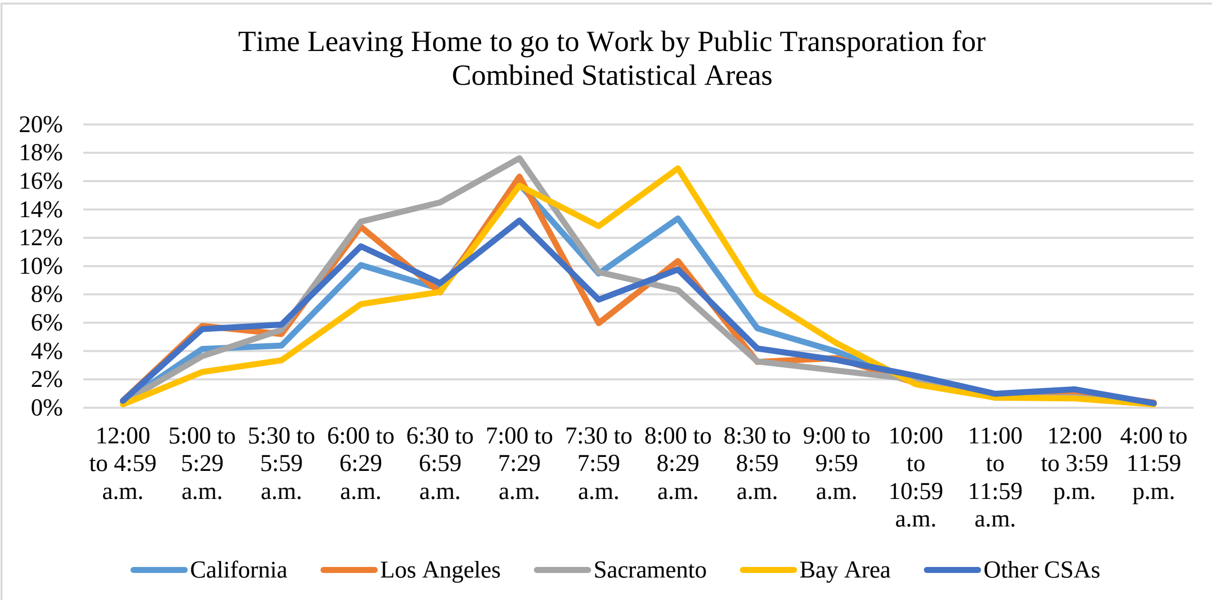
This concept of high-quality transit is related to terminologies defined in the California Public Resources Code relating to "major transit stops" and "high-quality transit" and that are consistent with SB 375:

- 21064.3.[33] "Major transit stop" means a site containing an existing rail transit station, a ferry terminal served by either a bus or rail transit service, or the intersection of two or more major bus routes with a frequency of service interval of 15 minutes or less during the morning and afternoon peak commute periods.
- 21155.[34] "High-quality transit corridor" means a corridor with fixed route bus service with service intervals no longer than 15 minutes during peak commute hours.

The state's definitions do not explicitly define what period falls under morning and afternoon peak hours. These decisions are often left to MPOs or a regional-planning authority to decide. A statewide peak period is hard to nail down considering all the regional variability that exists in terms of commute time. For example, peak periods in the Los Angeles and Bay Area CSAs are much different from the peak periods in Sacramento and even more so than the rural areas. Figure 2-69 showing the time workers leave for work by public transportation, illustrates these regional variations across California.

[33] https://leginfo.legislature.ca.gov/faces/codes_displaySection.xhtml?sectionNum=21064.3.&lawCode=PRC (accessed on January 3, 2022)
[34] http://leginfo.legislature.ca.gov/faces/codes_displaySection.xhtml?lawCode=PRC&sectionNum=21155 (accessed on January 3, 2022)

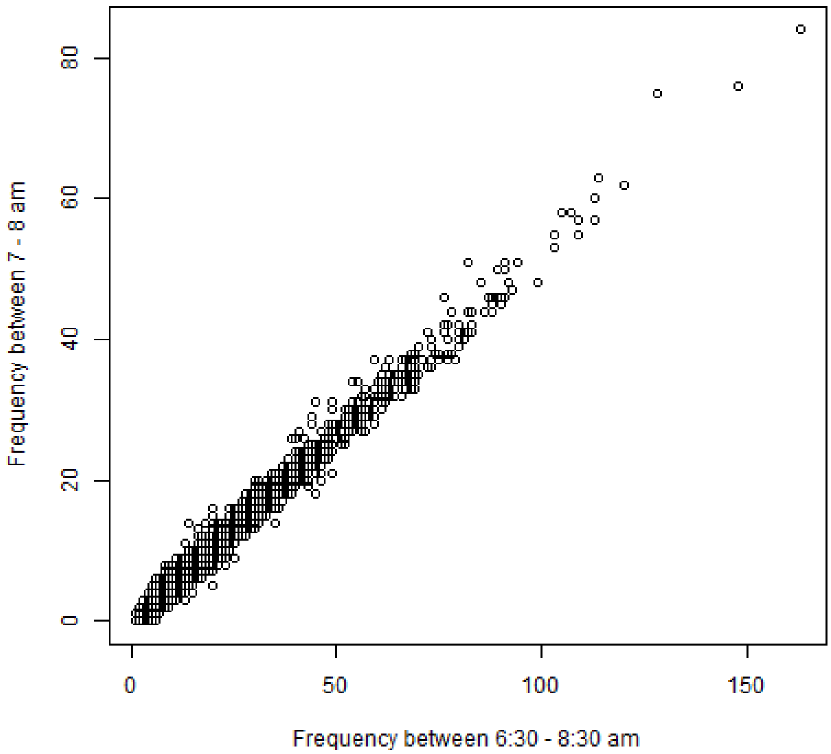
Figure 2-69. Time Leaving Home to go to Work by Public Transportation for Combined Statistical Areas



Source: 2012–2016 five-year ACS

Despite the regional variation in commute hours, a consistent definition for the state of what period constitutes peak hours is needed for a statewide measure. Figure 2-69 was presented to the Advisory Committee for their input on some possible definitions of morning peak hours. Two periods for morning peaking hours were suggested: 6:30–8:30 AM and 7:00–8:00 AM. An assessment of the two periods indicates that they are highly correlated (r = 0.995), which would suggest that choosing one over the other would not make that much of a difference. Figure 2-70 displays the scatter plot comparing the frequencies in stops during 6:30–8:30 AM and 7:00–8:00 AM periods for California as whole. The 6:30–8:30 AM time slot was selected over the 7:00–8:00 AM time slot because this period captures most of the region’s morning peak hours. Although the state’s definition includes both morning and afternoon peak hours, this research only focuses on morning peak hours due to limited time and resources. There is also the challenge of defining afternoon peak hours, as there are even further regional variations than morning peak hours.

Figure 2-70. Comparing Transit Frequencies by Locations between 6:30–8:30 AM and 7:00–8:00 AM



Identifying High-Quality Transit Stops for Counties with no GTFS

We used GTFS data to identify HQTLs, but there were counties with no GTFS data coverage. For these, a different method was adopted by using printed bus schedules online. This section describes the methodology to identify high-quality bus stops for those agencies with no GTFS data for the following six counties that do not have GTFS coverage: Alpine, Colusa, Glenn, Imperial, Sierra, and Mono.

For each of these counties, we identified the largest transit agency that serves the county. Due to limited resources and time, we only looked at the largest agency in the county but acknowledged that a county may be served by more than one transit agency. Published schedules, often made available on the agency's website, were collected and downloaded. Many of these schedules are in .pdf format, which required us to convert the paper schedules into an Excel format or similar formats to be readable in ArcGIS and SAS, the two primary analytical software programs used for this project. This process required a considerable amount of time to ensure that each schedule was converted correctly. Agencies were directly contacted to ask if they had their schedules in an Excel format, but many directed us to the online .pdf schedules.

It is important to note that not all bus stops are reported in the printed schedules. Bus stops on major streets or intersections are generally the ones that are reported. Stops located on non-major streets or intersections with fewer routes serving the stop are often omitted from the printed schedules. For each stop, we first determine whether the stop is considered "high quality" based on the definition used for this project.
For each stop, we first identify all routes that serve the bus stop and extract their schedules. Some bus stops are served by more than one route. From this, a matrix is created with the stop names. Only morning schedules, between 6:30 to 8:30 AM, were extracted because this is the time frame used in CNK's HQTL definition. Table 2-24 provides an example of this.

Table 2-24. Stop Time Table for High-Quality Stops in Imperial County

7th Street and State		Imperial Valley College		3rd Street and Paulin	
Arrival Time	Route	Arrival Time	Route	Arrival Time	Route
6:58	Green Line	7:00	21 IVC Express	6:30	21 IVC Express
6:58	Blue Line	7:15	21 IVC Express	6:30	32 Direct AM
7:00	45 West	7:26	3 West	6:45	21 IVC Express
7:00	1 North	7:30	22 IVC Express	6:55	1 North
7:10	41 South	7:35	2 South	7:20	31 Direct AM
7:10	Blue Line	8:00	4 East	7:40	21 IVC Express
7:10	1 South	8:10	21 IVC Express	7:45	1 North
7:10	Green Line	8:25	21 IVC Express	7:50	32 Direct AM
7:40	4 East	8:30	2 North	7:55	21 IVC Express
7:45	1 South			8:20	1 North
7:55	1 North			8:30	31 Direct AM
7:55	2 South			8:30	21 IVC Express
8:00	4 East				
8:00	3 West				
8:08	Green Line				
8:08	Blue Line				
8:10	3 East				
8:10	2 North				
8:20	1 South				
8:20	Green Line				
8:20	Blue Line				
Frequency = 21		Frequency = 4		Frequency = 7	
High Quality		**Not High Quality**		**Not High Quality**	

Notes: Imperial Valley College (IVC) Express operates on school days only. Because IVC Express only operates on school days, its schedule is excluded. Only services operating year-round are included in CNK's HQTL. Imperial Valley College and 3rd Street and Paulin bus stops do not qualify as high quality because the frequency of stops does not meet nine or more stops during the morning peak hours.

For each bus stop, the number of stop schedules during the 6:30 to 8:30 AM time frame was summed up. If the sum of stops exceeds nine, then the stop is designated as high quality. It is important to note that this process only identifies high-quality bus stops and not locations. For this project, we look at high quality transit locations. As noted before, a location includes all nearby bus stops where both the longitude and latitude when rounded to three digits are identical. If their sum of stops exceeds nine then the location is designated as high quality.

Unlike GTFS data, where information on a stop's geographic location by latitude and longitude is given, the printed schedules do not include this information. Only the names of the bus stop, which are oftentimes the street name or intersection that the stop is located on, are listed in the printed schedules. As such, it is difficult to apply the location method of rounding latitude and longitude, when this information is not provided.

Table 2-25 reports the total number of high-quality bus stops for the six counties that have no GTFS data. The transit agency used for this analysis is listed in the table. Of all six counties, only Imperial County had bus stops that qualified as being high quality.

Table 2-25. High-Quality Stops Number and Transit Agency for Counties without GTFS

	Number of High-Quality Stops
Alpine	
Alpine County Dial-a-Ride	0
Colusa	
Colusa County Transit (dial-a-ride)	0
Glenn	
Glenn Transit Service	0
Imperial	
Imperial Valley Transit	1
Sierra	
Sierra County Transportation Commission	0
Mono	
Eastern Sierra Transit	0

Again, this process only identifies high-quality stops and not locations. It may be the case that some of the agencies listed in the following text might have HQTL when all nearby bus stops are added together, but this is difficult to determine without all the necessary information, including the schedules for stops not listed in the printed schedules.

Assessment of Consistency

An important part of constructing any indicator is an assessment and evaluation of the indicator to external sources. This process allows us to test the robustness of our indicator and to make refinements and modifications to the methodology where needed. One approach to assessing and evaluating the HQTL indicator is to compare it to similar indicators constructed by MPOs, particularly those that have been done by the two largest MPOs in the state: Metropolitan Transportation Commission (MTC) and Southern California Association of Governments (SCAG). MTC, for example, makes available two shapefiles related to our high-quality transit measure: (1) major transit stops and (2) high-quality transit corridors. Only the major transit stops' shapefile was assessed against our measure. SCAG provides a shapefile for high-quality transit areas.

What we find is that our high-quality transit indicator covers a large proportion of both MTC's and SCAG's transit measures and that our measure captures more area. We find differences, but these differences are understandable. For example, some of the discrepancies are due to differences in transit data sources, agencies covered, methods and calculations, and definitions. MTC, for example, uses transit data from 511 Regional Transit Database while we use GTFS. SCAG uses GTFS but only covers a small number of transit agencies compared to our high-quality indicator. MTC also did not cover as many agencies as we did.[35] There are also differences in methods and calculations. For example, there are differences in the concept of locations. MTC uses individual stops while location in our approach can include multiple transit stops. Differences in definitions, such as what hours constitute peak hours, also have a major impact on consistency between agencies. SCAG, for example, uses both morning and afternoon peak hours, while our measure only includes the morning commute.[36] SCAG also defines morning peak hours differently than the

[35] This discrepancy may be due to MTC's more narrow definition of high-quality transit. While all Bay Area operators may be represented, some may not provide frequent enough service to qualify as "high quality" by this project's definition.
[36] There are some limitations to focusing only on peak hours (e.g. capturing transit stops that serve only commuters and may exclude members of the general public who rely on transit during off-peak times; capturing commuter bus

definition used for this project. SCAG defines morning peak hours as 6:00 to 9:00 AM and MTC defines morning peak as 6:00 to 10:00 AM. Our measure includes 6:30 to 8:30 AM.[37]

Despite these differences and limitations described earlier, the access to HQTLs indicator constructed for this project, to the best of our knowledge, is perhaps the most comprehensive access to transit measure available for the state. In particular, we do not know of any access to high-quality transit metric that has been created for the state. Some MPOs have created their own measures but each vary in their data source, methods, and have slightly different definitions of what is considered high quality. Additionally, CNK's HQTL measure covers more transit agencies even more so than for those constructed by some of the MPOs. Although not perfect, the HQTL measure includes a consistent method and definition.

Results

Unlike previous indicators, the access to HQTL indicator cannot be evenly distributed into ordinal deciles because the very bottom range of accessibility (no access to HQTL) has a cluster of census tracts that comprises more than 10 percent of total tracts. Because of this clustering, we create a separate category for tracts with no access to HQTL and then distribute the remaining tracts across nine ordinal categories, from very low access to complete access.

There are two notable patterns. First, HQTLs are completely absent in approximately four-in-ten census tracts. (These neighborhoods could have some transit service, but not sufficiently frequent to be designated as being HQTL.) Approximately a tenth of the tracts in the state are areas where all residents within a given tract have access to HQTL.

Figure 2-71 displays the median proportion of the population with access to HQTL for each of the neighborhood ranking categories. Neighborhoods that fall in the "0" category represent census tracts where none of the residents have access to HQTL. Neighborhoods that fall in the category designated with a "9" represent census tracts where all residents have access to HQTL.

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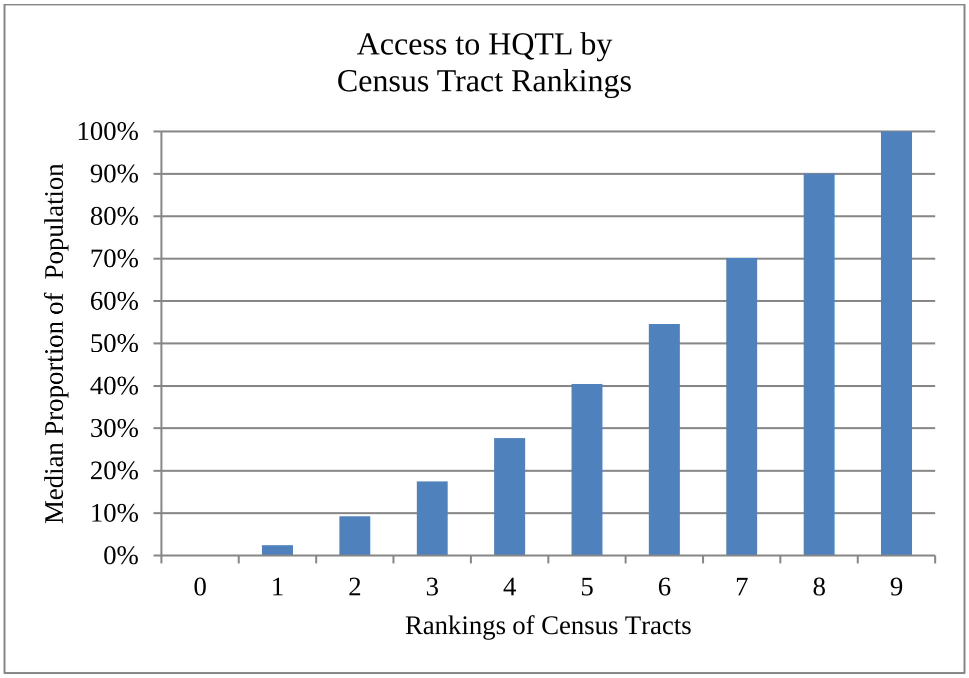
service as high-quality during commute hours which can differ from all-day frequent service). However, since the focus of this project is work-related travel, we focus on morning peaks to best capture these commute trips.

[37] Additional details on the external verification process can be found in Appendix A of Phase II report for the Statewide Monitoring System project - "Developing Statewide Sustainable-Communities Strategies Monitoring System for Jobs, Housing, and Commutes" (Caltrans Agreement No. 65A0636) visit: https://dot.ca.gov/-/media/dot-media/programs/research-innovation-system-information/documents/final-reports/ca18-2931-final-report-a11y.pdf

Figure 2-71. Proportion of Population with Access to HQTL by Census Tract Rankings



Maps

The following maps display the access to HQTL indicator by census tract.

California
Residents in rural areas and non-urban areas tend to have low access to HQTL. This is not surprising since they have low population density that cannot support frequent transportation services. (See Figure 2-72)

Bay Area
In the Bay Area, neighborhoods with greatest transit services are areas with highest population and job density (e.g. areas around downtown San Francisco and downtown Oakland). Suburban and exurb areas have less access to HQTL. (See Figure 2-73)

Los Angeles
In the Los Angeles area, neighborhoods with the greatest transit services are areas with highest population and job density (e.g. areas around downtown Los Angeles). Suburban and exurb areas have less access to HQTL. (See Figure 2-74)

Figure 2-72. Map of Access to High-Quality Transit Locations, all of California

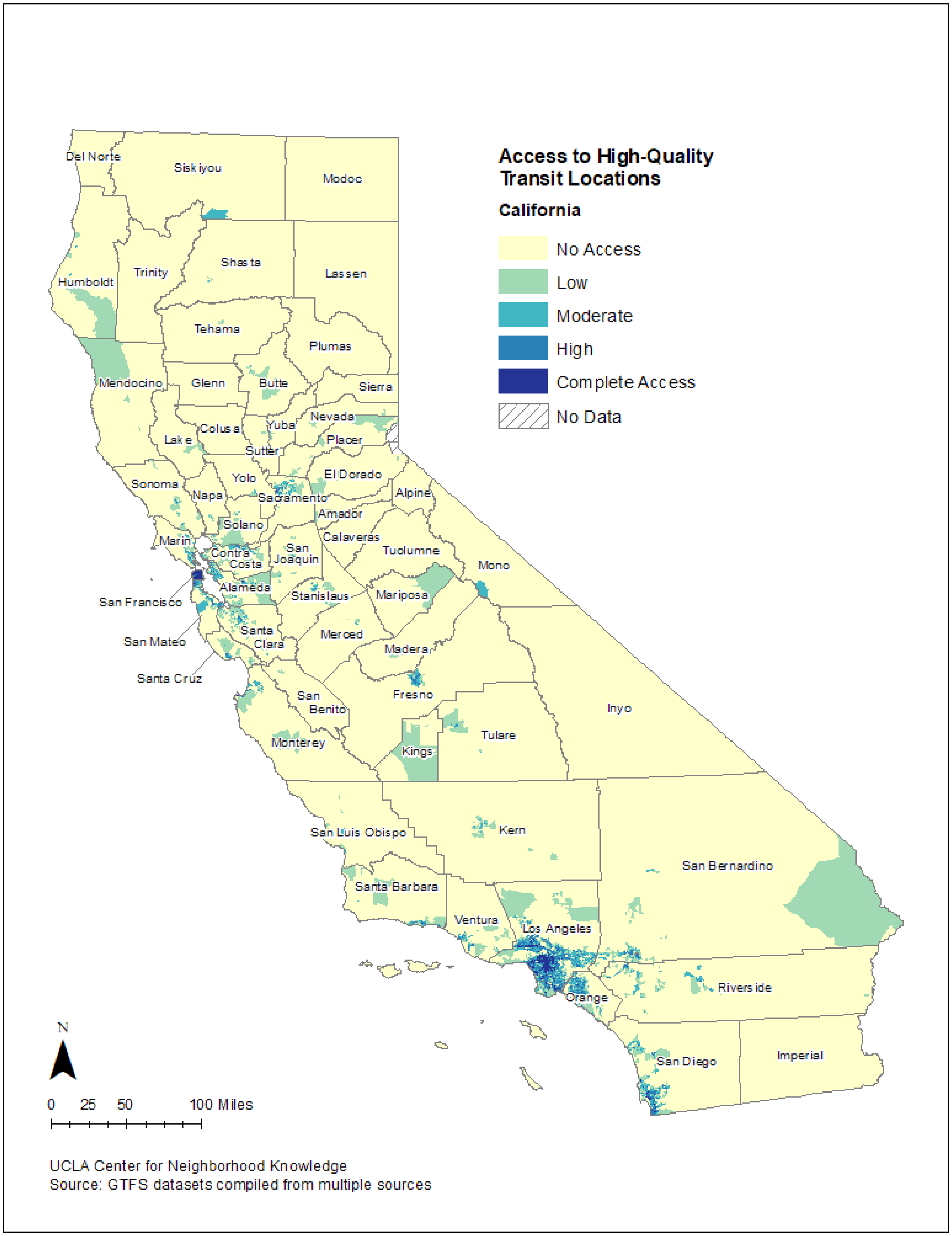


Figure 2-73. Map of Access to High-Quality Transit Locations, San Francisco Area

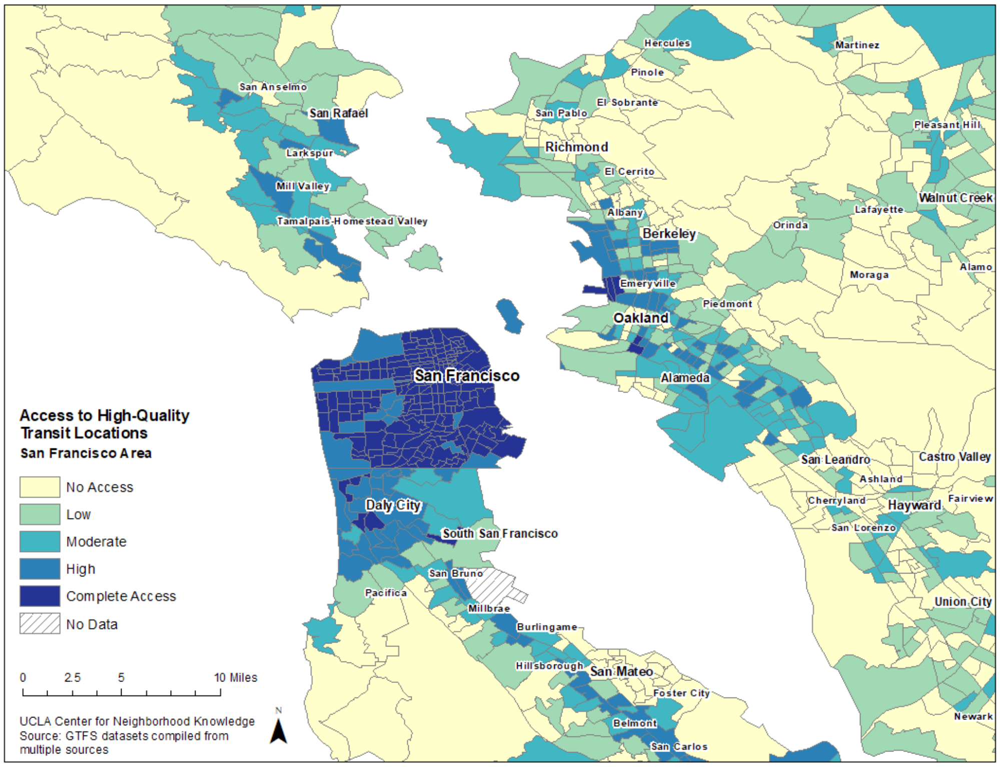
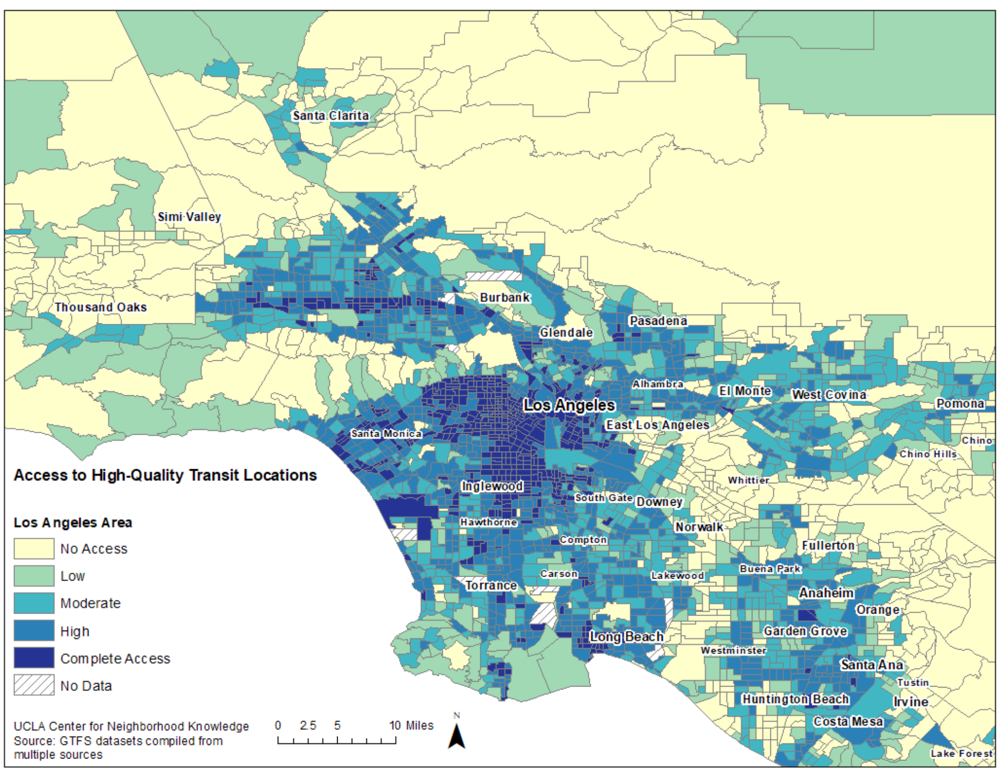


Figure 2-74. Map of Access to High-Quality Transit Locations, Los Angeles Area



2.3.13 Jobs-Housing Fit

This subsection documents the construction of the jobs-housing fit indicator. This indicator analyzes the nexus between affordable housing and job commutes for workers at the lower end of the labor market (e.g., low-wage workers or workers with low earnings). Our indicator adjusts for regional differences in the labor and housing markets.

Table 2-26. Summary Table for Jobs-Housing Fit Indicator

Key Indicator Information	
Units	Ratio of low-wage jobs within a tract relative to the availability of nearby affordable rental housing
Category in Mapping Tool	Accessibility
Display Method in Mapping Tool	Decile (visualized in quintiles)
Precision	Assumed to be relatively fair
Methodological Complexity	Moderately complex involving multiple imputations, data matching and allocations.
Geographic Resolution	Census tract
Key Information about Data Sources Used to Construct Indicator	
Data Sources Used to Construct	CTPP and ACS
Sample Size	Relies on ACS data that is based on a sample (approximately 12% of population)
Biases	May be affected by short-term business cycle
Geographical Unit	Census tract
Geographic Coverage	Covers all of California
Data Vintage	2006-10 for CTPP and 2008-12 for ACS
Other Important Notes (if applicable)	Due to differences in housing costs and distribution of low-wage workers throughout the state, the jobs-housing fit indicator is regionally adjusted to account for these differences.

The indicator measures the relative number of low-wage jobs to the availability of nearby affordable housing. If there is a lack of affordable housing, then workers are forced to commute longer distances. Where there is a better spatial match of jobs and housing, we expect a higher likelihood for reduced travel and congestion (also fewer GHG and pollutant emissions, and lower travel costs for commuters). Where there is an imbalance, we can expect increased commutes, congestion, and emissions because a shortage of nearby jobs will mean more residents having to find work farther away and, similarly, a shortage of nearby housing at job centers will mean fewer residents have the option of living near their place of work. This measure of the degree of mismatch between earnings and affordability focuses specifically on low-wage earners. Low-earners, on average, drive older, less fuel-efficient vehicles. The environmental benefits come from decreasing the VMT of these less fuel-efficient vehicles. On top of this, the focus on low-earners allows for consideration of equity issues in transportation and housing, as higher transportation costs impose the greatest burden on low-earners.

To the best of our knowledge, no jobs-housing fit measure has been constructed for the state. Existing and related works have focused largely on a specific region. CNK's jobs-housing fit measure fills this gap by constructing a statewide jobs-housing fit measure with regional adjustments to account for differences in the cost of living throughout the state.

Data Source

We relied on two publicly available datasets to construct the jobs-housing fit measure. Data on jobs by earnings level were derived from the 2006–2010 five-year Census Transportation Planning Products (CTPP), which is based on the ACS 2006–2010 five-year estimates. Data on housing units by rent levels come from ACS 2008–2012 five-year estimates. Both datasets represent five-year averages.[38]

CTPP was chosen over LEHD, another widely used data source for job counts, because CTPP has more detailed information on earnings levels. For example, CTPP covers nine different earnings levels while LEHD only covers three levels of earnings. The lowest monthly earning category reported in LEHD is $1,250 or less, which is equivalent to $15,000 per year. Recent studies (Benner and Karner, 2016) on the jobs-housing balance have used this earnings category to define low-earners. Unfortunately, using this earnings cutoff throughout the state creates inconsistencies across counties. The proportion of workers that make less than $1,250 per month varies from a low 13.5 percent (San Francisco) to a high 40 percent (Mono) across counties in California. This wide variation means that we are not looking at equivalent bottom segments of the labor force.

Construction Method

Multiple steps were taken to construct the jobs-housing fit indicator. They are described as follows.

1. **Identify analytical regions for regional adjustments.** Due to differences in housing costs and distribution of low-wage workers throughout the state, the jobs-housing fit index required constructing specific regional adjustments to account for these differences. Combined statistical areas (CSAs) were used as the core to determine the different regions into which to assign counties. The Census Bureau defines *CSAs* as "consisting of two or more adjacent metropolitan and micropolitan statistical areas that have substantial employment interchange,"[39] In other words, CSA can be considered an integrated regional economy. Counties that do not fall in a CSA were either assigned into the region that was geographically nearby or shares similar characteristics. Figure 2-75 displays the six analytical regions used to construct the jobs-housing fit indicator.

[38] Census tract–level data from the ACS are only reported through its five-year estimates due to sample size. The 2006–2010 CTPP is based on the 2006–2010 five-year ACS.
[39] https://www.census.gov/geo/reference/webatlas/csa.html. Date accessed: September 12, 2018

Figure 2-75. Map of Analytical Regions for Calculating Jobs-Housing Fit Index

2. **Determine the earnings cutoffs that represent the bottom quintile of the labor force for each region.** We define *low-earnings jobs* as jobs with earnings that fall within the bottom fifth of the labor force within each analytical region. For our purpose, they are equivalent to low-earners. The earnings cutoff that defines the bottom fifth of the labor force varies across regions due to variations in the cost of living. For example, the earnings level that corresponds roughly to the bottom fifth of the labor force in the Bay Area is $18,000 and $11,000 for Northern California. For the state as a whole, jobs with earnings of no more than $15,000 constitute the bottom fifth. The earnings cutoffs for each region were determined using interpolation and each earnings level is rounded to the nearest thousand.

3. **Determine maximum rent level for each region.** For each region, we determine the equivalent maximum rent that a low-earner can pay given their earnings level. We focus on rental units because workers with low earnings are more likely to be renters than homeowners. We adopt Benner and Karner's approach of calculating the maximum rent levels that can be afforded by those with low earnings. Benner and Karner use a combination of a standard definition of housing affordability and some multiple of the monthly low-earnings category to derive an affordable monthly rent cutoff for low-earners. The authors adopt the 30-percent rule to define *affordability*—that is, an affordable rental home is one in which the household pays no more than

30 percent of its income on housing and utility costs. This definition of *affordability* is the most widely adopted standard and is used by many government agencies. For example, the Department of Housing and Urban Development (HUD) and local public housing agencies use this standard in their administration of rental assistance programs including Section 8 HCVs. Along with this definition of *affordability*, Benner and Karner also adopt the approach where rent does not exceed two times the monthly threshold of the low-earnings category.[40] Table 2-27 lists the earnings cutoff that constitutes low-earners in each region (roughly the bottom quintile of the labor force for each region) and their equivalent maximum monthly rent. Using a modified version of Benner and Karner's approach, an affordable monthly rent for a low-earner in Southern California with annual earnings of $15,000 or less would be $750. All rental units with rent levels at or below the maximum monthly rent are designated affordable rental units. As such, total affordable rental units is the sum of all rental units with rents level at or below the maximum rent determined for the region.

Table 2-27. Cutoffs for Low-Earners and Maximum Monthly Rent by California Regions

	Annual Earnings	**Maximum Monthly Rent**	**Maximum Monthly Rent Calculation**
California	15,000	750	(30% × 15,000/12) × 2
Northern CA +	11,000	550	(30% × 11,000/12) × 2
Sacramento	15,000	750	(30% × 15,000/12) × 2
Bay Area	18,000	900	(30% × 18,000/12) × 2
Central Valley	12,000	600	(30% × 12,000/12) × 2
Coastal	13,000	650	(30% × 13,000/12) × 2
SoCal	15,000	750	(30% × 15,000/12) × 2

Low-earnings jobs-housing fit: For each tract, we use a catchment area defined as a 2.5-mile buffer around the tract's centroid. The metric is the ratio of the total number of low-earnings jobs within a 2.5-mile buffer[41] of a census tract to the total number of affordable rental units. The indicator should be interpreted as the characteristics of the larger geography that surrounds that tract, including the tract's own characteristics. It has similarity to a spatial moving average.

Assessment of Consistency

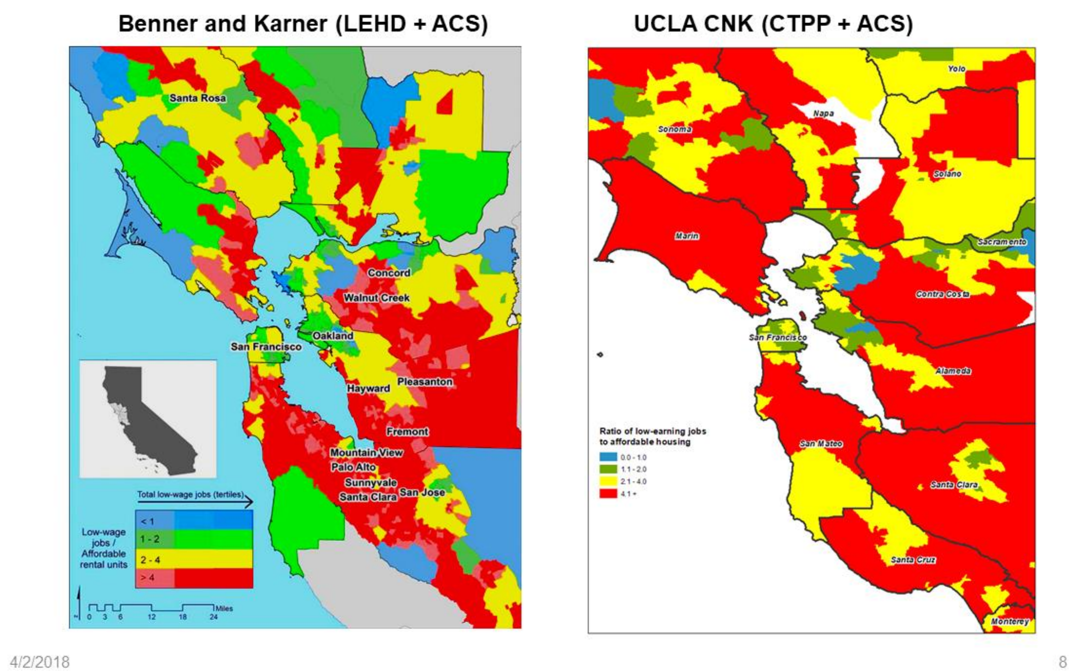
An important part of constructing any indicator is an assessment and evaluation of the indicator to external sources. This process allows us to test the robustness of our indicator and to make refinements and modifications to the methodology where needed. One external source that was suggested by the Advisory Committee for the CARB/Caltrans project is the jobs-housing fit index that was constructed by Benner and Karner's for the Bay Area. We originally adopted Benner and Karner's method of calculating jobs-housing fit but found that the method could not be applied to the whole state. CNK's jobs-housing fit index is a

[40] Karner and Benner use LEHD data which uses a $1,250/month wage threshold (equivalent to an annual income of $15,000). Taking into account the characteristics of the San Francisco Bay Area's jobs-to-housing ratio and the composition of jobs per household, the authors experimented with using a threshold that is 1.2 times and 1.5 times LEHD's $1,250/month. These produced annual incomes well below what is defined by the area's affordable housing developers as low-income. Given this, the authors set their low-wage threshold at two times $1,250/month, defining low-income with an annual income threshold of $30,000.
[41] The 2.5-mile straight-line distance of the population-weighted centroid of a census tract.

modified version of Benner and Karner's method as well as earlier works on jobs-housing fit/balance including the work done by Cervero (1989, 2006).

This section evaluates CNK's jobs-housing fit measure against Benner and Karner. Figure 2-76 compares CNK's jobs-housing fit measure against Benner and Karner's index for the Bay Area. The two measures are fairly consistent, particularly within the major urban areas including the East Bay and San Francisco. The differences between the two, mainly in the less urban areas, may be related to the differences in job counts between the two different datasets being used. Benner and Karner uses 2011 LEHD LODES for jobs while our metric relies on 2006–2010 five-year CTPP. CTPP includes workers not in the unemployment insurance (UI)/disability insurance (DI) system, such as many agriculture workers. This could contribute to a higher jobs-housing fit index in less urban areas. CTPP also includes self-employed, thus a possible job-housing ratio in areas with relatively more self-employed workers such as in the Silicon Valley. LEHD only reports job counts that receive UI/DI and does not include the self-employed.

Figure 2-76. Map Comparing CNK's Jobs-Housing Fit Index to Benner and Karner's Index for the Bay Area



The differences may also be due to differences in housing data used. Housing unit data for Benner and Karner's jobs-housing fit metric comes from the 2007–2011 five-year ACS. CNK's also uses the ACS data but a different vintage—the 2008–2012 five-year ACS.

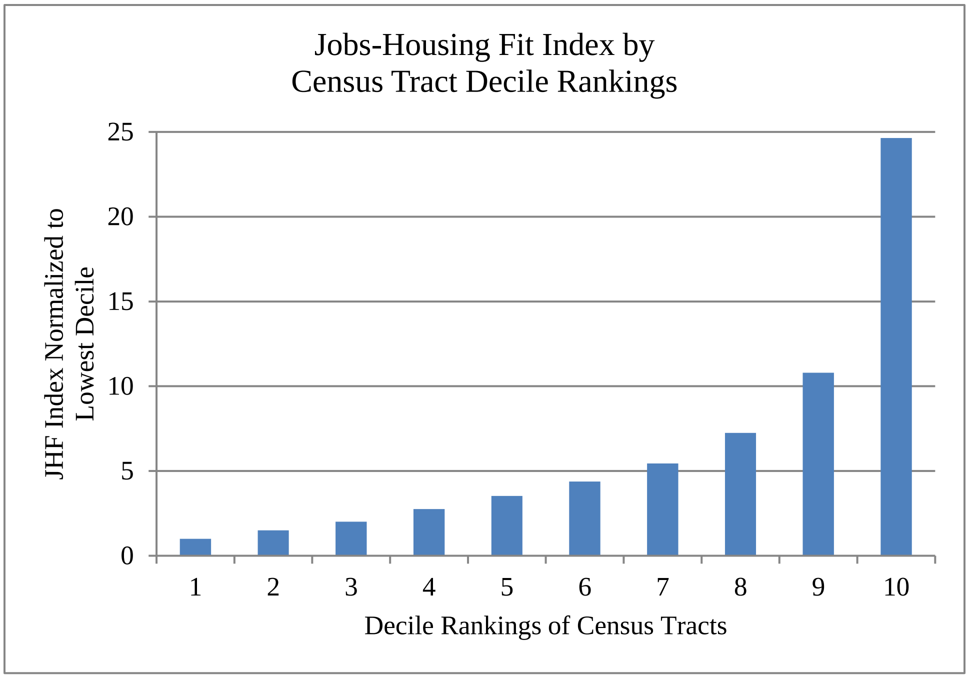
Differences in the definitions for what constitute low-earners and affordable rental units are also some possible reasons that may explain the differences between the two measures. Benner and Karner define *low-wage jobs* as jobs with monthly earnings of $1,250 or less which is equivalent to $15,000 per year. Rather than using one earnings cutoff and applying it for the whole state to define *low-earners*, CNK's defines *low-earners* with earnings that fall roughly within the bottom one-fifth of the labor force. Benner and Karner use a cutoff of $750 per month as the cutoff for affordable housing. Any rental units with rent levels at or less than $750 would be considered "affordable" in the Bay Area. As with defining low-earners, CNK uses a different rent-level cutoff for each region to determine what constitutes affordable rental units.

CNK uses a cutoff of $950 per month as the maximum monthly rent for low-earners in the Bay Area, although the *Bay Area* is defined differently than the definition used by Benner and Karner.

Results

California census tracts are categorized into ordinal deciles according to each tract's calculated jobs-housing fit index. Each decile category represents roughly 10 percent of the census tracts in California. Higher deciles represent neighborhoods with the most affordable housing deficit relative to the number of low-wage jobs, and the lower deciles represent neighborhoods with a deficit of low-wage jobs relative to the amount of affordable rental housing. Figure 2-77 compares the median JHF index in each decile category normalized by the lowest decile. A value greater than one indicates that the JHF index is higher than the lowest decile category by that value.

Figure 2-77. Jobs-Housing Fit Index by Census Tract Decile Rankings



Maps

The map displays the jobs-housing fit index by census tract. California census tracts are divided into five quintiles based on the tract's jobs-housing fit index. Each quintile contains roughly 20 percent of all census tracts in the state. Neighborhoods in the highest quintile represent areas with the most affordable housing deficit relative to the number of low-wage jobs and neighborhoods in the lowest quintile are areas with the most low-wage jobs deficit relative to the amount of affordable rental housing.

California

California's major metropolitan areas visually appear to have the highest affordable housing deficit, while more rural areas show a low-wage jobs deficit relative to the amount of affordable rental housing. (See Figure 2-78). This may partially be due to the fact that many of the rural areas are geographically large with small populations.

Bay Area

In the Bay Area, neighborhoods where there is a scarcity of affordable housing relative to low wage jobs tends to be in the urban areas (e.g. eastern part of San Francisco and the western part of East Bay). Neighborhoods outside of the urban core tend to have the opposite patterns (e.g. eastern parts of the East Bay and parts of Marin County). (See Figure 2-79)

Los Angeles

The urban core of Los Angeles and Long Beach has a relative deficit of low wage jobs, and neighborhoods in the surrounding rings have the opposite (e.g. the coastal neighborhoods). (See Figure 2-80).

Figure 2-78. Map of Jobs-Housing Fit Index, California

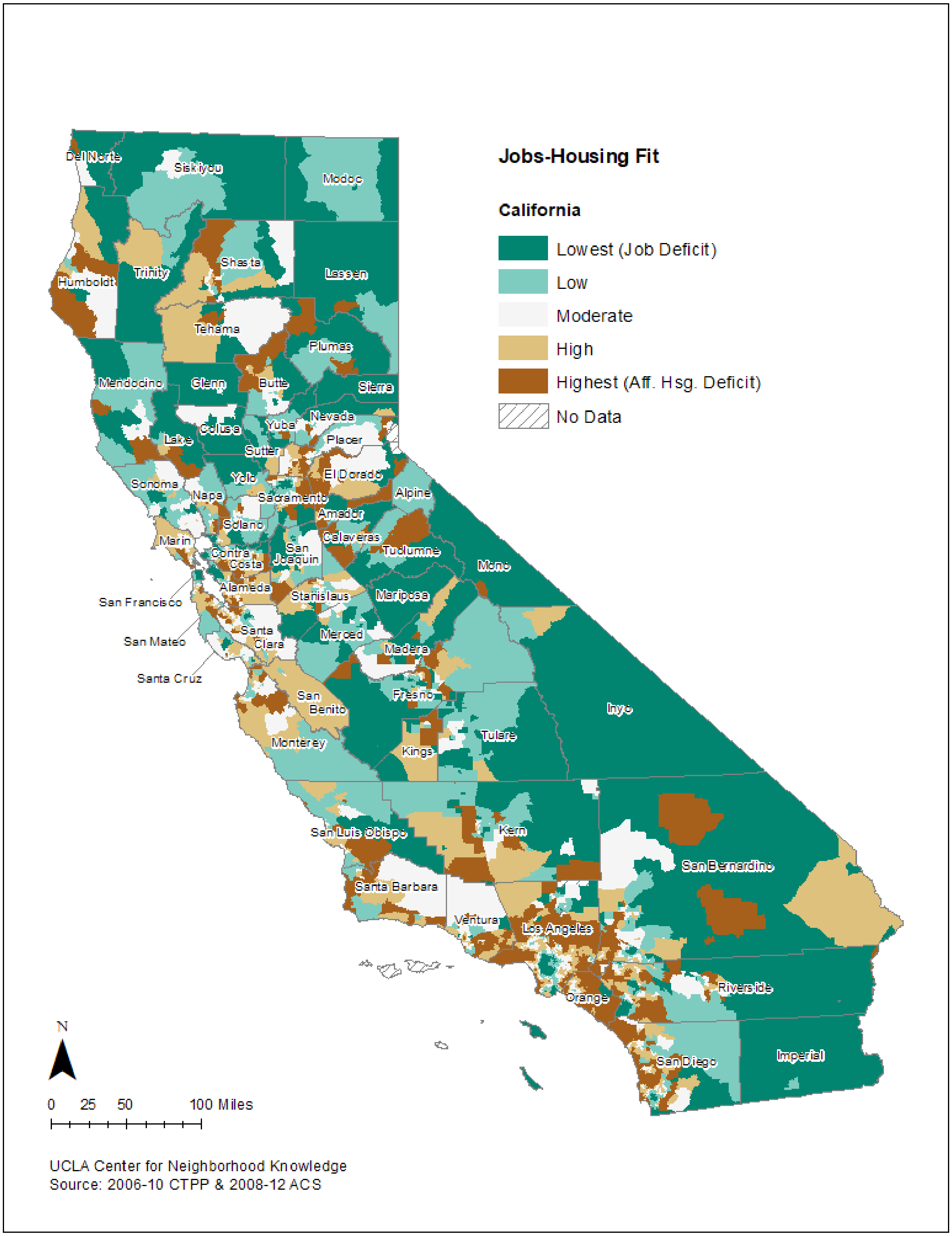


Figure 2-79. Map of Jobs-Housing Fit Index, San Francisco Area

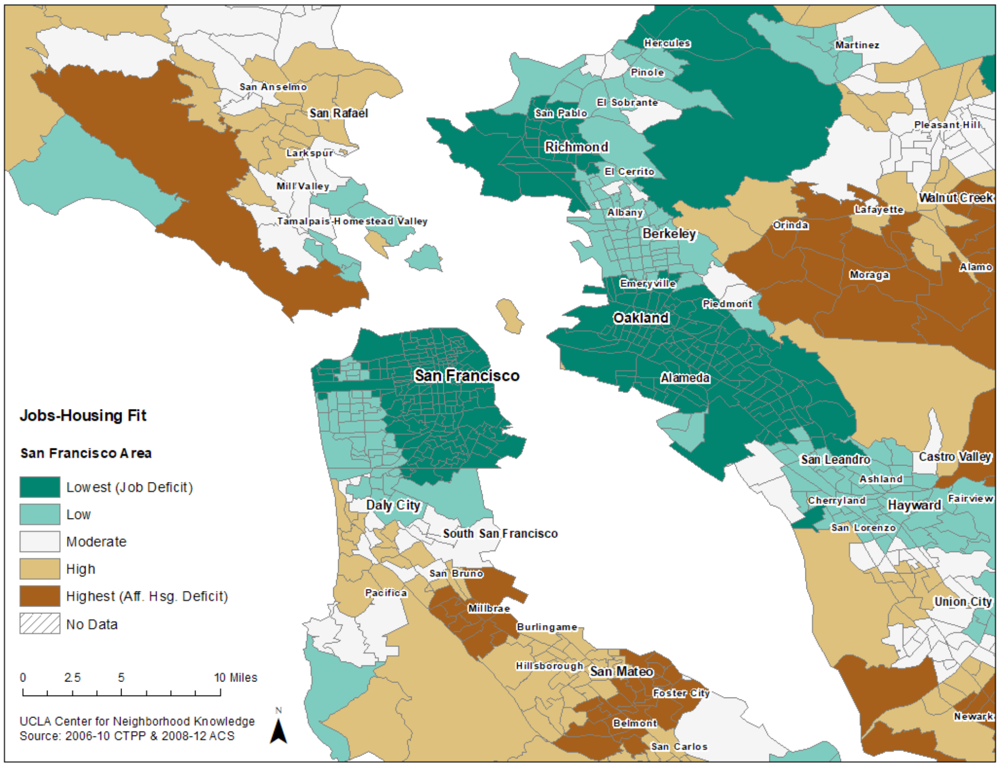
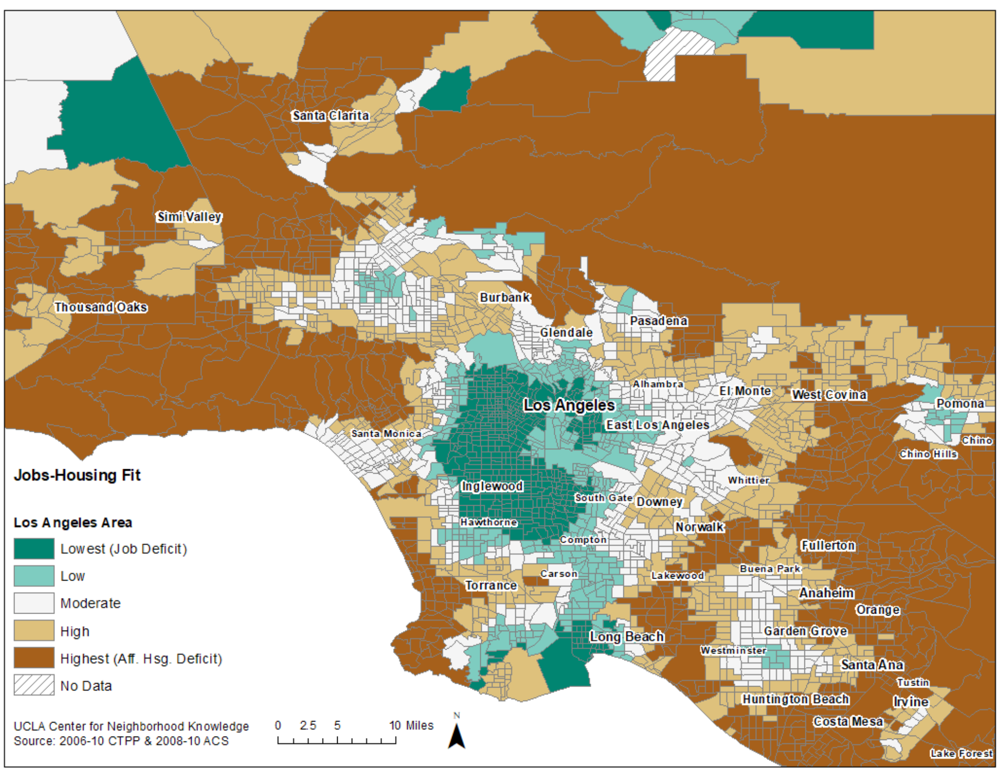


Figure 2-80. Map of Jobs-Housing Fit Index, Los Angeles Area



References

Benner, C., & Karner, A. (2016). Low-wage jobs-housing fit: identifying locations of affordable housing shortages. *Urban Geography*, *37*(6), 883-903.

Cervero, Robert. “Jobs-housing balancing and regional mobility.” *Journal of the American Planning Association* 55.2 (1989): 136–150.

Cervero, Robert, and Michael Duncan. “Which Reduces Vehicle Travel More: Jobs-Housing Balance or Retail-Housing Mixing?” *Journal of the American Planning Association* 72.4 (2006): 475–490.

2.3.14 Job Density

This subsection documents the construction of the job density (jobs per square mile) indicator.

Table 2-28. Summary Table for Job Density Indicator

Key Indicator Information	
Units	Number of jobs per square mile
Category in Mapping Tool	"Socio-Demo-Econ"
Display Method in Mapping Tool	Decile (visualized in quintiles)
Precision	Assumed to be relatively high
Methodological Complexity	Simple calculation of density
Geographic Resolution	Census blocks aggregated into Census tracts
Key Information about Data Sources Used to Construct Indicator	
Data Sources Used to Construct	LEHD LODES (jobs) and U.S. Census Bureau (land area for tracts)
Sample Size	Jobs data not based on sampling; large number of observations based on administrative data
Biases	Jobs data does not include workers outside of the UI/DI programs. May be affected by the short-term business cycle.
Geographical Unit	Census tract
Geographic Coverage	Covers all of California
Data Vintage	2017
Other Important Notes (if applicable)	Counts of jobs represents "All Jobs" (includes both public and private and primary and secondary jobs)

<u>Data Source</u>

Jobs data is derived from the 2017 Workplace Area Characteristics file in LEHD LODES. The WAC file shows where jobs are physically located. This data is available down to the census block level and was aggregated to the census tract for this project. (See description of LEHD dataset in the job access section). Census tract information on land area in square miles comes from the U.S. Census Bureau.

<u>Construction Method</u>

We compute job density as the number of jobs divided by a census tract geographic area in square miles.

$$(\text{Job Density})_i = J_j / A_i$$

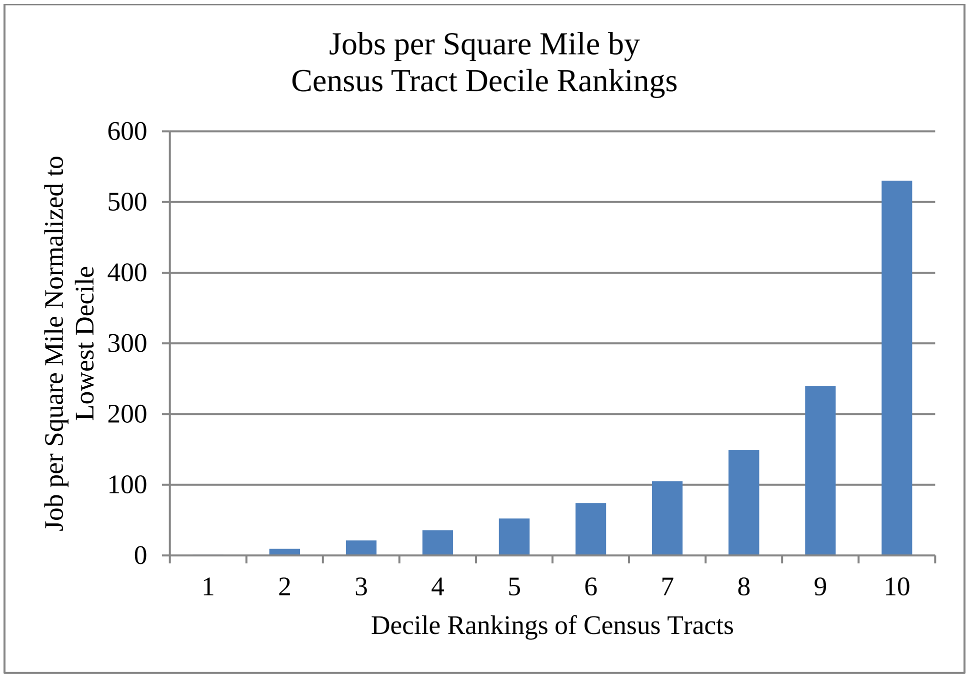
For census tracts j = 1 .. n

J is the number of jobs reported by LEHD, and A is the area.

<u>Results</u>

California census tracts are categorized into ordinal deciles according to each tract's job density measure. Each decile category represents roughly 10 percent of the census tracts in California. Figure 2-81 compares the median job density in each decile category normalized by the lowest decile. A value greater than one indicates that the job density for that decile is higher than the lowest decile category by that value. For example, the median job density in the highest area is over 500 times as great as in the lowest area, representing neighborhoods with the most concentrated jobs.

Figure 2-81. Jobs per Square Mile by Census Tract Decile Rankings



Maps

The following maps displays job density (jobs per square mile) by census tracts. California census tracts are divided into five quintiles based on the tract's job density measure. Each quintile contains roughly 20 percent of all census tracts in the state. Neighborhoods in the highest quintile represent areas where job density is highest and neighborhoods in the lowest quintile are areas where job density is lowest.

California
On the state level, job density tends to be higher in the urban areas. Rural areas have less jobs and jobs are more geographically dispersed. (See Figure 2-82)

Bay Area
In the San Francisco area, neighborhoods with the highest job density are concentrated around central business districts (e.g. the downtown areas of San Francisco and Oakland) and around other employment centers (e.g. the sites for high tech firms). (See Figure 2-83)

Los Angeles Area
In the Los Angeles area, neighborhoods with the highest job density are concentrated around central business districts (e.g. the downtown areas of Los Angeles and Orange county), major employment centers (e.g. sites for firms in the entertainment industries), and business corridors (e.g. Wilshire corridor

in Los Angeles). There are neighborhoods within the urban core with low job density such as South LA. (See Figure 2-84)

Figure 2-82. Map of Jobs per Square Mile, all of California

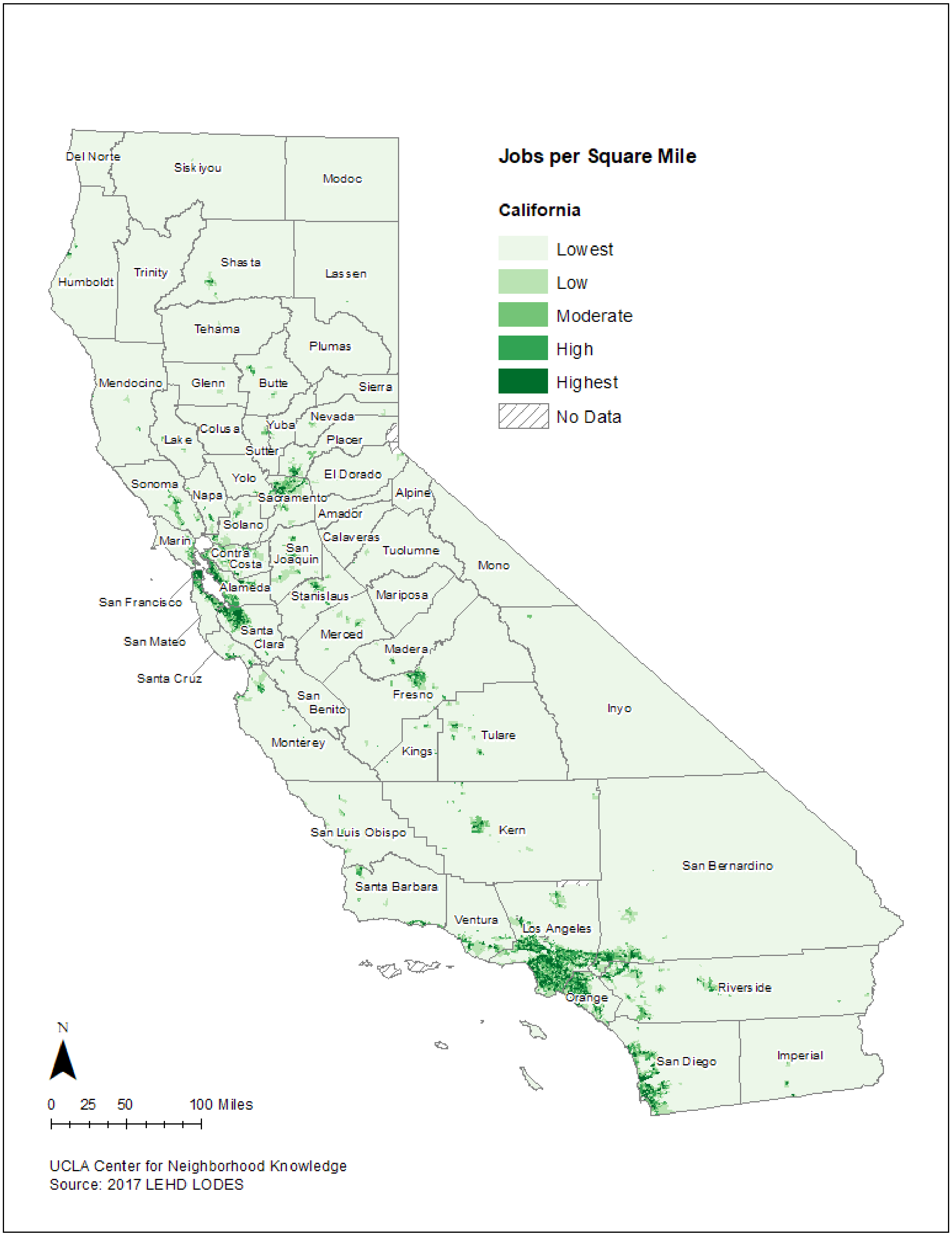


Figure 2-83. Map of Jobs per Square Mile, San Francisco Area

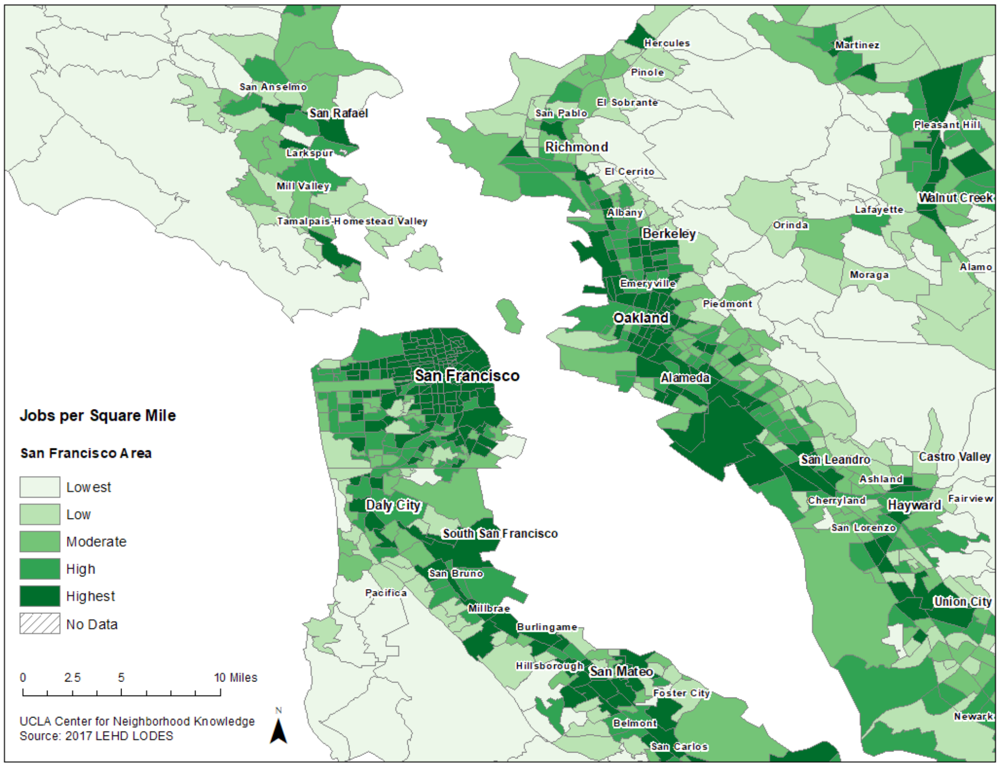
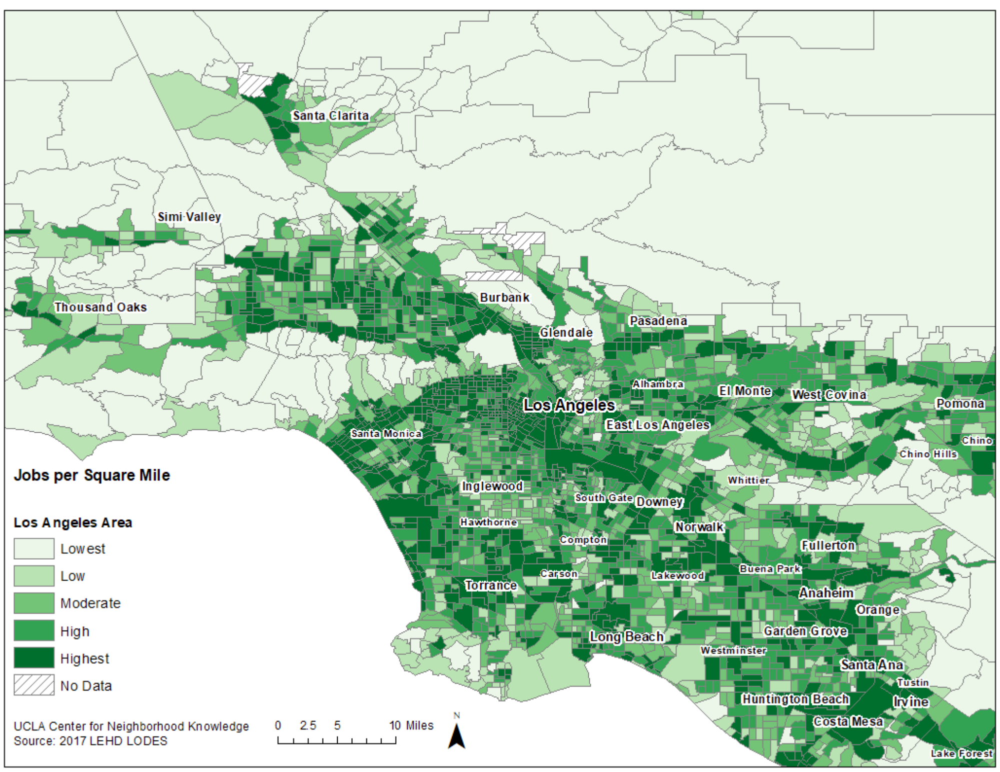


Figure 2-84. Map of Jobs per Square Mile, Los Angeles Area



Chapter 3 Distributional Analysis: Neighborhood Variations in Transportation Disparities by Income Group

This section illustrates one way of utilizing the transportation disparity database by examining how transportation disparities vary across neighborhoods in California. We do this by comparing variations among tracts categorized by household income. Tracts are grouped based on their median income relative to their region's average median income (CNK's region-specific AMIs). Using the regional average accounts for geographic differences in earnings and cost of living. We use the following four ranges: 0–60 percent (lowest income neighborhoods), 60–80 percent (low-income neighborhoods), 80–140 percent (middle-income neighborhoods), and 140+ percent (high-income neighborhoods). These categories are often used directly or indirectly (through correlation with poverty) by policy to designate eligibility for place-based programs.[42] The numbers of tracts in each category are not identical because income is not evenly distributed (skewed to the right). Approximately 13 percent of tracts are in the lowest range, 18 percent in the low-income range, 48 percent in the middle, and 20 percent at the top.

3.1 Characteristics by AMI Neighborhood Categories

Table 3-1 provides sociodemographic profiles of the AMI neighborhood categories. The lowest income neighborhoods have disproportionately more Hispanic and Black residents and fewer White residents; conversely, the most affluent neighborhoods have more White residents and fewer Hispanics and Blacks. Three times as many Black Californians reside in the most economically disadvantaged neighborhoods than in the most affluent neighborhoods. Moreover, immigrants with English-language barriers are more concentrated in the lowest income tracts. Not surprisingly, the lowest income places have higher average poverty rates than affluent neighborhoods. The average poverty rate in the former is more than five times the rate in the latter. Lastly, the lowest income neighborhoods are predominately renter neighborhoods. On average, nearly three-quarters of households in the lowest income tracts are renter households compared to roughly a quarter of households in the highest AMI tracts.

Table 3-1. Sociodemographic Profiles by AMI Neighborhood

	Lowest Income (0–60% AMI)	**Low Income (60–80%)**	**Middle Income (80–140%)**	**High Income (140%+)**
% NH White	17%	26%	43%	58%
% Black	11%	7%	5%	3%
% Hispanic	59%	54%	35%	17%
% Asian	11%	10%	14%	17%
% Immigrants	36%	31%	25%	21%
% LEP HHs	20%	14%	7%	4%
% Poverty	31%	21%	11%	6%
% Renters	74%	59%	41%	24%
n (census tracts)	1,071	1,460	3,840	1,595

[42] For examples, see Noli Brazil and Amanda Portier. (2020). *Investing in Gentrification: The Eligibility of Gentrifying Neighborhoods for Federal Place-Based Economic Investment in U.S. Cities*; Hilary Gelfond and Adam Looney. (2018). "Learning from Opportunity Zones: How to improve place-based policies." Brookings Institution.

3.2 Methodological Approach to Distributional Analysis

For each AMI-based category, we also develop a profile of how many neighborhoods fall into one of our transportation disparity categories. We illustrate this approach with an example in Table 3-2 using the data on the number of "clunkers" as a share of the total vehicle stock in each neighborhood. These values are ranked (from tracts with the highest share to the lowest share) into quintiles from those with the fewest clunkers as proportion of the neighborhood vehicle stock to those with the most clunkers as proportion of the neighborhood vehicle stock. Each "clunker" quintile contains roughly 20 percent of all tracts. (It should be noted that not all disparity indicators can be ranked into equal quintiles. See discussion in previous section.) Table 3-2 lists the distribution of tracts by clunker quintiles and AMI income range.

Table 3-2. Presence of "Clunkers" by Neighborhood Income, Number of Tracts

	Lowest Income Neighborhoods	Low-Income Neighborhoods	Middle-Income Neighborhoods	High-Income Neigborhoods	
Number of Tracts	0-60% of Regional AMI	60-80% of Regional AMI	80-140% of Regional AMI	140%+ of Regional AMI	Row Total
All Neighborhoods by Income Relative to Regional Average	1,071	1,460	3,838	1,593	7,962
Fewest Clunkers as Share of Neighborhood Vehicle Stock	87	114	650	739	1,590
2nd Fewest Clunkers as Share of Neighborhood Vehicle Stock	90	187	854	465	1,596
Middle Range of Clunkers as Share of Neighborhood Vehicle Stock	178	276	922	222	1,598
2nd Most Clunkers as Share of Neighborhood Vehicle Stock	307	427	771	88	1,593
Most Clunkers as Share of Neighborhood Vehicle Stock	409	456	641	79	1,585

The table reveals two notable phenomena. The first is that relatively few of the lowest income neighborhoods are in the "fewest clunkers" quintile compared to the high-income neighborhoods. The opposite pattern also holds: relatively more of the lowest income neighborhoods are in the "most clunkers" quintile compared to the high-income neighborhoods. These outcomes are not surprising because residents in the lowest income places do not have the financial ability to purchase newer (and cleaner) vehicles. The second phenomenon is that there is heterogeneity within each of the income categories. In other words, one should not assume that all of the lowest income neighborhoods are identically characterized as being overwhelmed by "clunkers." (This does not negate the fact that a disproportionately high number of low-income tracts face this problem.) This heterogeneity has policy implications. For example, an incentive program to remove clunkers would be appropriate for many of the lowest income neighborhoods but may not be appropriate for others.

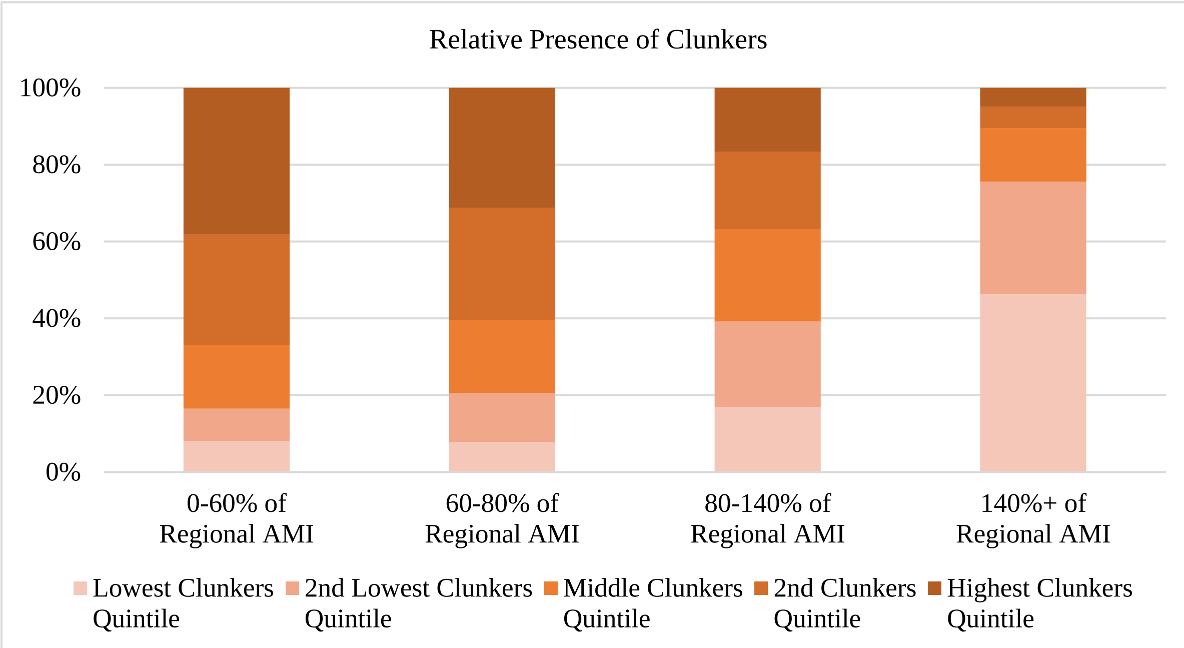
Table 3-3 uses the information from the previous table to calculate column percentages. For example, the percent in the second cell in the first column ("fewest clunkers" row and "0–60% AMI" column) is 87 tracts divided by 1,071 tracts, or 8 percent. The sum of individual percentages in a column is by definition equal to 100 percent. The advantage to these calculations is that it normalizes the statistics, thus accounting for the uneven distribution by income categories. These statistics show that the lowest income neighborhoods are less than one-fifth as likely to be in the “fewest clunker” quintile compared to high-income neighborhoods. Moreover, the lowest income neighborhoods are nearly eight times as likely to be in the “most clunker” quintile compared to high-income neighborhoods. These are substantial differences that have implications, including the generation of mobile-source pollution.

Table 3-3. Presence of “Clunkers” by Neighborhood Income, Column Percent

		Lowest Income Neighborhoods	Low-Income Neighborhoods	Middle-Income Neighborhoods	High-Income Neigborhoods	
Column Percents		0-60% of Regional AMI	60-80% of Regional AMI	80-140% of Regional AMI	140%+ of Regional AMI	Row Total
All Neighborhoods by Income Relative to Regional Average		100%	100%	100%	100%	100%
	Fewest Clunkers as Share of Neighborhood Vehicle Stock	8%	8%	17%	46%	20%
	2nd Fewest Clunkers as Share of Neighborhood Vehicle Stock	8%	13%	22%	29%	20%
	Middle Range of Clunkers as Share of Neighborhood Vehicle Stock	17%	19%	24%	14%	20%
	2nd Most Clunkers as Share of Neighborhood Vehicle Stock	29%	29%	20%	6%	20%
	Most Clunkers as Share of Neighborhood Vehicle Stock	38%	31%	17%	5%	20%

Figure 3-1 is a graphic representation of Table 3-3. The illustration makes the overall pattern of income inequality in the distribution of clunkers visually evident.

Figure 3-1. Relative Presence of Clunkers



We use comparable graphs to summarize the patterns of other indicators by neighborhood income categories. The percentage values for each graph can be found in Appendix C.

3.3 Distribution of Indicators by AMI Neighborhood Categories

Figure 3-2 shows the distribution of auto-insurance premium quintiles by AMI-based neighborhoods. The darkest shade of yellow in the figure represents neighborhoods with the highest auto insurance premium. (Higher insurance premiums can reduce one's ability to own a private vehicle due to the cost of insurance.) Proportionally more lowest income neighborhoods fall into the highest quintile for auto insurance premium rate compared to the more affluent census tracts. In other words, drivers in low-income areas are significantly more likely to pay a higher auto insurance premium than their high-income counterparts.

Figure 3-2. Distribution of Auto Insurance Premiums Quintiles by Regional AMI-Based Neighborhoods

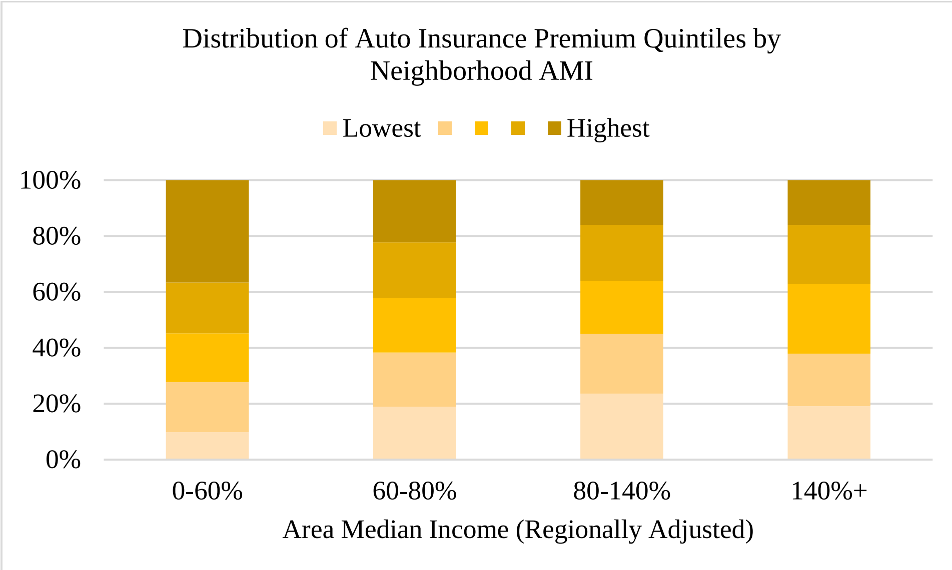


Figure 3-3 describes the distribution of subprime mortgage loans, our proxy for "auto lending barrier," across CNK's AMI-based neighborhoods in California. (Higher borrowing rates reduce the ability to own a private vehicle.) The darkest shade of blue represents neighborhoods with the highest subprime mortgage loans, and the lightest shade represents neighborhoods with the fewest share of subprime loans. Lowest income neighborhoods are much more likely to fall into the quintile with the highest subprime mortgage loans, about 17 times more likely than affluent neighborhoods (41 percent vs. 2 percent). This means that residents in the lowest income neighborhoods are significantly more likely to face financial barriers because of high interest rates.

Figure 3-3. Distribution of Lending Barriers Quintiles by Regional AMI-Based Neighborhoods

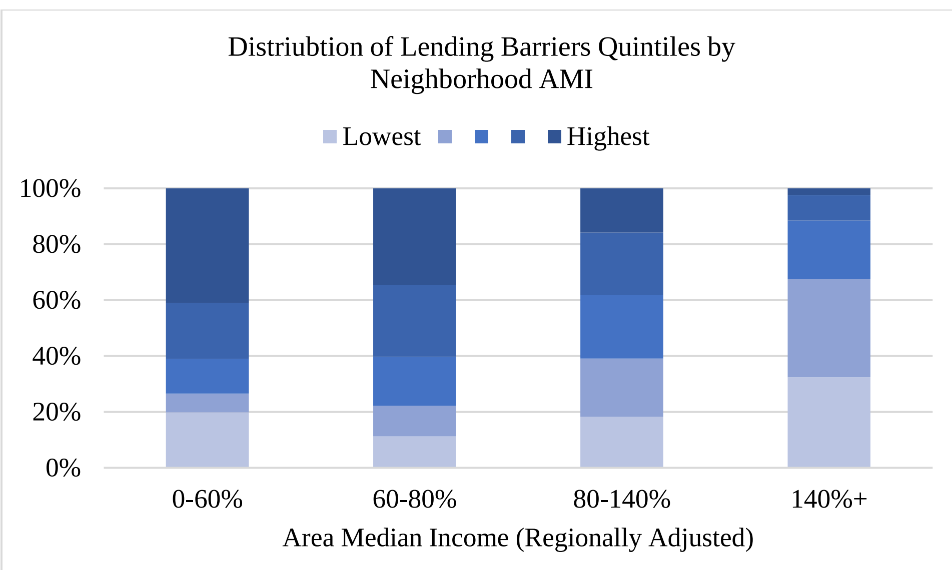


Figure 3-4 highlights the distribution of newer clean vehicles (model years between 2013 and 2017) across CNK AMI-based neighborhoods, with the darkest shade of green representing neighborhoods with the highest share of newer clean vehicles. Nearly half (46 percent) of the most affluent neighborhoods fall into the quintile with the highest share of newer clean vehicles. The opposite is true for lowest income neighborhoods whereby only 6 percent fall into the quintile with the highest share of clean vehicles. In contrast, nearly half (43 percent) of lowest income neighborhoods ranked in the quintile with the least share of newer clean vehicles. The findings are expected given that newer clean vehicles are often more expensive and attainable by those with higher incomes.

Figure 3-4. Distribution of “Newer” Clean Vehicles Quintiles by Regional AMI-Based Neighborhoods

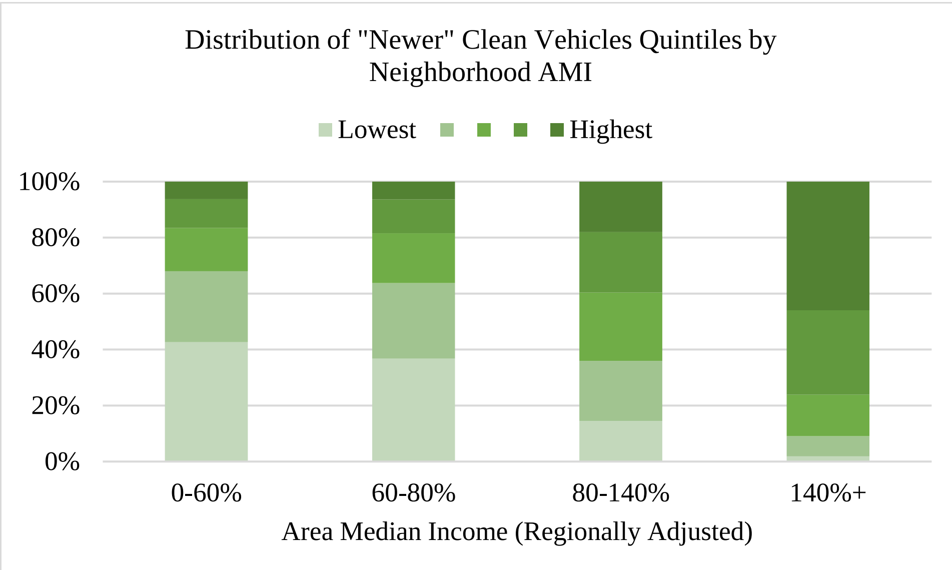


Figure 3-5 highlights the distribution of older clean vehicles (mainly hybrids, model year 2012 or earlier, which pollute less and have better gas mileage than other cars of the same vintage) across CNK’s AMI-based neighborhoods, with the darkest shade of green representing the highest share of older clean vehicles. The distribution of older clean vehicles is almost identical to the distribution of newer clean vehicles discussed previously. Lowest income neighborhoods have disproportionately fewer older clean vehicles compared to the most affluent neighborhoods.

Figure 3-5. Distribution of “Older” Clean Vehicles Quintiles by Regional AMI-Based Neighborhoods

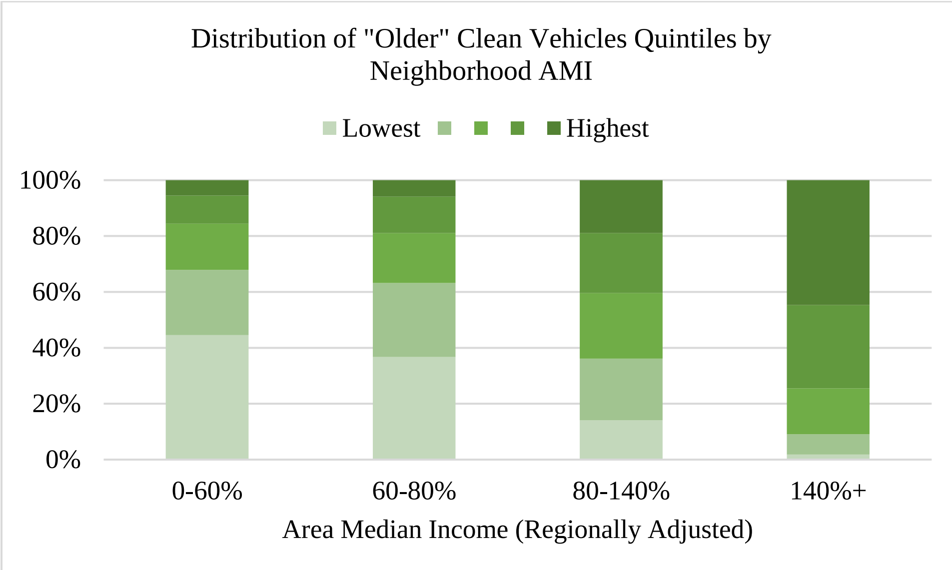


Figure 3-6 shows the distribution of clunker vehicles (model years of 20 years and older, which tends to pollute more than new cars) across CNK’s AMI-based neighborhoods with the darkest shade of brown representing neighborhoods in the quintile with highest share of clunker vehicles. This graph is almost the inverse of the previous two graphs on newer and older clean vehicles. Here, a disproportionate number of lowest income neighborhoods (38 percent) fall into the highest quintile of clunker vehicles compared to the highest income neighborhoods (5 percent), nearly eight times as likely.

Figure 3-6. Distribution of “Clunker” Vehicles Quintiles by Regional AMI-Based Neighborhoods

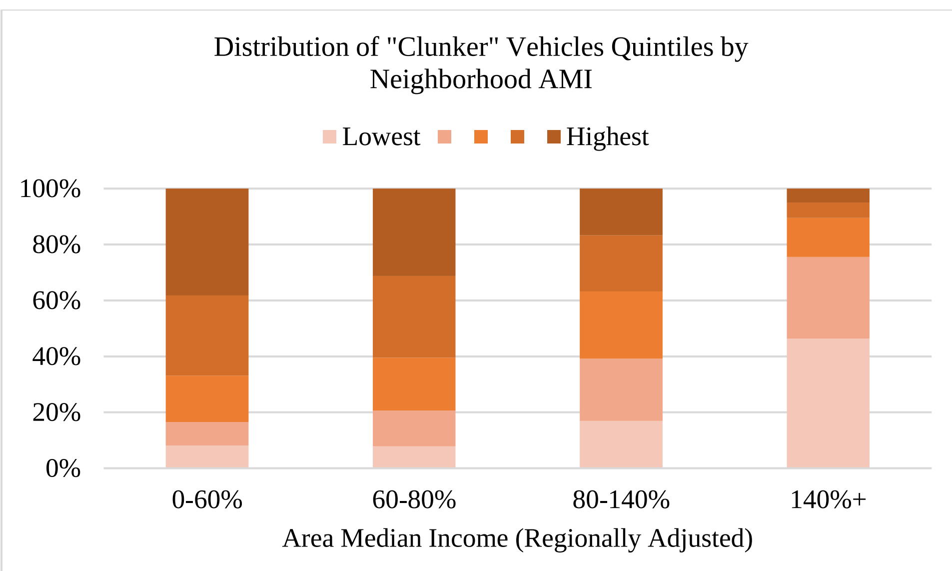


Figure 3-7 illustrates the distribution of average household vehicle miles traveled (HVMT), which includes trips covering all purposes, across CNK’s AMI-based neighborhoods. The darkest shade of gray represents neighborhoods in the quintiles with the highest average HVMT and the lightest shade of gray represents quintiles with the lowest average HVMT. The pattern indicates that average HVMT increases with household income. Affluent neighborhoods are much more likely to fall into the quintile with the highest HVMT, nearly 15 times more likely than lowest income neighborhoods (29 percent vs. 2 percent). In other words, residents in higher income neighborhoods generate more household VMT on average than their lower income counterparts.

Figure 3-7. Distribution of VMT per Household Quintiles by Regional AMI-Based Neighborhoods

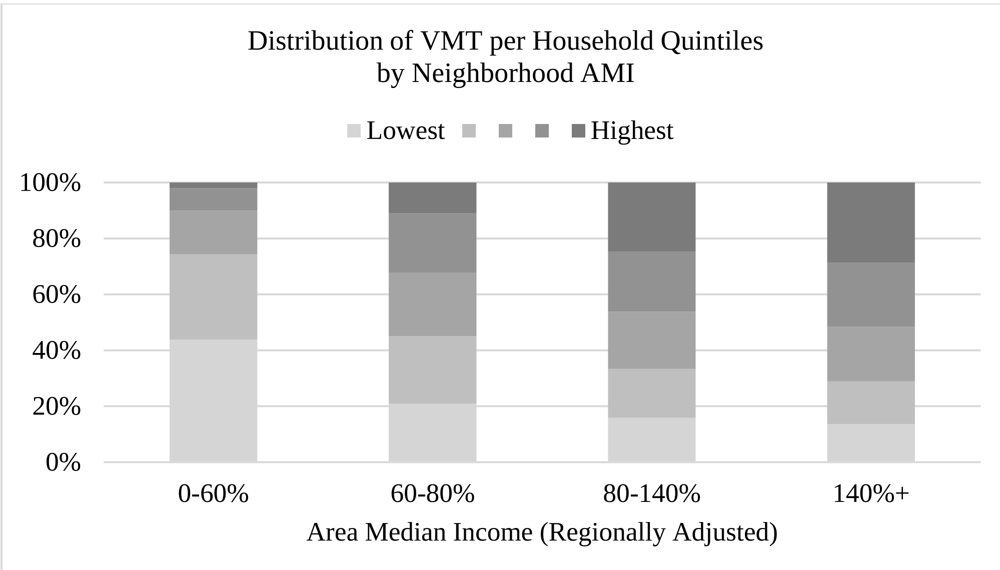


Figure 3-8 illustrates vehicles miles traveled for commute purposes across CNK's AMI-based neighborhoods where the darkest shade of gray represents neighborhoods with the highest average CVMT and the lightest shade represents neighborhoods in the lowest CVMT quintile. Similar to the previous analysis on HVMT, affluent neighborhoods also have higher than average CVMT. Nearly a quarter (23 percent) of high-income neighborhoods fall into the quintile with the greatest CVMT compared to less than one-fourth (15 percent) of lowest income neighborhoods. In other words, workers in high-income neighborhoods generate more VMT for commute purposes than workers in lowest income neighborhoods.

Figure 3-8. Distribution of Commute VMT per Worker Quintiles by Regional AMI-Based Neighborhoods

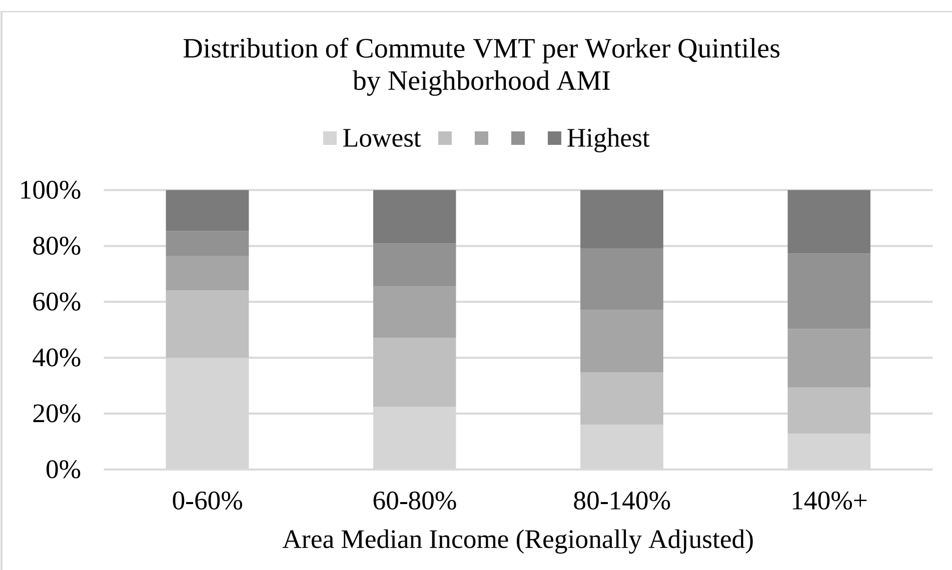


Figure 3-9 highlights the access to employment opportunities indicator across CNK's AMI-based neighborhoods, where the darkest shade of yellow represents census tracts with the highest access and the lightest shade of yellow for the lowest access. Roughly one in three (34 percent) lowest income neighborhoods fall into the quintile with the greatest access to employment opportunities, which is nearly three times as likely than affluent neighborhoods (34 percent vs. 13 percent). This trend partially aligns with the CVMT distributional analysis in which lowest income neighborhoods have the lowest average CVMT partially due to their higher access to employment opportunities. However, their increased access to employment opportunities does not mean that these households work in these employment areas due to a possible skills mismatch.

Figure 3-9. Distribution of Access to Employment Opportunity Quintiles by Regional AMI-Based Neighborhoods

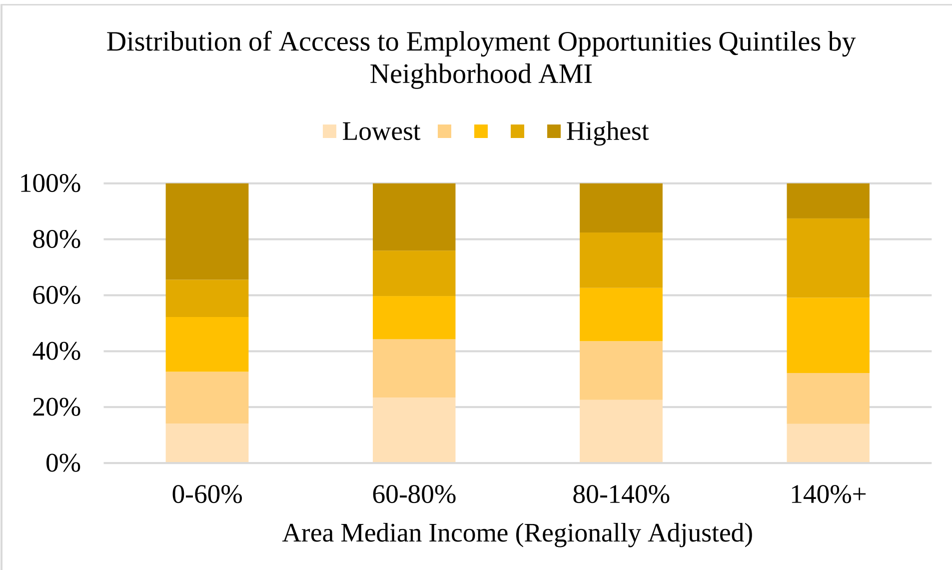


Figure 3-10 represents the distribution of the availability of public park space per population across CNK's AMI-based neighborhoods where the darkest shade of green represents neighborhoods ranked in the highest park availability quintile and the lightest shade represents those ranked in the lowest quintile. Access to parks promotes active transportation and health. There is a stark difference in park availability between lowest and the highest income neighborhoods. Lowest income neighborhoods are much more likely to fall into the quintile with the lowest availability of public parks and open space, more than five times as likely as affluent neighborhoods (40 percent vs. 7 percent).

Figure 3-10. Distribution of Availability of Public Park Space by Regional AMI-Based Neighborhoods

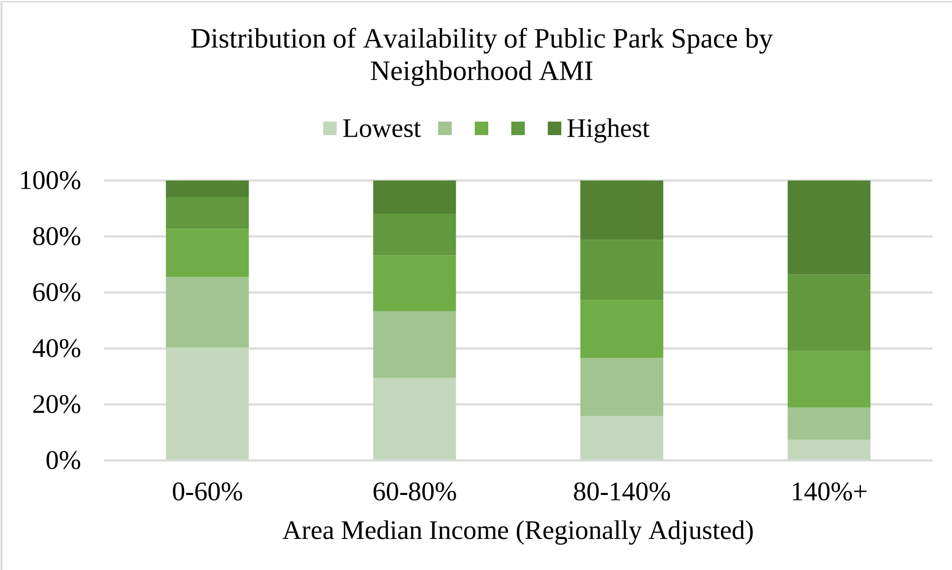


Figure 3-11 represents the distribution of bikeway availability per population across AMI-based neighborhoods where the darkest shade of green represents neighborhoods ranked in the highest bikeway availability quintile and the lightest shade represents those ranked in the lowest quintile. Bikeway availability promotes active transportation and follows a similar pattern as public park availability previously discussed in which lowest income neighborhoods have the least availability and highest-income neighborhoods have the most availability. For example, lowest income neighborhoods are more than two times as likely than their high-income counterparts to fall in the quintiles with the least bikeway availability (28 percent vs. 11 percent).

Figure 3-11. Distribution of Availability of Bikeways by Regional AMI-Based Neighborhoods

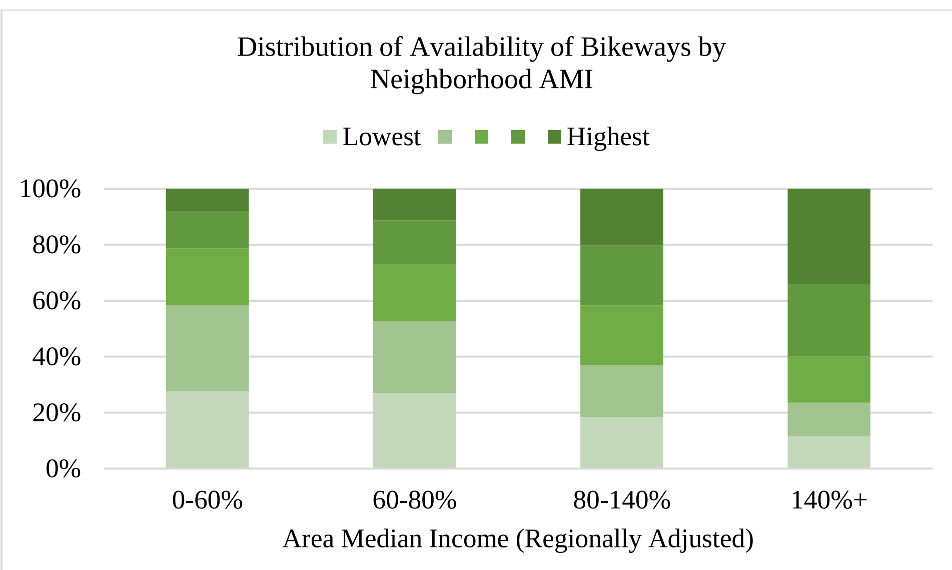


Figure 3-12 illustrates the distribution of traffic collisions per weighted roadways across CNK's AMI-based neighborhoods with the darkest shade of brown representing neighborhoods in the quintile with the highest rates of traffic collisions and the lightest shade representing neighborhoods in the lowest quintile. There is a clear trend that traffic collisions decrease with higher income neighborhoods. Lowest income neighborhoods are much more likely to fall into the quintile with the highest share of traffic collisions, about 10 times more likely than affluent neighborhoods (50 percent vs. 5 percent). In other words, residents in lower income neighborhoods significantly have more traffic collisions than higher-income neighborhoods.

Figure 3-12. Distribution of Traffic-Collisions Quintiles by Regional AMI-Based Neighborhoods

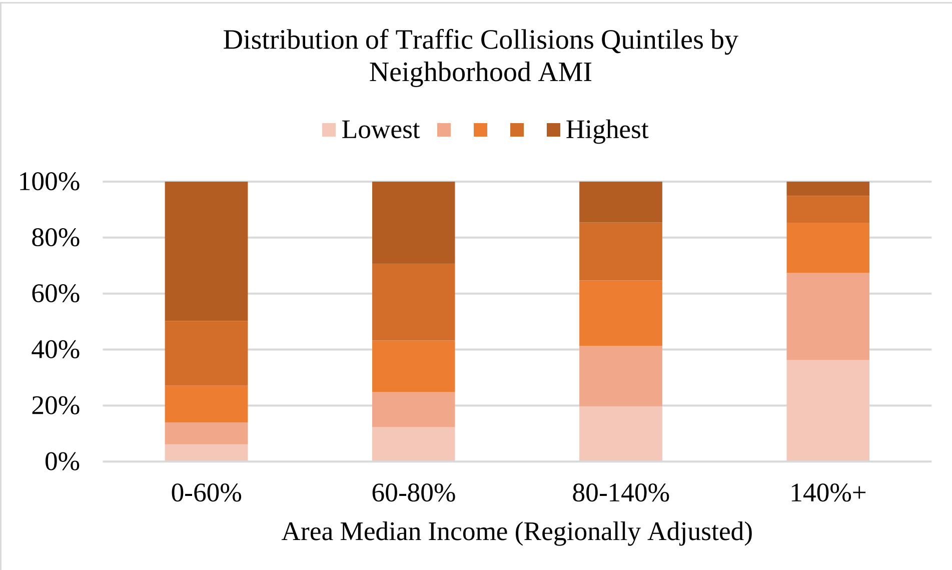


Figure 3-13 shows the distribution of changes in the rental housing market across CNK's AMI-based neighborhoods. This indicator incorporates changes in the neighborhoods share of renters, average rent, and rental housing burden. The darkest shade of brown represents neighborhoods in the quintile with the highest degree of neighborhood change and the lightest shade represents neighborhoods in the lowest quintile. The results indicate an uneven recovery of the rental housing market. More affluent neighborhoods are more likely to be in the highest change quintile, indicating robust increase in demand. However, lowest income neighborhoods are disproportionately overrepresented in the lowest change quintile, indicating a lesser increase in demand. The difference in demand is consistent with the following findings on neighborhood change in socioeconomic status. The stakeholders for this project are interested in whether the changes in the rental market indicate gentrification in low-income neighborhoods, which would be manifested by rapid increases in rent and housing burden. Only 16 percent of lowest income neighborhoods fall into the top quintile, and this pattern does not suggest widespread gentrification. It is still possible, however, that some of these lowest income neighborhoods in the top quintile are experiencing gentrification pressures.

Figure 3-13. Distribution of Changes in Housing Market Variables by Regional AMI-Based Neighborhoods

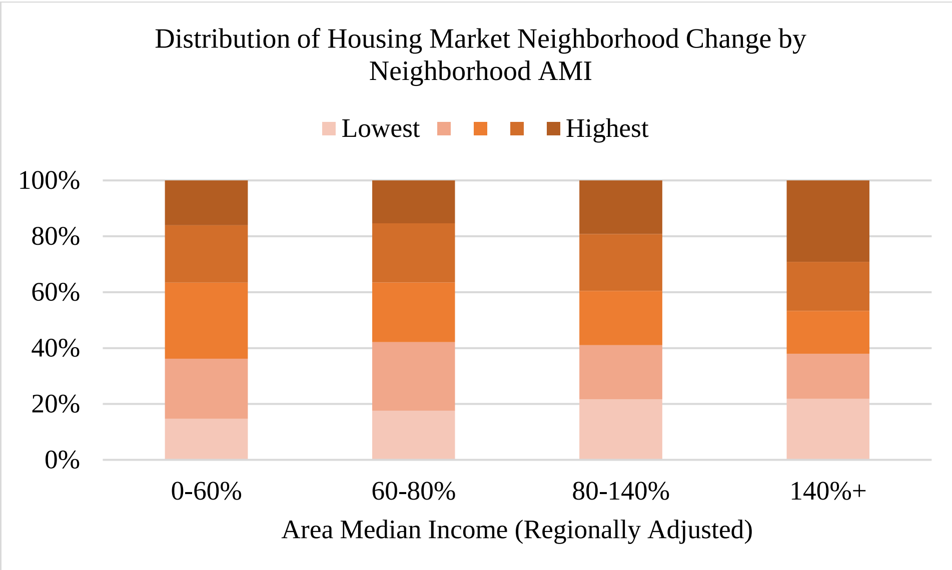


Figure 3-14 shows the distribution of neighborhood change as it relates to socioeconomic characteristics across CNK's AMI-based neighborhoods. The underlying indicator incorporates changes in a neighborhood's average household income, earnings, and college-educated population (human capital). The darkest shade of blue represents neighborhoods falling into the quintile with the highest degree of change (improvement) and the lightest shade represents the lowest. The results capture a disparity in the economic recovery from the Great Recession. Affluent neighborhoods tend to be more likely to experience better recovery (disproportionately more in the top quintile), while lower income neighborhoods tend to be more likely to experience worse recovery (disproportionately more in the bottom quintile). However, 17 percent of lowest income neighborhoods are more likely to fall into the quintile with the least economic improvements. This indicates a widening economic divide between places at the opposite ends of the economic ladder.

Figure 3-14. Distribution of Changes in Socioeconomic Variables by Regional AMI-Based Neighborhoods

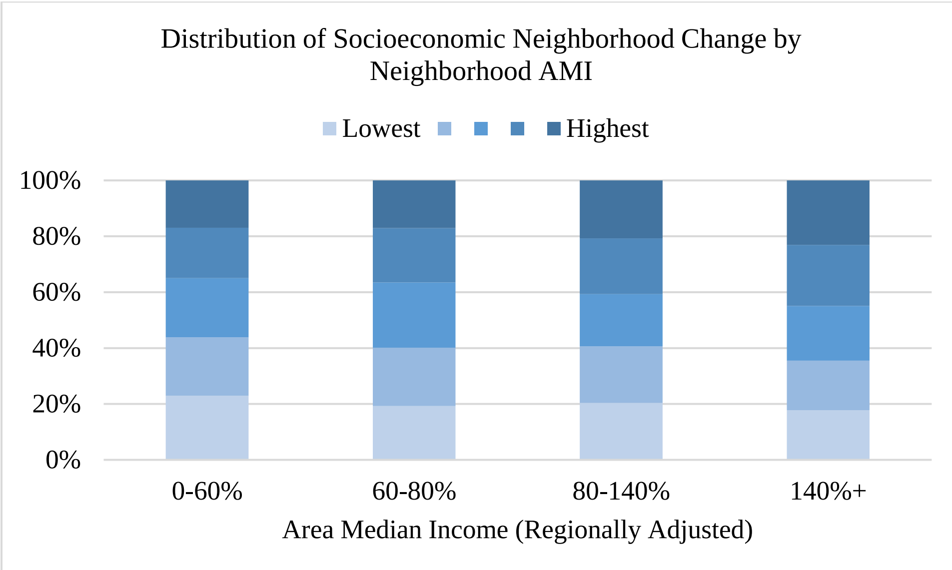


Figure 3-15 illustrates job density across CNK's AMI-based neighborhoods with the darkest shade of green representing the highest value of job density and the lightest shade representing the lowest. Job density tends to increase as neighborhood income decreases. More than a third (35 percent) of lowest income neighborhoods fall into the quintile with the highest job density, about three times as likely as high-income neighborhoods (35 percent vs. 12 percent). This is expected given that there is a concentration of jobs centers in the urban core where many low-income populations reside as opposed to a dispersal of high-income neighborhoods away from the core to predominantly residential suburbs.

Figure 3-15. Distribution of Job-Density Quintiles by Regional AMI-Based Neighborhoods

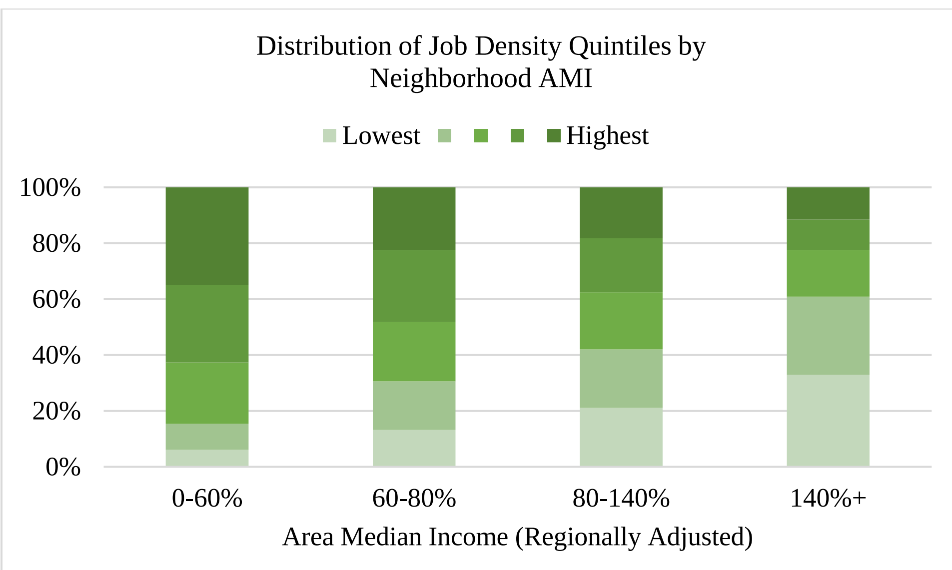
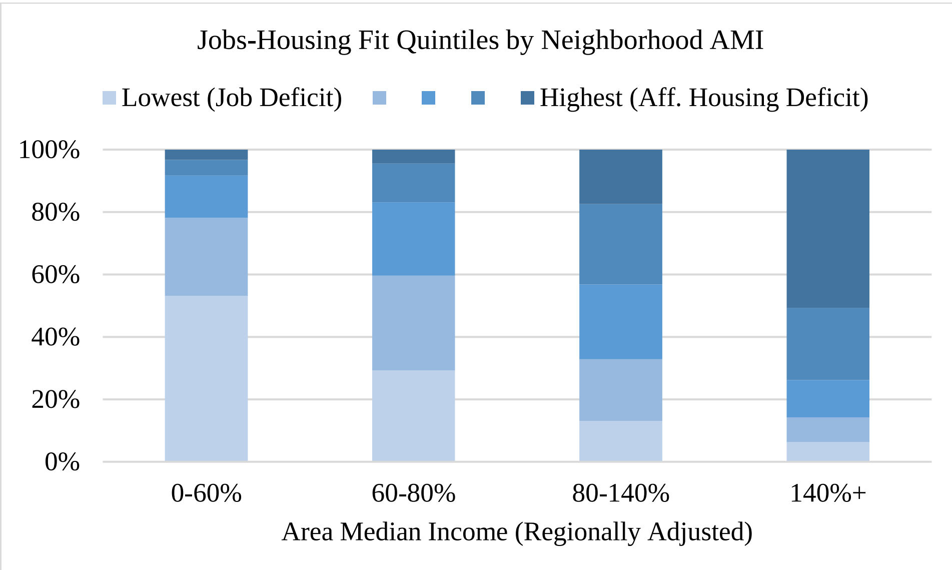


Figure 3-16 summarizes the indicator of jobs–housing fit across CNK's AMI-based neighborhoods where the darkest shade of blue represents neighborhoods with the most affordable housing deficit relative to the number of low-wage jobs, and the light shade of blue represents a deficit of low-wage jobs relative to the amount of affordable rental housing. More than half (53 percent) of lowest income neighborhoods experience a low-wage job deficit. In addition, almost 51 percent of census tracts in high-income areas are ranked the highest category, meaning they have an affordable housing deficit. The observed job–housing mismatch can contribute to more commute VMT.

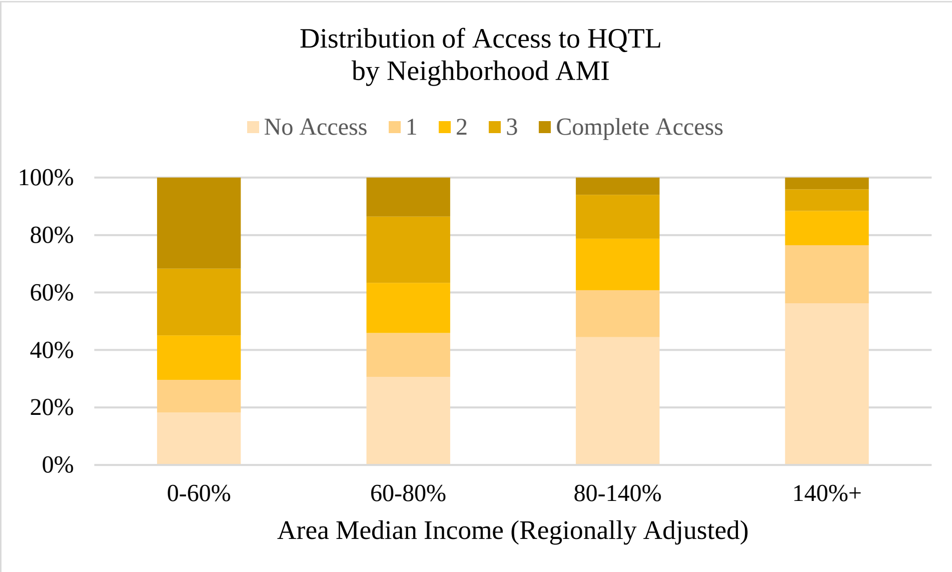
Figure 3-16. Distribution of Jobs–Housing Fit Quintiles by Regional AMI-Based Neighborhoods



Unlike previous indicators, the access to HQTL indicator cannot be evenly distributed into quintiles because the very bottom range of accessibility (no access to HQTL) has a cluster of census tracts that comprises more than 20 percent of total tracts. Because of this clustering, we create a separate category for tracts with no access to HQTL and then redistribute the remaining tracts across four categories, from very low access to complete access.

Figure 3-17 summarizes a distributional analysis of HQTL by AMI category and includes the adjustments made to the HQTL categories. There are two notable patterns. First, HQTLs are completely absent in approximately 4 in 10 census tracts. (These neighborhoods could have some transit service, but not sufficiently frequent to be designated as being HQTL.) The lack of HQTL is particularly noticeable in high-income tracts (more than half of tracts). However, this is not a particularly severe barrier to mobility because these neighborhoods have readily available access to private vehicles. The second notable pattern is a significant number of lowest income tracts (0–60 percent AMI) have good HQTL coverage. The residents in roughly one-in-three tracts in the lowest income neighborhoods have complete access to HQTL. These findings are not surprising given that many lower income neighborhoods are more likely to be in the urban core in or near commercial and job centers, which tends to have denser transit service for incoming workers and consumers. Further, lower income residents are more likely to be public transit users, due in part to barriers to automobile ownership. Unfortunately, many residents in the lowest income neighborhoods do not have good access to HQTL. About 3 in 10 of these neighborhoods either lack any HQTL or have far too few (the bottom two categories).

Figure 3-17. Distribution of Access to HQTL by Regional AMI-Based Neighborhoods



Summary of Findings

The distributional analysis shows considerable transportation disparities across neighborhoods by economic (relative AMI) status. Lower income neighborhoods experience several challenges: more barriers to vehicle ownership, disproportionately fewer clean vehicles and more clunkers, more limited ability to travel (lower VMT), and less access to infrastructure supporting active transportation. Differences for the other indicators (e.g., neighborhood change, jobs–housing fit, job density) also show systematic differences, ones that require additional analysis to fully understand the consequences and implications. The diversity of transportation characteristics, even within income quintiles, indicate that California has a complex and highly heterogeneous neighborhood system, and a need to go beyond a simple "one-size" approach to promoting equitable sustainable development. Practical solutions should be customized to the particular characteristics of each place.

Similar distributional analysis should be conducted using definitions of "disadvantaged neighborhoods" designated by CalEPA and "low-income communities" in Assembly Bill 1550. This would ensure more equitable and effective implementation of environmental and climate change policies. Additionally, the same type of analysis can be replicated to look at the distribution of ethnoracial groups by the transportation disparity indicators. While Proposition 209 limits the use of race in allocating funds and services, it is still important to understand analytically how marginalized people of color are affected by unequal access to transportation and transportation-related resources. These insights could identify the (overtly nonracial) social and economic mechanisms that generate inequality and enable the state to develop policies and programs to address those unfair processes.

Chapter 4 Conclusion and Recommendations

The purpose of this project is to develop a set of key indicators to help public agencies and stakeholders identify the causes, characteristics, and consequences of transportation disparities. The project's major products are a statewide database and data/mapping portal.[43] This project will contribute to the state's commitment to ensure that low-income populations and neighborhoods benefit from its climate change policies, which include AB 32, SB 375, SB 350, and SB 150. Our products, findings, and recommendations complement other efforts to increase the effectiveness of transportation-related investments, interventions, and other efforts to improve employment, educational, and health outcomes for low-income populations and neighborhoods.

The indicators utilize the most recent and available data from the past decade to document neighborhood-level (census tract) disparities across the state in access, quality and burden of transportation resources, along with other relevant phenomena such as neighborhood changes. The final products are not comprehensive given data limitations and limited resources; nonetheless, many of the indicators significantly augment, refine, and expand the state's information on systematic inequalities relevant to its goal of attaining equitable sustainability in response to climate change.

The development of the statewide database, screening tool, and data/mapping portal was guided by three principles: factors identified in the literature as being important; technical feasibility with the available data, time, and funding; and priorities identified by an Advisory Committee and CARB staff.

4.1 Assessing the Data, Indicators, and Measures

The transportation disparity database contains two types of indicators. The first includes those previously developed by CNK prior to this project and preexisting ones from other sources, which were evaluated to determine the ones relevant for inclusion. Some of the prior CNK information comes from an earlier project that examined factors relevant to sustainable community strategies.

The second type of indicators includes new ones constructed by the project. This effort involved five steps. The first was to access and assemble data from multiple sources: readily available public data (e.g., from the U.S. Census Bureau), specialized data from public agencies (e.g., clean and clunker vehicles), and nonpublic entities (e.g., insurance premiums). Step two assessed potential input data for quality, timeliness, precision and accuracy, and consistency. Step three used spatial tools to construct metrics (e.g., the availability of nearby parks to neighborhood residents). Step four evaluated those newly constructed metrics by comparing to similar preexisting ones. And step five ranked the metrics where appropriate.

Overall, the statewide database includes a total of 40 indicators of which 17 are CNK-constructed indicators. Of the 17, 13 are newly constructed for this project and 4 were adopted and/or refined from a previous project conducted by the researchers for CARB and Caltrans. The remaining 23 indicators are from other sources.

Before summarizing the results of the analysis, it is important to note the limitations in our data and methods in the construction of indicators and measures. The indicators are not perfect. Some of the underlying input data have limitations because of inconsistency in reporting period, variations in definitions, sampling and other types of errors, geographic coverage, spatial misalignment, data suppression, and missing information. Moreover, there can be methodological and subjective disagreements on how to transform and

[43] To access the data/mapping portal visit:
https://experience.arcgis.com/template/9c13f35df3904dcb80530d0df49bdf9e

weigh input variables, report and categorize outputs, and interpret the results. When an indicator suffers from one or more of these limitations, this project reports the outcomes in ways to avoid false precision, such as using ordinal ranking into broad categories. Despite these limitations, analyzing the project's new information sheds new light on the nature, patterns, and magnitude of transportation inequity.

4.2 Results and Findings

The project conducted a distributional analysis to determine patterns of transportation disparities across neighborhoods (tracts). This was done by comparing lower income neighborhoods with more affluent ones, which are defined by a tract's median household income relative to the regional average. The analysis found and quantified that low-income tracts experience several challenges: more barriers to vehicle ownership, disproportionately fewer clean vehicles and more clunkers, more limited ability to travel (lower VMT),[44] and less access to infrastructure supporting active transportation. Differences for the other indicators (e.g., neighborhood change, jobs–housing fit, job density) also show systematic inequities. These disparities must be addressed and considered when refining and implementing California's climate change initiatives.

The other major finding is a significant diversity in transportation characteristics among low-income neighborhoods (and higher income ones). For example, while most low-income neighborhoods are park poor, some are not (albeit disproportionately fewer in number). Not all low-income neighborhoods are identical in terms of their transportation challenges and opportunities. California's complex and highly heterogeneous neighborhood system means that equity policy should go beyond a simple "one-size" approach to promoting equitable and just sustainable development.

4.3 Recommendations

Given the results of the analysis, our recommendations include the following:

<u>On data and methods:</u>

1. **Update and refine data and indicators used in the statewide database, screening tool, and data/mapping portal.**
    a. Evaluate the indicators to identify possible enhancements.
    b. Refine indicators to address data construction issues documented in this report, for example data on accessibility to bikeways.
    c. Expand indicators to incorporate broader opinions of data construction, specifically relating to the park availability per population indicator.
        i. In addition to measuring the amount of public park space available to a population in and around a tract (park availability), it is also important to measure the proportion of a population that is within a one-half mile buffer around the park (park access).
2. **Incorporate nontraditional data sources like "big data" to track traffic and travel.**
    a. Utilize "big data" such as smartphone GPS or traffic cameras to track traffic and travel. These data can improve accuracy of our indicators like vehicle miles traveled for both personal and work trips or quality of public transportation locations.

[44] The societal implications of VMT are complicated. There are positives and negatives. For example, higher VMT is partially correlated with greater access to opportunities. At the same time, higher VMT can generate pollution that can impact the environment and health. The relationship between VMT and outcomes are also mediated by other factors such as availability of public transit, amenities within one's neighborhood, and availability of clean vehicles. Therefore, there is no single positive or negative value that can be reasonably assigned to VMT.

3. **Develop a composite score for a selected number of transportation related indicators**
    a. Currently, the database has a large number of indicators that the existing literature and previous research have documented as being associated with the causes, characteristics, and consequences of transportation disparities. For some users, a single overall ranking of transportation disparity may be useful. This has been done for other topics, such as the composite ranking in CalEnviroScreen 3.0 to identify environmentally disadvantaged neighborhoods, or the CDC's Social Vulnerability Index used for disaster planning and more recently for prioritizing COVID-19 responses. Developing a single composite score for transportation disparities would involve at least two elements.
        i. The first element is analytical to identify commonality and differences in the input indicators. This can be done using correlation, principle components, or cluster analysis. Input indicators that are very similar can be consolidated without much loss in underlying information. Disparate indicators can still be aggregated, but this can be more challenging because the final scores or rankings are more difficult to interpret. Whether this outcome is prevalent or not should be determined empirically.
        ii. The second element is weighting the input, deciding which input variables are more important (greater weight) or less important (lesser weight). This can be partially done empirically, using analytical techniques such as cost effectiveness of competing investments; however, there are subjective values that reflect normative judgments. Promoting equity and fairness, for example is normative, a goal that many value independent of objective costs. Normative values are likely to also exist in prioritizing what transportation equity goals are preferred. Although difficult to quantify, these subjective preferences are important in formulating public policy.

<u>On findings:</u>

4. **Use findings to refine and revise Regional Transportation Plan (RTP)/Sustainable Communities Strategy (SCS) plans.**
    a. The RTP/SCS plans are evaluated primarily to ensure the reasonableness of long-term forecast models and their application to alternative policies, plans, and projects. This research should complement the RTP/SCS evaluations as it provides a clearer picture of causes, characteristics, and consequences of transportation disparities at the neighborhood level. CARB must refine the RTP/SCS plans to address these inequities and provide appropriate solutions to meet their SB 375 goals.
    b. Findings regarding income and access is an assessment of systemic inequities at the local, regional, and state level. CARB must address these inequities in their RTP/SCS plan revisions.
        i. Programs specific to low-income communities or undergoing significant neighborhood change would benefit from place-based resources catered to fill gaps in access to quality transportation, health care, parks, etc.

<u>On future and expanded efforts:</u>

5. **Standardize data collection, data reporting, and appropriate adjustments to compare data across California.**
    a. Jurisdictions have a number of dimensions, standards, and timetables for data collection. While we understand that this may meet their particular needs, these inconsistencies make it difficult to draw comparisons across regions for the state as a whole.
        i. Measuring availability of bikeways resulted in a number of inconsistencies as MPOs differed greatly in how they classified bikeways and mapped their length.

    b. Data are difficult to compare across regions without adjusting.
        i. Cost of living differs based on basic expenses in a given area and determines how affordable it is to live there. We constructed our AMI-based neighborhoods by comparing census tracts' median household incomes with their respective region. California should consider standardizing adjustments for other indicators such as transit quality because access to a high-quality transit differs in high-density urban areas versus rural or low-density regions.
    c. California should only use state-specific data and measures when constructing indicators. The state should limit the use of models that are based on non-California locations. Efforts that impute California values into these models may produce inaccurate or misleading results.
        i. The Center for Neighborhood Technology H+T Index used Chicago and St. Louis VMT information and behavior to build their model and therefore would produce misleading results using California values.

6. **Public access and data transparency should be prioritized, which means we should regularly evaluate how well the data portal meets the needs of stakeholders and local and regional planners.**
    a. Tools and approaches are constantly evolving and improving. It is important to take advantage of these refinements if it enables stakeholders and local and regional planners to have better access to data and information that is present in a much more accessible and usable way. For example, GIS dashboards have evolved and been widely adopted as a result of COVID-19. As users are becoming more comfortable with tools like a GIS dashboard, agencies should prioritize creating tools that increase public access and data transparency.

7. **Refine web portal to improve usability to stakeholders and local and regional planners.**
    a. Collect feedback and input from users on how to enhance the data/mapping portal to better meet their needs. Can be done by survey, adding a comment section to the portal, adding a forum section, and focus groups.
    b. Review new and innovative data-dissemination practices that have emerged during the pandemic (e.g., COVID-19 dashboards), and identify best and effective efforts.
    c. Use the preceding to enhance the transportation disparity portal.

8. **Host hands-on training on the statewide database, screening tool, and data/mapping portal for community stakeholders and local and regional planners.**
    a. CNK's guidebook is a starting point to teach community stakeholders and local and regional planners on how to use the statewide database, screening tool, and data/mapping portal products. However, these products can be too complex to navigate for the typical user even with the assistance of a guidebook. Therefore, a hands-on training workshop is more beneficial for teaching users how to navigate the products and utilize the content for their respective research, programs, or campaigns.

We acknowledge that COVID-19 has fundamentally disrupted how people live, work, learn, and travel. These disruptions will have profound impacts on labor and housing markets, businesses, and educational institutions. It is quite likely that there will be long-term and dramatic implications on where people and businesses will choose to locate. This could have profound implications for California's efforts to address climate change and to invoke effective energy, environmental, and sustainable community strategies. While the data from this project are relevant for the old norms, there are sound reasons to believe that will quickly become outdated and irrelevant. Therefore, it is crucial to significantly reconceptualize the data and indicators needed for the post-pandemic "new norms." Ideally this would be done sooner rather than later if the information will be used to guide the recovery along an environmentally and sustainable trajectory. At the same time the current indicators produced by this project are nonetheless useful as a pre-pandemic baseline and given the results of the analysis, our additional recommendations include the following:

9. **Acknowledge the coronavirus disease 2019 (COVID-19) has already changed, and may exacerbate, the neighborhood-level causes, characteristics, and consequences of transportation disparities described in this report.**
    a. The data and findings highlight the disparities among neighborhoods prior to COVID-19 and may not accurately reflect the current transportation needs. These indicators, as developed, can be seen as a baseline to showcase how communities across the state lived prior to COVID-19 and what shifts have occurred in transportation and mobility use and patterns.
    b. Indicators, especially those revolving around transportation needs and access to employment opportunities, will drastically differ as a result of broader acceptance of remote work. In the post-pandemic period it is possible that fewer workers will commute, and there may be changes in business operations that allow employees to work at home. Specifically, indicators such as commute vehicle miles traveled (CVMT) will dramatically decrease for California residents who have the ability to work from home or were let go from their jobs as a result of business closures. In addition, indicators that highlight disparities in access to employment opportunities, jobs–housing fit, and job density will significantly change due to changes in COVID-19 prevention measures, stay-at-home orders, and definition of essential work and essential workers.
    c. Indicators focused on socioeconomic and housing characteristics, specifically low-income neighborhoods and neighborhood change, will reflect a much different landscape of where people live before and after the COVID-19 pandemic. Characteristics, such as median household income, renter-occupied and rent-burdened households, and the percentage of the adult population with a bachelor's degree or higher, will differ.
    d. Overall, there has been drastic change in the way we live, work, and play. As we have seen already, there will be lasting changes to consumption (online shopping and product delivery), education (in-person teaching vs. remote learning), perception of built environment (high density now seen as a liability), cultural basis in institutions (access to amenities like theaters and museums will become less important), and socializing (parties and nightlife).
10. **Support further analyses and research on transportation disparities.**
    a. The project's database and distributional analysis are important contributions to strengthening CARB's and stakeholders' ability to redress systematic transportation disparities; however, the real-world impacts will depend on actively analyzing to inform equity policies, programs, and actions. There are three major recommendations related to applied and basic research, as provided in the following text.
        i. Conduct applied research similar to the project's distributional analysis using other definitions of "disadvantaged neighborhoods" such as those set forth by the State such as CalEnviroscreen 3.0 and Assembly Bill 1550. This is important because inequality is a multidimensional phenomenon. For example, being disadvantaged in the environmental arena is not identical to being disadvantaged in the labor market. Given this complexity, analyzing and comparing alternative definitions provide a much richer understanding of the characteristics and patterns of transportation inequality.
        ii. Support basic research on the fundamental causes of transportation inequality. Transportation disparities are embedded in larger structures of economic, social, and political systems of stratification. Findings from such research can identify underlying the factors and processes that produce transportation inequalities. The

results can have practical applications by identifying new points of intervention for policies and investment beyond the immediate transportation arena. The insights can highlight new opportunities for CARB to partner with other public agencies and societal institutions.

iii. Fund research on the consequences of transportation inequality to better understand “downstream” impacts on outcomes such as employment, health, and the overall quality of life. The insights can be useful to identify cobenefits (e.g., improving life expectancy), which should be factored into any cost-effectiveness calculations, policy formation, and prioritization of investments. Responsible transportation decisions should incorporate the externalities to maximize net societal benefits.

b. The last research-oriented recommendation is to explicitly address racial inequality in transportation. While Proposition 209 limits the use of race in allocating funds and services, it does not prohibit conducting analyses to understand how marginalized people of color are affected by unequal access to transportation and transportation-related resources. The decision-making process on research topics and priorities should include meaningful input from the communities most adversely impacted by current disparities and most likely to benefit from any resulting evidence-based changes. These insights could identify the (overtly nonracial) social and economic mechanisms that generate inequality and enable the state to develop policies and programs to address those unfair processes.

Appendices

Appendix A: Indicator Construction

The following provides additional information for selected indicators discussed in Chapter 2 ("Indicator Construction"). Specifically, it includes additional information for the availability of public park space and availability of bikeways indicators.

<u>Availability of Parks</u>

Figure A-1. Golden Gate Park in San Francisco (DPR's Park Access Tool)

Figure A-2. Golden Gate Park in San Francisco (CNK)

Figure A-3. Balboa Lake in Los Angeles (DPR’s Park Access Tool)

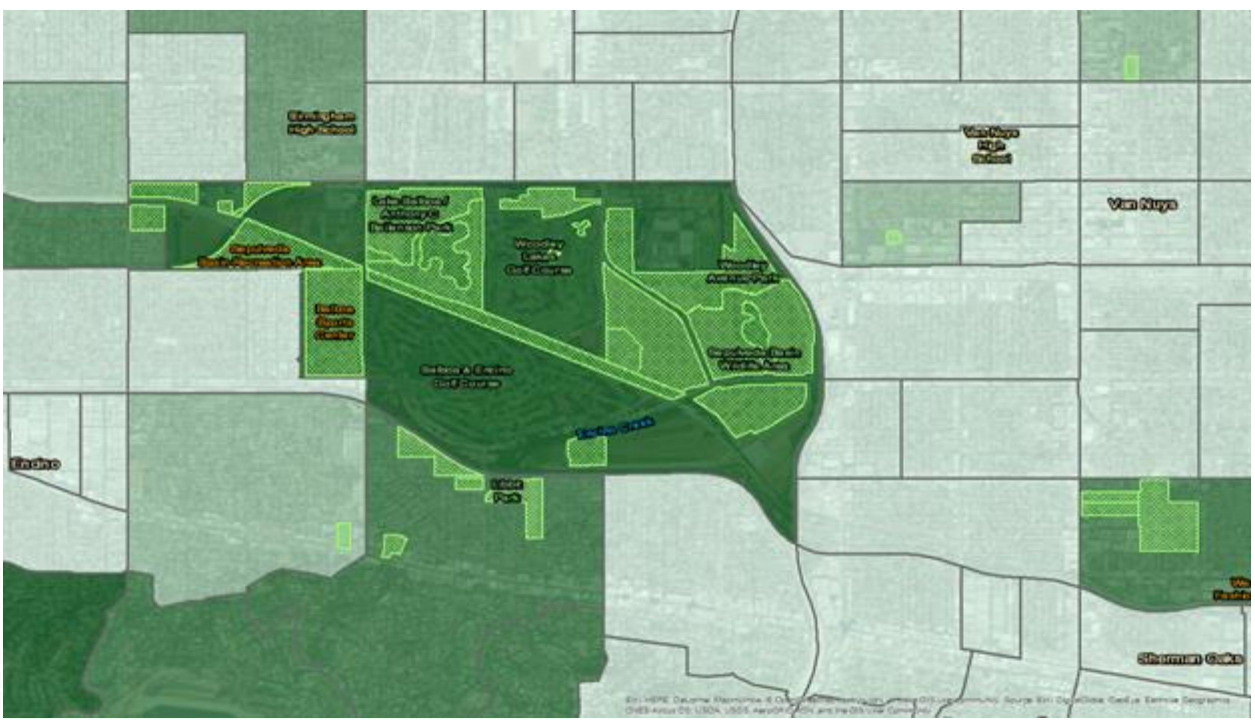


Figure A-4. Balboa Lake in Los Angeles (CNK)

Figure A-5. Rancho Park in Los Angeles (DPR’s Park Access Tool)

Figure A-6. Rancho Park in Los Angeles (CNK)

Availability of Bikeways

Bikeway data was obtained for 17 out of the 18 MPOs in California.

Table A-1. Bikeway Data Availability by MPOs

Metropolitan Planning Organization	Bikeway Data Available
Association of Monterey Bay Governments	Yes
Butte County Association of Governments	Yes
Council of Fresno County Governments	Yes
Kern Council of Governments	Yes
Kings County Association of Governments	Yes
Madera County Transportation Commission	Yes
Merced County Association of Governments	Yes
Metropolitan Transportation Commission & Association of Bay Area Governments	Yes
Sacramento Area Council of Governments	Yes
San Diego Association of Governments	Yes
San Joaquin Council of Governments	Yes
San Luis Obispo Council of Governments	Yes
Santa Barbara County Association of Governments	Yes
Shasta Regional Transportation Agency	Yes
Southern California Association of Governments	Yes
Stanislaus Council of Governments	No
Tahoe Metropolitan Planning Organization	Yes
Tulare County Association of Governments	Yes

Note: The bikeway shapefile data was formatted in a unique way in which bikeways were drawn for each side of the road. In one road there were two lines representing bikeways in each direction. Two distinct lines would mean the number of miles would be doubled incorrectly because the data gathered for the other geographical areas provided bikeways a single line shapefile. Therefore, it was decided to manually delete one of the two lines. In addition, several lines in the shapefile ended before the road ended or ended at street intersections. After using Google Satellite imagery to verify the presence of a bikeway these shapefile lines were extended to complete the bikeway.

Out of a total of 58 counties in California, data covered 36 counties, which is about 96 percent of the state's total population. We did not have data for the remaining 22 counties. One county had bikeway data but chose not to report it to us because it was not up to date.

Figure A-7. Availability of Bikeway Data by California MPO and Counties

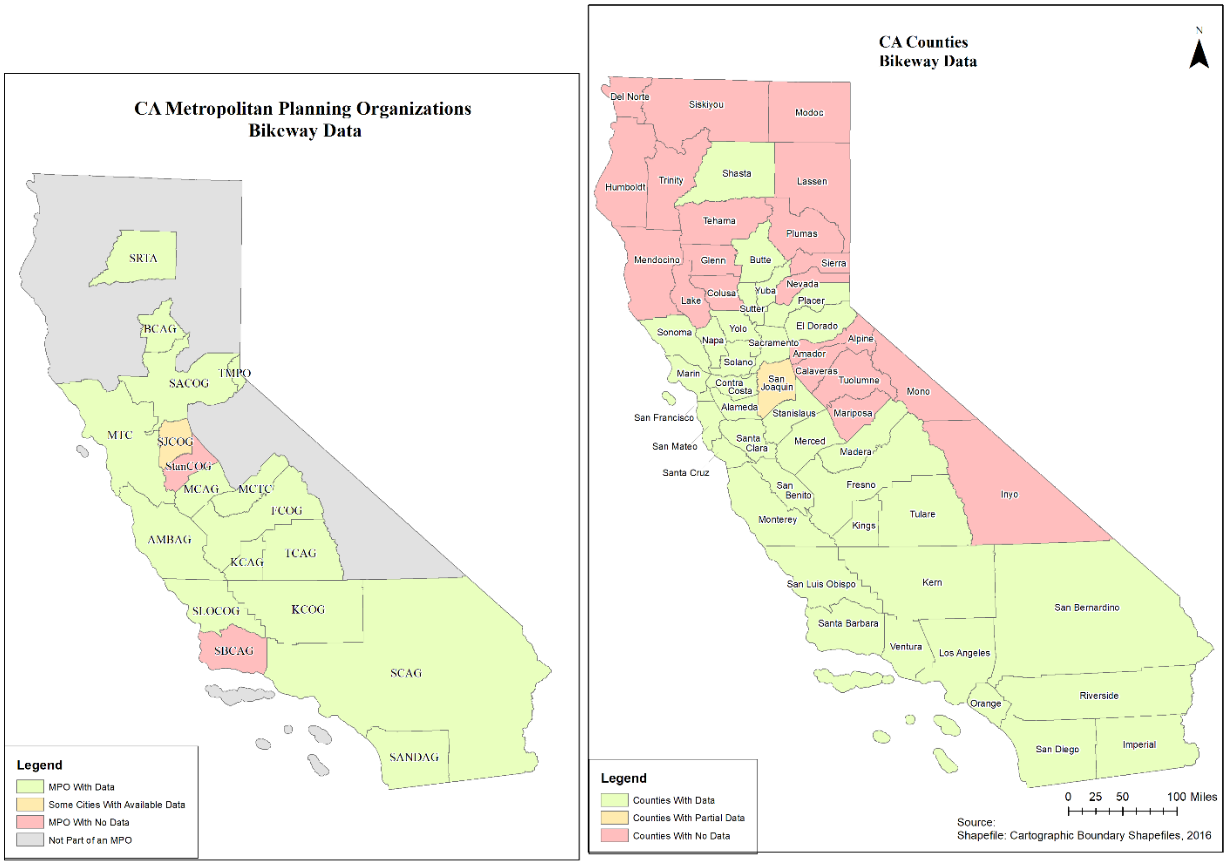
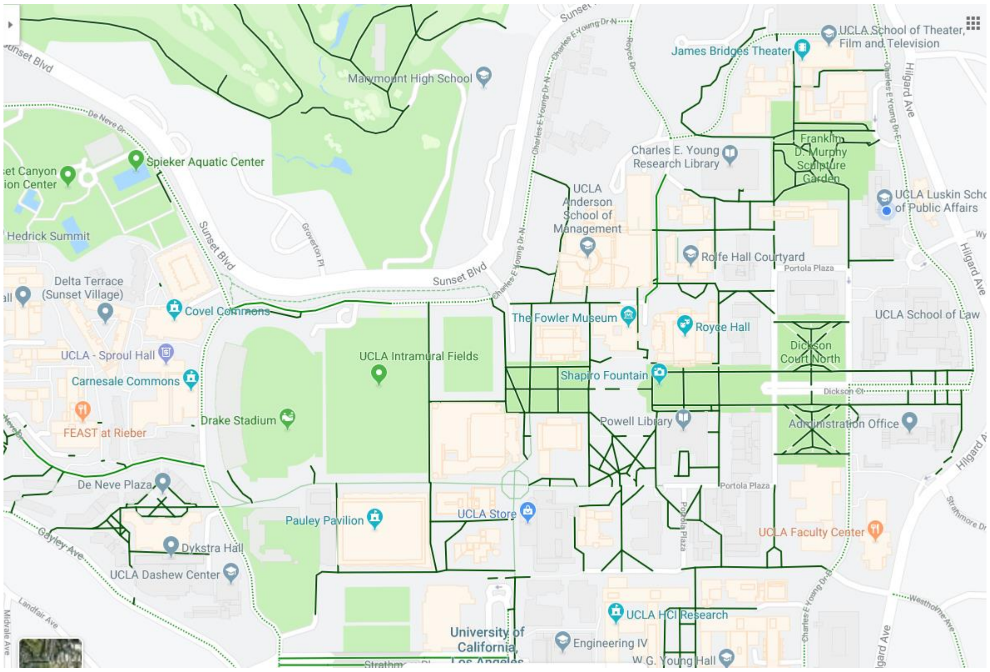
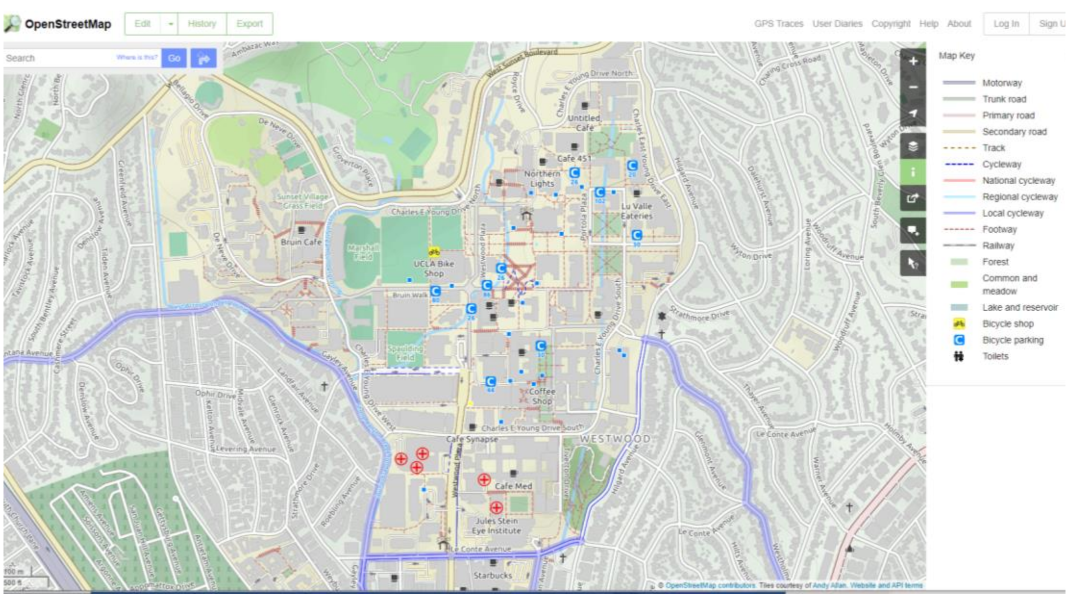


Figure A-8. Google Maps Bikeway Coverage at UCLA 9/13/19



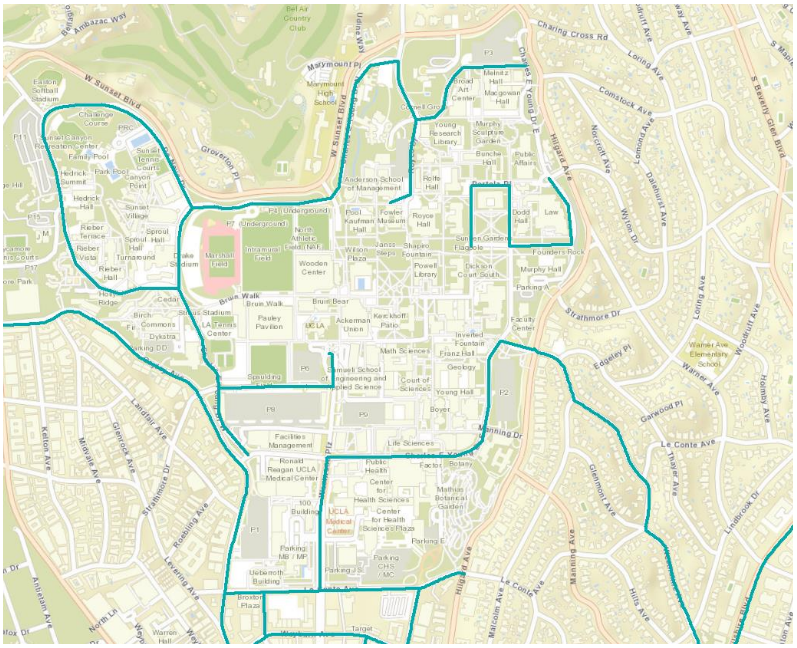
Note: There are bikeways shown on Google maps at UCLA in areas that are not allowed on campus, UCPD will give ticket citations to people if they are on their bikes.

Figure A-9. OpenStreetMaps Bikeway Coverage at UCLA 9/13/19



Note: OSM bikeway coverage does not include areas inside UCLA.

Figure A-10. SCAG Coverage of Bikeways at UCLA



Note: SCAG does not include bikeways in the UCLA campus but does include the bikeways on the extent of where there are official streets that are surrounding UCLA.

Appendix B: Core Formulas

The following provides the core and simplified formulas used to construct key indicators. More details about input data and methodology can be found in the body of this report or previous CNK report. [45]

Auto Insurance Premium: Average auto insurance premium in dollars

$$Average\ Premium_i = \frac{(DOI_i / \underline{DOI}) + (PP_i / \underline{PP})}{2}$$

DOI_i is the estimated Department of Insurance's average insurance premium for census tract i
$\underline{DOI}$ is the Department of Insurance's average insurance premium for all census tracts in California
PP_i is the estimated ProPublica's average insurance premium for census tract i
$\underline{PP}$ is the ProPublica's average insurance premium for all census tracts in California

Lending Barriers: Proportion of mortgage loans with high interest rates as a proportion of all mortgage loans reported in HMDA, which serves as a proxy for auto lending barrier

(Percent Higher Interest Loans)$_i$=(Higher Interest Loans)$_i$ / (Total Loans)$_i$
For census tracts i from 1 … n

Clean Vehicles: The percent of a neighborhood's estimated vehicle stock that falls into a given type of vehicle. Below is an example for clean vehicles.

(Percent for Clean Vehicles)$_i$=(Number of Clean Vehicles)$_i$ / (Total Vehicle Stock)$_i$
For census tracts i from 1 … n

The same formula is used for newer clean vehicles, older clean vehicles, and "clunkers.

HVMT: Estimated Average Annual VMT per Household:

HVMT$_i$=(Estimated Total VMT)$_i$ / (Number of Households)$_i$
For census tracts i = 1 .. n

Total VMT is estimated from DMV and BAR data, and number of households and vehicles taken from the American Community Survey.

CVMT: Estimated Average Annual Commute VMT Per Worker. CVMT measure is calculated as follows:

CVMT$_i$=PMT$_i$ / (Vehicles per Commuter)$_i$
For census tracts i = 1 .. n

PMT is the estimated average person miles traveled based on LEHD data, and vehicles per commuter is

[45] The following four indicators were adopted and/or refined from a previous project conducted by the researchers for CARB and Caltrans: 1) Access to employment opportunities, 2) Job Density, 3) Jobs-Housing Fit, and 4) Access to High-Quality Transit Locations. For more details on these indicators, see: Ong, P. M., Pech, C., Cheng, A., & Gonzalez, S. R. (2018). Developing Statewide Sustainable-Communities Strategies Monitoring System for Jobs, Housing, and Commutes (Caltrans Agreement No. 65A0636). UCLA Center for Neighborhood Knowledge.

the estimated average number of persons per vehicle using means of transportation to work data from the American Community Survey.

Job Access: Accessibility to employment opportunities is estimated as the number of jobs inversely weighted by the estimated time to cover the road network distance. For census tract i,

$(\text{Job Access})_i = \text{SUM}(J_j/D_{i,j})$
For census tracts j = 1 .. n

SUM is the summing function of elements within the parentheses, J is the number of jobs in tract j as reported by LEHD, and $D_{i,j}$ is the time-distance decay function.

The functional form used to calculate the final access to jobs measure is exponential decay with author estimated parameter:

$$e^{-b(t-11)} where\ b = 0.0395\ and\ t = time$$

Availability of Public-Parks Space: Amount of public-park space per population.

$(\text{Availability of Public-Parks Space})i = (\text{Public-Park Space})i / (\text{Population})_i$
For census tracts i from 1 … n

Where "Public-Park Space" is the public-park area within and near a given tract, and the population within and near that tract.

Availability of Bikeways: Availability of bikeways per population, weighted by class of bikeways.

$(\text{Availability of Bikeways})_i = (\text{Weighted length of bikeways})_i / (\text{Population})_i$
For census tracts i = 1 .. n

Traffic Collision Rate: Estimated number of reported collisions per lane-weighted roadways.

$(\text{Traffic Collision Rate})_i = (\text{Number of Collisions})_i / (\text{Total roadway weighted by lanes})_i$
For census tracts i from 1 … n

Neighborhood Change: Difference in neighborhood characteristics between two time points. The indicators are constructed using principal components analysis to reduce multiple input variables to identify a smaller number of underlying latent of variables based on commonalities among the input variables. The chosen latent variable is based on the following:

$(\text{Change Indicator})_i = \text{MAX}(\text{Principle Component Latent Variables})_i$
For census tracts i from 1 … n

"MAX" denotes a function that identifies the principle component latent variable that accounts for the most variance in the input variables. This reduction process is done separately for socioeconomic input variables and for housing input variables.

Relative Neighborhood Income: A census tract's median household (HH) income as a percent of the region's median income.

$(\text{Relative Neighborhood Income})_i = (\text{Median HH Income})_i / (\text{Region Median HH Income})$

For census tracts i from 1 … n

Where the "Region Median HH Income" is for the region within which the tract is located.

Job Density: Jobs divided by a neighborhood's geographic area.

$(\text{Job Density})_i = J_j / A_i$
For census tracts j = 1 .. n

J is the number of jobs reported by LEHD, and A is the area.

Jobs–Housing Fit: Relative availability of affordable rental housing units to low-wage jobs.

$JHF_i = (\text{Low Wage Jobs})_i \ / \ (\text{affordable rental housing})_i$
For census tracts i = 1 .. n

JHF is the job-housing fit index, low-wage jobs are based on CTPP, and affordable rental housing is based on American Community Survey.

Access to High-Quality Transit Locations (HQTL): Availability of nearby HQTL.

$(\text{Access to HQTL})_i = (\text{Population with nearby HQTL})_i \ / \ (\text{Population})_i$
For census tracts i = 1 .. n

Appendix C: Distributional Analysis

The following tables provides a breakdown of the numeric values used to create the bar charts that are presented in Chapter 3 ("Distributional Analysis").

Table B-1. Distributional Analysis

	Regionally Adjusted AMI			
Neighborhoods Ranked by Average Insurance Premium (Quintiles)	**0–60%**	**60–80%**	**80–140%**	**140%+**
Lowest	10%	19%	24%	19%
Low	18%	19%	21%	19%
Moderate	17%	20%	19%	25%
High	18%	20%	20%	21%
Highest	37%	22%	16%	16%

	Regionally Adjusted AMI			
Neighborhoods Ranked by Lending Barriers (Quintiles)	**0–60%**	**60–80%**	**80–140%**	**140%+**
Lowest	20%	11%	18%	32%
Low	7%	11%	21%	35%
Moderate	12%	18%	23%	21%
High	20%	26%	22%	9%
Highest	41%	35%	16%	2%

	Regionally Adjusted AMI			
Neighborhoods Ranked by Share of Newer Clean Vehicles (Quintiles)	**0–60%**	**60–80%**	**80–140%**	**140%+**
Lowest	43%	37%	15%	2%
Low	25%	27%	21%	7%
Moderate	16%	18%	24%	15%
High	10%	12%	22%	30%
Highest	6%	6%	18%	46%

	Regionally Adjusted AMI			
Neighborhoods Ranked by Share of Older Clean Vehicles (Quintiles)	**0–60%**	**60–80%**	**80–140%**	**140%+**
Lowest	45%	37%	14%	2%
Low	23%	27%	22%	7%
Moderate	17%	18%	23%	16%
High	10%	13%	21%	30%
Highest	6%	6%	19%	45%

	Regionally Adjusted AMI			
Neighborhoods Ranked by Share of Clunker Vehicles (Quintiles)	**0–60%**	**60–80%**	**80–140%**	**140%+**
Lowest	8%	8%	17%	46%

Low	8%	13%	22%	29%
Moderate	17%	19%	24%	14%
High	29%	29%	20%	6%
Highest	38%	31%	17%	5%

	Regionally Adjusted AMI			
Neighborhoods Ranked by Average Household VMT (Quintiles)	**0–60%**	**60–80%**	**80–140%**	**140%+**
Lowest	44%	21%	16%	14%
Low	31%	24%	18%	15%
Moderate	16%	23%	20%	20%
High	8%	21%	22%	23%
Highest	2%	11%	25%	29%

	Regionally Adjusted AMI			
Neighborhoods Ranked by Average Commute VMT (Quintiles)	**0–60%**	**60–80%**	**80–140%**	**140%+**
Lowest	40%	22%	16%	13%
Low	24%	25%	19%	16%
Moderate	12%	18%	22%	21%
High	9%	15%	22%	27%
Highest	15%	19%	21%	23%

	Regionally Adjusted AMI			
Neighborhoods Ranked by Accessibility to Jobs (Quintiles)	**0–60%**	**60–80%**	**80–140%**	**140%+**
Lowest	14%	23%	23%	14%
Low	19%	21%	21%	18%
Moderate	20%	15%	19%	27%
High	13%	16%	20%	28%
Highest	34%	24%	18%	13%

	Regionally Adjusted AMI			
Neighborhoods Ranked by Park Availability	**0–60%**	**60–80%**	**80–140%**	**140%+**
Lowest	40%	29%	16%	7%
Low	25%	24%	21%	11%
Moderate	17%	20%	21%	20%
High	11%	15%	21%	27%
Highest	6%	12%	21%	34%

	Regionally Adjusted AMI			
Neighborhoods Ranked by Bikeways Availability (Quintiles)	**0–60%**	**60–80%**	**80–140%**	**140%+**
Lowest	28%	27%	18%	11%
Low	31%	26%	18%	12%

Moderate	20%	21%	21%	16%
High	13%	16%	21%	26%
Highest	8%	11%	20%	34%

	Regionally Adjusted AMI			
Neighborhoods Ranked by Traffic Collisions (Quintiles)	**0–60%**	**60–80%**	**80–140%**	**140%+**
Lowest	6%	12%	20%	36%
Low	8%	13%	22%	31%
Moderate	13%	18%	23%	18%
High	23%	27%	21%	10%
Highest	50%	29%	15%	5%

	Regionally Adjusted AMI			
Neighborhoods Ranked by Housing Market Neighborhood Change (Quintiles)	**0–60%**	**60–80%**	**80–140%**	**140%+**
Lowest	15%	18%	22%	22%
Low	21%	25%	19%	16%
Moderate	27%	21%	19%	15%
High	21%	21%	20%	18%
Highest	16%	15%	19%	29%

	Regionally Adjusted AMI			
Neighborhoods Ranked by Socioeconomic Neighborhood Change (Quintiles)	**0–60%**	**60–80%**	**80–140%**	**140%+**
Lowest	23%	19%	20%	18%
Low	21%	21%	20%	18%
Moderate	21%	23%	19%	20%
High	18%	19%	20%	22%
Highest	17%	17%	21%	23%

	Regionally Adjusted AMI			
Neighborhoods Ranked by Job Density (Quintiles)	**0–60%**	**60–80%**	**80–140%**	**140%+**
Lowest	6%	13%	21%	33%
Low	9%	17%	21%	28%
Moderate	22%	21%	20%	17%
High	28%	26%	19%	11%
Highest	35%	22%	18%	12%

	Regionally Adjusted AMI			
Neighborhoods Ranked by Jobs–Housing Fit (Quintiles)	**0–60%**	**60–80%**	**80–140%**	**140%+**
Lowest *(Job Deficit)*	53%	29%	13%	6%
Low	25%	30%	20%	8%

Moderate	14%	23%	24%	12%
High	5%	12%	26%	23%
Highest *(Affordable Housing Deficit)*	3%	4%	17%	51%

	Regionally Adjusted AMI			
Access to HQTL	**0–60%**	**60–80%**	**80–140%**	**140%+**
No Access	18%	31%	44%	56%
1	11%	15%	16%	20%
2	16%	17%	18%	12%
3	23%	23%	15%	8%
Complete Access	32%	14%	6%	4%

Appendix D: Indicators Derived from Other Sources

This appendix provides information on additional indicators derived from other sources but incorporated into the transportation disparity data/mapping portal. They are described in the following text.

American Community Survey Indicators

The project uses the American Community Survey (ACS) census tract–level statistics for neighborhood characteristics including demographic (racial and ethnic composition of the neighborhood), economic status (median household income or poverty), housing (tenure and housing costs), and transportation (means of transportation to work, vehicle ownership). The ACS is a continuous survey that collects social, economic, demographic, and housing characteristics information about the population. The ACS pools a series of monthly samples to provide an ongoing stream of detailed and updated information. The ACS provides two period estimates, 1-year and 5-year, in two formats: tabulated (or summary) and microlevel data. Period estimates are determined by the population size of an area: 1-year estimates for geographies with a population of more than 65,000 and 5-year estimates for all areas. The ACS surveys about 2.5 percent of the population annually or 12.5 percent over 5 years. The 5-year survey will be used for this project because it provides the largest sample size of all the ACS data products, making data available for small geographies such as a census tract. This project specifically uses the 2014–18 5-year ACS.

Socioeconomic

Median Household Income

Median income for households is based on the distribution of the total number of households and families, including those with no income. The median income for households is computed on the basis of a standard distribution and the median divides the income distribution into two equal parts.

Poverty Rate

The poverty rate indicator measures the percentage of people (individuals for whom poverty status is determined) in the census tract living below the federal poverty level. The Census Bureau determines the federal poverty level each year.

Transportation Resources

Households with No Vehicle

Occupied housing units that reported having no vehicles kept at home and available for use of household members. These vehicles include passenger cars, vans, and pickup or panel trucks of one-ton capacity or less.

Vehicle Ownership Per Household

Vehicle ownership per household was calculated by dividing the total number of vehicles, used for noncommercial purposes, per household in a given area by the total population of that area.

Means of Transportation to Work

The data cover workers 16 years of age and older who were employed during the week prior to the ACS reference week and did not work at home. Respondents answered questions about the means of transportation used to get to work.

The percentage of workers using a specific travel mode was obtained by dividing the number of workers in that category by the total population of workers.

Public Transit for Job Commute
Number of individuals in a given area who use public transportation (primarily bus or trolley bus, streetcar or trolley car, subway or elevated, railroad, or ferryboat) as their primary means of travel between home and work during the reference week

Bike for Job Commute
Number of individuals in a given area who bike as their primary means of travel between home and work during the reference week

Walk for Job Commute
Number of individuals in a given area who bike as their primary means of travel between home and work during the reference week.

Drive Alone for Job Commute
Number of individuals in a given area who drove alone to work or people who were driven to work by someone who then drove to a nonwork destination.

Carpool for Job Commute
Number of individuals in a given area who usually rode to work in a vehicle with two or more people.

Average (Mean) Travel Time to Work (in Minutes)
Average travel time that workers usually took to get from home to work (one-way). This was calculated by dividing the total number of minutes of their one-way travel by the number of workers 16 years old and older who did not work at home. This measure is obtained by dividing the total number of minutes taken to get from home to work (the aggregate travel time) by the number of workers 16 years old and older who did not work at home.

<u>Health</u>

No Health Insurance Coverage
Lack of health insurance coverage is defined as the share of individuals without health insurance. It is calculated by dividing the total number of individuals who reported not having health insurance coverage in a census tract by the total population (civilian noninstitutionalized population) in that area.

Respondents of the ACS were instructed to report their current coverage and to mark "yes" or "no" for each of the eight types listed.

a. Insurance through a current or former employer or union (of this person or another family member)
b. Insurance purchased directly from an insurance company (by this person or another family member)
c. Medicare, for people 65 and older, or people with certain disabilities
d. Medicaid, Medical Assistance, or any kind of government-assistance plan for those with low incomes or a disability
e. TRICARE or other military health care
f. VA (enrolled for VA health care)
g. Indian Health Service
h. Any other type of health insurance or health coverage plan

Respondents reporting "No" to all the preceding items would be considered as having no health insurance coverage.

Medicaid Health Insurance Only
Medicaid is "a program administered at the state level, which provides medical assistance to the needy. Families with dependent children, the aged, blind, and disabled who are in financial need may be eligible for Medicaid." In California, the Medicaid program is known as Medi-Cal. This indicator represents the share of individuals who are covered by the Medicaid health insurance program. It is calculated by dividing the total number of individuals with Medicaid health insurance coverage in a census tract by the total population (civilian noninstitutionalized population) in that area.

<u>Housing</u>

Percent Renter-Occupied Households
All occupied housing units that are not owner-occupied are classified as renter-occupied regardless of whether they are rented or occupied without payment of rent. The percentage of renter-occupied households was calculated by dividing the number of renter-occupied households by all occupied housing units.

Percent Households Paying 30–49 Percent of Income Toward Housing Costs
The percentage of households (both renters and homeowners) who pay 30–49 percent of their household income toward housing costs are considered cost-burdened.

Percent Households Paying 50 Percent or More of Income Toward Housing Costs
The percentage of households (both renters and homeowners) who pay 50 percent or more of their household income toward housing costs are considered severely cost-burdened.

Percent Multifamily Housing Units
The percentage of multifamily housing units is calculated by dividing the total housing in structures with two or more units by the total housing stock in a given census tract. These multifamily housing units would include structures like duplexes, triplexes, quadruplexes, and larger apartment buildings.

Housing Units Per Square Miles (Land Area)
Housing unit density is computed by dividing the total number of housing units within a census tract by the land area in square miles. Housing unit density is expressed as housing units per square per square mile of land area.

<u>Population</u>

Population Density
Population density is computed by dividing the total population within a census tract by the land area in square miles. Population density is expressed as people per square per square mile of land area.

Largest Ethnoracial Group
Ethnorace refers to the six major demographic groups widely adopted by academic researchers, policy analysts, government, and the media: Non-Hispanic Whites, Black or African Americans, Asian Americans, Hispanic or Latinos, Native Hawaiian or other Pacific Islander, and American Indian or Alaskan Native. These terms have components that are both ethnic and racial and that are difficult to disentangle. The largest ethnoracial group represents the group that makes up the majority of the population in a census tract (i.e., having a population size greater than or equal to 50 percent in a census tract). For example, if the population of Black or African Americans in a census tract is 50 percent or more then that neighborhood is designated as a "Majority Black" neighborhood. Each ethnoracial group's share of the population is calculated by dividing the total population of each group in a given area by the total population in that area.

EPA's Walkability Index

The Walkability Index indicator characterizes every census tract based on its relative walkability. It was constructed by the U.S. EPA and represent Version 2.0 (released in July 2013). The index is based on the physical characteristics (pedestrian-oriented intersections, quantity of occupied housing), business activities (mix of worksite jobs by economic sector), and travel behavior (commute mode). Areas with more intersections, mixed uses, and carpooling are designated as being more conducive to walking, and therefore have higher index scores. It should be noted, however, the index does not account for other key factors, such as aesthetics, open space, and safety. More information can be found here.[46] The EPA constructs the walkability index at the block group level, which we summarize into census tracts for this project by taking the average of all block groups within each tract.

Asthma (Emergency Department Visits)

This indicator uses the emergency department visits for asthma as a proxy to understand the prevalence of asthma. The data was taken from the California Office of Environmental Hazard Assessment, which reported the emergency department visits for asthma in CalEnviroScreen 3.0. The data specific to emergency department visits and hospitalizations came from the California Office of Statewide Health Planning and Development, which collects emergency department visit data. More information can be found here.[47]

Cardiovascular Disease (Emergency Department Visits for Heart Attacks)

This indicator uses the emergency department visits for heart attacks per year as a proxy to understand the prevalence of cardiovascular disease. The data was taken from the California Office of Environmental Hazard Assessment, which reported the emergency department visits for heart attacks in CalEnviroScreen 3.0. The data specific to emergency department visits and hospitalizations came from the California Office of Statewide Health Planning and Development, which collects emergency department visit data. More information can be found here.[48]

Life Expectancy at Birth (Years)

This indicator represents estimates of life expectancy at birth—the average number of years a person can expect to live—for census tracts and for the 2010–15 period. These estimates are the result of the collaborative project, "U.S. Small-Area Life Expectancy Estimates Project," between the National Center for Health Statistics, the National Association for Public Health Statistics and Information Systems, and the Robert Wood Johnson Foundation. More information can be found here.[49]

Primary Care Shortage Areas

Primary care shortage areas (PCSAs) are a designation defined by the State of California for the purposes of identifying medically underserved areas to inform funding decisions for programs within the Office of Statewide Health Planning and Development (OSHPD). PCSAs are classified based on two criteria: poverty and patient-to-primary-care-provider ratio. A PCSA is defined as having more than 25 percent of the total population living in poverty and a ratio of patients-to-primary-care-provider higher than 1:3,000 or with no providers at all. For more details on the definition and methodology of PCSA, see OSHPD memorandum.[50]

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[46] See https://www.epa.gov/smartgrowth/smart-location-mapping#walkability. Accessed on January 11, 2021.
[47] See https://oehha.ca.gov/calenviroscreen/indicator/asthma. Accessed on January 11, 2021.
[48] See https://oehha.ca.gov/calenviroscreen/indicator/cardiovascular-disease. Accessed on January 11, 2021.
[49] See https://www.cdc.gov/nchs/nvss/usaleep/usaleep.html. Accessed on January 11, 2021.
[50] See https://oshpd.ca.gov/wp-content/uploads/2020/10/Attachment-E-FNPPA.pdf. Accessed on January 13, 2021.

Our assessment indicates that tracts fit completely within the geographic boundaries of PCSA. Because no tract is split between two or more PCSAs, we are able to determine whether a census tract is fully in a shortage area (with a simple dichotomous assignment of yes or no).

Appendix E: Data/Mapping Tool User Guide

The following includes the "User Guide" for the data/mapping tool. To access the data/mapping portal visit: https://experience.arcgis.com/template/9c13f35df3904dcb80530d0df49bdf9e

TRANSPORTATION DISPARITIES MAPPING TOOL USER GUIDE

California Air Resources Board
UCLA Center for Neighborhood Knowledge

Draft Version 5.16.2021
800-242-4450 | helpline@arb.ca.gov
1001 I Street, Sacramento, CA 95814 | P.O. Box 2815, Sacramento, CA 95812

TABLE OF **CONTENTS**

ABOUT THE **TOOL**

What is the Transportation Disparity Mapping Tool?

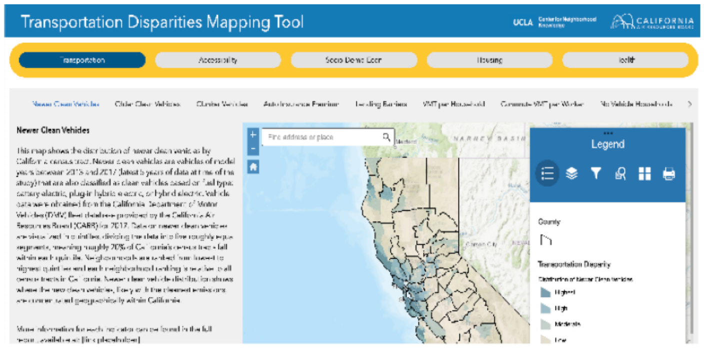
The Transportation Disparity Mapping Tool is a project developed to better understand transportation disparities and built environment-related determinants of health in California. It is a component of larger initiatives of the California Air Resources Board (CARB). According to Senate Bill 150, CARB is mandated to assess progress toward meeting greenhouse gas reduction goals. While striving to meet these goals, CARB also aims to ensure all segments of society benefit from CARB's climate change agenda, including disadvantaged communities (SB 535 and AB 617). In accordance with CARB goals, this mapping tool is a web-based information visualization portal that contains indicators related to the causes, characteristics, and consequences of transportation disparities. This tool provides useful indicators for CARB and other organizations to help fulfill state mandates related to climate change, greenhouse gas emissions, and environmental justice, and to evaluate progress towards a more sustainable and environmentally just future.

This tool was developed with an advisory committee and analyzed four major categories of disparities, including private vehicle ownership, public transit, active transportation, and transportation networks. The advisory committee, which aimed to provide stakeholder engagement, included representation from health experts, academics and researchers, and community organizations. The advisory committee also assisted in selecting which indicators and disparities should be prioritized and with the overall construction of the mapping tool. Additionally, a team of researchers and academics, led by Principal Investigator Paul Ong of UCLA Center for Neighborhood Knowledge (CNK), developed and visualized the indicators used in this tool. The development of this guide was funded in part by the **California Initiative for Health Equity and Action**.

This guide shows where to find documentation and methodology for each indicator. It provides guidance on how to navigate the map so that the user can work through the features and see the full scope of the information.

As a land grant institution, the authors acknowledge the Gabrielino and Tongva peoples as the traditional land caretakers of Tovaangar (Los Angeles basin, Southern Channel Islands), and recognize that their displacement has enabled the flourishing of UCLA.

MAPPING TOOL



The Transportation Disparities Mapping Tool is available here.

▷ Data Highlights

This mapping tool includes four domains of transporation disparities and multiple built environment determinants of health. Here is a select list of the indicators included in each of the primary data domains of the mapping tool:

Transportation | Accessibility | Socio-Demo-Econ | Housing | Health

Transportation
- Newer Clean Vehicles
- Vehicles per Household
- % Public Transportation for Job Commute

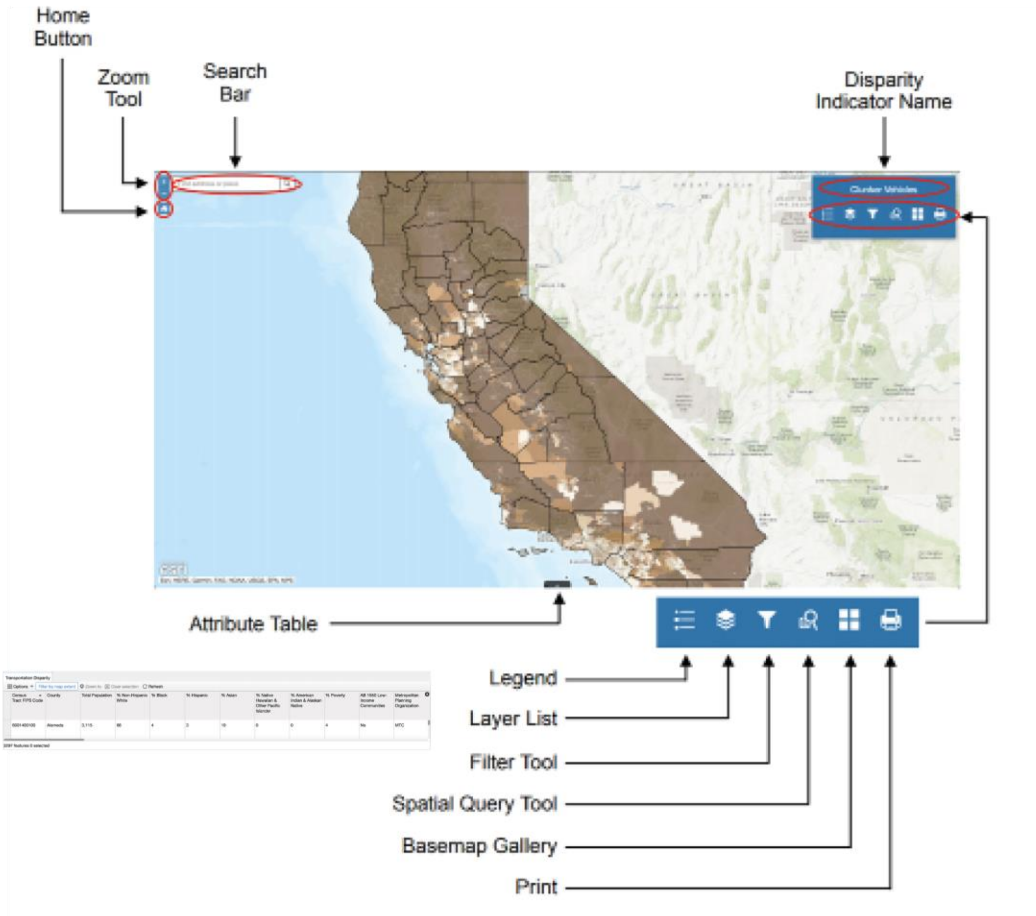
Accessibility Measures
- Access to High-Quality Transit Locations
- Accessibility to Employment Opportunities
- Jobs-Housing Fit

Socio-Demo-Econ
- Largest Ethnoracial Group
- Job Density
- Neighborhood Change, Socioeconomic Variables

Housing
- % Multi-Family Housing Units
- % Households Paying 50% or More of Income Towards Housing Costs
- % Renter-Occupied Households

Health
- Traffic Collisions per Weighted Roadways
- Primary Care Shortage Areas
- Cardiovascular Disease

▷ Main Navigation Overview



Use the tools on the top corners to navigate the mapping tool. On the top right, there are widgets that allow you to search for an area of interest and on the top left, you will find various tools to conduct your analysis.

We recommend exploring the different tools on the platform first before diving straight into the next section of the user guide, which provides detailed information and instructions.

Who to contact?

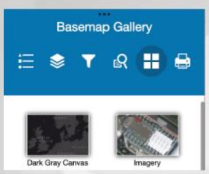
Please contact CARB at helpline@arb.ca.gov if you have any questions or feedback regarding the mapping tool.

How do I use the mapping tool?

To search for a specific location, type a county, city, zip code, address, or place into the search bar and the map will automatically zoom to that location. Once you have typed your desired search location, you can either select it from the options that appear below the search bar or click on the magnifying glass icon to zoom to that location.

To zoom, use the boxes with the + and - symbols on the lefthand side of the map to zoom in and out. Clicking the "+" will zoom in to wherever your page is centered around, and clicking the "–" will zoom out. You can also place your mouse over a desired location and swipe with two fingers on your trackpad to zoom in and out. Alternatively, you can click and hold your mouse anywhere on the map while dragging to pan around the screen.

Click the ***home button*** with the home icon at any time to return to the original map extent.



To change the basemap, click on the highlighted icon composed of 4 white squares titled "Basemap Gallery," the fifth icon from the left. From there, a list of 12 optional basemaps will appear below. You can select whichever basemap you prefer and can change the basemap at any point without affecting your other selections/zoom.

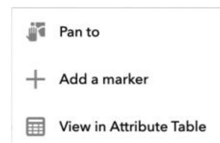
▷ Pop-Up Window

Click on any tract within the map and a pop-up window will appear. Within it, you will see:

1. The title, indicating what indicator this map is displaying
2. The unique Census Tract number
3. What category the specific census tract falls under for your given indicator (listed as a decile, number, etc.)
4. The total population number
5. Demographics of the population within that census tract.

Press "Zoom to" in the bottom left corner to zoom the map scale to the selected tract. Press the three dots in the bottom right corner for a list of options:

1. "Pan to" re-centers the selected tract to the middle of your screen
2. "Add a marker" places a marker on the tract so that it may be located easily if zoomed out to a greater extent
3. "View in Attribute Table" will cause the attribute table with information to appear at the bottom of your screen which can be exported if desired



Close the pop-up window by pressing the X in the top right corner of the window box.

▷ Turning on Data Filtering Tools

Select the ***Filter Tool*** from the main panel of widgets. You can utilize a single filter or a combination of filters to analyze patterns across California. Once filters have been selected, make sure the switch within the legend at the top of the filter list is green, indicating that the map has been turned 'on'. The various filters operate as follows:

Geography Filters
- County is: (select a county)
- Metropolitan Planning Organization is: (select an MPO)
- SB 535 Disadvantaged Communities is: (select yes or no)
- AB 1550 Low-Income Communities is: (select yes or no)
- Area Median Income (Regionally Adjusted) is: (select a percentage range)

Socio-Demo-Econ
- Median Household Income is Between: (enter a range of values)
- % Poverty is between: (enter a range between 0 and 100)
- Largest Ethnoracial Group is: (select an option)
- Population Density (Decile) is: (select a range of deciles)
- Job Density (Decile) is: (select a range of deciles)
- Neighborhood Change, Socioeconomic Variables (Decile) is: (select a range of deciles)

Transportation
- Auto Insurance Premium (Decile) is: (select a range of deciles)
- Lending Barriers (Decile) is: (select a range of deciles)
- Newer Clean Vehicles (Decile) is: (select a range of deciles)
- Older Clean Vehicles (Decile) is: (select a range of deciles)
- Clunker Vehicles (Decile) is: (select a range of deciles)
- Average VMT per Household (Decile) is: (select a range of deciles)
- Average Commute VMT (Decile) is: (select a range of deciles)
- Vehicles per Household is between: (enter a range of values)
- % Households with No Vehicle is between: (enter a range of values)
- % Drove Alone for Job Commute is between: (enter a range between 0 and 100)
- % Carpooled for Job Commute is between: (enter a range between 0 and 100)
- % Public Transportation for Job Commute is between: (enter a range between 0 and 100)
- % Bike for Job Commute is between: (enter a range between 0 and 100)
- % Walk for Job Commute is between: (enter a range between 0 and 100)
- Average Travel Time to Work (Minutes) is between: (enter a range of values)

Accessibility Measures
- Access to High-Quality Transit Locations is: (select an option; consult guidebook) *see note below
- Availability of Weighted Bikeways per Population is: (select an option; consult guidebook) *see note below
- Availability of Parks & Public Open Space per Population (Decile) is: (select a range of deciles)
- Accessibility to Employment Opportunities (Decile) is: (select a range of deciles)
- Jobs-Housing Fit (Decile) is: (select a range of deciles)

Housing
- Housing Unit Density (Decile) is: (select a range of deciles)
- % Multi-Family Housing Units is between: (enter a range between 0 and 100)
- % Renter-Occupied Households is between: (enter a range between 0 and 100)
- % Households Paying 30 - 49% of Income Towards Housing Costs is: (enter a range between 0 and 100)
- % Households Paying 50% or More of Income Towards Housing Costs is: (enter a range between 0 and 100)
- Neighborhood Change, Housing Variables (Decile) is: (select a range of deciles)

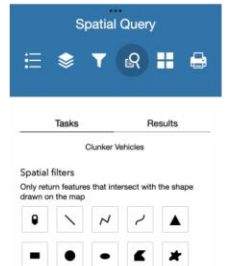
Health
- % with Medicaid Health Insurance Only is between: (enter a range between 0 and 100)
- % No Health Insurance is between: (enter a range between 0 and 100)
- Life Expectancy at Birth is between: (enter a range of values, in years)
- Traffic Collisions per Weighted Roadways (Decile) is: (select a range of deciles)
- Primary Care Shortage Areas is: (select yes or no)
- Walkability Index (Decile) is: (select a range of deciles)
- Asthma Prevalence (Decile) is: (select a range of deciles)
- Cardiovascular Disease (Decile) is: (select a range of deciles)

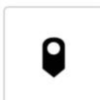
**Both high-quality-transit location and availability of bikeways indicators cannot be reported as decile rankings due to the nature of the data (see report for further details). For both of these indicators, the higher the filter value the more access to a high-quality-transit location or more availability of bikeway infrastructure. A value of "0" represents no access to a high-quality-transit location or no availability of bikeway infrastructure.*

More information for each indicator can be found in the full report, available at: [link placeholder]

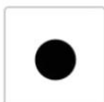
▷ Exploring Data with Spatial Query Tools

The ***spatial query tool*** can be used to select and analyze certain census tracts or groups of tracts. Shapes can be drawn over the map, then tracts that intersect with the shape's area can be analyzed. There are 10 different methods of drawing points or shapes, depending on how you want to spatially filter the data. These specifications can be found under the "Tasks" section of the spatial query tool:

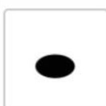


	**Point:** The point tool allows you to place a point anywhere on the map and analyze the census tract in which the point is placed. Select the point icon, then select anywhere on the map. You will see a small gray point appear where you clicked on the map. If you want to place your point somewhere else, simply reselect the point icon and click a new location on the map where you prefer to analyze.
	**Line:** The line tool allows you to draw a straight line anywhere on the map and then analyze tracts that intersect with that line. Select the line icon, then click and hold anywhere on the map. Continue holding as you drag your cursor for a desired length and direction over the map. Release when you are satisfied with the line. You should see a blue dotted line appear where you drew. If you want to change the location of your line, simply reselect the line icon and follow the same steps for a new location.
	**Polyline:** The polyline tool allows you to draw multiple segments of straight, connected lines anywhere on the map and then analyze tracts that intersect with that line. Select the polyline icon, then click anywhere on the map. Move your cursor to your desired location and click again to complete a segment. Continue clicking and releasing for each segment. Once satisfied with your polyline, double-click to complete the line. If you want to change the location of your polyline, simply click the polyline tool again and follow the same steps for a new location.
	**Freehand Polyline:** The freehand polyline tool allows you to draw a freehand line (not necessarily straight) anywhere on the map and then analyze tracts that intersect with that line. Select the freehand polyline tool, then click and hold anywhere on the map. Continue holding as you move your cursor around the map. The freehand polyline will trace where you move your cursor. Release when you are satisfied with the line. You should see a blue dotted line appear where you drew. If you want to change the location of your line, simply reselect the freehand polyline icon and follow the same steps for a new location.
	**Triangle:** The triangle tool allows you to draw a triangle of any size anywhere on the map and then analyze tracts that intersect that triangle. Select the triangle tool, then click and hold anywhere on the map. Continue holding as you move your cursor out and in, changing the size of the triangle but remaining centered around your initial click location. Release when you are satisfied with the triangle. You should see a translucent blue triangle appear on the map. You may also simply click and release immediately for a generic sized triangle shape. If you want to change the location of your triangle, simply reselect the triangle icon and follow the same steps for a new location.

Extent: The extent tool allows you to draw a rectangle of any size anywhere on the map and then analyze tracts that intersect that triangle. Select the rectangular extent tool, then click and hold anywhere on the map. Continue holding as you move your cursor around, changing the size of the rectangle while one corner remains anchored around your initial click location. Release when you are satisfied with the extent. You should see a translucent blue rectangle appear on the map. If you want to change the location of your extent, simply reselect the extent icon and follow the same steps for a new location.



Circle: The circle tool allows you to draw a circle of any size anywhere on the map and then analyze tracts that intersect that circle. Select the circle tool, then click and hold anywhere on the map. Continue holding as you move your cursor out and in, changing the size of the circle but remaining centered around your initial click location. Release when you are satisfied with the circle. You should see a translucent blue circle appear on the map. You may also simply click and release immediately for a generic sized circle shape. If you want to change the location of your circle, simply reselect the circle icon and follow the same steps for a new location.



Ellipse: The ellipse tool allows you to draw an ellipse of any size on the map and then analyze tracts that intersect that ellipse. Select the ellipse tool, then click and hold anywhere on the map. Continue holding as you move your cursor out and in, changing the size of the ellipse but remaining centered around your initial click location. Release when you are satisfied with the ellipse. You should see a translucent blue ellipse appear on the map. You may also click and release immediately for a generic sized ellipse shape. If you want to change the your ellipse's location, reselect the ellipse icon and follow the same steps.

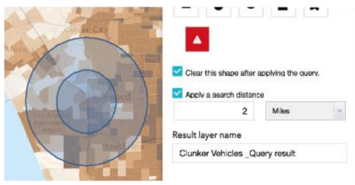
Polygon: The polygon tool allows you to draw a polygon of any size or shape with straight edges anywhere on the map and then analyze tracts that intersect that polygon. Select the polygon tool, then click anywhere on the map. Move your cursor to your desired location and click again to complete a segment. Move and click again to add another side. Continue adding your desired number of sides then double-click when you are satisfied. Note that the polygon must have at least 1 side (two clicks) making a line. If you cross sides over one another, a negative area may appear. You should see a blue translucent polygon specifying the areas of analysis appear on the map. If you want to change the location of your polygon, simply click the polygon tool again and follow the same steps for a new location.

Freehand Polygon: The freehand polygon tool allows you to draw a polygon of any size or shape with anywhere on the map and then analyze tracts that intersect that polygon. Select the freehand polygon tool, then click and hold anywhere on the map. Move your cursor to draw a freehand polygon shape and release when completed. If you cross sides over one another, a negative area may appear. You should see a blue translucent polygon specifying the areas of analysis appear on the map. If you want to change the location of your polygon, simply click the tool again and follow the same steps for a new location.

Clear: If at any point you want to clear a drawn shape, either select your desired tool and redraw, or press the red icon with the exclamation point within a triangle to clear the drawn shapes.

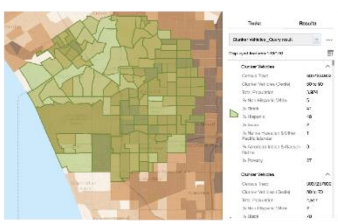
▷ Applying a Search Distance

1. After a shape is drawn, you can specify a search distance to increase the area of analysis. Check the box labeled "Apply a search distance" and type a number and select the units.



2. You will see your shape along with a slightly more translucent blue border around it, visualizing the specified search distance. If you do not want a search distance, either uncheck the box or type a value of zero.

3. Once satisfied, you may rename the resulting layer (optional). Then select the green button at the bottom labeled "Apply"



4. Upon pressing "Apply", the tool will bring you to the "Results" section of the spatial query tool and zoom to the selection of tracts that you selected with your shape. You can then click on any tract in the list to zoom to that specific tract.

5. To show or hide the information about a tract in the results window, click on the small up arrow in the upper right corner of the tract's information section. If you want to display or hide the information for all tracts, press the symbol consisting of lines and an arrow. This will either collapse or expand all results depending on if you have your information sections open or closed currently.

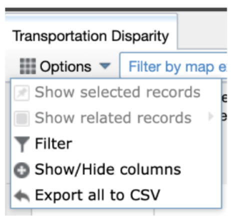
Note:

You can only draw one singular spatial-filter shape at any time. Once you begin to draw a new shape, whether of the same type as the previous shape or a new type, your old shape will disappear and be replaced by the new drawing.

▷ How do I export data?

How do I export as a CSV file?

Click on the small black box with the arrow at the bottom of the page to bring up a table with data on indicators by census tract. You can drag the top of the table up and down to change how much of it you want to see, and at any point you can click the black arrow again to hide the table and return to the map view.



Within this table, you can choose to filter the tracts by clicking “Options” -> “Filter”. You can also choose to show or hide column options by clicking “Options” -> “Show/ Hide columns” then checking the columns you desire in the window that pops up.

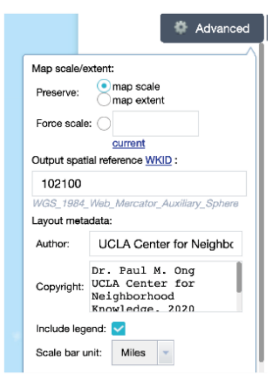
To export the data table as a comma separated value file (.csv), click “Options” -> “Export all to CSV” then click “OK” in the window that pops up.

How do I export a map image?

To print the map, select the “Print” widget from the list of options. Within the widget, you can specify the Map title, Layout, and Format. The following file type options are available under “Format”:

- AIX
- EPS
- GIF
- JPG
- PDF
- PNG32
- PNG8
- SVG
- SVGZ

(PDF, JPG, and PNG are the most common formats)



Customize your map using the options in the “Advanced” window as follows:

1. Preserve:
   - Map scale: the level of zoom will be preserved
   - Map extent: the extent of the map seen on screen will be preserved
   - Forced scale: type your own scale, or press current to use the current scale
2. Output spatial reference WKID:
   - Enter the WKID for the spatial reference. For example, “WGS_1984_Web_Mercator_ Auxillary_Sphere” has a WKID of 102100
3. Layout metadata:
   - Check or uncheck “Include legend”
   - Scale bar unit: Miles, Kilometers, Meters, or Feet

Once desired options have been selected, click “***Print***”. Once completed, a map image file will be displayed. Click on it to send to a printer or download in the file format specified. Press “***Clear prints***” to remove previous print layouts.


Metro Local

TRANSPORTATION
CASE EXAMPLES

The following are four case examples that use data from the Transportation Disparities Database to explore the relationship between transportation and health, and the causes, characteristics, and consequences of transportation disparities. The examples highlight how different stakeholders working on related policies, plans, and programs, used the information to enhance the effectiveness of transportation-related investments, interventions, and other efforts to improve employment, educational, and health outcomes.

Case Examples

1. Bikeway Planning in the South Bay
2. Understanding Transit Barriers to Health Care Access in Oakland
3. Determinants of Active Transportation in California
4. Heterogenity Among Disadvantaged Neighborhoods

▷ Bikeway Planning in the South Bay

- Indicators of use: Availability of Weighted Bikeways per Population; Traffic Collisions per Weighted Roadways
- Purpose: Informing bikeway planning

This case example describes a plan for full implementation of a master bikeway plan in Los Angeles County's South Bay. The South Bay is a coastal area in southwest Los Angeles County that includes the relatively affluent cities of Hermosa Beach, Manhattan Beach, and Redondo Beach. The community group South Bay Bicycle Coalition (SBBC) is advocating for these bikeways to promote more active transportation and improved safety in these cities. SBBC is a 501(c)(3) nonprofit founded in 2009 by a group of bike-loving advocates. The areas where the proposed bikeway would exist is relatively high income and predominantly non-Hispanic White.

Specifically in Redondo Beach, SBBC hopes to implement its 38.8 miles Bicycle Master Plan that would connect existing bikeway infrastructure to their proposed bike paths, lanes, and routes. The Bicycle Master Plan in Redondo Beach is aimed at connecting schools, businesses, services, and recreation venues as a way to promote wellness, increase access to low-cost transportation, and reduce traffic and greenhouse gas emissions.

The analysis involved:

1. **REVIEW OF CARB INDICATOR MAPS:** SBBC analyzed "availability of bikeway" and "vehicle accident" indicator maps to get a better understanding of the area's need and ability to support new bikeways.

2. **GATHERING MORE DATA:** SBBC supplemented the indicator maps with additional data on "bicycle accidents". SBBC used UCLA-CARB metadata to find the source of the accident data, which allowed them to better understand where the greatest bicycle safety concerns were located.

3. **ANALYSIS OF SUPPLEMENTAL DATA:** SBBC further analyzed 2019 and 2020 cycle counts to complement the "availability of bikeway" indicator maps. While the availability maps provided a picture of the supply of bikeway infrastructure, the raw 2019 and 2020 cycling counts provides a picture of the demand (usage) of bikeways.

4. **COLLABORATION WITH REGIONAL OFFICES:** Working alongside the regional office of the Los Angeles County public health department, the analysis of cycling counts showed that there was an increase in cycling in Redondo beach during the COVID-19 pandemic.

5. **PRESENTATION OF DATA ANALYSIS TO CITY:** Using UCLA CARB and supplemental data, the SBBC presented this information to the Redondo Beach City Council and city staff to increase awareness and encourage bikeway development.

6. **RESULTS:** Starting with UCLA CARB data, the SBBC used their supplementary data to construct two maps of the north and south portions of North Redondo Beach (see Map 1.1 and Map 1.2, respectively) that showed existing and proposed bikeways. The organization documented existing bikeways and illustrated where new paths, lanes, and routes should be developed. The South Bay Bicycle Master Plans was developed into a presentation to be pitched at the upcoming Commission and City council meetings.

Map 1.1: North Redondo Beach Existing and Proposed Bikeways

Map 1.2: South Redondo Beach Existing and Proposed Bikeways

▷ Understanding Transit Barriers to Health Care Access in Oakland

- Indicators of use: Availability of Weighted Bikeways per Population; Traffic Collisions per Weighted Roadways; % No Health Insurance; Primary Care Shortage Areas
- Purpose: Enhancing health service provision

This case example develops a service area profile using demographic data from the Transportation Disparities Database to measure geographic access to medical care by public transit and understand transit barriers. The purpose of the analysis was to help Asian Health Services gain a better understanding of the population and health-care providers within a reasonable bus trip from their clinic to enhance their health service provision. Asian Health Services in Oakland aims to serve the underserved, especially Asian immigrants and refugees, and provides health care services in 15 languages as well as advocacy services.

The analysis involved five steps:

1. **DEFINING A SERVICE AREA OF INTEREST:** To define the service area and boundary, we used the location of Asian Health Services' medical clinic in Oakland as our starting point to define a "catchment area," a proxy for a reasonable service area within a bus ride.

2. **OVERLAY OF CENSUS GEOGRAPHIES:** Next, we determined what constitutes a reasonable bus trip. The U.S. Department of Health and Human Services deems that 30 minute is a reasonable travel time to access health care. To determine the geographic areas within the allowable travel time, we use the Google Maps API platform to identify all census block groups reachable during a 30-minute bus trip from the clinic. The block groups are subunits of census tracts, which make it easy to join our "catchment area" with other census-based products and the Transportation Disparities Database. Map 2.1 provides an overview of the boundaries of our catchment area of interest.

3. **LOCATING & MERGING VARIABLES FROM TRANSPORTATION DISPARITIES DATABASE:** We identified four variables from the Transportation Disparities Database that are relevant to helping us understand the providers and characteristics of the population within a 30 minute bus ride from Asian Health Services:
   - population race/ethnic breakdown
   - % of the population in poverty
   - % of households without a car
   - % residents without health insurance

4. **LINKING WITH EXTERNAL DATA:** In SAS, we linked the Transportation Disparities Database variables of interest to our catchment area using the census tract ID and other external data of interest, including the number of primary care physicians providers that accept Medi-Cal, a public health care program for those with limited income.

5. **RESULTS:** We produced three types of statistics as part of our profile. The first summarizes the geographical characteristics of the catchment area. The area is about 31 square miles and the distance accessible within a 30-minute bus ride is less than 4 miles. The second statistics are selected demographic characteristics of the area, which shows the service area is disproportionately people of color, low income and transit dependent relative to California. Finally, the third set measures the number of Medi-Cal enrollees and Medi-Cal providers, and health insurance coverage. The data indicate there is about 1 medical provider per 70 people in the catchment area. About 11% of the population does not have health insurance coverage within the service area (see Map 2.1 and Table 2.1).

Map 2.1: Asian Health Services Catchment Area

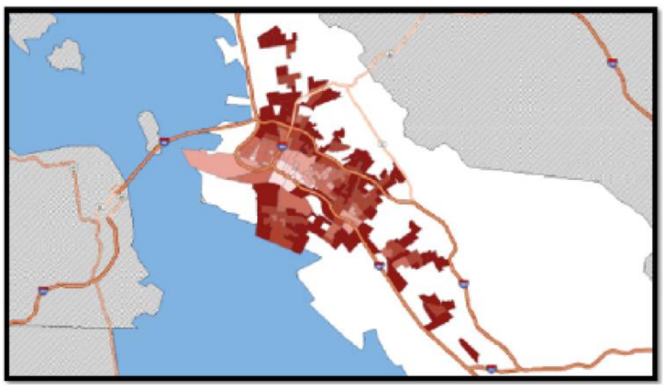


Table 2.1: Transit-Accessible Service Area Profile

Area Accessible Within a 30-minute Bus Ride from Oakland Clinic		
Area (mi²)		30.6
Median Distance (mi)		3.3
Mean Distance (mi)		3.7
Demographic Characteristics of Area		
	Catchment Area	*California*
Total Population	340,339	38,982,847
Non-Hispanic White	29.5%	37.9%
Non-Hispanic Black	18.7%	5.5%
Non-Hispanic Asian	21.2%	13.9%
Hispanic	24.2%	38.8%
Below Federal Poverty Level	19.8%	15.1%
Households w/o vehicle	18.8%	7.4%
Medical Care Characteristics of Area		
Percent Population with Medicaid Only	19.8%	18.9%
Percent Population Not Insured	10.8%	10.5%
Total Medi-Cal Providers	955	52,539
Medi-Cal Providers to Medicaid-only Population	1:70	1:138

▷ Determinants of Active Transportation in California

- Indicators of use: Availability of Parks & Public Open Space per Population; Access to High-Quality Transit Locations
- Purpose: Academic research on walking

This case example uses data from the California Health Interview Survey at the zip code tabulation area (ZCTA) and accessibility measures from the Transportation Disparities Database to examine the determinants of walking in California's neighborhoods. The analysis uses ecological regression models to inform both disciplinary knowledge and professional practice related equitable community development policies and practices.

The statistical analysis involved three steps:

1. **LOCATING & MERGING VARIABLES FROM TRANSPORTATION DISPARITIES DATABASE:** We identified four variables from the Transportation Disparities Database that are relevant to helping us understand determinants of walking in California's neighborhoods: park and open space availability, EPA Walkability, high-quality transit locations, and % households without a vehicle.

2. **LINKING WITH EXTERNAL DATA:** In SAS, we linked the variables of interest from the Transportation Disparities Database to information from the California Health Interview Survey and the American Community Survey at the ZCTA level. The Transportation Disparities indicators, which are at the census tract level, were allocated to the ZCTA geographies using area weights.

3. **RESULTS:** Using multivariate ecological regression, we modeled the propensity of walking on the linear combination of variables related to demographic, health, socioeconomic status, environmental, and the accessibility measures from the Transportation Disparities Database. The measures were subsequently reviewed to assess the relative importance in the prediction of walking propensity. The regression results are presented in Table 3.1 for three models. The first model examines only the relationship between ethnoracial composition and walking. The second model includes controls for other relevant measures, and the final parsimonious model includes only variables that are statistically significant as well as racial and ethnic composition.

The regression models indicate that neighbohoods with higher percentages of Latinos correlate with a lower propensity of walking, but the direction of the relationship for Latinos changes when controlling for other factors as does the magnitude of the coefficients, as shown in model 2 and the parsimonious model 3. There is an unexpected positive correlation between propensity of walking and heart disease. The negative correlation between walking and lifetime asthma prevalence is not significant and an inverse relationship between walking and child dependency, air pollution, and poor access to parks is observed. Measures of socioeconomic status and access to neighborhood resources perform as expected. For instance, higher household income and educational attainment is associated with an increase in walking. While not shown, there is also a threshold effect for parkland access.

Neighborhoods with the worst parkland access ("park deserts") play a detrimental effect on walking. However, there is no relationship between park-rich areas and walking. There is also a positive relationship between walking in neighborhoods with a higher proportion of workers that commute to work by walking, with no vehicle, and with access to public transit. One interesting relationship is the positive association with bike/pedestrian collisions, which could indicate people are walking in higher-risk environments. Traffic collisions are higher along major arterials, and this is often where commercial, retail, and other neighborhood resources may be located and where people would walk in these neighborhoods (see Table 3.1).

Table 3.1: Walking Ordinary Least Squares Regression

	Model 1: Ethnorace	Model 2: Full	Model 3: Parsimonious
Independent Variables	n = 1,469	n = 1,403	n = 1,413
Demographic			
% Asian	0.106 ***	–0.024 +	–0.019 *
% Black	0.075 ***	–0.005	–0.001
% Latino	–0.029 ***	0.062 ***	0.065 ***
% Other	0.020	0.099 ***	0.093 ***
Child dependency ratio		–0.024 *	–0.029 **
Elderly dependency ratio		0.007	
Foreign born		0.001	
Other Health Indicators			
% Lifetime asthma		–0.046	
% Heart disease prevalence		0.174 **	0.199 ***
Socioeconomic Position			
Median household income (log)		0.017 ***	0.016 ***
% College degree		0.117 ***	0.124 ***
Chemical Environment			
Ozone ppm		–0.981 ***	–0.945 ***
PM2.5 µg/m3		–0.002 ***	–0.002 ***
Average heat days		0.000	
Built Environment			
Park desert		–0.009 ***	–0.008 ***
Bike + ped/road network density		1.850 ***	1.904 ***
EPA walkability (1–20)		0.000	
Accessibility to Neighborhood Resources			
% Workers commute by walking		0.060 **	0.060 **
% Households with no vehicle		0.183 ***	0.190 ***
% Pop with high-quality transit access		0.051 ***	0.054 ***
Constant	0.316 ***	0.106 *	0.114 **
Adjusted R-Squared	0.100	0.632	0.640

Probabilities: +p < 0.10; *p < 0.05; **p < 0.01; ***p < 0.001.

▷ Heterogeneity Among Disadvantaged Neighborhoods

- Indicators of use: UCLA Center for Neighborhood Knowledge's Regional Area Median Income (AMI); Availability of Weighted Bikeways per Population; Traffic Collisions per Weighted Roadways
- Purpose: Promoting active transportation in disadvantaged neighborhoods by identifying neighborhoods most in need of bikeway funding (hypothetical scenario)

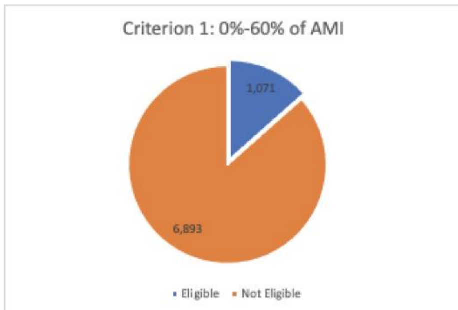
Although disadvantaged neighborhoods are similar in many ways, they can differ from one another in the causes, characteristics, and consequences of transportation disparities. It is therefore critical to be able to differentiate disadvantaged neighborhoods by their specific transportation needs, challenges, and opportunities. The transportation disparity dataset can be used to reveal this heterogeneity among disadvantaged neighborhoods. We provide an example of this using a hypothetical scenario.

The hypothetical statewide policy goal is to increase active transportation in the poorest neighborhoods by funding bikeways. Because of limited funds, the public agency must identify and prioritize places that are invited to submit a proposal.

There are three initial steps:

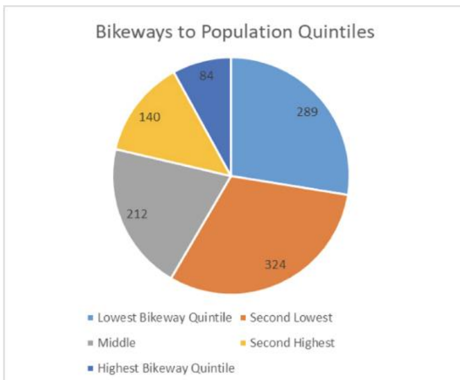
1. **The first step** is identifying the eligible neighborhoods by defining poorest tracts as having median household income that is no more than 60% of the regional median household income. Out of 7,966 tracts with AMI data, 1,071 or 13.4% fulfill this criterion (see Figure 4.1).

Figure 4.1



2. **The second step** is identifying the poorest tracts (those with no more than 60% of regional AMI) with the lowest bikeway-to-population ratio, which is defined as those falling into the lowest quintile for the bikeway-to-population index. It is important not to wrongly assume a priori that all low-income neighborhoods are the same in bikeway infrastructure. The data show considerable heterogeneity or diversity among poor neighborhoods, with at least some tracts falling into each of the bikeway-to-population categories. Nonetheless, the lowest-income tracts are disproportionately more likely to fall into the quintile with the least bikeway resources. Among the 1,049 lowest-income tracts with data on bikeways, 289 or 27.0% fall into the lowest bikeway quintiles, and these neighborhoods fulfill the second criterion (see Figure 4.2).

Figure 4.2



3. **The final step** is to prioritize choices among the 289 tracts by promoting safety. Here, we use traffic collisions per weighted roadways by quintile to categorize risk in the neighborhoods. Again, the data shows heterogeneity among the places, although all are among the poorest in income and bikeways. There are 29 tracts in the lowest quintile (safest), 14 in the second lowest, and 30 in the middle segment. Which neighborhoods are invited to compete depends on other considerations such as the amount of available funding and the agency's capacity to review applications.

What else can the Mapping Tool be used for?

▷ Policy

Simulations of different criteria and standards to examine which neighborhoods would be covered by a policy. For example, users can use two or more filters and thresholds to simultaneously identify areas that would be covered by a policy.

▷ Program

Identifying neighborhoods or other areas that fulfill **programmatic criteria**. For instance, using the spatial filters to highlight census tracts with few clean vehicles.

▷ Professional Practice

Develop profiles of the transportation resources and transportation needs of a neighborhood that may be used for **community planning efforts**. This can be done by identifying two or more census tracts that constitute a planning site.

▷ Individual Stakeholders

Look up information about their specific neighborhood. For example, a user can use the address search bar to locate their neighborhood and learn more about the resources or issues impacting their neighborhood.

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CALIFORNIA AIR RESOURCES BOARD

UCLA Center for Neighborhood Knowledge

Appendix F: Description of Indicators Displayed on Data/Mapping Portal

The following are descriptions of indicators displayed on the data/mapping portal. To access the data/mapping portal visit: https://experience.arcgis.com/template/9c13f35df3904dcb80530d0df49bdf9e

Socio-Demo-Econ

- Largest Ethnoracial Group
  - This map shows the distribution of the largest ethnoracial groups in each census tract. The largest ethnoracial group is defined as the group that makes up the majority of the population in a census tract (i.e., comprising 50 percent or more of the population in the neighborhood). For example, if the population of Black or African Americans in a census tract is 50 percent or more then that neighborhood is designated as a "Majority Black" neighborhood. The following ethnoracial groups were considered: Non-Hispanic White, Black, Hispanic (any race), Asian, Native Hawaiian or Other Pacific Islander, and American Indian and Alaska Native. A designation is included for tied groups if two groups are tied for the largest group within a particular tract.
- Percent in Poverty
  - This map shows the percentage of individuals who live below the U.S. poverty threshold, as defined by the U.S. Office of Management and Budget, for each census tract. Poverty thresholds are the dollar amounts used to determine poverty status. Poverty status is not determined for people in military barracks, institutional quarters, or for unrelated individuals under age 15 (such as foster children). Data on the share of individuals living in poverty come from the 2014–18 5-year American Community Survey and are visualized in quintiles, dividing the data into five roughly equal segments, meaning roughly 20 percent of California's census tracts fall within each quintile. Neighborhoods are ranked from lowest to highest quintiles and each neighborhood's ranking is relative to all census tracts in California.
- Population Density
  - This map shows population density, which is the measurement of population per unit area. In this map, density is calculated by taking the number of individuals within a given tract and dividing the population per tract by the land area (square miles) of that tract. Visualizing population density shows how individuals are distributed across California and which areas are more densely populated than others. Population data come from the 2014–18 5-year American Community Survey and population density are visualized in quintiles, dividing the data into five roughly equal segments, meaning roughly 20 percent of California's census tracts fall within each quintile. Neighborhoods are ranked from lowest to highest quintiles and each neighborhood's ranking is relative to all census tracts in California.
- Job Density
  - This map shows job density, which is the measurement of jobs per unit area. In this map, density is calculated by taking the number of all jobs within a given tract and dividing it by the land area (square miles) of that tract. Visualizing job density shows where jobs are located across California and which areas have more jobs than others. Data on job counts come from LEHD for 2017 and job density is visualized in quintiles, dividing the data into five roughly equal segments, meaning roughly 20 percent of California's census tracts fall within each quintile. Neighborhoods are ranked from lowest to highest quintiles and each neighborhood ranking is relative to all census tracts in California.
- Neighborhood Change: Socioeconomic Variables
  - This map shows neighborhood change by census tract with a focus on change in socioeconomic variables, a proxy for gentrification. Socioeconomic characteristics

include median household income, median earnings, and percentage of the adult population (age 25+) with a bachelor's degree or higher. Although changes in socioeconomic characteristics and the housing market do not represent gentrification per se, they can give a sense of changes in indicators related to gentrification in disadvantaged neighborhoods. Data are from the 2014–18 American Community Survey. Data on the level of neighborhood change are visualized in quintiles, dividing the data into five roughly equal segments, meaning roughly 20 percent of California's census tracts fall within each quintile. Neighborhoods are ranked from lowest to highest quintiles and each neighborhood ranking is relative to all census tracts in California.

- Median Household Income
  - This map shows the distribution of median household income by census tract. According to the U.S. Census Bureau, "median income is the amount which divides the income distribution into two equal groups, half having income above that amount, and half having income below that amount." In calculating median household income, the Census Bureau looks at the incomes of only those people who are 15 or older in the household. Visualizing median household income is one way of showing how income is distributed geographically across California. Data on median household income come from the 2014–18 American Community Survey and are visualized in quintiles, dividing the data into five roughly equal segments, meaning roughly 20 percent of California's census tracts fall within each quintile. Neighborhoods are ranked from lowest to highest quintiles and each neighborhood ranking is relative to all census tracts in California.

Housing

- Percent Multifamily Housing Units
  - This map shows the percentage of multifamily housing units as a share of total housing units within each census tract. A "multifamily" housing unit is a housing unit that is contained within a building or complex that has multiple housing units as separate living quarters. A housing unit may be a house, apartment, group of rooms, or a single room serving as separate living quarters. For this project, a multifamily property is any residential building in which there are at least two separate housing units. Data on the share of multifamily housing units come from the 2014–18 American Community Survey and are visualized in quintiles, dividing the data into five roughly equal segments, meaning roughly 20 percent of California's census tracts fall within each quintile. Neighborhoods are ranked from lowest to highest quintiles and each neighborhood ranking is relative to all census tracts in California.
- Percent Renter-Occupied Households
  - This map shows the percentage of housing units that are renter-occupied per census tract. All housing units that are not occupied by their owner are classified as renter-occupied. This metric measures the percent of households that are renter-occupied out of the total occupied households of that area. This visualization shows areas that are more highly concentrated with renters. Data on the share of renter-occupied housing units come from the 2014–18 American Community Survey and are visualized in quintiles, dividing the data into five roughly equal segments, meaning roughly 20 percent of California's census tracts fall within each quintile. Neighborhoods are ranked from lowest to highest quintiles and each neighborhood ranking is relative to all census tracts in California.
- Percent Households Paying 30–49 Percent of Income Toward Housing Costs
  - This map shows the percentage of households paying 30 percent to 49 percent of their monthly income toward housing. These data include owners and renters. For owners, housing costs are typically mortgage payments. For renters, housing costs are typically rent. Data come from the 2014–18 American Community Survey (ACS). The ACS provides additional data on Selected Monthly Owner Costs for owners and Gross Rent for renters. This metric takes the housing costs (typically mortgage or rent) and divides

them by household income. Only households where the percentage of housing costs as a total of household income is 30–49 percent are selected. Households paying more than 30 percent of income toward housing are considered housing “cost-burdened.” Those paying 30–49 percent are considered moderately cost-burdened. Data on the share of households paying 30–49 percent of income toward housing cost are visualized in quintiles, dividing the data into five roughly equal segments, meaning roughly 20 percent of California’s census tracts fall within each quintile. Neighborhoods are ranked from lowest to highest quintiles and each neighborhood ranking is relative to all census tracts in California.

- Percent Households Paying 50 Percent or More of Income Toward Housing Costs
    - This map shows the percentage of households paying 50 percent or more of their monthly income toward housing. These data include owners and renters, and their rent and mortgage payments, respectively. Data come from the 2014–18 American Community Survey (ACS). The ACS provides additional data on Selected Monthly Owner Costs for owners and Gross Rent for renters. This metric takes the housing costs (typically mortgage or rent) and divides them by household income. Only households where the percentage of housing costs as a total of household income 50 percent or higher are included. Households paying more than 50 percent of income toward housing are considered “severely cost-burdened.” Data on the share of households paying 50 percent or more of their income toward housing cost are visualized in quintiles, dividing the data into five roughly equal segments, meaning roughly 20 percent of California’s census tracts fall within each quintile. Neighborhoods are ranked from lowest to highest quintiles and each neighborhood ranking is relative to all census tracts in California.
- Housing Unit Density
    - This map shows housing unit density, or the density of housing units within each census tract. According to the American Community Survey (ACS), a housing unit can be individual houses, apartments, groups of rooms or single rooms, or mobile homes that are either occupied or intended to be occupied as separate living quarters. To obtain the density, the number of housing units in a given census tract is divided by the land area (square miles) of that tract. From there, the density (housing units per square mile) is visualized on the map. Data on housing units come from the 2014–18 ACS. This indicator shows how closely or sparsely housing units are geographically within a given tract. Data on housing unit density are visualized in quintiles, dividing the data into five roughly equal segments, meaning roughly 20 percent of California’s census tracts fall within each quintile. Neighborhoods are ranked from lowest to highest quintiles and each neighborhood ranking is relative to all census tracts in California.
- Neighborhood Change: Housing Market Variables
    - This map shows the distribution of neighborhood change by census tract with a focus on changes in housing variables. Housing characteristics include median gross rent, rent-burdened households (households paying more than 30 percent of their income toward housing) and new housing units (built within the past 5 years [2014–18]). We place particular focus on renter related variables (e.g., percent renter, median gross rent, and housing burden for renter households) rather than variables related to homeowners because our stakeholders (advisory committee) expressed concerns about the impacts of neighborhood change, particularly gentrification, in disadvantaged neighborhoods, many of which are comprised of more renter households. Data comes from two ACS datasets—2008–12 and 2014–18—and the level of neighborhood changes are visualized in quintiles, dividing the data into five roughly equal segments, meaning roughly 20 percent of California’s census tracts fall within each quintile. Neighborhoods are ranked from lowest to highest quintiles and each neighborhood ranking is relative to all census tracts in California.

Transportation

- Percent Households with No Vehicles
  - This map shows the percentage of households that lack access to vehicles in a given census tract. This includes cars, vans, and pickup/panel trucks as well rented vehicles (1+ month lease), company vehicles, and government/police vehicles if used for nonbusiness purposes. Immobile vehicles, motorcycles, and other recreational vehicles are excluded. Households reporting no vehicles are calculated as a percentage of total households per census tract. This map can show which communities have the least access to personal transportation. Data on households with no vehicle come from the 2014–18 American Community Survey and are visualized in quintiles, dividing the data into five roughly equal segments, meaning roughly 20 percent of California's census tracts fall within each quintile. Neighborhoods are ranked from lowest to highest quintiles and each neighborhood ranking is relative to all census tracts in California.
- Vehicle Ownership Per Household
  - This map shows the average number of vehicles per household in each census tract. This includes cars, vans, and pickup/panel trucks as well rented vehicles (1+ month lease), company vehicles, and government/police vehicles if used for nonbusiness purposes. Immobile vehicles, motorcycles, and other recreational vehicles are excluded. Vehicle ownership per household is the total number of vehicles in a given census tract divided by the total number of households in that tract. This map can show which communities have the least access to personal transportation per household. Data on vehicle ownership per household come from the 2014–18 American Community Survey and are visualized in quintiles, dividing the data into five roughly equal segments, meaning roughly 20 percent of California's census tracts fall within each quintile. Neighborhoods are ranked from lowest to highest quintiles and each neighborhood ranking is relative to all census tracts in California.
- Percent Drive Alone for Job Commute
  - This map shows the percentage of workers who drove alone for their job commute. The data comes from the 2014–18 American Community Survey (ACS). Respondents to the ACS could indicate "drove alone" in a car, truck, or van as their means of transportation to work. This percentage is calculated by taking the number of individuals in a census tract who drove alone and dividing it by the total number of workers (who did not work at home). The map is visualized in quintiles, dividing the data into five roughly equal segments, meaning roughly 20 percent of California's census tracts fall within each quintile. Neighborhoods are ranked from lowest to highest quintiles and each neighborhood ranking is relative to all census tracts in California.
- Percent Carpool for Job Commute
  - This map shows the percentage of workers who carpooled for their job commute. The data comes from the 2014–18 American Community Survey (ACS). Respondents to the ACS could indicate "carpooled" as their means of transportation to work. "Carpooling" is defined as commuting with two or more people in the same vehicle. This percentage is calculated by taking the number of individuals in a census tract who carpooled to work and dividing it by the total number of workers (who did not work at home). The map is visualized in quintiles, dividing the data into five roughly equal segments, meaning roughly 20 percent of California's census tracts fall within each quintile. Neighborhoods are ranked from lowest to highest quintiles and each neighborhood ranking is relative to all census tracts in California.
- Percent Public Transit for Job Commute
  - This map shows the percentage of workers who used public transportation for their job commute. The data comes from the 2014–18 American Community Survey (ACS). Respondents to the ACS could indicate "public transportation" as their means of

transportation to work. “Public transportation” includes bus, streetcar/trolley, subway, railroad, or ferry. This percentage is calculated by taking the number of individuals in a census tract who used public transportation and dividing it by the total number of workers (who did not work at home). The map is visualized in quintiles, dividing the data into five roughly equal segments, meaning roughly 20 percent of California’s census tracts fall within each quintile. Neighborhoods are ranked from lowest to highest quintiles and each neighborhood ranking is relative to all census tracts in California.

- Percent Bike for Job Commute
  - This map shows the percentage of workers who used a bicycle for their job commute. The data comes from the 2014–18 American Community Survey (ACS). Respondents to the ACS could indicate “bicycle” as their means of transportation work. This percentage is calculated by taking the number of individuals in a census tract who commuted by bicycle and dividing it by the total number of workers (who did not work at home). The map is visualized in quintiles, dividing the data into five roughly equal segments, meaning roughly 20 percent of California’s census tracts fall within each quintile. Neighborhoods are ranked from lowest to highest quintiles and each neighborhood ranking is relative to all census tracts in California.
- Percent Walk for Job Commute
  - This map shows the percentage of workers who walked for their job commute. The data comes from the 2014–18 American Community Survey (ACS). Respondents to the ACS could indicate “walk” as their means of transportation work. This percentage is calculated by taking the number of individuals in a census tract who walked to work and dividing it by the total number of workers (who did not work at home). The map is visualized in quintiles, dividing the data into five roughly equal segments, meaning roughly 20 percent of California’s census tracts fall within each quintile. Neighborhoods are ranked from lowest to highest quintiles and each neighborhood ranking is relative to all census tracts in California.
- Average (mean) Travel Time to Work
  - This map shows the average travel time that workers usually took to get from home to work (one-way) across all California census tracts. This measure is obtained by dividing the total number of minutes taken to get from home to work (the aggregate travel time) by the number of workers 16 years old and over who did not work at home. The data comes from the 2014–18 American Community Survey. The map is visualized in quintiles, dividing the data into five roughly equal segments, meaning roughly 20 percent of California’s census tracts fall within each quintile. Neighborhoods are ranked from lowest to highest quintiles and each neighborhood ranking is relative to all census tracts in California.
- Automobile Insurance Premium
  - This map shows the distribution of automobile insurance premiums across California census tracts. Auto insurance premiums are another barrier to vehicle ownership rates, which impacts whether individuals have access to vehicles and can help predict automobile purchase ability and public transportation needs. Data on automobile insurance premiums were obtained from two sources, ProPublica and the California Department of Insurance, by ZIP code and then allocated to census tracts. Data on automobile insurance premium are visualized in quintiles, dividing the data into five roughly equal segments, meaning roughly 20 percent of California’s census tracts fall within each quintile. Neighborhoods are ranked from lowest to highest quintiles and each neighborhood ranking is relative to all census tracts in California.

- Lending Barriers
    - This map shows the distribution of mortgage lending barriers that serves as a proxy for automobile lending barriers. Empirical research has shown that lending practices impact the rate of vehicle ownership, meaning that neighborhoods that experience higher loan interest rates may have lower vehicle ownership even when controlling for other variables. Because data on automobile loans for small geographies is not readily available, we used census tract–level data from the 2015–17 Home Mortgage Disclosure Act (HMDA) to construct a proxy measure related to lending practices: the proportion of originated mortgage loans that have subprime interest rates. Data on lending barriers are visualized in quintiles, dividing the data into five roughly equal segments, meaning roughly 20 percent of California's census tracts fall within each quintile. Neighborhoods are ranked from lowest to highest quintiles and each neighborhood ranking is relative to all census tracts in California.
- Newer Clean Vehicles
    - This map shows the distribution of newer clean vehicles by California census tract. Newer clean vehicles are vehicles of model years between 2013 and 2017 (latest 5 years of data at time of the study) that are also classified as clean vehicles based on fuel type: battery electric, plug-in hybrid electric, or hybrid electric. Vehicle data were obtained from the California Department of Motor Vehicles (DMV) fleet database provided by the California Air Resources Board (CARB) for 2017. Data on newer clean vehicles are visualized in quintiles, dividing the data into five roughly equal segments, meaning roughly 20 percent of California's census tracts fall within each quintile. Neighborhoods are ranked from lowest to highest quintiles and each neighborhood ranking is relative to all census tracts in California. Newer clean vehicle distribution shows where the new clean vehicles, likely with the cleanest emissions, are concentrated geographically within California.
- Older Clean Vehicles
    - This map shows the distribution of older clean vehicles by California census tract. Older clean vehicles are vehicles of model years 2012 or earlier that are also classified as clean vehicles based on fuel type: battery electric, plug-in hybrid electric, or hybrid electric. Vehicle data were obtained from the California Department of Motor Vehicles (DMV) fleet database provided by the California Air Resources Board (CARB) for 2017. Data on older clean vehicles are visualized in quintiles, dividing the data into five roughly equal segments, meaning roughly 20 percent of California's census tracts fall within each quintile. Neighborhoods are ranked from lowest to highest quintiles and each neighborhood ranking is relative to all census tracts in California. Data on older clean vehicle distribution shows where the older but clean vehicles are concentrated geographically within California.
- Clunker Vehicles
    - This map shows the distribution of clunker vehicles by California census tract. Clunker vehicles are defined as vehicles that are more than 20 years old based on model year, and vehicle data were obtained from the California Department of Motor Vehicles (DMV) fleet database provided by the California Air Resources Board (CARB) for 2017. For this project, vehicles with a model year of 1997 or earlier are designated as "clunkers". Data on older clean vehicles are visualized in quintiles, dividing the data into five roughly equal segments, meaning roughly 20 percent of California's census tracts fall within each quintile. Neighborhoods are ranked from lowest to highest quintiles and each neighborhood ranking is relative to all census tracts in California. The clunker vehicle distribution shows where the oldest vehicles, likely emitting the most emissions, are concentrated geographically within California.

- Vehicle Miles Traveled Per Household
    - This map shows the distribution of average vehicle miles traveled per household (HVMT) in California census tracts. HVMT measures a household's amount of travel for their vehicles in a given period, providing insight on a household's general travel patterns. VMT data are based on odometer readings from 2016 to 2017 collected by the Bureau of Automotive Repairs and provided by the California Air Resources Board. Data on HVMT are visualized in quintiles, dividing the data into five roughly equal segments, meaning roughly 20 percent of California's census tracts fall within each quintile. Neighborhoods are ranked from lowest to highest quintiles and each neighborhood ranking is relative to all census tracts in California. HVMT distribution data shows how different amounts of household vehicle use are concentrated geographically within California.
- Commute Vehicle Miles Traveled Per Worker
    - This map shows the distribution of average commute vehicle miles traveled (CVMT) per worker in California census tracts. CVMT per worker measures the average (mean) distance a worker drives to work by vehicle in a given period, providing insight on a commuters' general travel patterns. VMT data are based on odometer readings from 2016 to 2017 collected by the California Bureau of Automotive Repairs (BAR) and provided by the California Air Resources Board (CARB). Data on CVMT are visualized in quintiles, dividing the data into five roughly equal segments, meaning roughly 20 percent of California's census tracts fall within each quintile. Neighborhoods are ranked from lowest to highest quintiles and each neighborhood ranking is relative to all census tracts in California. CVMT distribution data shows how commute miles are concentrated geographically within California.

Accessibility

- Access to Employment Opportunities
    - This map shows the distribution of access to employment opportunities within California census tracts. This indicator measures the relative number of jobs that are accessible by residential location. It is calculated using an exponential decay method with a state-calibrated parameter. Calculations used employment flow data from the 2017 LEHD LODES database. Time and distance data were obtained from the HERE road network. The methodology for this indicator was adopted from an earlier project conducted by the researchers for CARB/Caltrans. Data on access to employment opportunities are visualized in quintiles, dividing the data into five roughly equal segments, meaning roughly 20 percent of California's census tracts fall within each quintile. Neighborhoods are ranked from lowest to highest quintiles and each neighborhood ranking is relative to all census tracts in California.
- Access to High-Quality Transit Locations
    - This map shows the distribution of access to high-quality transit locations in California census tracts. This indicator defines a high-quality transit location as being within a quarter-mile of transit stops with a high level of service during the morning commute. Planners generally accept the quarter-mile as the distance a typical person is willing to walk to local transit service. It was constructed using General Transit Feed Specification format (GTFS) and developed as part of an earlier project by the researchers for CARB/Caltrans. To the best of our knowledge, this indicator is the most comprehensive access to transit measure available for California.
- Availability of Weighted Bikeways Per Population
    - This map shows the distribution of bikeways per population across California census tracts. Access to bikeways has profound impacts on health and well-being. Further, cycling has indirect links to health by reducing air quality pollution as it could replace

trips by car. Given that there is no single source for bikeway data in California, data were obtained from various Metropolitan Planning Organizations (MPOs) and counties in California. Data on availability of bikeways per population are visualized in quintiles, dividing the data into five roughly equal segments, meaning roughly 20 percent of California's census tracts fall within each quintile. Neighborhoods are ranked from lowest to highest quintiles and each neighborhood ranking is relative to all census tracts in California.

- Availability of Public Park Space per Population
  - This map shows the availability of public park space per population in California census tracts. With some modifications to address limitations in the data, the original data comes from the California Department of Parks and Recreation's park access tool. This tool uses neighborhood-level park access and demographic information from 2015. It specifically looks into (1) areas within a half mile of a public park and (2) ratio of park acres per population. Data on the availability of public park space are visualized in quintiles, dividing the data into five roughly equal segments, meaning roughly 20 percent of California's census tracts fall within each quintile. Neighborhoods are ranked from lowest to highest quintiles and each neighborhood ranking is relative to all census tracts in California.
- Jobs–Housing Fit
  - This map shows the distribution of jobs–housing fit across California census tracts. This indicator analyzes the connection between affordable housing and job commutes for workers at the lower end of the labor market (e.g., low-wage earners) and adjusts for regional differences. The map shows areas with jobs deficits relative to the amount of affordable rental housing and vice versa. This indicator was developed as part of an earlier project by the researchers for CARB/Caltrans and uses two datasets: jobs by earnings level from the 2006–10 5-year Census Transportation Planning Products and housing units by rent levels from the 2008–12 5-year American Community Survey. The jobs–housing fit indicator is visualized in quintiles, dividing the data into five roughly equal segments, meaning roughly 20 percent of California's census tracts fall within each quintile. Neighborhoods are ranked from lowest to highest quintiles and each neighborhood ranking is relative to all census tracts in California.

Health

- No Health Insurance Coverage
  - This map shows the distribution of the percentage of people with no health insurance by census tract. The data are based on the 2014–18 American Community Survey (ACS), that asked respondents about their health insurance coverage status. Health insurance is defined as "plans and programs that provide comprehensive health coverage" as opposed to coverage for specific conditions or other kinds of coverage like dental, life, or disability insurance. If respondents marked "no" for all health insurance options on the ACS, they are considered as having no health insurance. Data on no health insurance coverage are visualized in quintiles, dividing the data into five roughly equal segments, meaning roughly 20 percent of California's census tracts fall within each quintile. Neighborhoods are ranked from lowest to highest quintiles and each neighborhood ranking is relative to all census tracts in California.

- Medicaid Insurance Coverage

  This map shows the distribution of the population with Medicaid insurance by census tract. Medicaid is a government program "administered at the state level, which provides medical assistance to the needy. Families with dependent children, the aged, blind, and disabled who are in financial need may be eligible for Medicaid." In California, the Medicaid program is known as Medi-Cal. The data are based on the 2014–18 American

Community Survey, which asked respondents about their health insurance coverage status. This indicator represents the share of individuals who are covered by the Medicaid health insurance program. It is calculated by dividing the total number of individuals with Medicaid health insurance coverage in a census tract by the total population (civilian noninstitutionalized population) in that area. The indicator on Medicaid insurance coverage is visualized in quintiles, dividing the data into five roughly equal segments, meaning roughly 20 percent of California's census tracts fall within each quintile. Neighborhoods are ranked from lowest to highest quintiles and each neighborhood ranking is relative to all census tracts in California.

- EPA's Walkability Index
    - This map displays a walkability index for each neighborhood. The Walkability Index indicator characterizes every census tract based on its relative walkability. It was constructed by the U.S. EPA and represent Version 2.0 (released in July 2013). The index is based on the physical characteristics (pedestrian-oriented intersections, quantity of occupied housing), business activities (mix of worksite jobs by economic sector), and travel behavior (commute mode). The index ranges from 1–20, with areas with more intersections, mixed uses, and carpooling are designated as being more conducive to walking, and therefore have higher index scores. It should be noted, however, the index does not account for other key factors, such as aesthetics, open space, and safety. More information can be found here.[51] The indicator is visualized in quintiles, dividing the data into five roughly equal segments, meaning roughly 20 percent of California's census tracts fall within each quintile. Neighborhoods are ranked from lowest to highest quintiles and each neighborhood ranking is relative to all census tracts in California.
- Asthma Emergency Department Visits
    - This map shows the distribution of asthma-related emergency visits across California census tracts. This indicator uses the emergency department visits for asthma as a proxy to understand the prevalence of asthma. The data are from the California Office of Environmental Health Hazard Assessment (OEHHA), which reported the emergency department visits for asthma in CalEnviroScreen 3.0. The data specific to emergency department visits and hospitalizations came from the California Office of Statewide Health Planning and Development (OSHPD), which collects emergency department visit data. More information can be found here.[52] The indicator is visualized in quintiles, dividing the data into five roughly equal segments, meaning roughly 20 percent of California's census tracts fall within each quintile. Neighborhoods are ranked from lowest to highest quintiles and each neighborhood ranking is relative to all census tracts in California.
- Cardiovascular Disease (emergency department visits for heart attacks)
    - This map shows the distribution of cardiovascular disease–related emergency visits across California census tracts. This indicator uses the emergency department visits for heart attacks per year as a proxy to understand the prevalence of cardiovascular disease. The data are from the California Office of Environmental Health Hazard Assessment (OEHHA), which reported the emergency department visits for heart attacks in CalEnviroScreen 3.0. The data specific to emergency department visits and hospitalizations came from the California Office of Statewide Health Planning and Development (OSHPD), which collects emergency department visit data. More information can be found here.[53] The indicator is visualized in quintiles, dividing the data into five roughly equal segments, meaning roughly 20 percent of California's census

[51] https://www.epa.gov/smartgrowth/smart-location-mapping#walkability (Accessed January 26, 2021)
[52] https://oehha.ca.gov/calenviroscreen/indicator/asthma (Accessed January 26, 2021)
[53] https://oehha.ca.gov/calenviroscreen/indicator/cardiovascular-disease (Accessed January 26, 2021)

tracts fall within each quintile. Neighborhoods are ranked from lowest to highest quintiles and each neighborhood ranking is relative to all census tracts in California.

- Life Expectancy at Birth (years)
    - This map shows the distribution of estimates of life expectancy at birth—the average number of years a person can expect to live—for census tracts and for the 2010–15 period. These estimates are the result of the collaborative project, “U.S. Small-Area Life Expectancy Estimates Project,” between the National Center for Health Statistics, the National Association for Public Health Statistics and Information Systems, and the Robert Wood Johnson Foundation. More information can be found here.[54]
- All Traffic Collisions Per Weighted Roadways
    - This map shows the distribution of all traffic collisions per weighted roadway for each census tract. Collisions that occurred between 1/1/2011 to 12/31/2015 are represented in the map. Collision data comes from UC Berkeley’s Transportation Injury Mapping System, which obtains data from California Highway Patrol (CHP) Statewide Integrated Traffic Records System (SWITRS). Data on traffic collisions per weighted roadways are visualized in quintiles, dividing the data into five roughly equal segments, meaning roughly 20 percent of California’s census tracts fall within each quintile. The indicator can support safer transportation planning, particularly related to Vision Zero efforts, a widely adopted initiative to eliminate traffic fatalities and severe injuries through strategic decisions and action to promote safe mobility.
- Primary Care Shortage Areas

    Primary care shortage areas are a designation defined by the State of California for the purposes of identifying medically underserved areas to inform programmatic funding decisions by the Office of Statewide Health Planning and Development (OSHPD). Primary care shortage areas are classified based on two criteria: poverty ratios and patient-to-primary-care-provider ratio. A PCSA is defined as having more than 25 percent of the total population living in poverty and a patients-to-primary-care-provider ratio higher than 1:3,000 or no providers at all. More information can be found here.[55]

[54] https://www.cdc.gov/nchs/nvss/usaleep/usaleep.html (Accessed January 26, 2021)
[55] https://oshpd.ca.gov/wp-content/uploads/2020/10/Attachment-E-FNPPA.pdf (Accessed January 26, 2021)