The Relationship of Historic Redlining & Mortgage Lending Bias with the Neighborhood Food Environment in California

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Abstract

The evolving social movement in the United States around creating a healthier and more equitable food system has popularized grassroots initiatives such as farmers markets, community gardens, and farm-to-school projects – just to name a few. We argue that identifying structural inequities, such as housing access, that are intertwined with access to food will provide much needed evidence about how policymakers can best target their efforts. Specifically, the purpose of this research is to investigate the role that mortgage lending bias and historic redlining practices play in inequitable access to food in California. We conclude that without addressing structural inequities, the grassroots initiatives of the food movement will have a diminished effect.

Introduction

The evolving social movement in the United States around creating a healthier and more equitable food system has popularized grassroots initiatives such as farmers markets, community gardens, and farm-to-school projects – just to name a few. However, we argue that without understanding and addressing structural inequities in the neighborhood environment, these grassroots initiatives will continue to have a diminished effect. Therefore, this paper proposes that identifying structural inequities, such as historical "redlining," mortgage lending bias, and the interrelationship with food access can better direct these grassroots efforts. Overall, the goal is to provide more comprehensive contextual information so policymakers can better target their efforts in California neighborhoods.

By combining several important sources of data, we examine the following three research questions:

1. *What is the relationship between historic redlining and food access in major metropolitan areas in California?*
2. *What is the relationship between mortgage lending bias and food access in California?*
3. *What are the primary reasons for mortgage denial for individuals residing in low income areas with low food access compared to those who are not, and do these reasons vary by race/ethnicity and urban versus rural residence?*

Access to Food in the United States

All three of the research questions involve ascertaining whether individuals reside in neighborhoods that have food access challenges. This section provides the background and definition for the food access measure utilized in this research. Furthermore, the data section will subsequently provide the details of the measure.

The United States boasts a diversified food production system growing everything from fresh fruits and vegetables to grains, meats and dairy, yet many communities in the United States remain hungry and unable to access affordable, nutritious foods. There are a variety of methods for measuring access to food, with advantages and disadvantages that are discussed in Ver Ploeg, Dutko, & Breneman (2015). For purposes of this research, we use area-based measures provided at the census tract level available through the Food Access Research Atlas, produced by the U.S. Department of Agriculture's (USDA) Economic Research Service (2019).

We have chosen the Food Access Research Atlas measures primarily because, first, the USDA utilizes them in reporting about food access to Congress and second, these measures provide more comprehensive criteria for calculating the distance to supermarkets and grocery stores. In other words, as discussed in Ver Ploeg, Dutko, & Breneman (207-208) the USDA measures are a combination of both relative and absolute measures to access. Specifically, the USDA defines low access to food as "low-income census tracts with a substantial number or share of residents with low levels of access to retail outlets selling healthy and affordable foods" (Ver Ploeg, Nulph, & Williams 2011)--the details of which are discussed in the proceeding "Data" section.

Communities with food access concerns were initially referred to as "food deserts," and in 2008, the Farm Bill directed the USDA to measure the extent of these "food deserts'' in the U.S. and discuss the causes and consequences. The Economic Research Service then led a study to better understand access to nutritious foods, and in 2013 replaced the term "food deserts" with the term "low income, low access" (Food Access Research Atlas 2019). In addition, community activist and cofounder of the Black Urban Growers organization, Karen Washington, argued to replace the term "food desert" with "food apartheid," asking the more important question, "what are some of the social inequities that you see, and what are you doing to erase some of the injustice?" (Brones 2018). Similarly, Holt-Giménez and Harper (2016) and Joyner et al. (2021) contend that the food desert designation does not adequately capture the political, economic, and geographic factors that contribute to structural inequities in food access. Furthermore, Cachelin et al.'s (2019) research underscores the central role of food culture by identifying practices connected to traditional foods, cultural identity, and community building . Overall, a "food apartheid framework" underscores the idea that food equity is not a natural occurrence, but rather human-caused through structural inequities (Reese 2019; Brones 2018). In summary, Siegner et al. (2018, 5) argue that "the term 'apartheid' demands an intersectional approach incorporating race, class, education, geography and the environment." Consequently, this research utilizes the USDA's measure and term "low income, low access" (LILA) and the research questions presented here are motivated by geography, race, class, and the environment – hence, a "food apartheid" context.

Historic Redlining and the Home Owners' Loan Corporation Maps

The Home Owners' Loan Corporation (HOLC) originated as a federal agency established in the 1930s to assess the "residential security" –or the relative riskiness of mortgages– of neighborhoods with populations over 40,000. In collaboration with real estate experts and local lenders throughout the United States, the HOLC designed an A through D grading system, with A being the "safest" investment for mortgage lenders and D designated as "hazardous." The A grade neighborhoods were mapped in green and the D grade neighborhoods mapped in red, thus establishing the term, "redlining." These grades were then assigned to over two hundred residential neighborhoods as a gauge for mortgage lenders in determining their willingness to take risks. The term "redlining" became the term used when mortgage lenders used discriminatory practices which denied access to credit and insurance for borrowers in neighborhoods that were economically disadvantaged and/or had high percentages of minorities (Nelson 2022).

Mapping Inequality, a project launched in 2016 by University of Richmond researchers, created interactive maps of the HOLC map records allowing free access to these troubling historical documents. "While Mapping Inequality is by itself a powerful tool for exploring housing policy and segregation eight decades ago — which was the goal of the historian-led team that created it — one of the great surprises of the project has been the innovative work on contemporary equality that other researchers have produced using its data" (Richardson, et al.). The project has allowed contemporary researchers to make correlations between historic redlining practices and contemporary risks facing the communities who have continued to live in these neighborhoods for generations (Nelson 2022).

The 1975 Home Mortgage Disclosure Act

The second and third research questions involve examining lending bias at the individual (mortgage loan applicant) level. The 1975 Home Mortgage Disclosure Act (HMDA) has provided decades of data on mortgage lending applications in the United States, along with the race and ethnicity of the applicants. The HMDA was passed on the heels of the 1968 Fair Housing Act and to date provides the main source of data to examine mortgage lending bias in the United States. Recent analyses from authors at the Federal Reserve Board (Bhutta, Gizmo, and Ringo 2021) and the FDIC's Center for Financial Research (Popick 2022) continue to find evidence for racial bias, even when accounting for the rise of computer algorithms for processing mortgages. This research utilizes the HMDA data to examine mortgage lending denials in the context of the geography of food access in California. Further details about these data are described below.

Methods

Design

This research merges several sources of data to explore the three research questions and methods described in Table 1. Furthermore, we conduct analyses at multiple levels–both at the individual level and at the level of the neighborhood environment. We use the census tract as an analogue for the neighborhood environment, since this is the closest available data and is the analogue most commonly utilized, for example, by city planners (The Data Center).

Table 1.

Research Question	**Level of Analysis**	**Analysis Methods**
1. What is the relationship between historic redlining and food access in major metropolitan areas in California?	Census Tract Level	Frequencies Mean Comparisons
2. What is the relationship between mortgage lending bias and food access in California?	Census Tract Level Individual Level	Frequencies Cross Tabulations
3. What are the primary reasons for mortgage denial for individuals residing in low income areas with low food access compared to those who are not, and do these reasons vary by race/ethnicity and urban versus rural residence?	Census Tract Level Individual Level	Frequencies Cross Tabulations

Data

The data utilized in this research provides an original perspective by synthesizing several important secondary sources for measures of food access, historic redlining, mortgage lending, and some additional characteristics about the neighborhood environment. These existing sources of data have fostered numerous publications and web sites that promote an improved understanding of these issues separately, but have not, to the best of our knowledge, been merged in order to examine possible interrelationships. The sources of data are listed below and proceeding this list are explanations of the variables utilized in our analyses.

- **Census tract (neighborhood) level data:**
    - USDA Economic Research Service's Low Income and Low Access to Food – formerly "food deserts" – (Food Access Research Atlas 2019). Additional description provided by Ver Ploeg, Nulph, & Williams (2011) ; Ver Ploeg, Dutko, & Breneman (2015).
    - Historic Redlining Scores (Meier & Mitchell 2021).
    - UCLA Center for Neighborhood Knowledge's measures of lending bias and public transportation access (see also Ong et al. 2022).
    - California Office of Environmental Health Hazard Assessment (OEHHA). "SB 535 Disadvantaged Communities" (accessed 2022).

    - U.S. Census Bureau's American Community Survey 2014-18 5-year averages of percentages of renters and Blacks, Hispanics/Latines, and Asians (available from UCLA Center for Neighborhood Knowledge; see also Ong et al. 2022).

- **Individual level data on home mortgage loans:**
    - Public use files of the Home Mortgage Disclosure Act data are available from the Consumer Financial Protection Bureau (2020).

USDA Low Income and Low Access to Food

The USDA ERS designates communities with food access concerns as "Low Income – Low Access" census tracts (hereinafter, LILA). For purposes of this research, California census tracts are "low access" (hereinafter, LA) if it meets *at least one* of the following criteria–as defined by the USDA Economic Research Service (Food Access Research Atlas 2019):

1. "**LA at 1 mile and 10 miles**: A significant number or share of residents is more than 1 mile (urban) or 10 miles (rural) from the nearest food store; or
2. **LA at .0 mile and 10 miles**: A significant number or share of residents is more than .5 mile (urban) or 10 miles (rural) from the nearest food store; or
3. **LA at 1 mile and 20 miles**: A significant number or share of residents is more than 1 mile (urban) or 20 miles (rural) from the nearest food store; or
4. **LA using vehicle access**: More than 100 housing units do not have a vehicle and are more than .5 mile from the nearest food store, or a significant number or share of residents are more than 20 miles from the nearest food store."

Furthermore, this research utilizes the Food Access Research Atlas' (2019) definition of "low income" if a census tract has *at least one* of the following characteristics:

1. "A **poverty rate** of 20 percent or greater, or
2. A **median family income** at or below 80 percent of the statewide or metropolitan area median family income."

Historic Redlining Scores (HRS) for Census Tracts in 7 California Metro Areas

This research uses a recently available measure to determine historic redlining at the 2010 census tract level calculated by Meier & Mitchell (2021), to correspond with the HOLC's 'A', 'B', 'C', & 'D' grades for "residential security" risk assigned in the 1930s-40s.[1] Meier & Mitchell's "Historic Redlining Scores" for census tracts indicate the degree of redlining and range from 1 through 4, whereby scores ranging from '3' to '4' indicate redlining and scores ranging from '1' through '2' indicate no redlining (for more detail see Meier & Mitchell 2021; Richardson et al. 2020).

[1] Meier & Mitchell (2021) also provide redlining scores for 2020 census tracts, but we utilize 2010 to align with the USDA food access measure, which at the time of this research, has not been updated using 2020 census tracts..

Additional Variables about the Neighborhood Environment (Efren)

Public Transportation Access - High Quality Transit Location Indicator (HQTL)

Ong et al. (2022, 142-153) provide a methodologically complex indicator of public transportation access at the census tract level, which they entitle the "High Quality Transit Location Indicator (HQTL)." By examining public transport locations and schedules, they create a measure that ranges from '0=no access' to '9=complete access' (150). We utilize this indicator in the proceeding analysis, given the role that location plays in determining food access..

Environmental Pollution and SB 535 Disadvantaged Communities

Another potential disadvantage to neighborhoods is the potentially disproportionate impact of environmental pollution. Issues of environmental justice are intertwined with racial justice, and this was recognized by the California legislature through the passage SB 535 in 2012, "which requires that 25 percent of cap-and-trade auction revenues be invested in projects that benefit disadvantaged communities, and at least 10 percent of the funds go toward projects located in those communities" (Allison et al. 2016, 7). The California Environmental Protection Agency (CalEPA), in accordance with SB 535, designates census tracts as "SB 535 disadvantaged communities" if they meet a ranking on a measure that combines socioeconomic characteristics, public health, environmental hazards. The CalEPA's Office of Environmental Health Hazard Assessment issued its first list of disadvantaged communities in 2014 and subsequently in 2017 and just recently in September 2022. This research utilizes the 2017 measure to be consistent with the USDA LILA, of which the most recent is 2017.

Lending Bias and Subprime Mortgage Rates

Residing in low income neighborhoods can negatively affect individuals' credit scores due to predatory lending practices (Cesare 2017, cited in Ong et al. 2020, 45). Consequently, home mortgages are higher "priced" due to unfavorable rates. To account for this in our analysis and interactive maps, we use the measure of lending bias from Ong et. al (2022, 44-52). This measure calculates the share of mortgage loans in a census tract that are offered at an unfavorable rate compared to the prime rate – or "subprime". Ong et al. divide all the census tracts in California into deciles ranking from 1 to 10 (each decile accounts for about 10% of tracts in California), whereby a higher decile indicates greater lending bias.

Percent Renters - U.S. Bureau of the Census American Community Survey

Our analysis and mapping also accounts for census tracts that have less opportunities for home ownership as indicated by the percentage of renters. The U.S. Census Bureau's American Community Survey (ACS) measures this annually, and we utilize this measure as provided by the California Transportation Disparities Mapping Tool (UCLA Center for Neighborhood Knowledge), which is the ACS 2014-18 5-year average. Ong et al. (2022, 110) provides further details.

Priority Neighborhoods

We argue that neighborhoods with multiple disadvantages should be prioritized for assistance. Consequently, we submit that for purposes of this research that a "priority" neighborhood is one that has experienced historical redlining (Meier & Mitchell 2021); has low income, low access to food (Food Access Research Atlas 2019); and has **one or more** of the following disadvantages (which are described in greater detail in the previous section):

1. No or low access to public transportation locations, as measured by the HQTL (UCLA Center for Neighborhood Knowledge 2022). Specifically, this is classified using scores of either a '0' (no access) or '1-3' (very low or low access) on this indicator.
2. Designated as SB 535 Disadvantaged.
3. Top two highest deciles in California for mortgage lending bias, as measured by unfavorable "subprime" mortgage rates (UCLA Center for Neighborhood Knowledge 2022).
4. High percentage of renters, as measured by the top quartile (25%) in each of the neighborhood's greater metropolitan statistical areas (ACS 2014-18 5-year average, as provided by the UCLA Center for Neighborhood Knowledge 2022).

HMDA Mortgage Application Data (Lori)

The Home Mortgage Disclosure Act data are available from the Consumer Financial Protection Bureau (2020). Since 2018, the HMDA data include the collection of additional information about borrowers such as debt-to-income ratios and credit scores. However, as of 2019, the credit scores, along with other data were removed from the public use files to protect confidentiality (Federal Financial Institutions Examination Council). Consequently, the analyses here are limited to the available information on debt-to-income ratios.

Specifically, our results presented in the proceeding section utilize the HMDA data on all the loan applications in the state of California from 2018 to 2021, in order to capture pre-pandemic information. From 2018 to 2021, there were well over 10 million mortgage loan applications in the state of California, but a large majority of those applications were not for the primary purchase of a home. Consequently, the subsequent analyses in this research only include home loans for primary residences, Table 2 presents the number of mortgage loan applications for primary residences from 2018 to 2021.

Table 2.	
	Number of CA Mortgage Loan Applicants for Primary Residences (not Refinance)[2]
2018	378,696

[2] The purpose of the mortgage loan is for a home purchase (loan_purpose) rather than home improvement, refinancing, or some other purpose. The occupancy (occupany_type) for the mortgage loan is for a primary residence, rather than a second residence or an investment property.

2019	761,230
2020	404,711
2021	453,444

Results

Historic Redlining and LILA Census Tracts in Seven California Metropolitan Areas

This section presents mean comparisons that explore the relationship between census tracts identified as either LILA or not LILA and historical redlining. We examine this relationship with the available data on historic redlining scores for seven major metro areas in California. In addition to our analysis, these results include an interactive map for each metro area – which allows stakeholders with interest in particular cities and neighborhoods to examine this merged data further.

Key Findings – Research Question 1

What is the relationship between historic redlining and food access in major metropolitan areas in California?

- In the Los Angeles-Long Beach, Sacramento–Roseville–Arden-Arcade, San Diego-Carlsbad, San Francisco-Oakland metro areas, LILA neighborhoods have significantly greater historic redlining scores than neighborhoods that are not LILA.
- In neighborhoods in the Fresno, Stockton-Lodi, and San Jose-Sunnyvale-Santa Clara metro areas, there is *not* a statistically significant relationship between LILA and historic redlining scores.

Appendix A depicts the results for all seven metro areas, but here we would like to highlight the results for Los Angeles-Long Beach as a robust example of the interrelationship between historic redlining and LILA. Immediately proceeding, we present San Jose-Sunnyvale-Santa Clara to illustrate when there is no relationship.

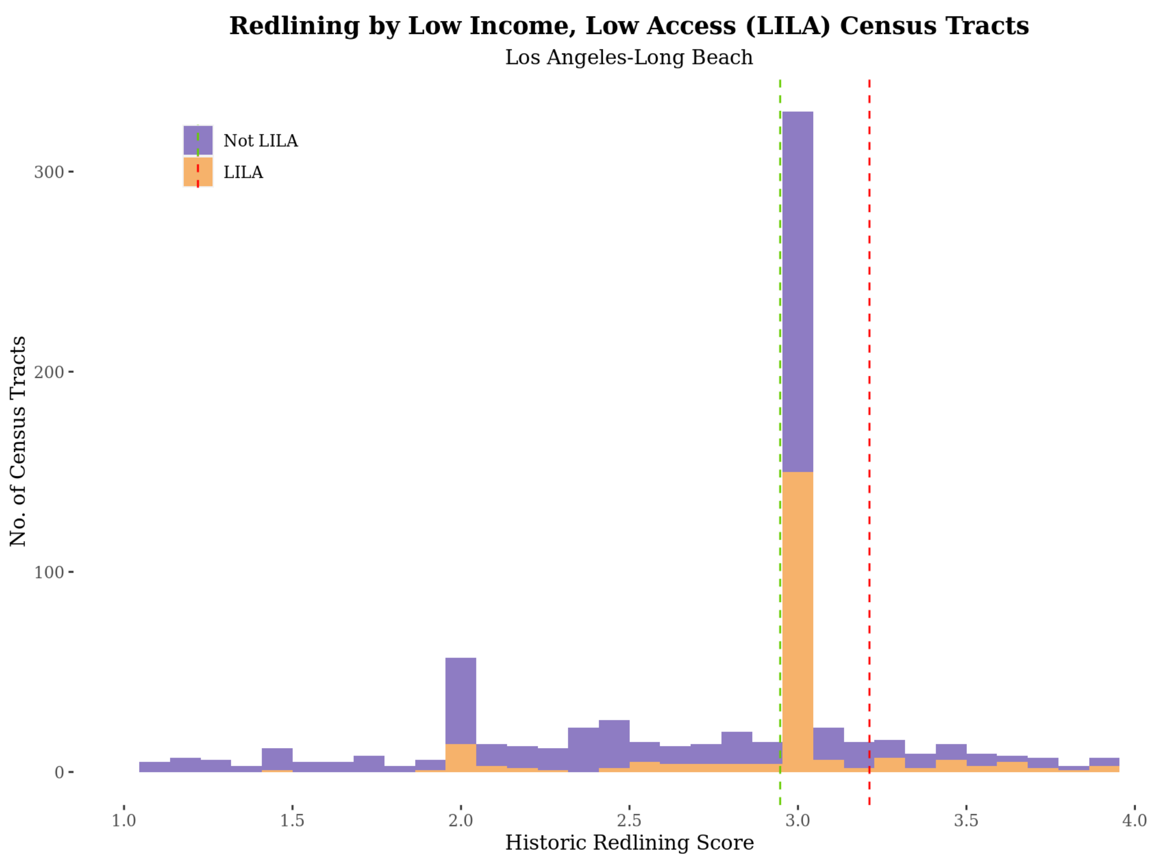
Nine out of ten (92%) of the LILA tracts in the LA-Long Beach metro area have a history of redlining. In comparison, there is a history of redlining in three-quarters (75.6%) of the tracts that are not LILA.[3] A comparison of means *t*-test, a statistical test that takes into account the variability along with the mean difference, reveals that the mean historic redlining score is significantly higher in LILA neighborhoods (Table 3). An overlaid histogram (Figure 1) illustrates the distribution of redlining scores for both LILA and not LILA tract in Los Angeles-Long Beach. The dashed lines show the mean for LILA areas compared to those that are not. Notably, the mean is higher for LILA tracts, but there is a presence of one outlying score just below 1.5, which is the census tract containing the UCLA

[3] The Los Angeles-Long Beach metro area had 2,925 census tracts in 2010, but there are only historic redlining scores available for 1,238 tracts due to growth of the area since the 1940s.

campus. The link to the interactive map in Table 3 depicts the relationship visually. The historic HOLC grades 'A', 'B', 'C', and 'D' are depicted by the colors green, blue, yellow, and red, and the diagonal lines indicate LILA tracts. In addition, selecting a particular census tract provides the historic redlining score, socioeconomic characteristics, along with additional neighborhood characteristics (described in the data section) – the public transportation indicator (HQTL), SB 535 disadvantaged, the subprime percentile, and whether it is a "priority" tract according to the designation in this research.

Table 3.			
Mean Comparison – Los Angeles-Long Beach Link to Interactive Map			
	Mean	**N**	**Std. Dev**
Not LILA	2.947	927	0.03
LILA	3.212	311	0.03
t = -6.52, p < .001			

Figure 1.



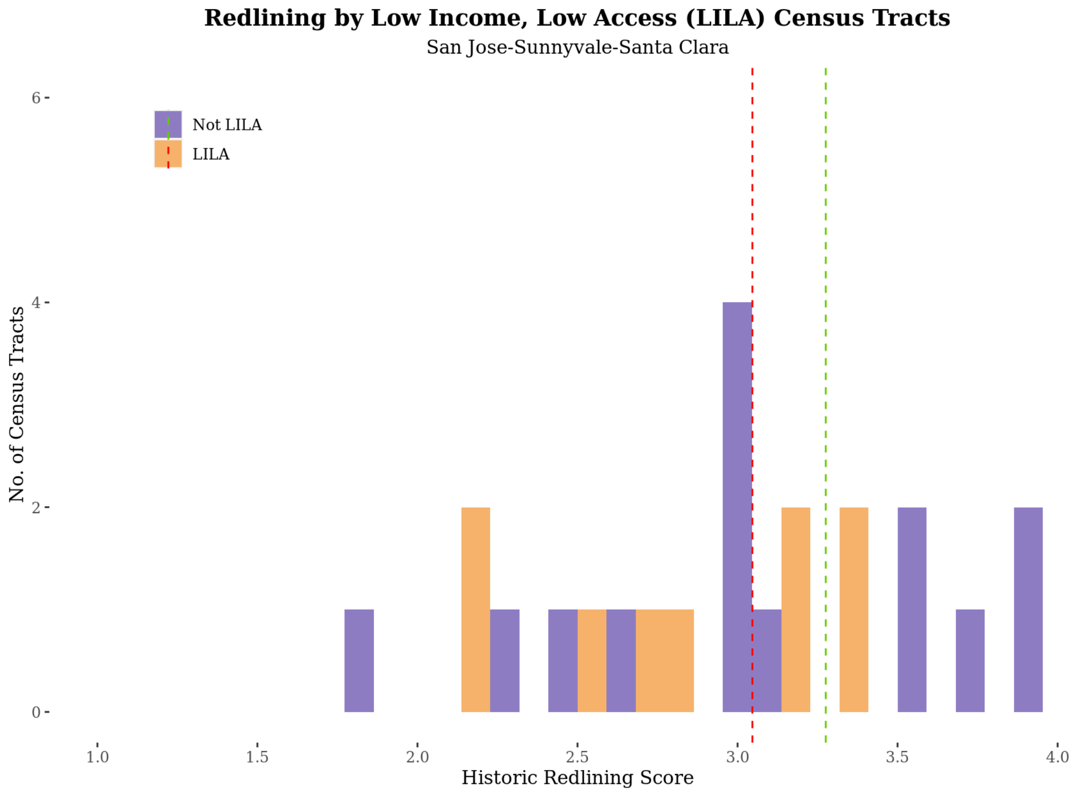
In the San Jose-Sunnyvale-Santa Clara metro area, about 8 out 10 (81.8%) of the LILA tracts have a history of redlining. Similarly, there is a history of redlining in of the tracts that are not LILA (84%).[4] A comparison of means *t*-test, a statistical test that takes into account the variability along with the mean difference, reveals that there is *not* a statistically significant difference in the mean historic redlining score for LILA and not LILA neighborhoods (Table 4). An overlaid histogram (Figure 2) illustrates the distribution of redlining scores for both LILA and not LILA tract in San Jose-Sunnyvale-Santa Clara. The dashed lines show the mean for LILA areas compared to those that are not. Notably, the mean historic redlining score is higher for tracts that are *not* LILA – but as aforementioned, this is not statistically significant. Again, the link to the interactive map in Table 4 depicts the relationship visually. The historic HOLC grades 'A', 'B', 'C', and 'D' are depicted by the colors green, blue, yellow, and red, and the diagonal lines indicate LILA tracts. In addition, selecting a particular census tract provides the historic redlining score, socioeconomic characteristics, along with additional neighborhood characteristics (described in the preceding data section) – the public transportation indicator (HQTL), SB 535 disadvantaged, the subprime percentile, and whether it is a "priority" tract according to the designation in this research.[5]

Table 4.			
Mean Comparison – San Jose-Sunnyvale-Santa Clara Link to Interactive Map			
	Mean	**N**	**Std. Dev**
Not LILA	3.28	25	0.13
LILA	3.05	11	0.18
t = 1.02, p =0.312			

[4] The San Jose-Sunnyvale-Santa Clara metro area had 383 census tracts in 2010, but there are only historic redlining scores available for 36 tracts due to growth of the area since the 1940s.

[5] Appendix A provides the results and links to interactive maps for all seven metro areas.

Figure 2.



Priority Neighborhoods with Multiple Disadvantages

We find that about one in five (19.1%) of the neighborhoods (of 1,780) qualify for the "priority" designation described in the previous section. Furthermore, about one in four of the priority neighborhoods have the top quartile of the population of Blacks/African Americans or Hispanics/Latines for each metro area. Again, the interactive maps in Appendix A reveal these priority neighborhoods, if one selects a single census tract on the map. Table 5 depicts the comparison of these additional disadvantages between neighborhoods that were *both* historically redlined and are LILA compared to those that are not.

Table 5.			
Additional Disadvantages by Historically Redlined & LILA Neighborhoods			
	Not HRS & LILA	**HRS & LILA**	**% DIFF**
Public Transportation - HQTL (No access, very low access, or low access)	14.6%	26.7%	+12.1%
SB 535 Disadvantaged[6]	35.4%	71.8%	+36.4%
Mortgage Lending Bias - Subprime Rate (Top 2 deciles in CA for unfavorable rates)	12.4%	31.9%	+19.5%
Percentage of Renters (Top quartile for respective metro area)	26.4%	20.6%	-5.8%
			Total N (census tracts) = 1780

Mortgage Lending Bias (HMDA) and LILA

The following section presents the results for the second and third research questions using the 2018-21 HMDA data described in the "Data" section above. Notably, HMDA data provides additional analytical leverage given that it is at the individual loan applicant level.

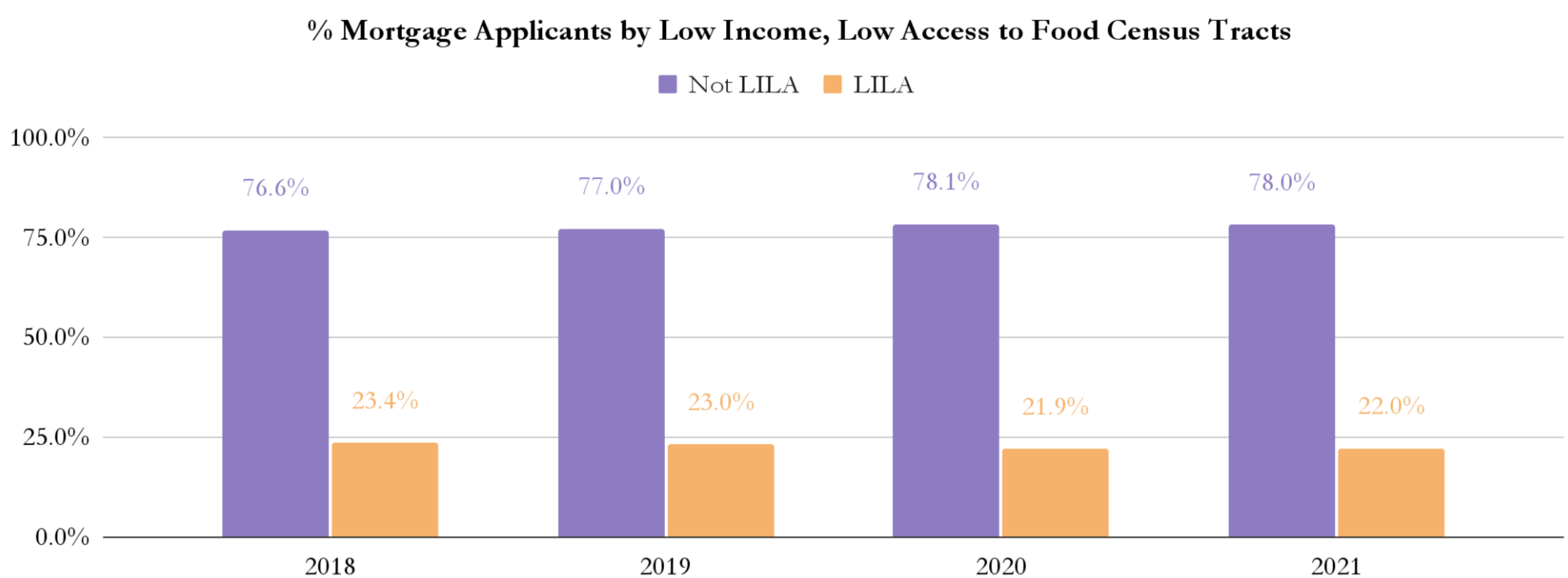
[6] We would like to acknowledge that this percentage is inflated for LILA areas because the definition of SB 535 also includes lower income neighborhoods - and therefore there is overlap with the USDA LILA definition. Although the metrics for determining "low income" are slightly different.

Key Findings – Research Question 2

What is the relationship between mortgage lending bias and food access in California?

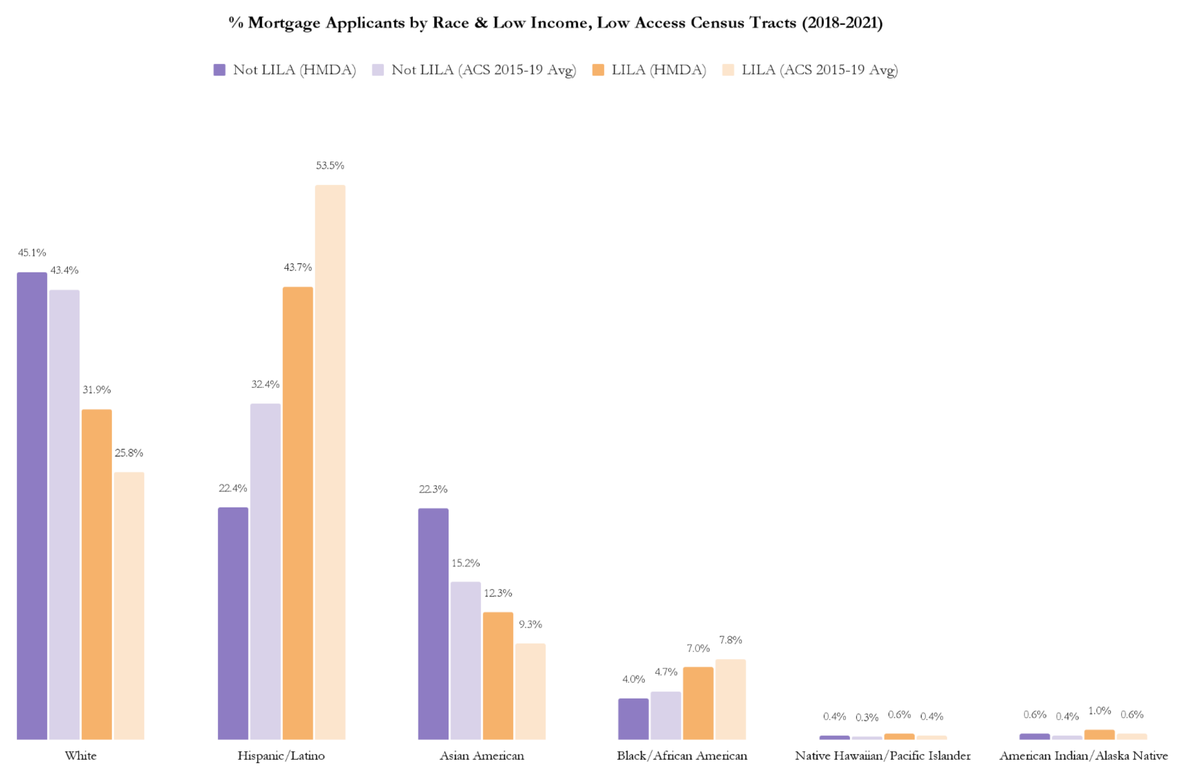
- Applications from individuals residing in low income neighborhoods with low access to food make up about only one-quarter of the mortgage loan applications, and this has not changed during the pandemic (Figure 3). While there is a lower supply of homes in LILA areas, this disparity is still notable since, for example, the percentage of renters in LILA neighborhoods is 55.6% compared to 41.6% in neighborhoods that are not LILA.

Figure 3.



- Asian American and White applicants are overrepresented in both LILA neighborhoods and those that are not LILA (Figure 4). Conversely, Hispanic/Latine applicants are underrepresented. For example, Hispanic/Latine applicants make up 43.7% of the population in LILA neighborhoods in CA, according the the American Community Survey 2015-19 average,[7] but only account for 32.4% of the applicants in 2018-2021. Finally, other underrepresented minorities make up for both a small percentage of applicants and the population, and this does not vary much by LILA or not LILA neighborhoods.

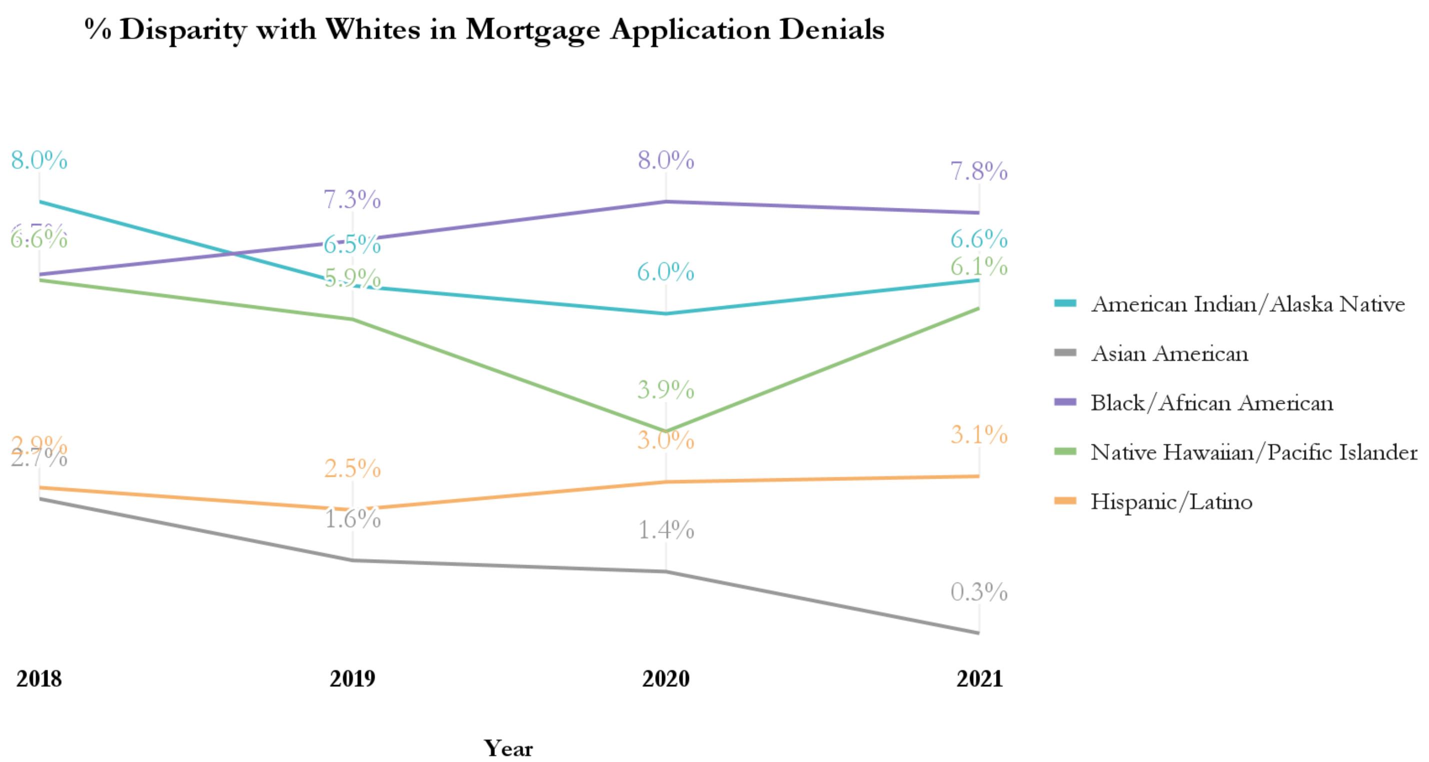
Figure 4.



[7] These American Community Survey data were accessed through Manson et al. (2021) and are the closest estimates using the 2010 census tracts, since the HMDA data does not provide 2020 census tract information until the 2022 data are released.

- Figure 5 reveals disparity with Whites in home mortgage loan denials is greatest for Blacks/African Americans (7.8% more denied than Whites), followed closely by Native Americans, and is the least for Asian Americans (0.3%).[8] Moreover, these disparities are similar for both LILA neighborhoods and neighborhoods that are not LILA (Appendix B, Table B.1)

Figure 5.



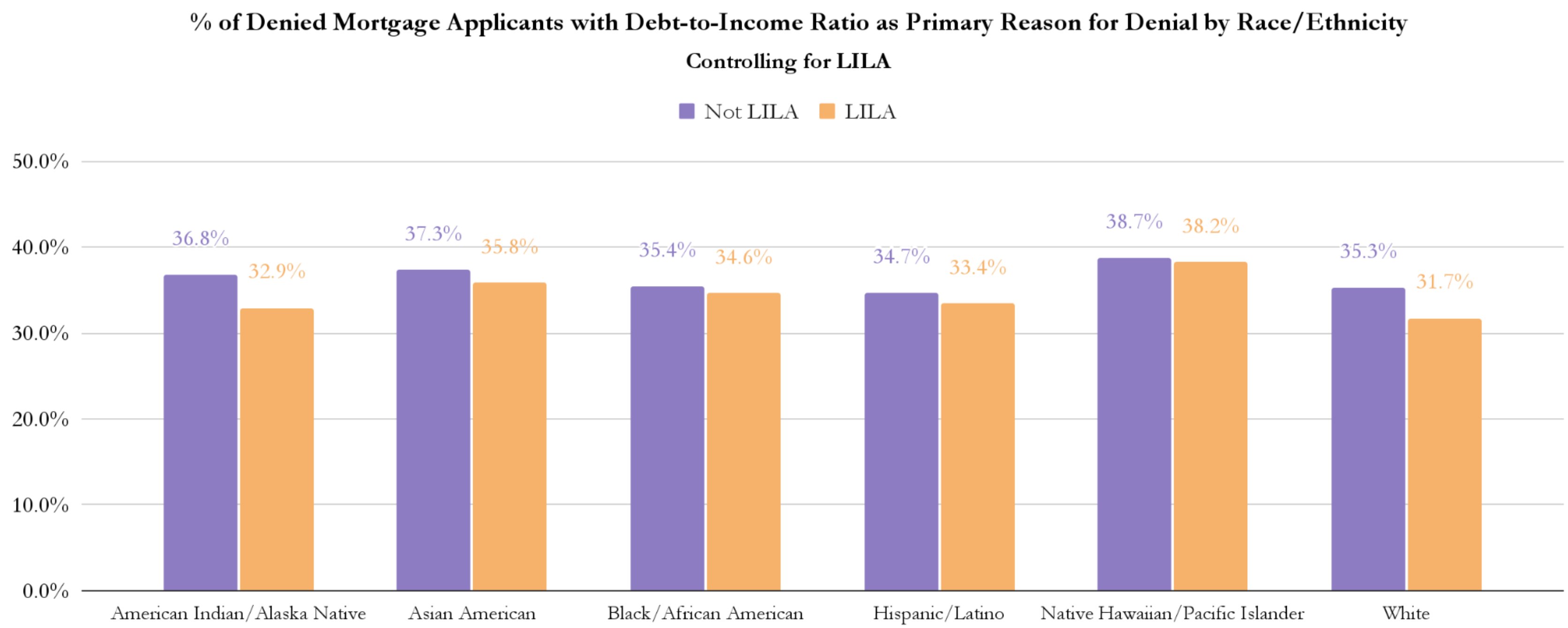
[8] Table B.1 in Appendix B presents the detailed results that are summarily depicted in this line chart.

Key Findings – Research Question 3

What are the primary reasons for mortgage denial for individuals residing in low income areas with low food access compared to those who are not, and do these reasons vary by race/ethnicity and urban versus rural residence?

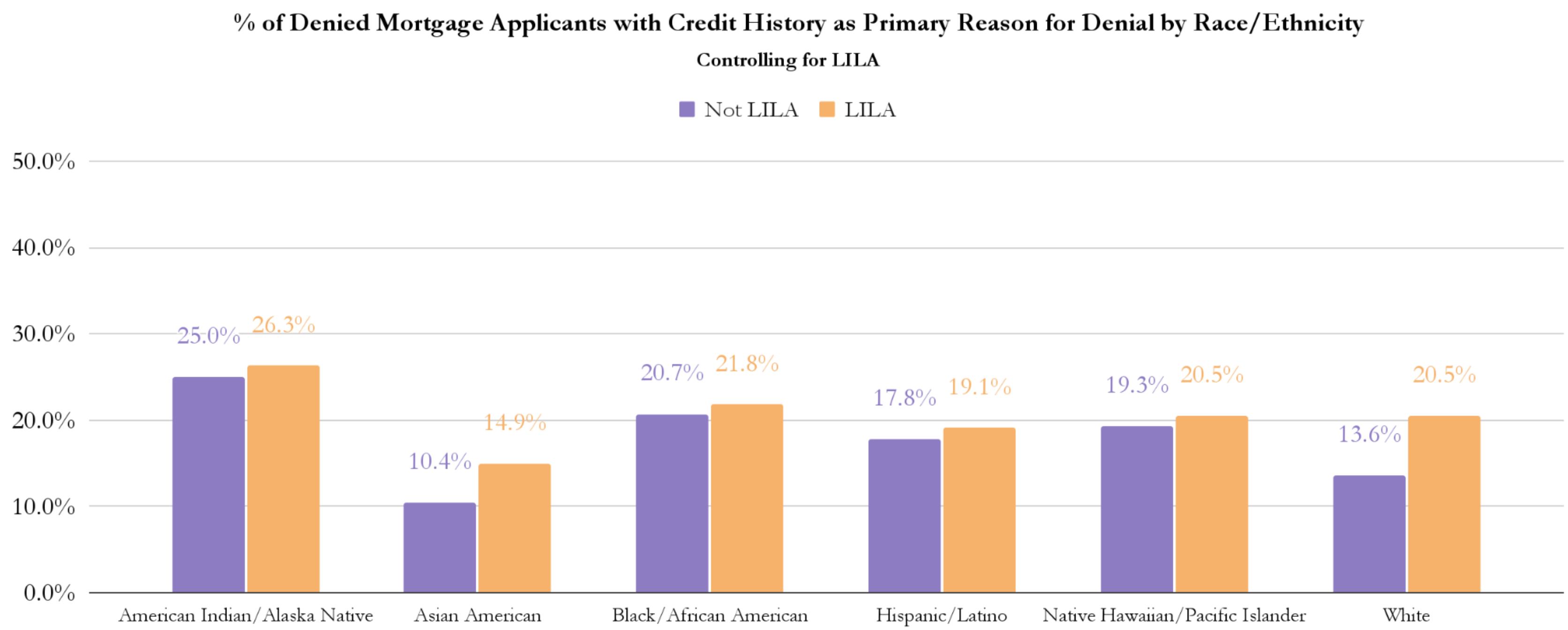
- In 2018-2021, debt-to-income ratio is the most common reason for denial, regardless of race/ethnicity or LILA neighborhood.

Figure 6.



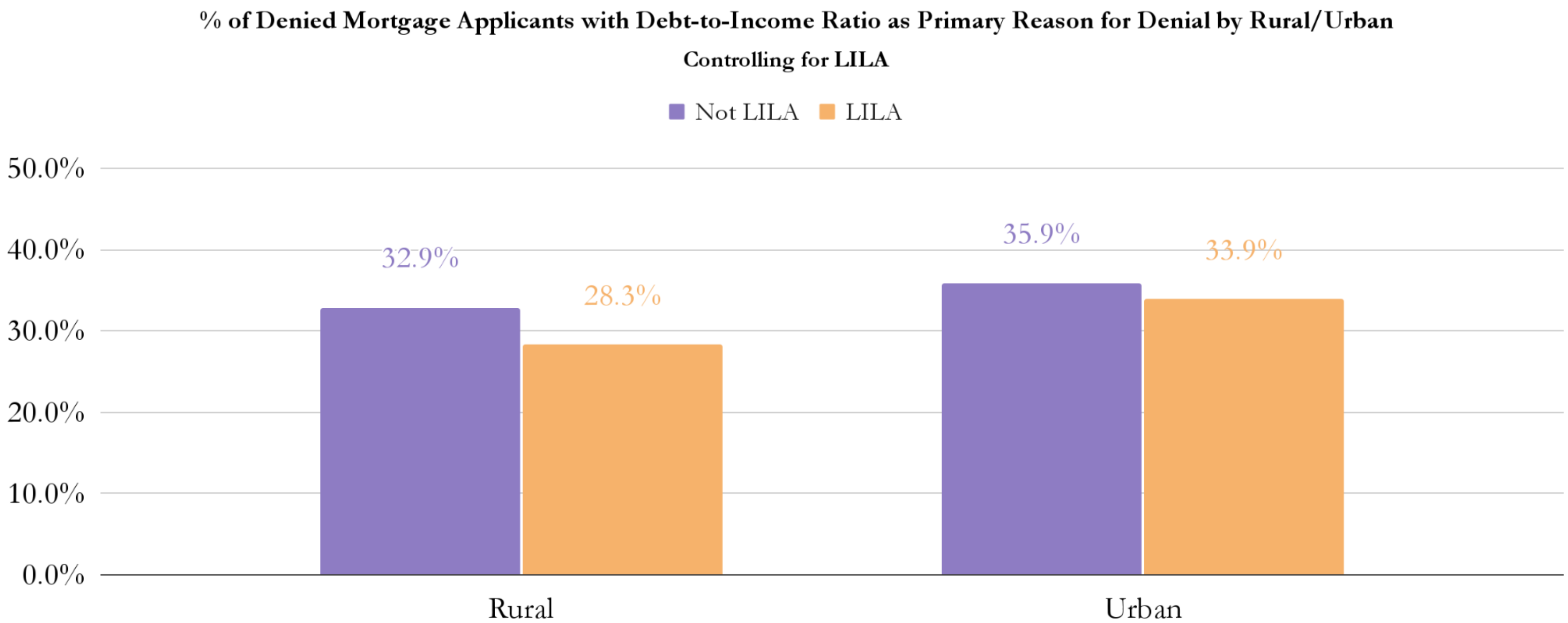
- In 2018-2021, the second most common reason for denial is credit history, and this is consistent across all four years (Appendix B, Figure B.1). Notably, a greater percentage of Whites and Asian Americans in LILA neighborhoods are denied (20.5% compared to 13.6% & 14.95 compared to 10.4%)). However, for other race/ethnic groups, the denial rate is similar (within 2%) for either LILA or not LILA neighborhoods.

Figure 7.



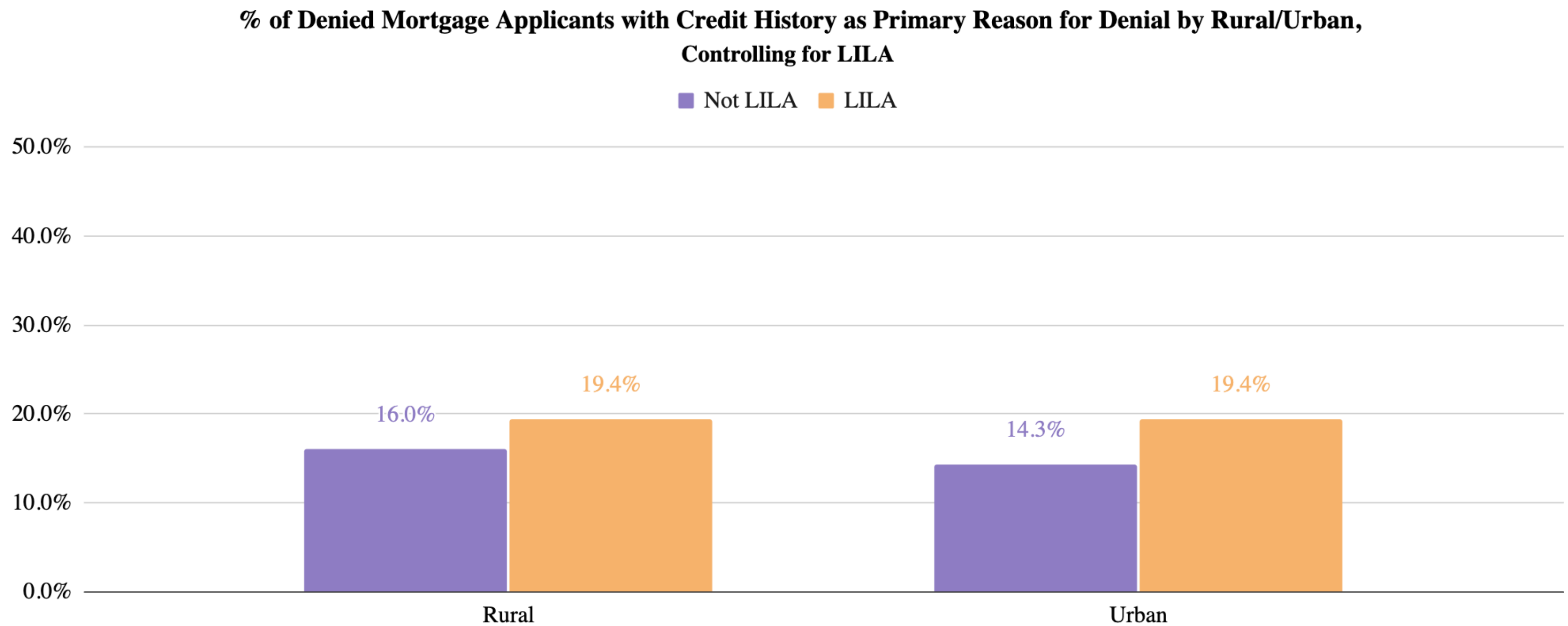
- Among rural applicants, there were less denied due to the debt-to-income ratio in LILA neighborhoods (28.3% compared to 32.9%). Among urban applicants, the denial rates were about the same (within 2%) regardless of neighborhood.

Figure 8.



- Denials due to credit history are slightly higher in both rural and urban LILA neighborhoods.

Figure 9.



Key Findings

- In four out of the seven California metropolitan areas analyzed, there is a significant relationship between historical redlining in neighborhoods with low income, low access to food.
- Neighborhoods in California metropolitan areas that do not exhibit a relationship between redlining and food access have grown in population in a greater proportion of their census tracts since the 1930s and, hence, there is no historic redlining data on those tracts which did not exist. Consequently, future investigation warrants utilizing alternative measures of redlining–such as racial covenants that are still on the books.
- Home mortgage loan applications in California are underrepresented in low income neighborhoods with low access to food, and Hispanics/Latines are particularly underrepresented.
- While Blacks/African Americans and Native Americans/Alaska Natives in California represent the smallest proportion of loan applicants, they have the greatest disparities compared to Whites in home mortgage loan denials, even when accounting for debt-to-income ratio.

Recommendations for Policymakers

- Identify neighborhoods with multiple disadvantages to prioritize for assistance.
- Encourage and support mortgage applications from underrepresented groups at favorable rates.
- Expand opportunities for home ownership in low income neighborhoods that have both historic redlining and low food access.
- Investigate alternative measures of redlining both historic (e.g., racial covenants) and recent (e.g., real estate appraisal practices).

References

Bhutta, Neil; Aurel Hizmo and Daniel Ringo. “How Much Does Racial Bias Affect Mortgage Lending? Evidence from Human and Algorithmic Credit Decisions.” August 28, 2022. Available at SSRN: https://papers.ssrn.com/sol3/Papers.cfm?abstract_id=3887663.

Brones, Anna. “Karen Washington: It’s not a Food Desert, It’s Food Apartheid.” *Guernica Magazine*, May 7, 2018. https://www.guernicamag.com/karen-washington-its-not-a-food-desert-its-food-apartheid/.

Allison, Juliann Emmons; Daniel Press; Cara Horowitz; Adam Millard-Ball, and Stephanie Pincetl. “Chapter 7. Paths to Carbon Neutrality: Lessons from California.” December 12, 2016. *Collabra* 2(1): 21, pp1-15. https://doi.org/10.1525/collabra.66.

Brones, Anna. “Karen Washington: It’s not a Food Desert, It’s Food Apartheid.” *Guernica Magazine*, May 7, 2018. https://www.guernicamag.com/karen-washington-its-not-a-food-desert-its-food-apartheid/.

Cachelin, Adrienne; Ivkovich, Liz; Jensen, Peter; and Neild, Milo. “Leveraging foodways for health and justice.” *Local Environment* 24, no. 5 (2019): 417–427. https://doi.org/10.1080/13549839.2019.1585771.

California Office of Environmental Health Hazard Assessment (OEHHA). “SB 535 Disadvantaged Communities.” 2017. https://oehha.ca.gov/calenviroscreen/sb535.

Cesare, Nicolas. *What Your ZIP Code Says About Your Credit Score*. November 9, 2017. Fiscal Tiger. https://www.fiscaltiger.com/zip-code-affects-credit-score/.

Federal Financial Institutions Examination Council. “Public HMDA - Data Fields with Values and Definitions,” Accessed July 10, 2022. https://ffiec.cfpb.gov/documentation/2020/lar-data-fields/.

Holt-Giménez, Eric and Breeze, Harper 2016. “Food Systems Racism: From Mistreatment to Transformation.” *Food First: Institute for Food & Development Policy,* Winter-Spring, no. 1 (2016): 1–7. https://archive.foodfirst.org/wp-content/uploads/2016/03/DR1Final.pdf.

Joyner, Leah, Blanca Yague, Adrienne Cachelin, and Jeffrey Rose. “Farms and Gardens Everywhere But Not a Bite to Eat? A Critical Geographic Approach to Food Apartheid in Salt Lake City.” *Journal of Agriculture, Food Systems, and Community Development* 11, no. 2 (n.d.): 1–22. https://doi.org/10.5304/jafscd.2022.112.013.

Manson, Steven, Jonathan Schroeder, David Van Riper, Tracy Kugler, and Steven Ruggles. “IPUMS National Historical Geographic Information System: Version 16.0 [Dataset].” Minneapolis, MN: IPUMS, 2021. Accessed September 23, 2022. http://doi.org/10.18128/D050.V16.0.

Meier, Helen C.S. and Bruce C. Mitchell. “Historic Redlining Scores for 2010 and 2020 US Census Tracts.” Ann Arbor, MI: Inter-university Consortium for Political and Social Research [distributor], 2021-10-15, n.d. https://doi.org/10.3886/E141121V2.

Consumer Financial Protection Bureau. “Mortgage Data (HMDA), 2020.” Accessed June 8, 2022. https://www.consumerfinance.gov/data-research/hmda/.

Nelson, Robert K. “Mapping Inequality: There Were No Dog Whistles, The Racism Was Loud And Clear.” Accessed August 10, 2022. National Community Reinvestment Coalition.

https://www.ncrc.org/mapping-inequality-there-were-no-dog-whistles-the-racism-was-loud-and-clear.

Ong, Paul, Chhandara Pech, and Justine Pascual. "Screening Method and Map for Evaluating Transportation Access Disparities and Other Build Environment-Related Determinants of Health." UCLA Center for Neighborhood Knowledge, March 7, 2022. https://escholarship.org/uc/item/3mn6q0zm.

Popick, Stephen J. "Did Minority Applicants Experience Worse Lending Outcomes in the Mortgage Market? A Study Using 2020 Expanded HMDA Data." *Federal Deposit Insurance Corporation - Center for Financial Research*, June 2022.

Reese, Ashanté M. "Black Food Geographies: Race, Self-Reliance, and Food Access in Washington, D.C." The University Of North Carolina Press, 2019. https://doi.org/10.5149/northcarolina/9781469651507.001.0001.

Richardson, Jason, Bruce C. Mitchell, Helen C.S. Meier, Emily E. Lynch, and Jad Edlebi. "The Lasting Impact of Historic 'Redlining' on Neighborhood Health: Higher Prevalence of COVID-19 Risk Factors." National Community Reinvestment Coalition, 2020. https://ncrc.org/holc-health/.

Siegner, Alana; Sowerwine, Jennifer ; and Acey, Charisma . 2018. "Does Urban Agriculture Improve Food Security? Examining the Nexus of Food Access and Distribution of Urban Produced Foods in the United States: A Systematic Review." *Sustainability* 10 (9), Article 2988. https://doi.org/10.3390/su10092988.

Thompson, Cheryl W. and Cristina Kim, Natalie Moore, Roxana Popescu, and Corinne Ruff. "Racial Covenants, a Relic of the Past, Are Still on the Books across the Country." November 17, 2021. National Public Radio. https://www.npr.org/2021/11/17/1049052531/racial-covenants-housing-discrimination

UCLA Center for Neighborhood Knowledge. "California Transportation Disparities Mapping Tool," Accessed August 10, 2022. https://knowledge.luskin.ucla.edu/2541-2/.

U.S. Department of Agriculture. "Food Access Research Atlas, 2019," 2019. Accessed August 10, 2022. https://www.ers.usda.gov/data-products/food-access-research-atlas/.

Ver Ploeg, Michele, David Nulph, and Ryan Williams. "Mapping Food Deserts in the United States." U.S. Department of Agriculture Economic Research Service, 2011. https://www.ers.usda.gov/amber-waves/2011/december/data-feature-mapping-food-deserts-in-the-us.

Ver Ploeg, Michele, Paula Dutko, and Vince Breneman. "Measuring Food Access and Food Deserts for Policy Purposes." *Applied Economic Perspectives and Policy* 37, no. 2 (2015): 205–25. https://doi.org/10.1093/aepp/ppu035.

The Data Center. "What Is a Neighborhood?" Accessed May 17, 2022. https://www.datacenterresearch .org/data-resources/neighborhood-data/what-is-a-neighborhood/.

Appendix A

Table A-1.			
Mean Comparison – Fresno [Link to Interactive Map]			
	Mean	**N**	**Std. Dev**
Not LILA	2.89	6	0.73
LILA	3.05	20	0.45
t = -0.56, p =0.58			

Figure A-1.

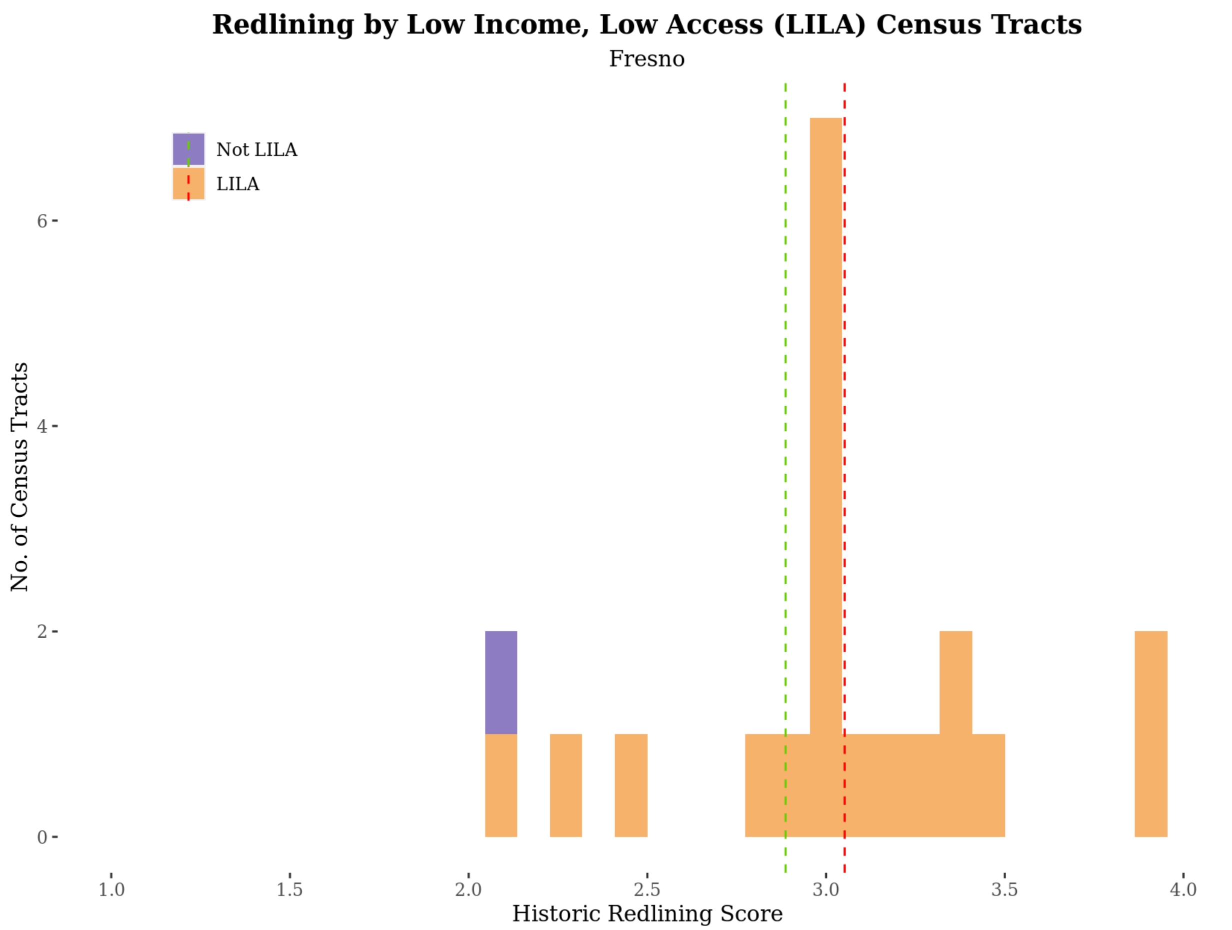


Table A-2.			
Mean Comparison – Los Angeles-Long Beach Link to Interactive Map			
	Mean	**N**	**Std. Dev**
Not LILA	2.95	927	0.77
LILA	3.21	311	0.56
$t = -6.52$, $p < .001$			

Figure A-2.

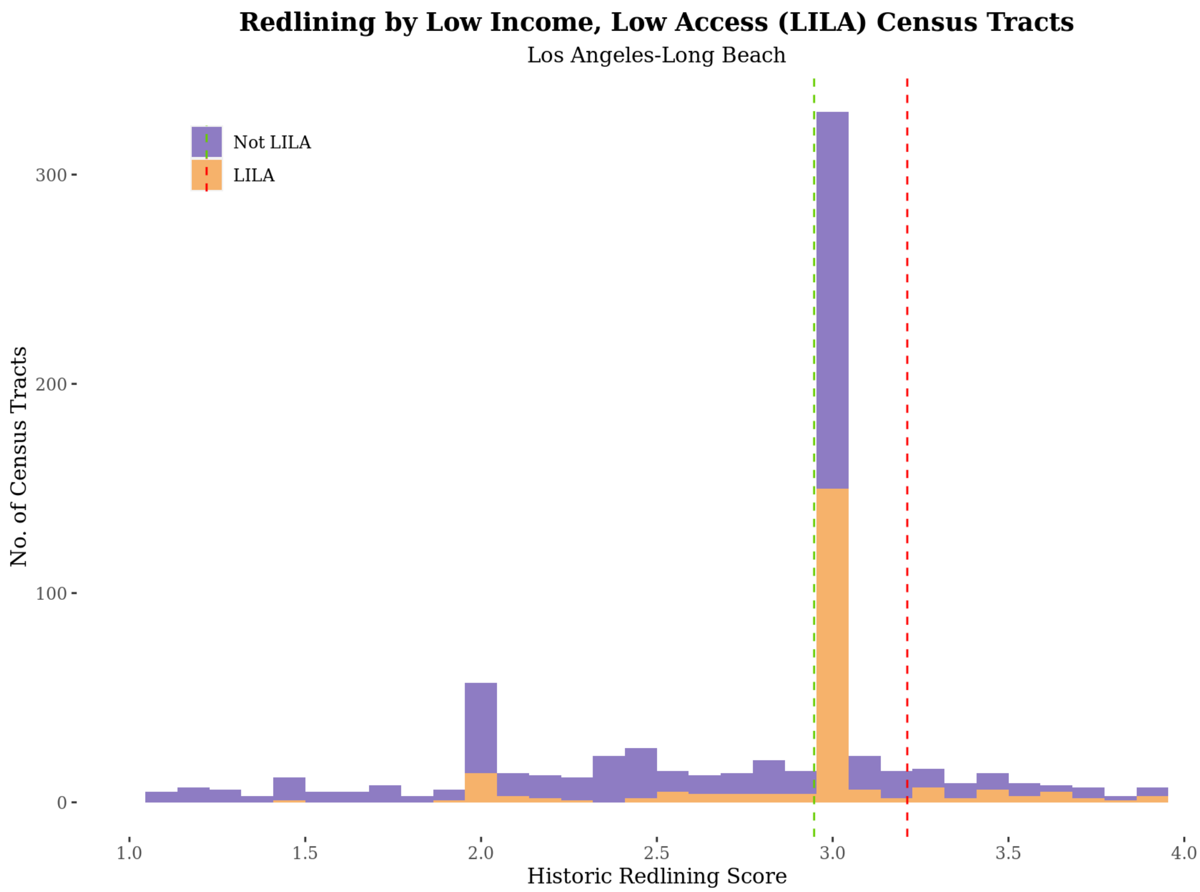


Table A-3.			
Mean Comparison – Sacramento--Roseville--Arden-Arcade [Link to Interactive Map]			
	Mean	**N**	**Std. Dev**
Not LILA	2.75	19	0.55
LILA	3.27	14	0.52
t = -2.80, p = .006			

Figure A-3.

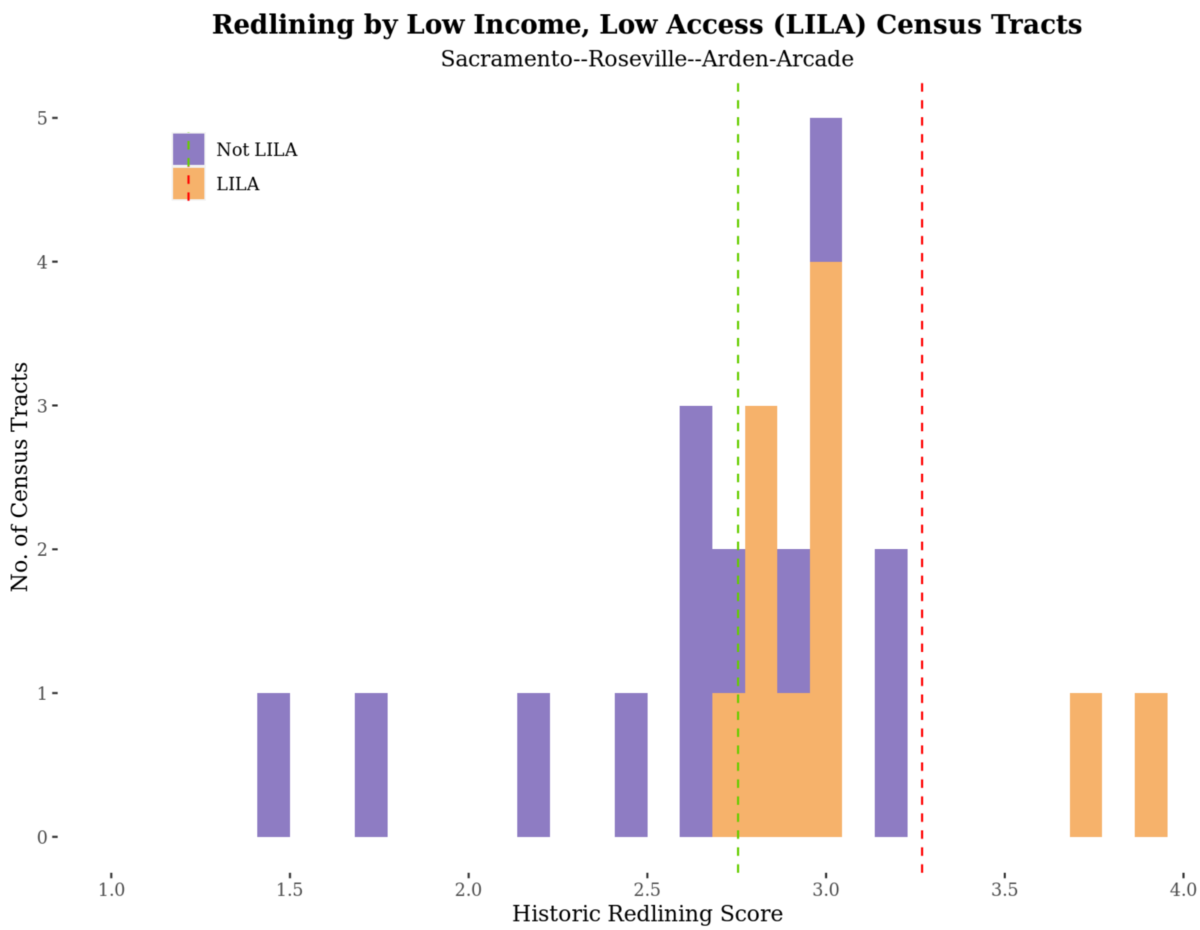


Table A-4.			
Mean Comparison – San Diego-Carlsbad Link to Interactive Map			
	Mean	**N**	**Std. Dev**
Not LILA	2.83	93	0.85
LILA	3.67	28	0.56
t = -6.16, p <.001			

Figure A-4.

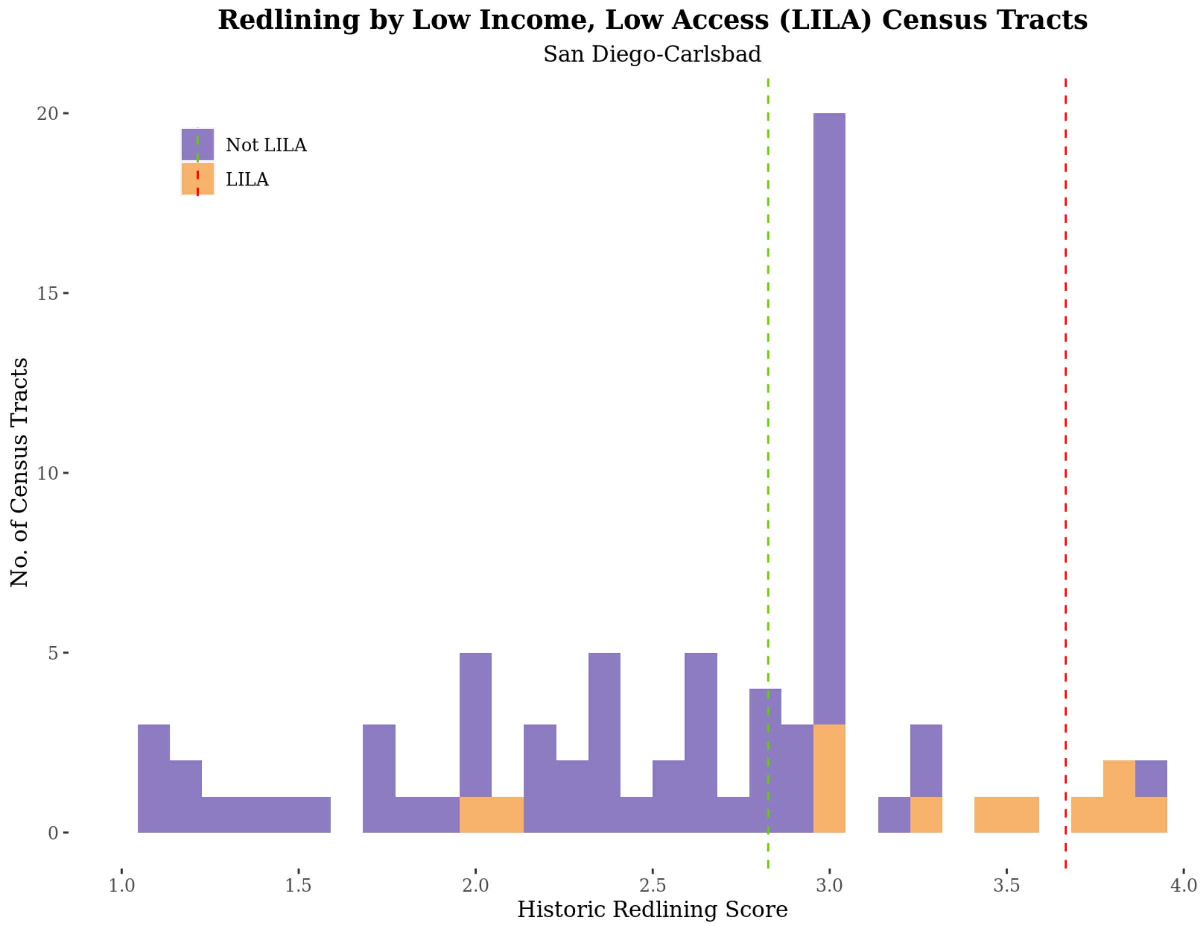


Table A-5.				
Mean Comparison – San Francisco-Oakland-Hayward [Link to Interactive Map]				
		Mean	**N**	**Std. Dev**
Not LILA		2.94	257	0.83
LILA		3.32	51	0.59
t = -3.87, p <.001				

Figure A-5.

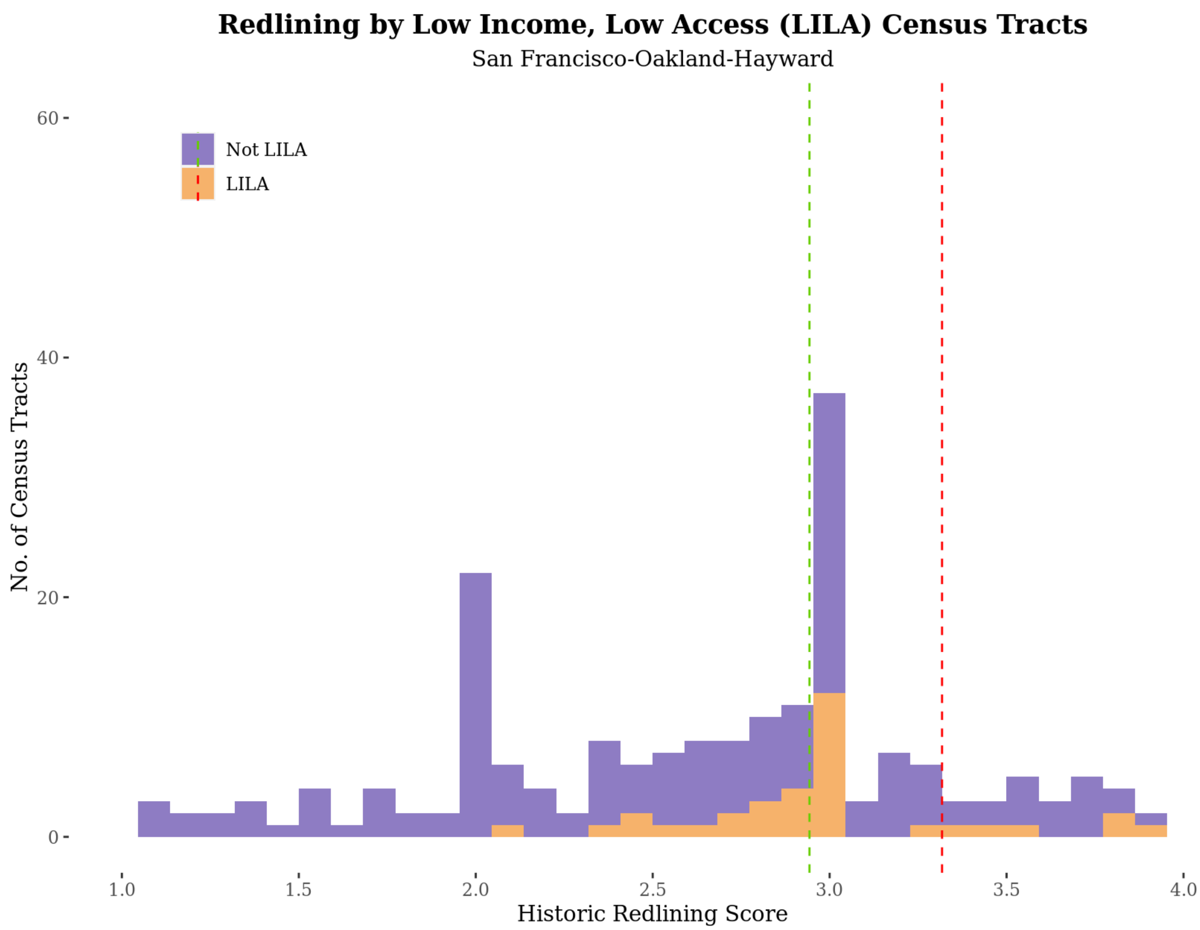


Table A-6.			
Mean Comparison – San Jose-Sunnyvale-Santa Clara [Link to Interactive Map]			
	Mean	**N**	**Std. Dev**
Not LILA	3.28	25	0.66
LILA	3.05	11	0.63
t = 1.02, p =.312			

Figure A-6.

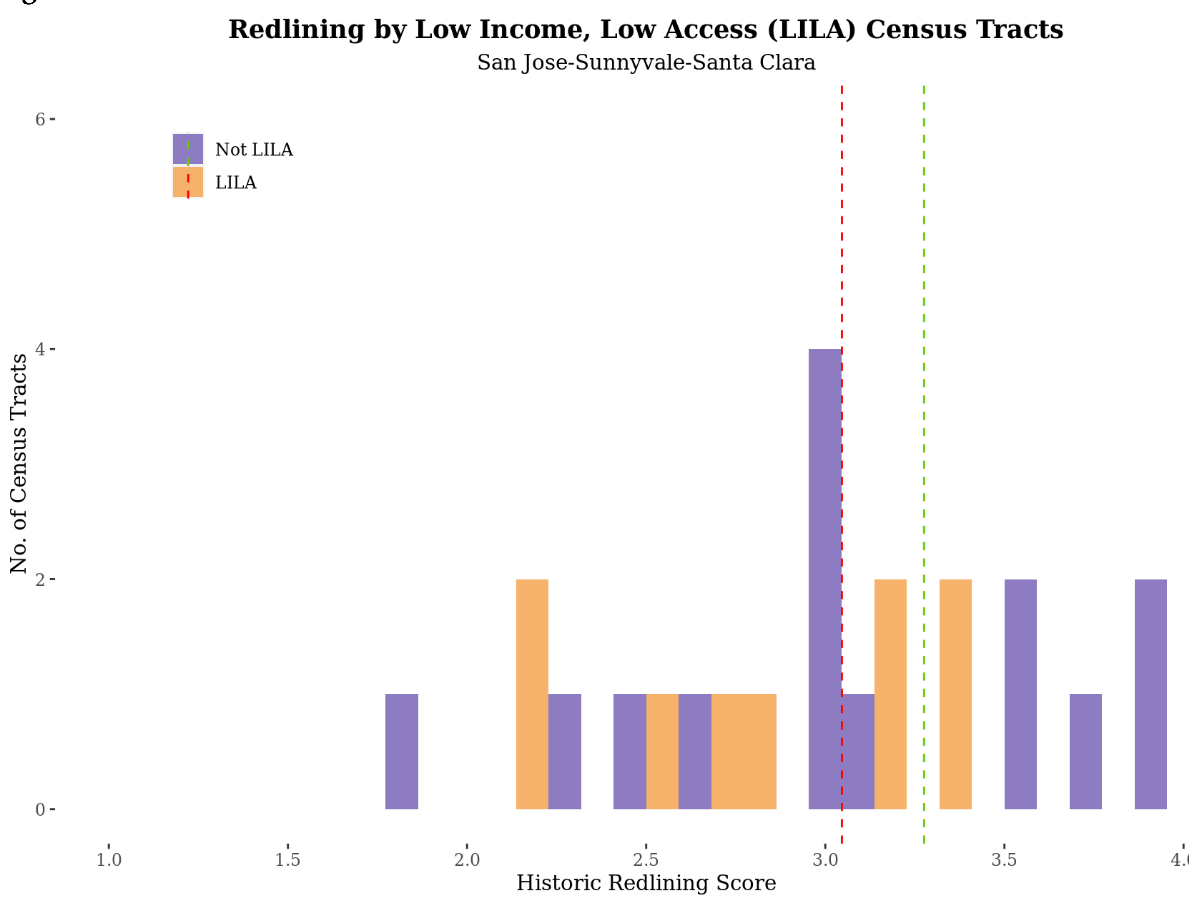
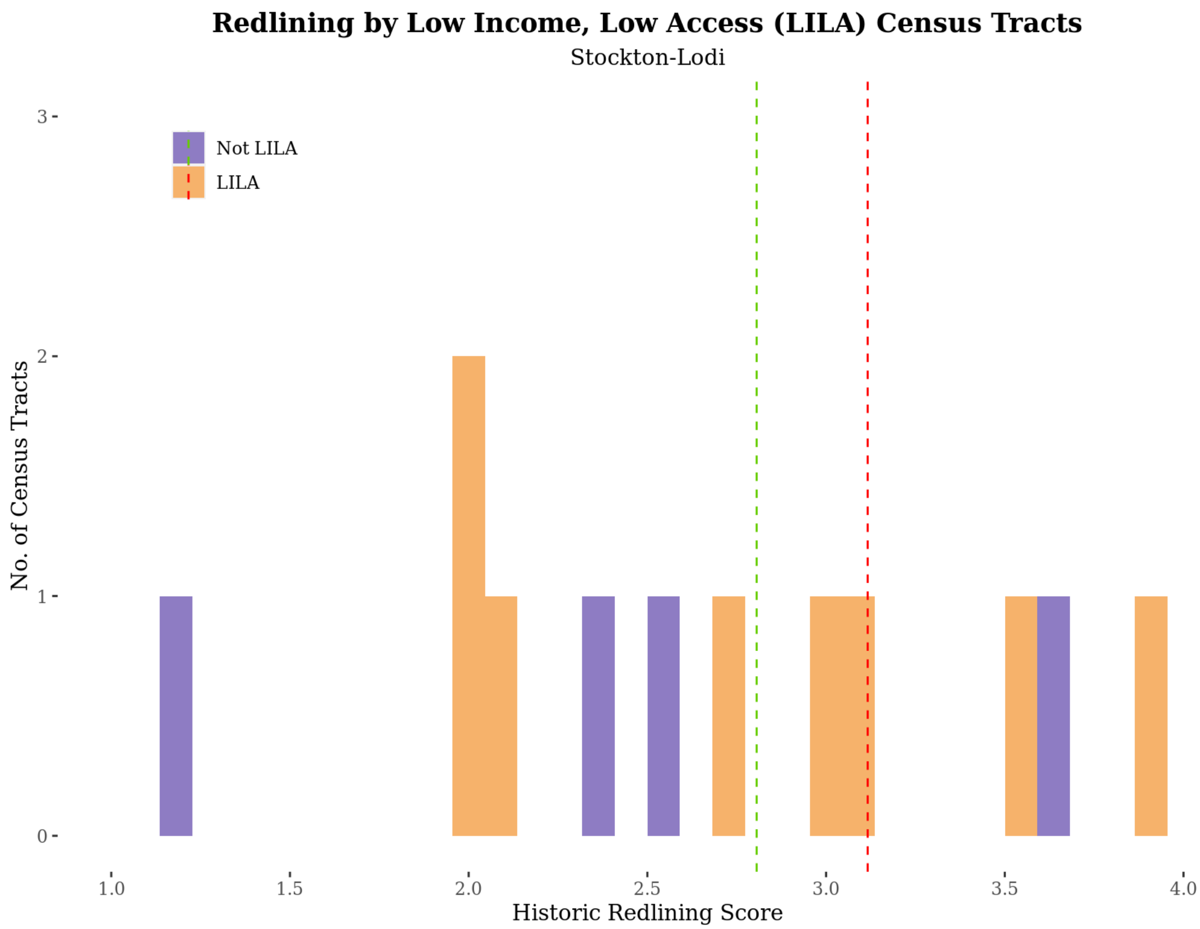


Table A-7.			
Mean Comparison – Stockton-Lodi [Link to Interactive Map]			
	Mean	**N**	**Std. Dev**
Not LILA	2.81	7	1.07
LILA	3.12	11	0.82
t = -0.68, p = .500			

Figure A-7.



Appendix B

Table B-1. Mortgage & Pre-Approval Denials by Race/Ethnicity				
Race/Ethnicity	**2018**	**2019**	**2020**	**2021**
American Indian /Alaska Native	18.2% (382)	15.6% (319)	14.7% (396)	14.8% (410)
Asian	12.9% (8181)	10.7% (6247)	10.1% (6144)	8.5% (7212)
Black /African American	16.9% (2321)	16.4% (2288)	16.7% (2463)	16.0% (2773)
Joint	9.4% (1301)	8.7% (1219)	7.7% (1200)	7.2% (1261)
Native Hawaiian/Pacific Islander	16.8% (277)	15.0% (222)	12.6% (191)	14.3% (206)
Multiracial	17.9% (150)	15.7% (107)	16.0% (147)	14.9% (172)
Hispanic/Latine	13.1% (11147)	11.6% (10306)	11.7% (10526	11.3% (10654)
White (Non-Hispanic/Latine)	10.6% (15227)	9.1% (12388)	8.7% (12361)	8.2% (11629)

Table B-2. Mortgage & Pre-Approval Denials by Race/Ethnicity, Controlling for Low Income-Low Access to Food Census Tracts (LILA)				
Race/Ethnicity	**2018**	**2019**	**2020**	**2021**
American Indian /Alaska Native				
Not LILA	15.9% (210)	13.1% (178)	16.1% (260)	11.8% (212)
LILA	18.6% (137)	15.7% (100)	16.1% (114)	16.3% (150)
Percent Difference	+2.7%	+2.6%	0.0%	+4.5%
Asian American				
Not LILA	11.8% (6338)	10.2% (5024)	9.5% (4967)	8.0% (5807)
LILA	13.4% (1265)	12.8% (1052)	12.3% (1018)	10.7% (1230)
Percent Difference	+1.6%	+2.6%	+2.8%	+2.7%
Black /African American				
Not LILA	15.6% (1351)	15.2% (1381)	15.4% (1521)	14.4% (1656)
LILA	16.9% (817)	17.1% (797)	17.4% (825)	17.2% (986)
Percent Difference	+1.3%	+1.9%	+2.0%	+2.8%
Joint				
Not LILA	8.8% (993)	8.1% (937)	6.9% (912)	6.3% (928)
LILA	9.1% (221)	10.5% (245)	10.2% (249)	10.0% (289)
Percent Difference	+0.3%	+2.4%	+3.3%	+3.7%
Native Hawaiian/Pacific Islander				
Not LILA	15.1%	13.6%	10.6%	11.8%

	(182)	(140)	(117)	(122)
LILA	19.9% (87)	15.9% (69)	15.2% (60)	18.7% (72)
Percent Difference	+4.8%	+2.3%	+4.6%	+6.9%
Hispanic/Latine				
Not LILA	12.2% (6283)	10.6% (5873)	10.4% (6097)	10.3% (6150)
LILA	13.3% (4349)	12.3% (4059)	12.9% (4030)	11.8% (3954)
Percent Difference	+1.1%	+1.7%	+2.5%	+1.5%
White (Non-Hispanic/Latine)				
Not LILA	9.9% (11534)	8.6% (9590)	8.2% (9564)	7.5% (8806)
LILA	11.0% (2814)	9.9% (2360)	10.2% (2424)	10.2% (2412)
Percent Difference	+1.1%	+1.3%	+2.0%	+2.7%

Figure B-1.

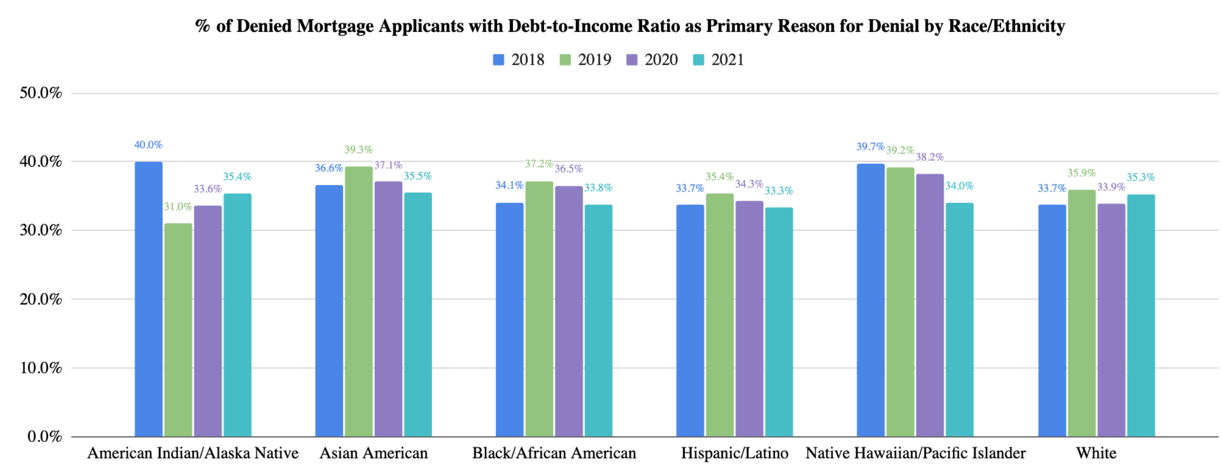
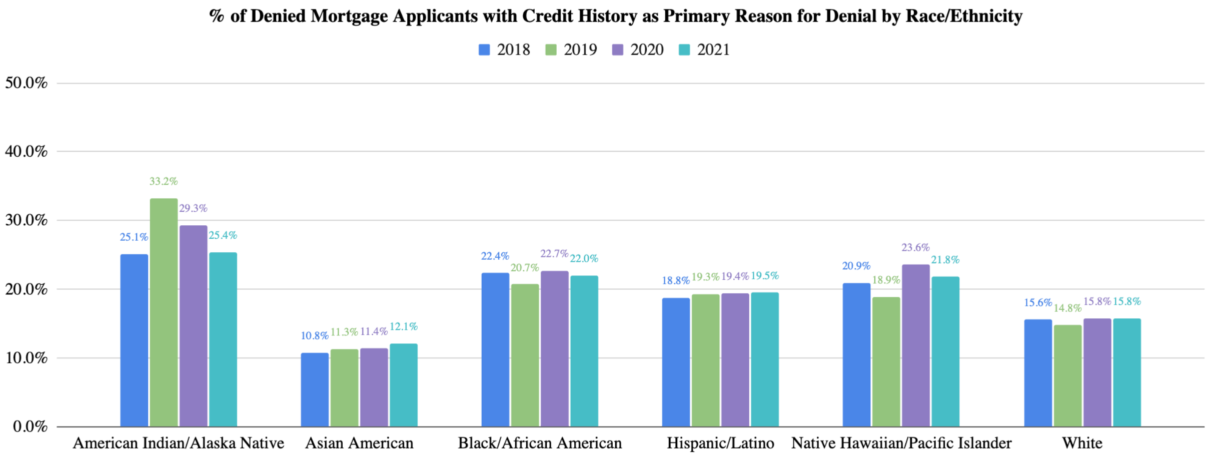


Figure B-2.


% of Denied Mortgage Applicants with Credit History as Primary Reason for Denial by Race/Ethnicity
2018
2019
2020
2021
50.0%
40.0%
30.0%
20.0%
10.0%
0.0%
25.1%
33.2%
29.3%
25.4%
10.8%
11.3%
11.4%
12.1%
22.4%
20.7%
22.7%
22.0%
18.8%
19.3%
19.4%
19.5%
20.9%
18.9%
23.6%
21.8%
15.6%
14.8%
15.8%
15.8%
American Indian/Alaska Native
Asian American
Black/African American
Hispanic/Latino
Native Hawaiian/Pacific Islander
White