MULTIMODAL NETWORK EQUITABLE ACCESS STUDY: TRANSPORTATION TECHNOLOGY ACCESSIBILITY

Prepared for the City of Richmond

MAY 2022

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ACKNOWLEDGMENTS

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ABOUT GAP-TA

Visit vtrans.org/about/GAP-TA for information about the Growth and Accessibility Planning Technical Assistance program.
OIPI will provide a blurb describing the GAP-TA program

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GLOSSARY AND ACRONYMS

ACS	American Community Survey
BRT	Bus Rapid Transit
CDC	Center for Disease Control
COPD	Chronic Obstructive Pulmonary Disease
CSV	Comma-Separated Value
CTIPS	Census Tract Federal Information Processing Standards
EEA	Equity Emphasis Areas
EPA	Environmental Protection Agency
GAP-TA	Growth and Accessibility Planning Technical Assistance program
GEOID	Geographic Identifiers
GINI	A measure of spatial income inequality
GIS	Geographic Information System
GRTC	Greater Richmond Transit Company
GTFS	General Transit Feed Specification
HOI	Health Opportunity Index
JSON	JavaScript Object Notation
KML	Keyhole Markup Language
MARTA	Metropolitan Atlanta Rapid Transit Authority
MSA	Metropolitan Statistical Area
n	Number of Survey Responses
NEHD	National Employment-Household Dynamics
NNIP	National Neighborhood Indicators Partnership
No_Broadba	Number of households without broadband internet access

No_Smartph	Number of households without smart phone access
OBJECTID	Object Identification Number
PLACES	Population Level Analysis and Community Estimates
pn_bank	Percent of responses indicating a lack of access to a bank account
pn_car	Percent of responses indicating a lack of access to a personal vehicle
pn_cell	Percent of responses indicating a lack of access to a cell phone
pn_compute	Percent of responses indicating a lack of access to a personal computer
pn_credit	Percent of responses indicating a lack of access to a credit or debit card
pn_webaccs	Percent of responses indicating a lack of access to the internet
POC	People of Color
PTE	Paths to Equity Survey
RTD	Regional Transportation District
ShareNoBB	Share of households without broadband internet access
ShareNoSP	Share of households without smart phone access
SLD	Smart Location Database
Smartphone	Number of households with smartphone access
TIGER	Topologically Integrated Geographic Encoding and Referencing
TOD	Transit Oriented Development
Tot_HH	Total number of households
UHC	Urban Health Collaborative
VCU	Virginia Commonwealth University
VDH	Virginia Department of Health
YWBI	Youth Well-being Index

1 - INTRODUCTION

The following Multimodal Network Equitable Access Study, developed under the Virginia Office of Intermodal Planning and Investment's Growth and Accessibility Planning Technical Assistance Program, identifies barriers and impacts related to multimodal transportation access in the City of Richmond through the analysis of data-driven performance metrics. The insights presented herein will provide the City with metrics and data points that will help the City mitigate physical and technological barriers, while quantifying the extent to which transportation connects people to jobs and essential services.

The way accessibility is defined, perceived, and experienced varies among regions and communities. Often, definitions emphasize access to economic activity over social or community-supportive activities. Any evaluation of accessibility must acknowledge that the mobility offered by major transportation investments may be experienced differently among different groups. This study recognizes the differences in "real accessibility" are observed most frequently and acutely across racial, ethnic, income, age, and gender lines.

This study begins by outlining a process for evaluating accessibility that is replicable, not only by the City, but other localities or agencies who may wish to perform a similar undertaking. The methodology presented includes information on what data sources were used, how they were used, and how they were obtained. The result of the accessibility analysis provides valuable insights into the differences in access experienced by diverse segments of the population. The findings from this analysis are presented in the following report.

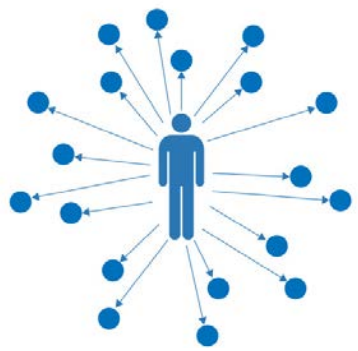
In addition to the accessibility analysis, this study also includes the findings of additional research and data analyses regarding barriers to multimodal use, transportation technology accessibility, outcome linked accessibility, and the multimodal transportation gentrification effect. Through the use of readily available data sources, insight was gained on why multimodal transportation usage may be low among certain segments of the population. Survey data previously collected by the City permitted the identification of population segments with a lack of access to banking or internet. An assessment of well-being and economic indicators identified areas that were below average in these characteristics. Finally, a look at property values following transportation investments provided insight on whether these investments are pricing the intended users out of the areas served. Finally, all of the data on indicators was compared to the accessibility analysis results to determine any correlations between these characteristics and transportation access. The findings of this study will assist the City of Richmond in meeting their goal of identifying transportation investments that don't simply facilitate the movement of people and goods, they aim to improve communities.

2 - EQUITABLE ACCESS METRICS

Overview

Accessibility is the ability to reach desired destinations, activities, goods, and services within a reasonable amount of time. The primary goal of all transportation systems is to provide accessibility – that is, to connect travelers to their destinations in a safe and timely manner. Which destinations are relevant and how much time is deemed reasonable to reach them vary from person to person, making comprehensive assessments of the accessibility provided by transportation systems elusive. For example, the number of jobs reachable from a given neighborhood is a common measure of accessibility. However, it is a poor metric for describing the accessibility experienced by retirees or children, since jobs are not germane to their daily travel needs. Indeed, for different members of the workforce, not all jobs have equal relevance.

This report presents a novel methodology for generating holistic measures of accessibility that account for demographic and socioeconomic characteristics of travelers with the aim of describing the equity of access offered by the multimodal transportation system. It focuses on the City of Richmond, VA and analyzes accessibility by the auto, highway, bike, and walk modes.



We all have important destinations to get to in our daily life. Accessibility measures our ability to get to those destinations. But not all destinations are equally relevant to all travelers.

The chapter is organized into the following sections:

- Background – Rising interest in accessibility and use in planning and project prioritization applications.
- Accessibility and Equity – Discusses some limitations of typical accessibility measures for addressing inequities built into transportation systems and opportunities to enhance measures to better reflect the needs of residents.
- Richmond's Equitable Accessibility Metrics –
  - Overview of Metrics – describes the measures generated in this study and how they address shortcomings in prevailing accessibility measures
  - Use and Interpretation of Metrics – Describes how the access measures produced by this study can be interpreted to understand underlying equity issues and applied in planning processes.
  - Methodology – Provides a detailed step-by-step walkthrough of how measures produced in this study are generated.
  - Action items/Next steps – Identifies opportunities to use the metrics produced by this study in forthcoming planning efforts, enrich the scoring constructs created here with additional data, enhance the scoring methods for more rigorous exploration of equitable access, and transfer the scoring approaches applied in this study to other contexts.
- Appendix A: Equitable Access Metrics Data Sources, Open Source Code Repository, and Data Dictionary for Study Outputs:
  - Data Sources - provides a comprehensive list of the data used to develop the equitable accessibility scores produced in this study.
  - Open Source Code Repository – provides a guide for acquiring, configuring, and executing the analysis steps described in this document.
  - Data Dictionary for Study Outputs – provides an orientation to the data products generated by this study, including descriptions of tables and fields.

Background

Accessibility has gained currency in transportation planning, policy language, performance measurement, and research over the past decade. Increasing the accessibility and mobility of people and freight is among the factors state departments of transportation (DOTs) and metropolitan planning organizations (MPOs) are required under federal law to consider as part of their statewide and metropolitan transportation planning processes. Accessibility is among the project prioritization factors that inform Virginia's SMART SCALE process for prioritizing funds for transportation projects. Nationwide data resources, such as EPA's Smart Location Database and the University of Minnesota's Accessibility Observatory, demonstrate accessibility measures and provide ready-made estimates of accessibility to jobs by multiple modes of travel. A forthcoming TRB report (NCHRP 08-121) outlines various approaches to analyzing accessibility and how those approaches can be deployed to support transportation planning at various phases (needs identification, project prioritization, etc.), scales (statewide, regional, local, etc.), and settings (metropolitan, urban, rural, etc.).

These diverse efforts that emphasize accessibility reveal the relevance of the concept for addressing contemporary transportation challenges. Within an accessibility framework, systems and projects that focus on different travel modes can be evaluated in common terms: their impact on access to destinations. Accessibility measures complement traditional transportation metrics that focus on mobility by coupling the speed and freedom of movement offered by mobility-focused systems/projects with the extent to which they augment access to destinations. After all, people travel to get somewhere. This also allows accessibility measures to reveal the extent to which land use changes provide shorter and faster connections among travelers and destinations. In these ways, accessibility measures can provide insight for assessing planning needs and/or prioritizing projects in terms of multimodal competitiveness, connectivity and mobility, and proximity to destinations (land use).

Separate from the growing importance of accessibility, there is a burgeoning recognition of equity as a central pillar of effective transportation planning and investment. The City of Richmond's Path to Equity Policy Guide establishes principles and guidelines for rethinking the City's transportation planning and investment processes and strategies to emphasize equity and community input, rectify historical injustices wrought by transportation and other public projects, and ensure future investments alleviate inequities arising from income disparities and systemic marginalization of communities of color.

This study aims to augment established measures of accessibility with socioeconomic and demographic considerations that shape the experience of the transportation system and the relevance of the accessibility it provides for diverse travelers. This effort constitutes a first step to identify and demonstrate methodological enhancements to common accessibility measures. Subsequent efforts are expected to refine and enrich these enhancements to generate more nuanced insights into how demographics shape accessibility and how understanding both can reveal needs and opportunities to plan for an equitable transportation future.

Common Measures of Accessibility

There are several common types of accessibility measures used to support planning applications as presented in Figure 1. Each of these measurement approaches can yield different insights about regional structures that shape travel patterns, from land use and urban design considerations to multimodal network availability, quality, and performance. Each measure can be estimated for differing modes (auto, transit, walk, and bike), times of day (peak versus off peak periods), and destinations (all jobs, housing, healthcare, education, etc.) to provide nuanced insights that holistically address all travel options.

The specific measures to utilize for a planning application depend on the goals, objectives, and contexts of the application; the role of the application within the larger process of identifying, prioritizing, and funding projects; and the scope and scale of analysis needed to inform decision-making. For example, cumulative opportunities measures can be expected to yield higher values in large metropolitan regions than in small cities or rural communities. For application in a statewide project prioritization process, this can pose a risk of bias in favor of projects in large metropolitan areas.

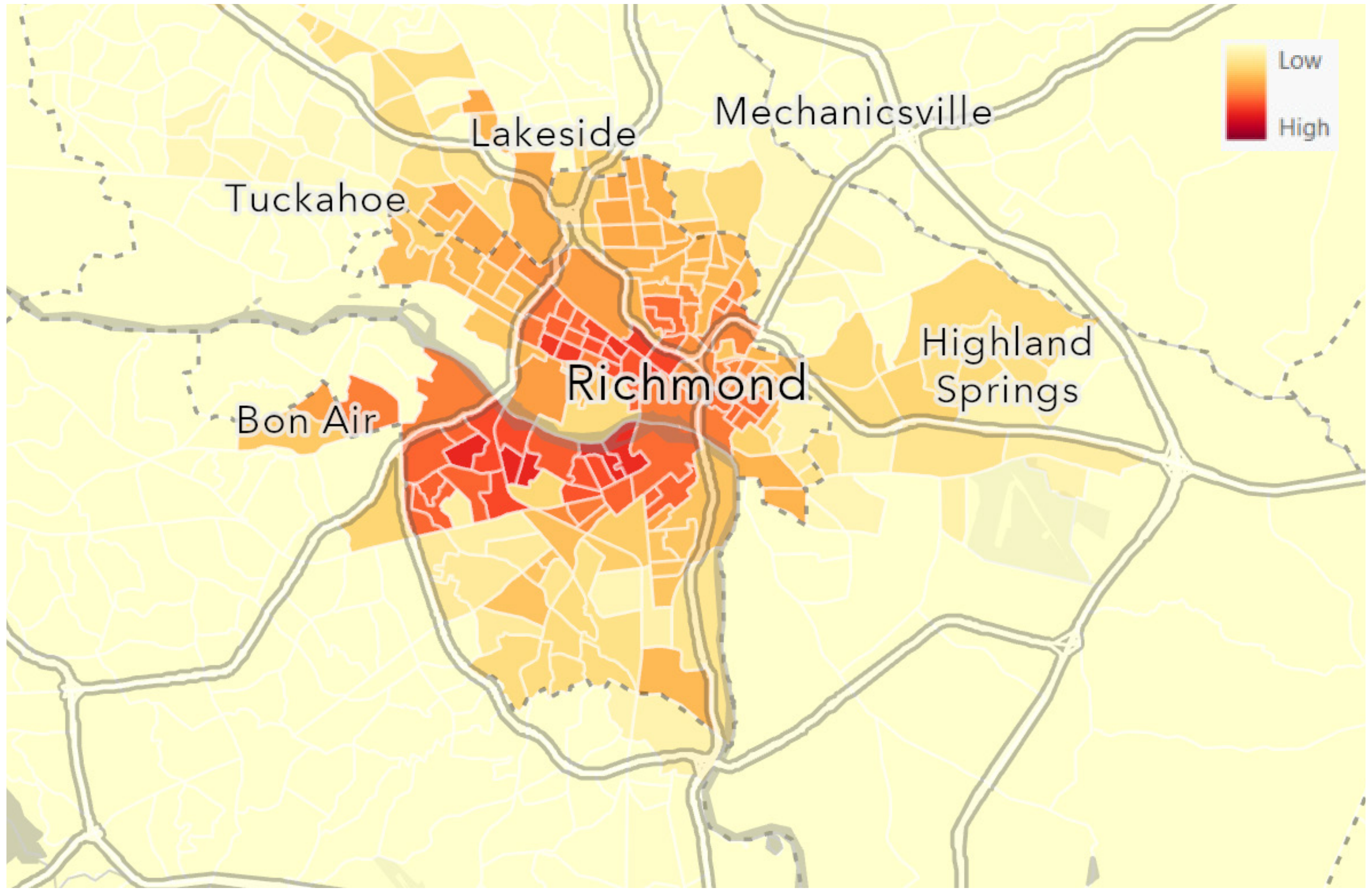
Examples of each scoring method are presented below to demonstrate the typical outputs and insights offered by each. Each example is based on data from the Environmental Protection Agency's Smart Location Database (SLD) to illustrate mapping of accessibility measures from a ready-made source. All accessibility estimates generated for this study differ from these illustrations in important ways methodologically.

Cumulative Opportunities: Cumulative opportunities measures are the most commonly reported accessibility measures, featuring in nationwide datasets like the SLD and Accessibility Observatory data products and in several notable project prioritization processes like SMART SCALE. This approach estimates the total number of activities within reach by a given mode, such as the number of jobs reachable within 30 minutes by driving. Typical outputs are heat maps of the accessibility offered by a given mode. Figure 2 shows an example of a cumulative opportunities heat map for the Richmond Area from the SLD, mapping access to jobs reachable within 45 minutes by transit. These heat maps reveal the relative reach of the transit system from each block group with respect to regional jobs centers. Areas with more access to jobs are generally more likely to commute to work by transit.

Figure 1: Common types of accessibility metrics

Cumulative Opportunities
How many destinations are reachable from here? Most commonly used accessibility metric (SMART SCALE, e.g.). Scores trend higher in more urban contexts meaning some normalization may be required.
Proximity
Which and how many assets are nearby? Common in planning applications like multimodal quality of service. Nearby assets contribute to higher scores even thought they may not be relevant or provide utility to travelers.
Trip Characteristics
How long (distance, duration) are trips to/from here? Common in transportation applications (VMT forecasting, e.g.). Scores are generally most sensitive to large-scale infrastructure investments.
Competitive Access
How many destinations are reachable from here, given the other travelers that can also reach them? Sometimes featured in academic analyses to normalize cumulative opportunities scores to mitigate urban bias. Computationally more complex than other methods.

Figure 2: Access to jobs via transit in 45 minutes (Smart Location Database)



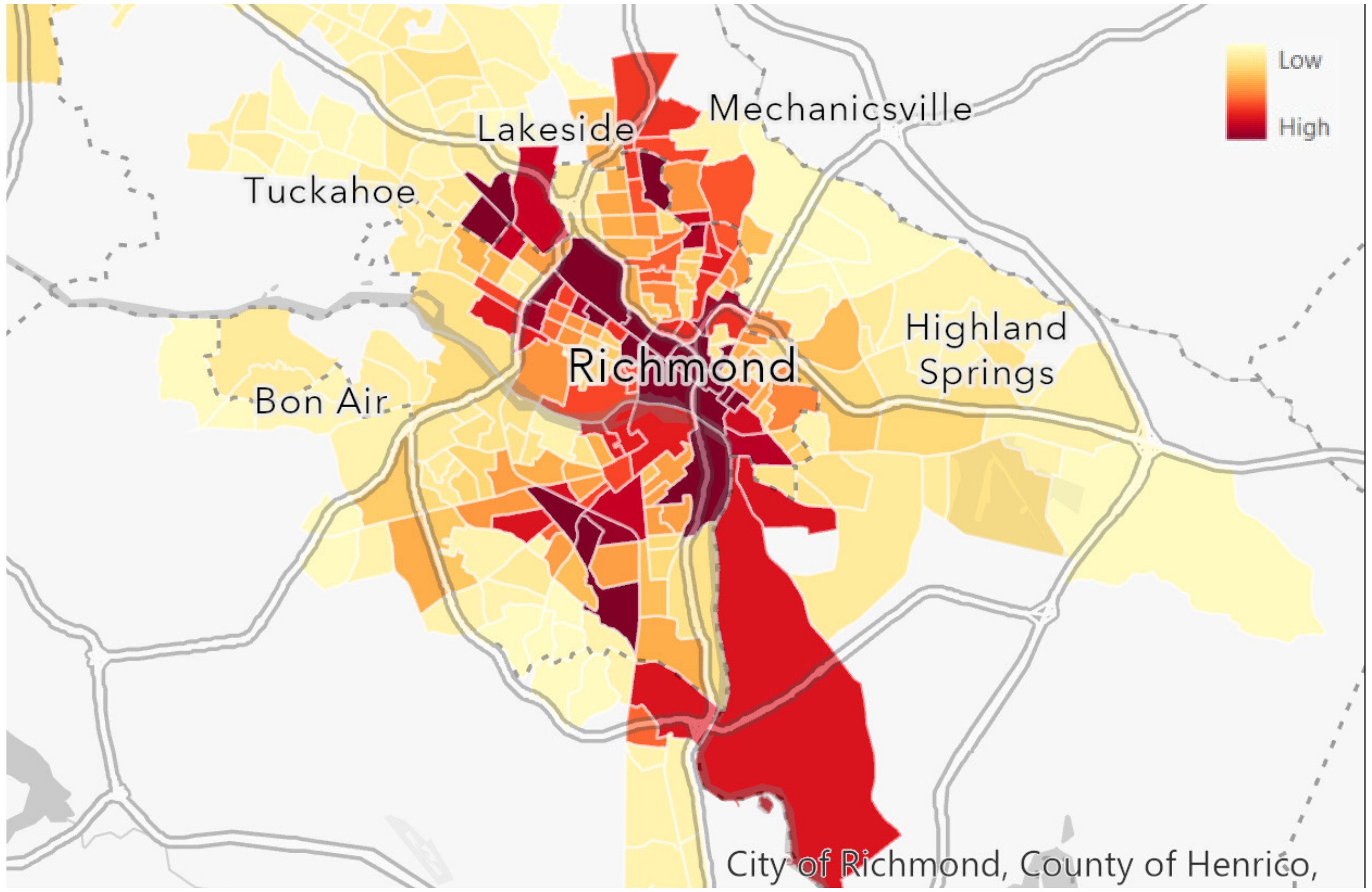
In this study, cumulative opportunities scores are reported for access to jobs, shopping, and various other destinations. The cumulative opportunities scoring approach is the basis for the decayed destinations and basic utility expressions of access developed for composite scoring.

Proximity: Proximity measures emphasize the availability of nearby destinations, infrastructure, or services. The minimum walk time to the nearest bus stop or the cumulative number of restaurants and bars within a half-mile area are examples of proximity metrics. They are easy to interpret since the results reflect the geography of the facilities of interest, such as transit stops, sidewalks, bike lanes, etc. Proximity measures are the basis for some commonly used planning analysis frameworks such as multimodal quality of service (MMQOS), although these frameworks are not always thought of as focusing on accessibility per se. In many cases proximity to multiple destinations or facilities is measured with results combined in a composite manner to describe the concentration of key services, destinations, etc. Figure 3 shows an example of proximity to transit expressed as the aggregate service frequency (total number of departures) in the evening peak period within a quarter-mile of each census block group. Areas with many departures in the vicinity do not always align with areas offering high access to jobs shown in Figure 2.

In this study, proximity measures are used to express the nearness of crisis destinations.

Trip Characteristics: Trip characteristic measures focus on trip attributes, such as the average travel time or vehicle miles of travel (VMT) generated for trips starting or ending in a given location. In principle, shorter typical trips are associated with more accessible places. Figure 4 shows average work-related VMT per worker by census block group in the Richmond area. Work-related VMT includes commutes and work-based travel for service calls, appointments, meetings, lunches, errands, etc. Many areas with low VMT generation overlap those with high transit access to jobs (Figure 2). Trip characteristics measures require detailed travel data and/or

Figure 3: Aggregate evening peak period transit service frequency within 1/4-mile of block group boundary (Smart Location Database)



models to estimate trip distribution, making them computationally more complex than cumulative opportunities or proximity measures. Because they generally reflect regional trip-making patterns, they are most sensitive to large-scale projects that alter those patterns, making them less suitable for local evaluations or for assessments of bicycle and pedestrian needs or projects.

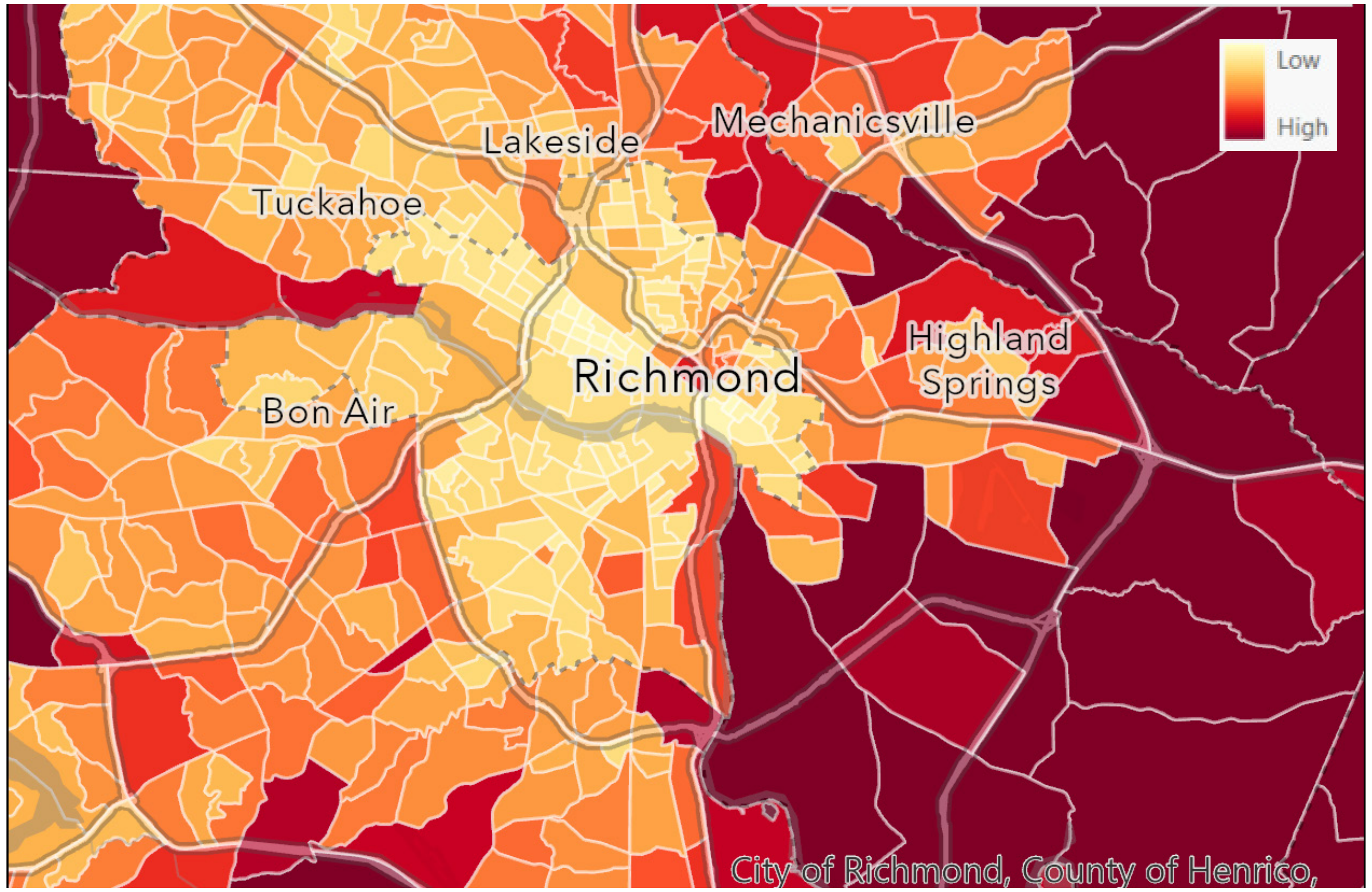
Trip characteristic measures are not part of the accessibility scoring framework developed for this study, but statistics about trip-making were used to understand how the accessibility scores generated relate to mode choice and other travel behaviors.

Competitive Accessibility: Competitive accessibility measures aim to normalize cumulative opportunities measures by the number of "competing" travelers, such as dividing the number of jobs reachable by the number of job seekers that can reach the same jobs. The goal of this normalization is to recognize that destinations often accommodate a finite number of travelers. For example, a job is only worked by one worker at a time. For job seekers, the number of jobs reachable may be diluted by the number of workers competing for the same job.

Figure 5 shows a naïve expression of competitive accessibility, mapping the number of jobs reachable from each block group per working-age-resident reachable by transit within 45 minutes. What the map reveals is that most of the transit service area in Richmond provides more access to jobs than to workers, indicating that for every job reachable by transit, there is less than one worker in the same travel shed. This would suggest that many jobs are worked by workers outside the transit service area, commuting to work predominantly by car. Block groups with more workers accessible than jobs are few and located at the periphery of the transit service area.

This example is an imperfect expression of competitive access, since the goal in competitive measures is to discount the activities (jobs) reachable from one location by the number of competitors (workers) that can reach those jobs from their respective origin locations. This means the normalization should occur within an origin-destination matrix, and there are no ready-made sources to

Figure 4: Mean total work-related VMT per worker by workplace (Smart Location Database)



support that analysis. The additional computational complexity required for a robust analysis of competitive access is one reason they are not frequently used outside of academic contexts.

In this study, [competitive access scores] were generated to provide comparisons for how the cumulative opportunities estimates are altered by accounting for competing travelers. The relationships among the competitive and non-competitive expressions of the score can help highlight mismatches in the locations and concentrations of residents and daily destinations.

Basic Components of Accessibility Measurement

While there are numerous ways to measure and report on accessibility, all measures rely on the same essential components (Figure 6):

- Land Use data provide insight into the number and types of destinations found in a given area (number of jobs in a census block group, e.g.) as well as the number and types of travelers residing in an area (number of households in a census block group, e.g.). Land use data are typically summarized within discrete zones such as census blocks, census block groups, or traffic analysis zones.
- Transportation data that represent travel networks provide the means to model connectivity among zones and estimate the lowest-cost path from each zone of origin to each zone of destination. At a minimum, transportation data include linear features that represent streets, paths, transit lines, etc. with attribute data describing the distance required to traverse each feature. Usually, richer cost attributes such as travel time are included as network attributes. In some cases, complex generalized cost formulas may be used to define the cost of traversing the facility as a combination of time, monetary costs, comfort factors, and more.

Figure 5: Jobs reachable within 45 minutes by transit per working-age resident (Smart Location Database)

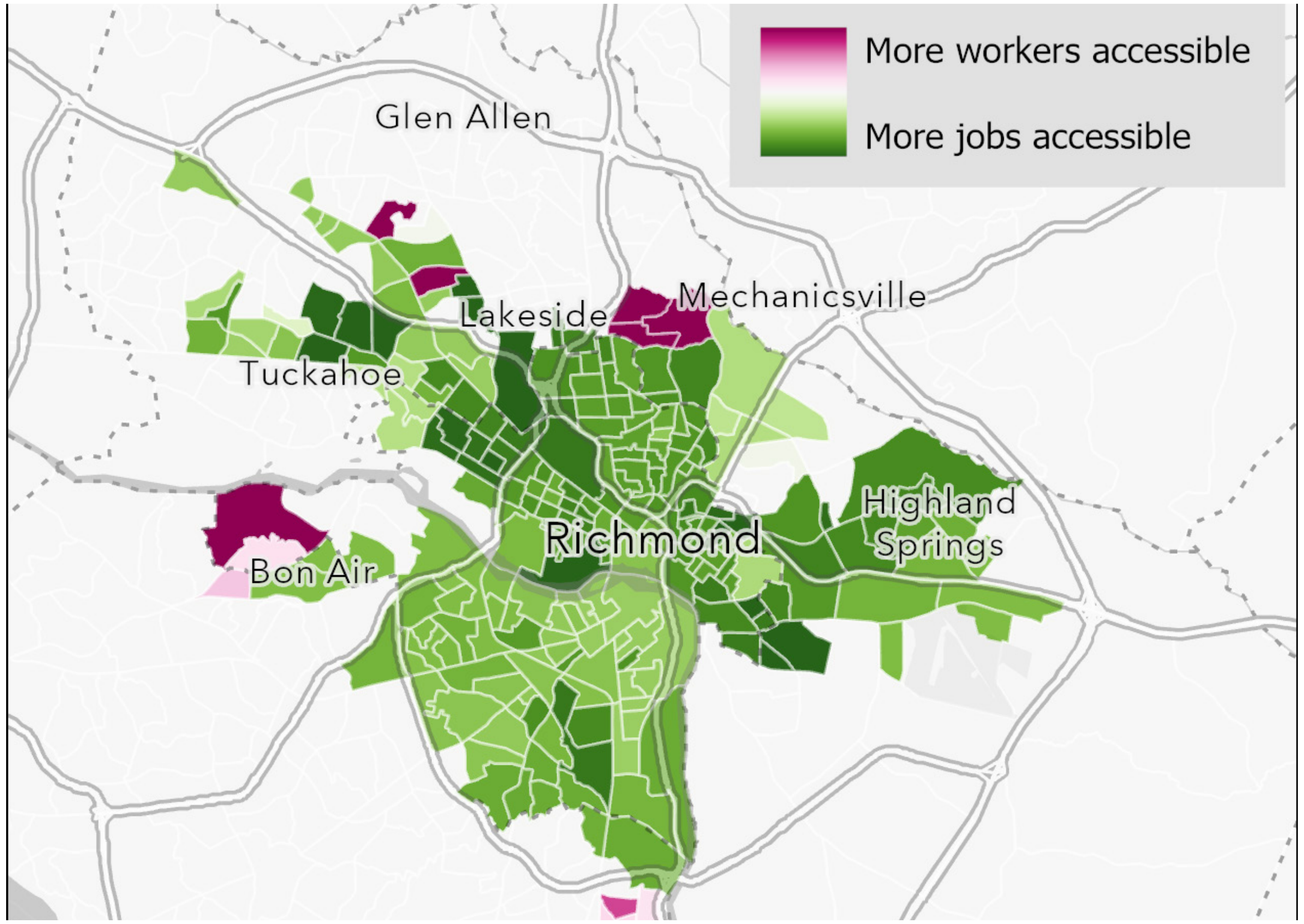


Figure 6: Essential components of accessibility analysis

Land Use
Which destinations are relevant to travelers? What key sites/services are available under extenuating circumstances?
Transportation
Which modes are available to travelers? What costs (time, money, etc.) are bearable to travelers?
Technology (emerging)
Which technologies are available for virtual access and what kinds of destinations/trips are these likely to replace?

Data needed to compute accessibility are usually readily available and the most commonly used analytical methods are relatively simple to develop and apply. Most accessibility measures rely on population and employment data for a standard set of zones and multimodal networks with travel distance, time, and/or cost information (e.g., regional or statewide travel models, Open Street Map, GTFS transit routes, etc.). Some accessibility measures also account for the amount of travel (trips by mode) and/or incorporate travel time or cost decay curves that describe the degrading propensity for travel as times or costs to reach destinations increase.

Future work on accessibility measures will require the additional consideration of access to technology and virtual substitution of destinations. This may include accounting for remote work opportunities, online retail, and virtual social gatherings/community spaces in the assessment of accessibility.

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Accessibility and Equity

When applying the concept of accessibility to questions of equity, the primary concern is the level of access provided to historically marginalized populations and how this compares with the general population. Generally, this can be assessed by taking an average of accessibility estimates among a collection of zones weighted by the number of people or households of a given type in each zone. For example, if zone A has access to 10,000 jobs and is home to 100 people and zone B has access to 20,000 jobs and is home to 100 people, the average access for zones A and B combined is 15,000 jobs. If, however, zone A is home to 60 people living in poverty and zone B is home to 20 people living in poverty, the combined average (12,500 jobs) will be lower for persons living in poverty than for the general population. This approach can be applied to all different types of accessibility metrics and focused on as many specific segments of the population as desired.

However, this approach suffers from several limitations. First, it requires accessibility estimates across multiple zones to generate the weighted average value. Therefore, it is best suited for describing aggregate conditions rather than a localized assessment of equitable access. Additionally, it effectively treats all destinations as equally relevant to all travelers. For example, access to jobs (a cumulative accessibility metric) is the most widely-used measure of accessibility since jobs are both opportunities to earn a wage as well as a reasonable proxy for where activities that attract non-work trips may be located. But not all jobs are equally relevant to all travelers. Educational attainment, workforce participation, worker life phase (single, married, presence of dependents, etc.) and other factors influence which jobs and non-work activities are most important to each person's daily travels. Additionally, not all travelers have the same tolerance for the costs of travel, including time and monetary costs.

To address these limitations, measures of equitable access would ideally seek to account for detailed characteristics of who is traveling. These demographic details would enable the estimates of travel costs among zones to be sensitive to traveler preferences, such as lighting along sidewalks and bike lane traffic separation. They would allow certain destination types to be scored as more or less important to different travelers, such as medical facilities for elderly residents. And they would enable daily travel budgets to influence the impact of time and other costs on the value of destinations.

In many cases, data allowing these considerations to be fully represented in accessibility measures are scarce, and even when the data are available, understanding their precise impact on traveler preferences can be difficult to calibrate. For example, it is reasonable to assert that narrow and broken sidewalks have a negative impact on people's feeling of safety and willingness to walk, but defining the effect size is difficult, especially considering that the effect size may vary for different types of travelers. Given these limitations, ideal expressions of equitable access are likely to remain elusive for some time.

Richmond's Equitable Accessibility Metrics

The estimates of accessibility generated in this study represent an initial foray into enriching accessibility measurement approaches to better reflect traveler needs and preferences and provide insight into the real access offered by a given mode to a set of destinations given the demographic composition of travelers residing in each zone. The methodological enrichments explored here build on three of the common ways of measuring accessibility listed above: cumulative opportunities, proximity, and competitive access. They focus on several key objectives:

- Understand the demographic composition of residents in a given zone.
- Understand how demographic characteristics influence daily travel needs and which destination types are most relevant to different people.
- Understand how demographic characteristics influence daily travel budgets and what costs over the network are bearable for different travelers.
- Provide analysis methods that allow facility attributes and conditions to influence estimated costs for travelers.
- Provide analysis methods to weight destinations reachable by travel costs and relevance to travelers for a demographically-informed estimate of accessibility.
- Provide analysis methods to estimate the number of relevant competitors that can reach destinations to normalize access at a zone interchange (origin-destination) level.
- Combine estimates of access to particular types of destinations into a composite score for a given travel mode and trip purpose.

In developing an analytical framework and toolkit to achieve these objectives, we generated several permutations of similar accessibility estimates with minor methodological differences, which can be organized into several dimensions as described below and presented in Table 1.

Table 1: Matrix of Types of Accessibility Metrics Generated

	Decayed destinations	Basic utility
True Time	Naïve estimate of destinations reachable with no interest in destination relevance or network characteristics	Accounts for relevance of destinations reachable to residents based on demographics
Effective time	Modified cumulative opportunities score that accounts for network effects to inform route choice and estimated costs to travelers	Destination relevance and network effects combined

All combinations of these scores were generated for cumulative opportunities and competitive expressions of access. Independent accessibility estimates were developed for the walk, bike, transit and auto modes. The trip purposes for which we produced composite accessibility scores include: work, shopping, school, community, social/recreational, and health care. Within each of these trip purposes, access to specific types of destination is also reported. Thus, there are myriad results reported. These different estimates of accessibility allow comparisons among their respective results to yield insight into the nature of accessibility deficiencies.

In addition to the accessibility estimates described above that reflect typical daily travel needs, we developed several proximity scores as well for describing the ease with which atypical destinations could be reached under extenuating circumstances or for non-routine travel. Access to these types of destinations may be especially important for historically marginalized populations. The proximity scores simply report the travel time to the nearest "crisis" destination for the walk, bike, transit, and auto modes. The crisis destinations included in the analysis are:

- Emergency services
  - Police stations and sheriff facilities
  - Fire and EMS stations
  - Urgent care facilities
- Other
  - Cooling stations
  - Shelters for persons experiencing homelessness
  - Food pantries
  - Social services
  - Polling places

Together, the accessibility estimates and supporting procedures generated in this study provide initial augmentations to common measures of accessibility. They demonstrate insights and procedures that can be further enriched and expanded in subsequent efforts to account for additional details as data become available and research yields further insight into the effect sizes of particular conditions for different travelers. Moreover, applications of these results to support local planning efforts in the City of Richmond will likely yield insights into the most effective ways of deploying the estimates for planning applications and prompt additional refinements.

Use and Interpretation of Metrics

This section presents illustrations of how the accessibility metrics generated in this study provide nuanced insights into the accessibility available in different neighborhoods throughout the City of Richmond. All illustrations focus on access via the walk mode.

Decayed Destinations Versus Basic Utility: Figure 7 shows the access to jobs by walking using the "decayed destinations" formulation on the left and the "basic utility" formulation on the right. The two maps exhibit very similar relative patterns of accessibility, with the highest accessibility observed in Downtown Richmond and spreading west through the Fan District. Figure 8 shows the ratio of the basic utility score to the decayed destinations score. This ratio highlights where the jobs reachable by walking are relevant to residents in each neighborhood. Areas with higher ratio values have higher proportions of relevant jobs reachable to total jobs reachable. Jobs relevance is estimated based on worker educational attainment (see Destination Relevance).

The map reveals that although the Fan District has relatively high walk access to total jobs, only a moderate proportion of those jobs are relevant to residents. Meanwhile, residents in southwest Richmond have relatively low walk access to jobs but a moderate-to-high proportion of those jobs are relevant to residents. Residents of Shockoe Bottom and Downtown enjoy both high accessibility and high relevance. Residents just north of I-64 near downtown Richmond have high access to the downtown jobs, but those jobs have very limited relevance to them.

Effective Time Versus True Time: As noted above, separate accessibility estimates were generated based on "true time" (a simple estimate of travel time) and "effective time" (a more nuanced estimate of time that reflects traveler experience). The effective time estimates account for facility characteristics that benefit travelers (e.g., sidewalks, bicycle lanes, etc.) and those that impede travelers (e.g., bridges, parking lots, alleys, etc.). Comparing these two formulations of accessibility can reveal areas where network enhancements may be warranted.

Figure 7: Access to jobs by walking: decayed destinations (L) vs. basic utility (R)

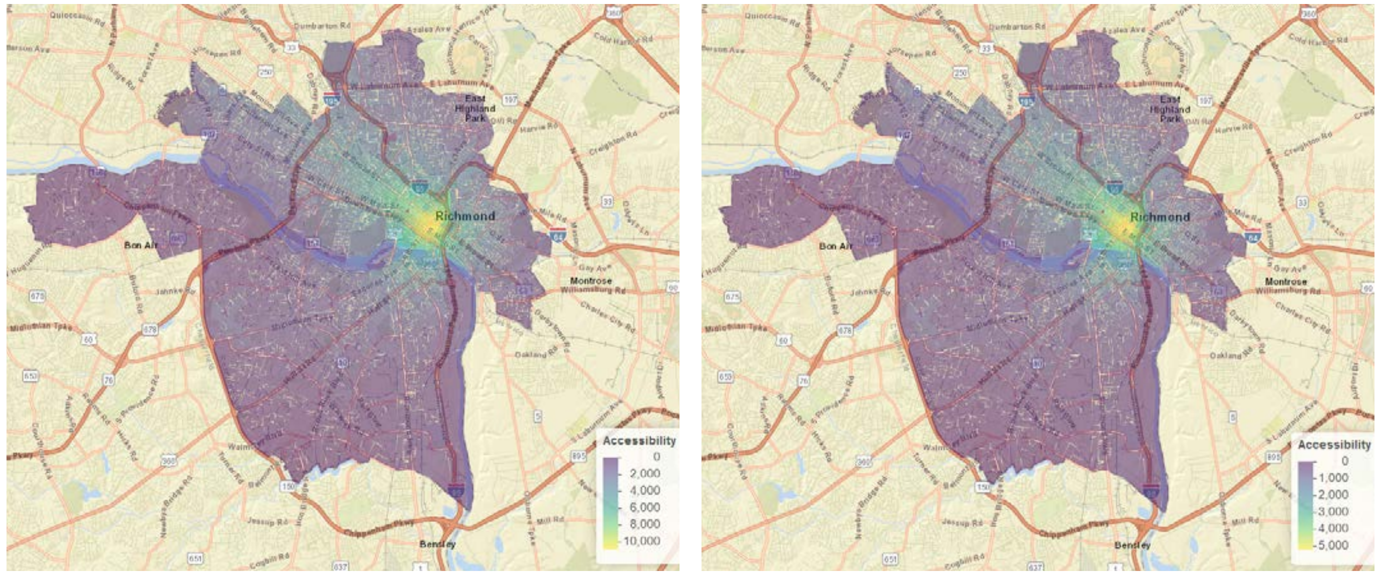


Figure 8: Access to jobs by walking: ratio of basic utility to decayed destinations

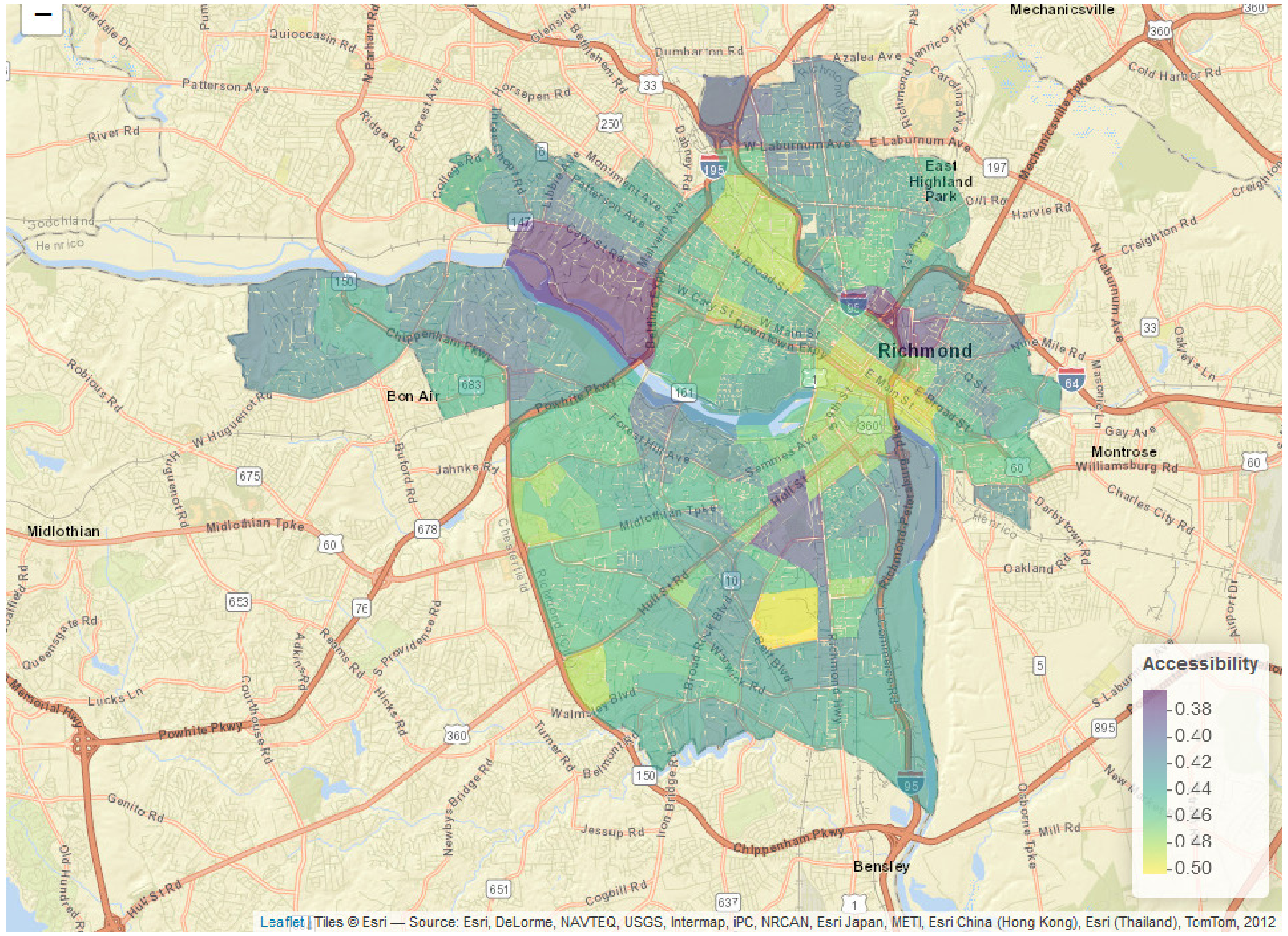


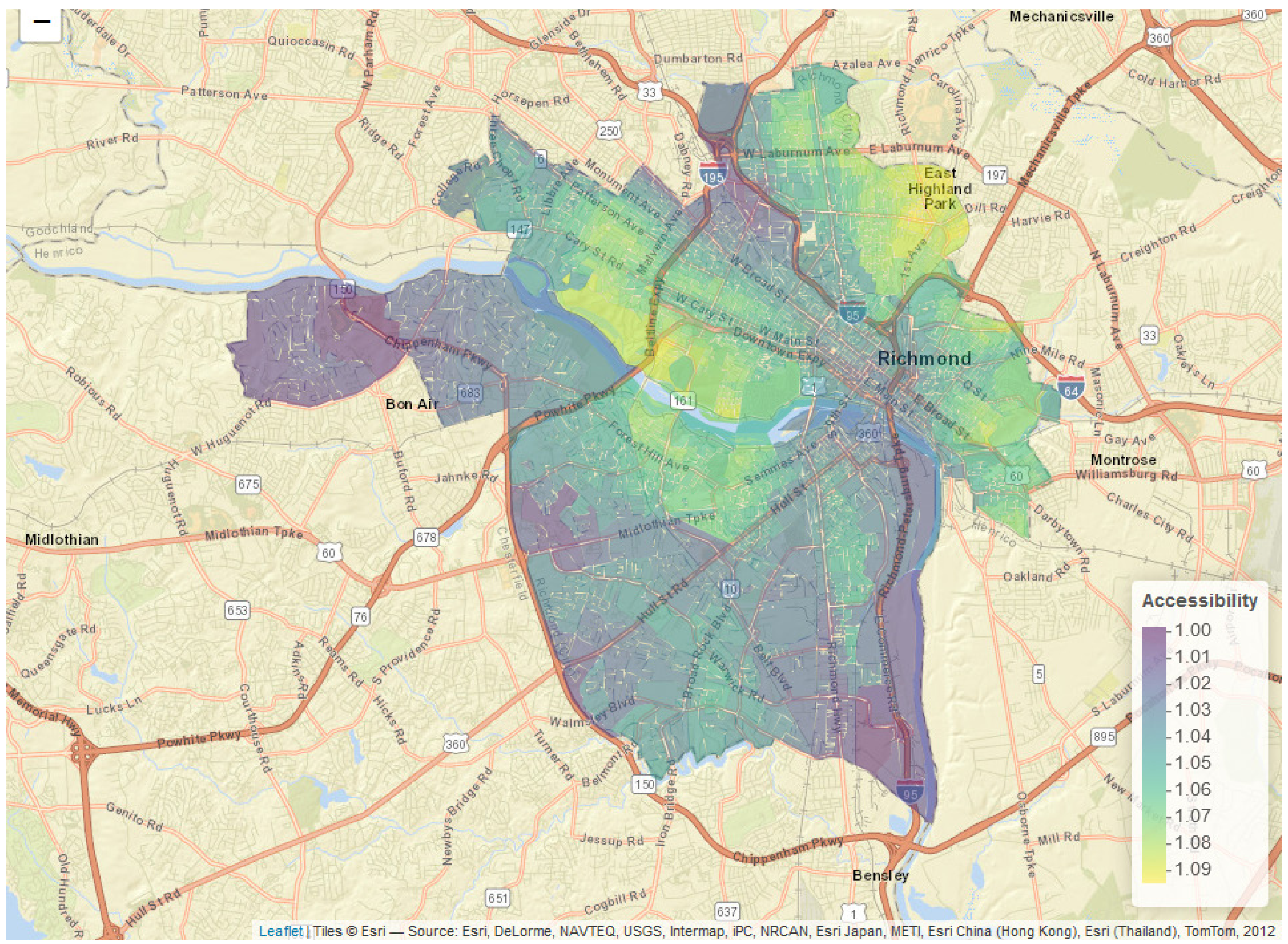
Figure 9 shows the ratio of walk access to jobs (basic utility) based on effective time to that based on true time. Throughout the City, the presence of sidewalks and other beneficial facility attributes outweighs the detrimental effects of bridges, alleys, and parking lots (see Action Items/Next Steps for discussion of the potential to refine and/or augment the facility characteristics considered). Sidewalk condition data were used to reduce the walk benefit provided by sidewalks in poor condition, such as those with vertical uplifting or significant ponding. Thus, the areas with the highest ratios in Figure 9 are those with sidewalks in good condition and with minimal exposure to parking lots, alleys and bridges.

More detail about how networks are enriched with facility information is available in the Network Embellishments section below.

Competitive Versus Non-Competitive Accessibility: The preceding examples have focused on cumulative opportunities approaches to measuring accessibility and relationships among those scores. This illustration introduces competitive accessibility, which normalizes the number of activities reachable by the number of potential competing travelers.

Figure 10 shows the access to jobs by walking (basic utility), comparing the non-competitive estimate on the left to the competitive estimate on the right. The comparison of the two maps reveals areas where high accessibility may be undermined by high concentrations of competing travelers. For example, when competitors are accounted for, the downtown core and Fan District are no longer highly accessible, meaning that the jobs reachable from those areas are also within reach by walking for a large number of workers. The highest estimates of competitive accessibility to jobs by walking are observed in peripheral locations where small numbers of jobs are reachable by even smaller numbers of workers.

Figure 9: Access to jobs by walking: ratio of effective time to true time



Equity of Access: The accessibility scores described above can be summarized among collections of zones enriched with socioeconomic and demographic data to understand average accessibility available to different segments of the population. The figures below present examples summarizing access across the entire City of Richmond for populations broken down by race (white vs. BIPOC), ethnicity (Hispanic vs. non-Hispanic), income (low-income vs. non-low-income), and vehicle ownership (zero-car households vs. households with at least one vehicle). Each figure presents the average citywide access for a target group relative to a control group, such that positive values indicate higher access for the target group than the control group and negative values indicate lower access for the target group. Each figure presents separate results for non-competitive and competitive accessibility scores, faceted by mode (auto, bike, transit, walk) and score formulation (basic utility versus decayed destinations).

Accessibility to Crisis Destinations: The final illustration of accessibility results shifts to focusing on crisis destinations reachable by walking. This score estimates the minimum travel time to the nearest crisis destination rather than the number of destinations reachable. These accessibility results can highlight areas where various crisis destinations are distant or difficult to access by a given mode. Figure 11 shows the access to food pantries by walking in Richmond.

Figure 10: Access to jobs by walking (basic utility): non-competitive (L) vs. competitive (R)

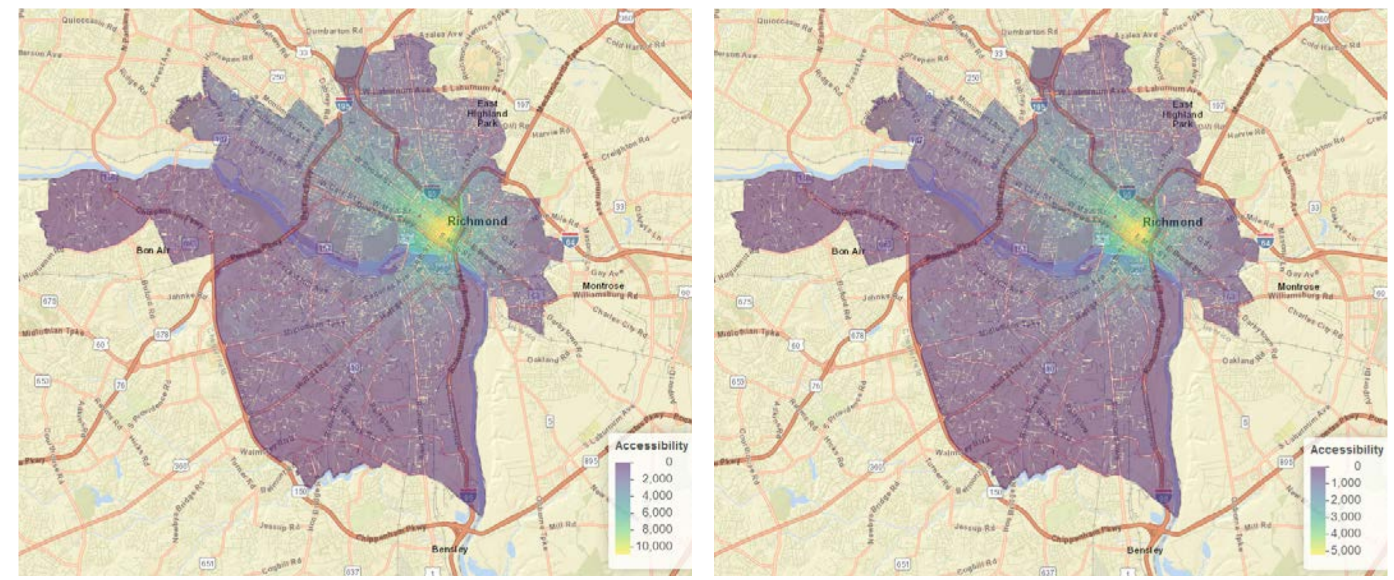
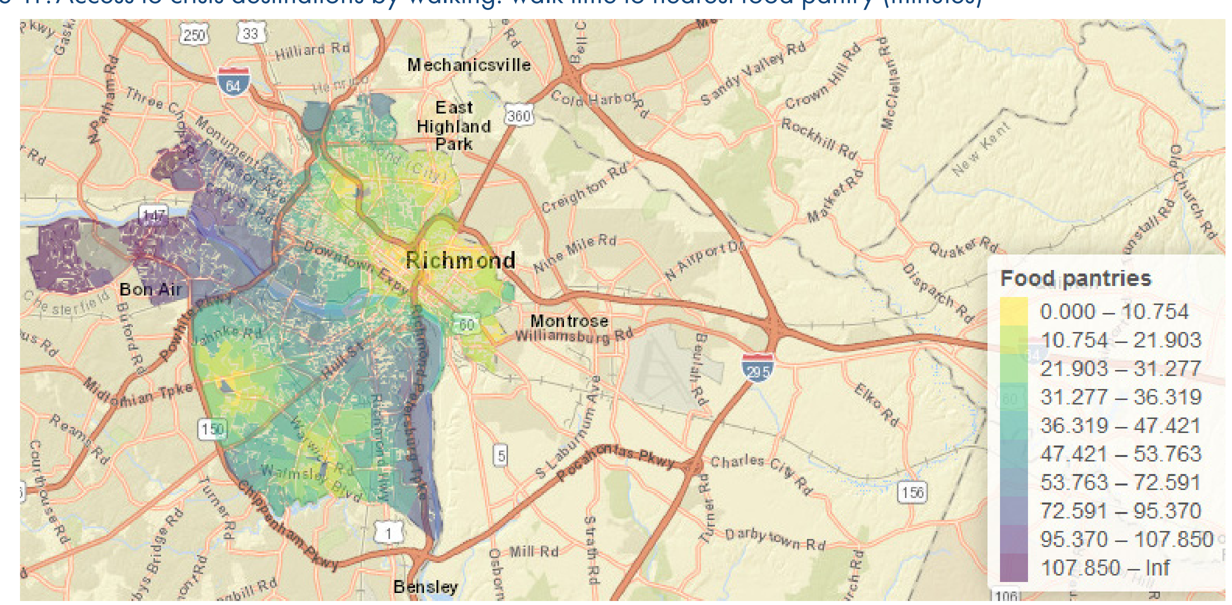


Figure 11: Access to crisis destinations by walking: walk time to nearest food pantry (minutes)



Equity of Access: The accessibility scores described above can be summarized among collections of zones enriched with socioeconomic and demographic data to understand average accessibility available to different segments of the population. The figures below present examples summarizing access across the entire City of Richmond for populations broken down by race (white vs. BIPOC), ethnicity (Hispanic vs. non-Hispanic), income (low-income vs. non-low-income), and vehicle ownership (zero-car households vs. households with at least one vehicle). Each figure presents the average citywide access for a target group relative to a control group, such that positive values indicate higher access for the target group than the control group and negative values indicate lower access for the target group. Each figure presents separate results for non-competitive and competitive accessibility scores, faceted by mode (auto, bike, transit, walk) and score formulation (basic utility versus decayed destinations).

Race

Target group: BIPOC residents

Control group: White residents

Figure 12 shows accessibility results for BIPOC residents relative to white residents in the City of Richmond. The upper half of the figure focuses on non-competitive access, while the lower half shows competitive results. In all scoring formulations, it is generally the case that BIPOC residents have lower access to destinations by every mode analyzed, except for schools. While schools are less accessible for BIPOC residents using the decayed destinations formulation, when destination relevance is considered (the basic utility formulation), access to schools is higher for BIPOC residents than for white residents. For the bike and transit modes, the basic utility access to health care is also higher for BIPOC residents. When competing travelers are accounted for, BIPOC residents also have slightly higher access to community destinations by walking. However, generally multimodal access to daily travel needs is lower for the City's BIPOC residents.

Ethnicity

Target group: Hispanic residents

Control group: Non-Hispanic residents

Figure 13 shows accessibility results for Hispanic residents relative to non-Hispanic residents in the City of Richmond. In all scoring formulations, it is generally the case that Hispanic residents have much lower access to destinations by every mode analyzed, except for schools. While schools are less accessible for Hispanic residents using the decayed destinations formulation, when destination relevance is considered (the basic utility formulation), access to schools by the auto and transit modes is higher for Hispanic residents than for non-Hispanic residents. When competing travelers are accounted for, Hispanic residents also have slightly higher access to schools by walking. However, generally multimodal access to daily travel needs is lower for the City's Hispanic residents.

Income

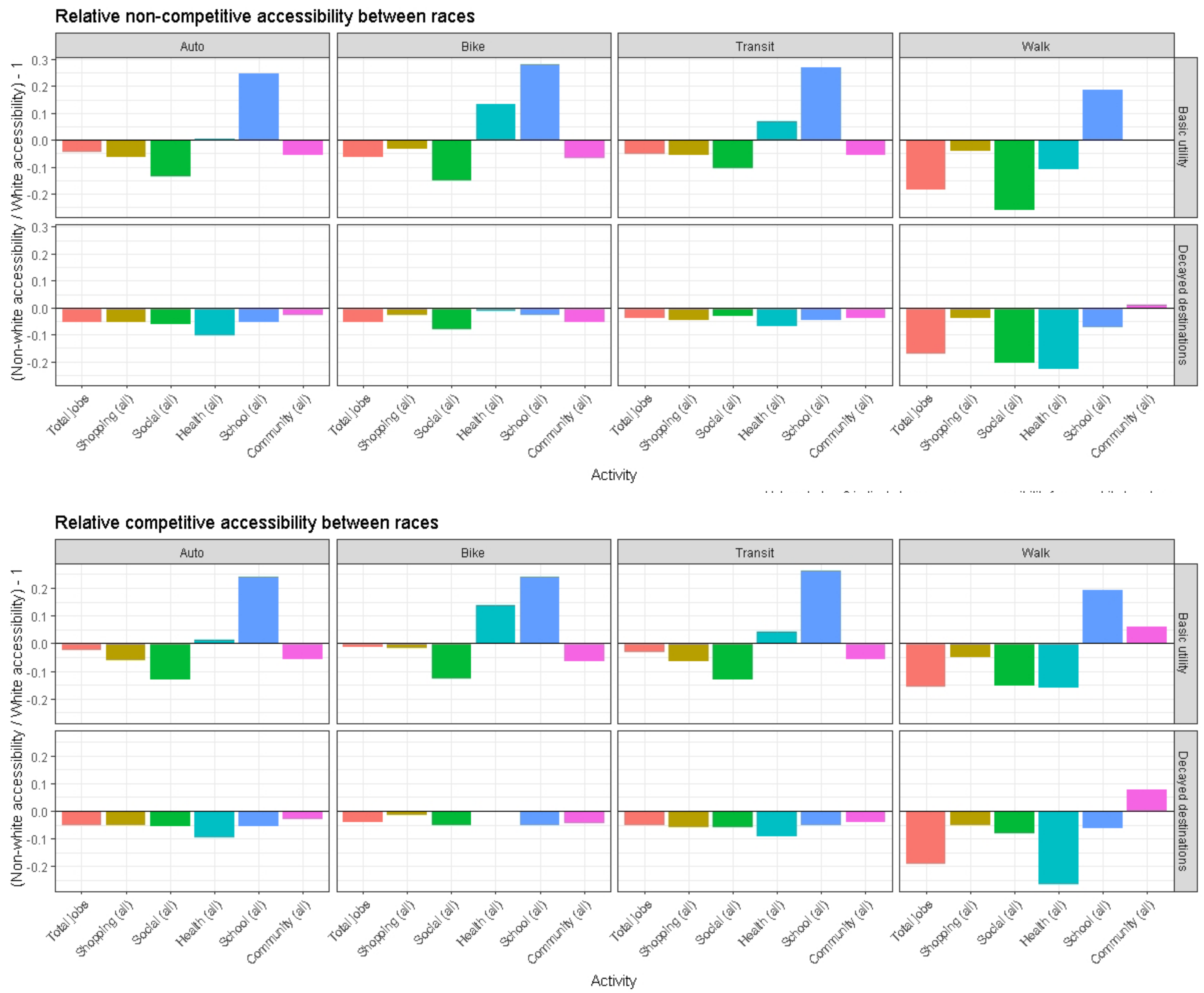
Target group: Low-income residents

Control group: Non-low-income residents

Figure 14 shows accessibility results for low-income residents relative to non-low-income residents in the City of Richmond. Low-income residents are defined as individuals living in households where the household income is less than two times the poverty level (for a household of that size). The non-competitive accessibility scores for low-income residents are generally lower for the auto mode and slightly higher for non-auto modes, but there are several exceptions. Schools are more accessible for low-income residents when destination relevance is accounted for. Health care destinations are less accessible for low-income residents by walking. When destination relevance is accounted for (basic utility), social destinations are less accessible for low-income residents by non-auto modes and community destinations are less accessibly by the bike and transit modes.

Competitive accessibility results are similar to the non-competitive results, except that many destinations become less accessible for low-income residents relative to non-low-income residents for the non-auto modes. While usually modest, these shifts indicate that consideration of potential competing travelers reveals most low-income residents have lower accessibility than would be modeled in the non-competitive analysis. The change is especially pronounced with respect to access to jobs by walking. This implies that while low-income residents often have relatively high access to jobs by walking (non-competitive), there are too many low-income workers competing for those jobs, and the competition for those opportunities effectively inverts the relative access scores.

Figure 12: Relative accessibility by travel purpose (various scoring formulations) - BIPOC residents relative to white residents



Vehicle Ownership

Target group: Zero-car household

Control group: Households with at least one car

Figure 15 shows accessibility results for zero-car households relative to households with at least one car in the City of Richmond. Zero-car households have better access to all destination types by non-auto modes when competing travelers are not accounted for. In the competitive formulations, zero-car households still have higher access to all destination by bike and transit. Access to jobs and health care by walking are lower for zero-car households when competing travelers are considered. For the auto mode, zero-car households generally have lower access than households with vehicles. These results can be interpreted in two ways. On the one hand, they reveal the role effective multimodal options can have in vehicle ownership decisions; on the other hand, they reveal the necessity of vehicle ownership in places with fewer non-auto options.

Figure 13: Relative accessibility by travel purpose (various scoring formulations) - Hispanic residents relative to non-Hispanic residents

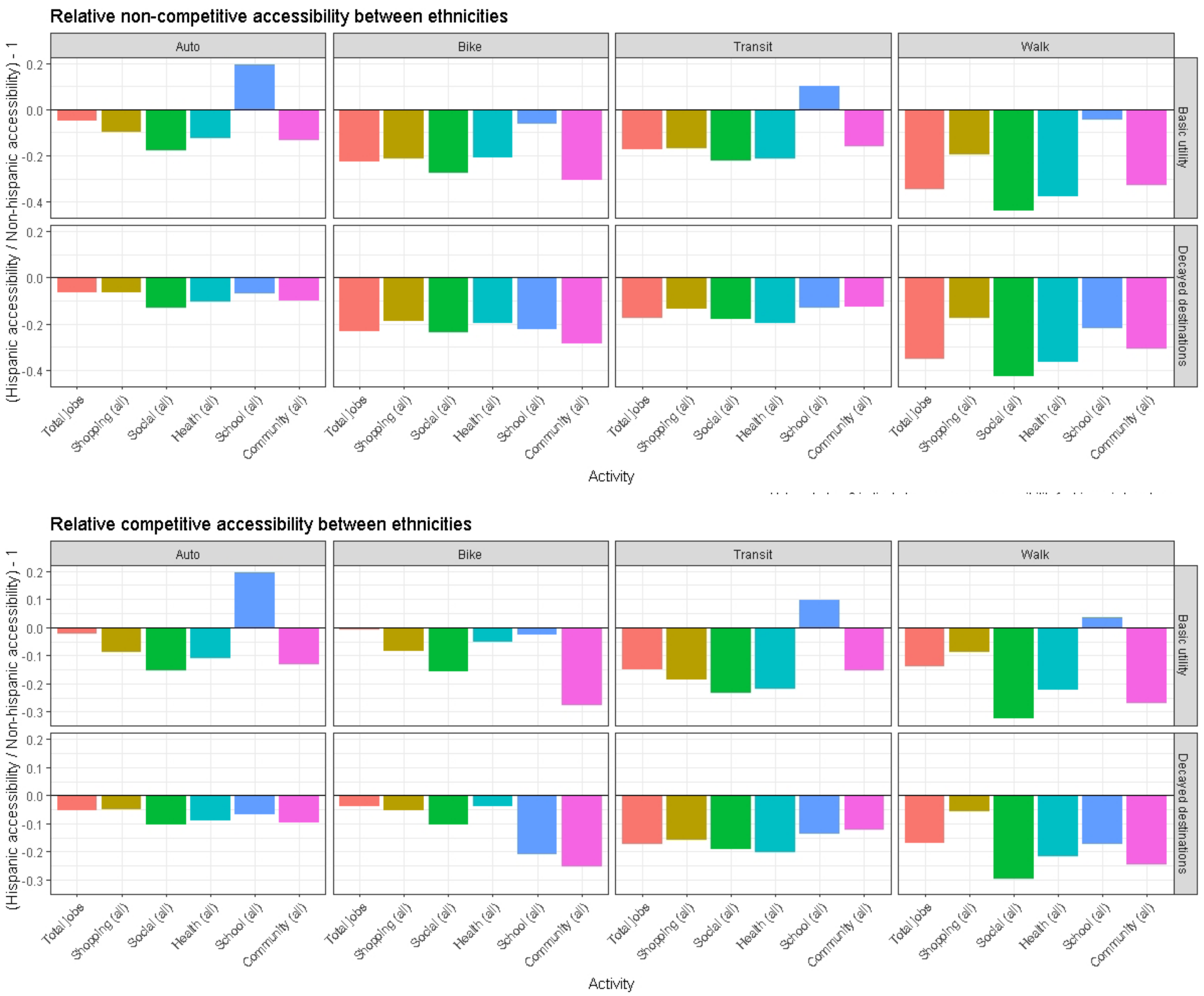


Figure 14: Relative accessibility by travel purpose (various scoring formulations) - low-income residents relative to non-low-income residents

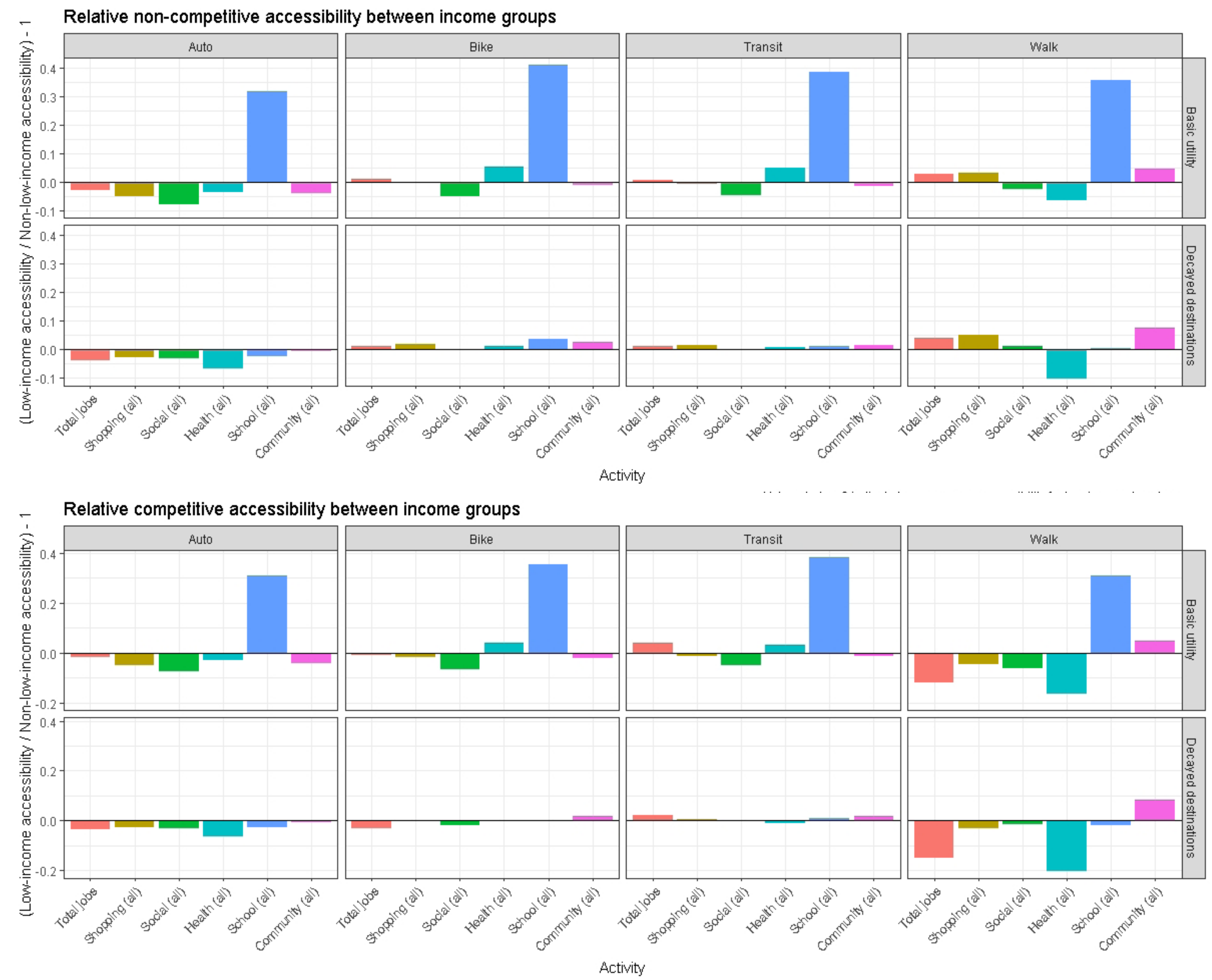
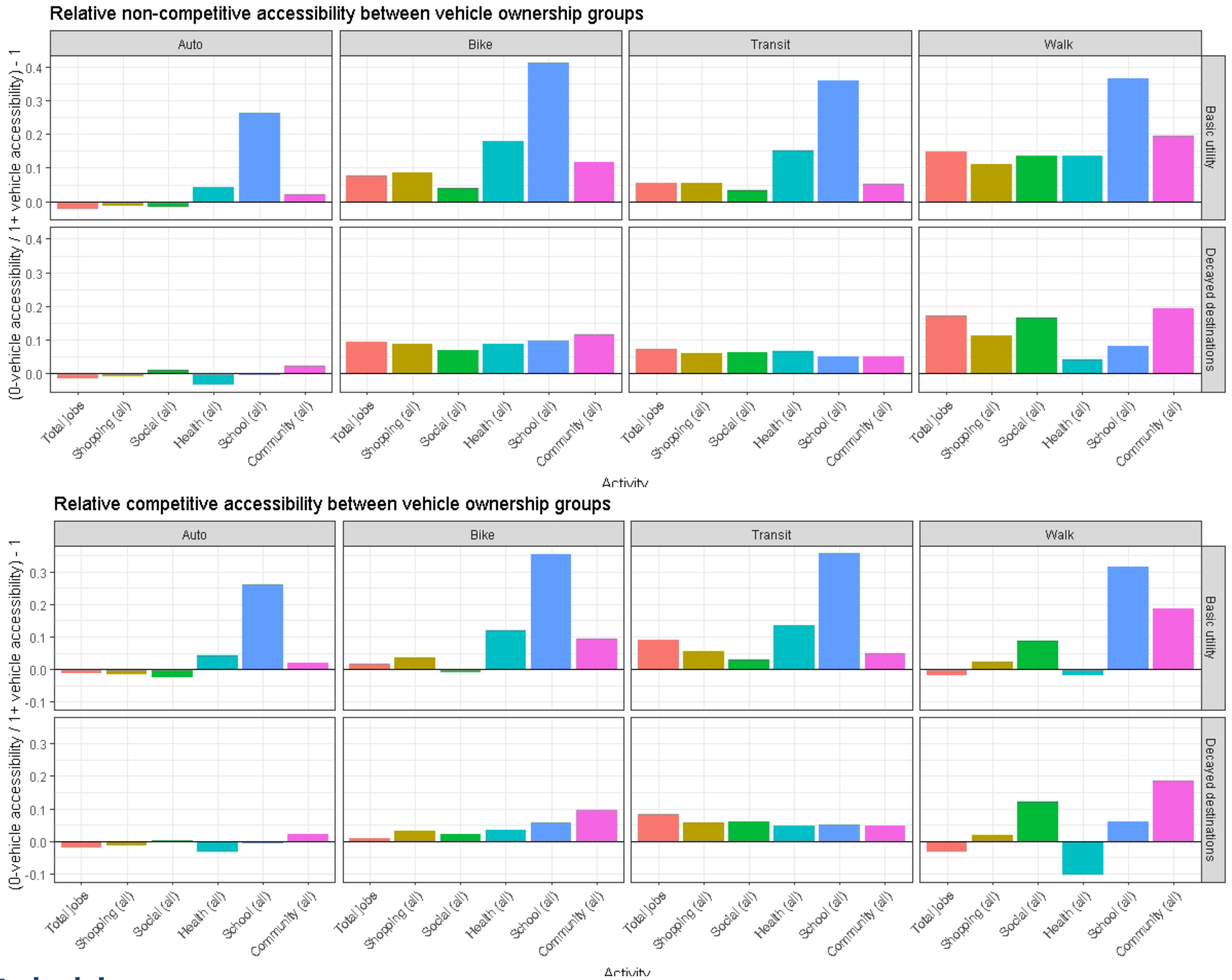


Figure 15: Relative accessibility by travel purpose (various scoring formulations) - zero-car households relative to households with at least one car



Methodology

The accessibility metrics developed for this study are calculated using a complex series of procedures to estimate the demographic characteristics of travelers living in each zone, their daily travel tendencies, and the location and relevance of each potential destination to summarize the total number of relevant destinations reachable from each zone (with and without accounting for potential competitors). These procedures are scripted in the Open Source Code Repository developed for the study. This section provides methodological details for each major step in the process:

- Setup: prepare data and analysis configuration files.
- Population synthesis: estimate the demographic characteristics of travelers residing in each zone.
- Destination relevance: estimate the relevance of each destination type to travelers based on socioeconomic and demographic attributes.
- Travel time budgets: estimate how trip-making probabilities decline as travel time increases for different travelers based on socio-economic and demographic attributes.
- Network embellishments: modify network costs based on facility attributes.
- Analyze competitors: estimate how many "competitive" travelers can reach destinations in each zone given the relevance of those destinations to each.
- Analyze accessibility: estimate how many destinations are reachable from each origin zone given travel times, relevance, and presence of competitors.
- Analyze travel time to crisis destinations: estimate the travel time to each "crisis" destination.

Setup: The following section details how to prepare the data analysis and configuration files.

Income: The scripts used to execute the Richmond equitable accessibility scoring process are available on github. Running the scripts requires setting up the development environment using Conda.[1] With Conda installed, follow the instructions on the github project page or in Appendix A to create an environment that installs all package dependencies needed to run the accessibility process. The appendix walks through the scripts that need to be run to generate the accessibility scores providing a brief description of each step and its outputs. References to each supporting script are also included in the relevant sections defining the analysis methodology below.

Input data: The accessibility analysis depends on numerous key input datasets, as outlined below. Appendix A offers more detail about each source.

- **Zonal geography:** The geographic unit of analysis within the City of Richmond is the census block. For all other jurisdictions in the Richmond metropolitan area, census block groups were used.
- **Networks:** The highway network is constructed from loaded highway features from the Richmond regional travel demand model. The walk and bicycle networks are sourced from OpenStreetMap, using the `osmnx`[2] python module to support feature consolidation and topological cleaning of the network. The transit network utilizes GTFS feeds from GRTC and Petersburg Area Transit. The walk network is integrated with the transit data using the `urbanaccess`[3] and `pandana`[4] python modules.
- **Network Enrichment:** Data used to enrich the walk and bike networks come from the City of Richmond's GIS. The current analysis incorporates features from the City's sidewalk inventory (including sidewalk condition attribute data), bicycle facilities inventory, and transportation surfaces inventory (including designations of bridges, alleys, parking lots, etc.).
- **Destinations:** Jobs data are sourced from statewide estimates of jobs by block tallied for the SMART SCALE process. Jobs are broken down into four different education levels (less than high school, high school or equivalent, some college/associates degree, and bachelors degree and higher) based on proportions derived from LEHD LODES[5] data. Point of interest (POI) data are used to support analysis of access to shopping, health care, social, community, and school destinations. POI data come from SMART SCALE, City of Richmond GIS, and ESRI Business Analyst Online.
- **Demographics:** All demographic characteristics are based on American Community Survey (ACS) data with detailed traveler characteristics estimated using a population synthesis.
- **Travel behavior:** Estimates of destination relevance and travel time tolerances based on traveler demographics were derived from the 2017 National Household Travel Survey.[6]

Configuration files: The scripts that execute the accessibility process are written in the R and Python programming languages. These scripts refer to several configuration files that guide the analysis. These configuration files are found in the `src/richmond_ea/config` folder within the locally-cloned project code repository. Each configuration file is described briefly below.

Data Configuration (data_config.py): This file defines variables that establish a path to a working directory and paths to expected subdirectories where various input, interim, and output datasets are stored. When executing the accessibility scoring process, generally there is only a need to update the path to the root directory (`DATA`) in this file to point to the location where all supporting data/will be stored.

The organization of data within the route directory is outlined in Table 2.

1. https://docs.conda.io/projects/conda/en/latest/user-guide/install/windows.html
2. https://osmnx.readthedocs.io/en/stable/
3. https://github.com/UDST/urbanaccess
4. https://udst.github.io/pandana/
5. https://lehd.ces.census.gov/data/
6. https://nhts.ornl.gov/

Table 2: Accessibility scoring working directory organization

Directory	Description
(ROOT)	Highest level directory within which all supporting data are found.
RAW	Raw input data, including networks, points of interest, zonal geographies, etc.
PRODUCTION	Final output data.
REF	Files that define some analysis parameters, which are generally used as lookup tables (fetching destination relevance or travel time budget parameters based on traveler demographics, e.g.)

Project Configuration (project_config.py): This file specifies key accessibility analysis parameters, primarily focusing on the definitions of points of interest (POIs) and how they are grouped together. These specifications are defined by the POI_SETS variable, which is a nested dictionary organized as shown below.

```
{destination group:
        {destination subgroup:
                [POI object 1, …, POI object n]
        }
}
```

Each destination group defines a composite level of accessibility scoring that is derived from each subgroup. For example, the "shopping and personal business" destination group consists of the "finance," "food," "grocery," "other shop," and "SNAP" destination subgroups. Each subgroup is specified as a POI object, which is a simple convenience class for storing information about the source data and analytical options that apply to each subgroup.

The project configuration file also specifies the spatial reference system to use throughout the analysis (for all geoprocessing operations), which counties to include in the analysis as "central" versus "outlying" locations (see zonal geography in input data), travel purposes specified for travel budget decay parameters, and some column naming parameters. Generally, the values in this file do not need to be updated other than to re-specify POIs and/or change the geographic focus of the analysis.

Network Configuration (net_config.py): This file specifies network analysis parameters, as follows:

- `RAW_NET` and `CLEAN_NET` define paths to directories where raw and interim network data are stored.
- `MODES` defines which modes will be included in the analysis.
- For each mode, a corresponding decay rate name is provided in the `MODES_DECAY` dictionary. This dictionary is provided since the names of decay rates do not always directly reflect mode names (e..g, the "non-motorized" decay rate applies to both the "walk" and "bike" modes).
- `Q` is a query defining which features in the openstreetmap walk and bike networks (see description of network data sources in Appendix A to include when evaluating potential walking and biking paths connecting travelers to destinations and to transit stops for the transit network analysis. If desired multiple different queries could be defined for each travel network analyzed, but the current configuration file only defines one query that applies to both the walk and bike networks.
- `MODE_QUERIES` is a dictionary defining a query string to apply to each mode.
- `LOAD_RADIUS` defines a distance (in units that are consistent the spatial reference system specified in project_config.py) beyond which zone features are assumed to have no valid network location. This is set to None in the current configuration, meaning all zones will load to the nearest network feature regardless of how far away it is. In an urban context like Richmond, there is very little risk of zones loading in inappropriate locations since the block structure is dense and strongly connected.
- `TIME_ATTR` and `EFF_TIME_ATTR` provide general names for the attributes that represent typical travel time and "effective" travel time, respectively, on each modal network. These attributes are generated by the script and do not refer to attributes in raw data. They generally will not need to be changed by a user.
- `VAL_FIELDS_DICT` is used internally to support the casting of travel budget decay rate matrices in the accessibility scoring process. It should not be modified unless novel impedance fields are added to the analysis.
- `MODE_SETTINGS` is dictionary defining a `ModeSetting` object for each travel mode to be analyzed.
- `GTFS_KWARGS` is a dictionary containing values used to build a transit network from one or more GTFS feeds. This variable generally will not need to be updated by the user.
- `GTFS_SETTINGS` is a `GTFSSettings` object that allows intuitive specification of transit analysis parameters, such as the day of week and time of day for which transit travel times will be estimated. The current configuration uses the PM peak period (4:30 pm to 6:30 pm) on Wednesday (as a typical weekday) to estimate transit travel times and support the assessment of transit accessibility.
- `MOD_CELL_SIZE` and `EXTRACTION_INTERVAL` are spatial parameters defining how datasets that support network embellishment are rasterized in the network embellishment process. Each variable is an integer expressing the number of linear units (corresponding to those used by the spatial reference system defined in project_config.py) defining the size of raster cells (`MOD_CELL_SIZE`) and the intervals along network edges at which to record underlying raster values (`EXTRACTION_INTERVAL`). This process is used to approximate the share of a link with sidewalk coverage, for example.
- `EDGE_BENEFIT_WEIGHT` and `EDGE_DETERIMENTS_WEIGHT` are variables that define the compound weight to apply to network embellishments that enhance or degrade the traveler experience, respectively (see Network Embellishments).
- `WALK_MODS` and `BIKE_MODS` are dictionaries that define NetMod objects for various factors that influence the traveler experience of walking and biking. Some factors enhance the experience while others degrade it. The NetMod class records data sources, definition queries, and analysis parameters for operationalizing these modifications. They are then assigned to a mode in the `MODES` list using the `MOD_SPECS_DICT`. These parameters need to be modified when applying additional factors to the network embellishment process.
- `EVAL_METHODS` is a nested dictionary specifying the calculation of impedance attributes for each modal network. Users will generally not need to modify this variable unless additional impedance attributes are specified.

Population Synthesis: Broadly, the goal of a population synthesis is to combine sets of related population estimates to produce cross-sections of population characteristics that are not generally available. A good example of this problem – and our use case – can be observed with US Census data. The American Community Survey (ACS) gives us access to several population and household characteristics relevant to travel behavior (e.g., age, sex, education, income). Sometimes, combinations of these variables can provide more detailed estimates of population (e.g., age by sex). However, high-order cross-classifications are not published for privacy reasons (e.g., no table reflects age by sex by education by income). A population synthesis applies a set of rules to integrate the available generalized data into these more expansive cross-classifications. This allows for more nuanced person-level analysis that considers individual demographic characteristics in the definition of accessibility.

In the case of Richmond's Equitable Access analysis, seven demographic characteristics were included in the synthesis, which would ultimately fuel destination relevance and travel time budget modeling. These characteristics were chosen based on their importance in these modeling applications as well as their availability in the modeling set for these analyses, the National Household Travel Survey (NHTS). The variables, and their classes, were defined as shown in Table 3.

In each block group, the characteristics of individuals were simulated using observed probabilities of each class in that block group. For example, if block group B had population 10, 8 of whom had a disability and 2 of whom did not, we would simulate the disability status of 10 individuals in B with probabilities 80%/20%. This type of simulation, in some form, was completed for all variables. Sometimes, additional constraints or adjustment to the probability were made prior to simulation to account for basic assumptions made in the case of incomplete data. For example, educational attainment data was not available for individuals under 18; thus, it was assumed that all people in the "<17" age bracket had educational attainment of "not a high school graduate".

A final component of this synthesis was to guarantee reasonable results relative to ACS margins of error (MOEs). Because simulation is random, unconstrained simulations can yield unreliable estimates of traveler characteristics. To ensure the detailed synthetic results reliably reflected the general ACS data, the simulated block group totals were compared to the 90%-confidence MOEs of the

Table 3: Dimensions of population synthesis

Population dimension	Categories included
Age	▪ <17 ▪ 18-24 ▪ 25-34 ▪ 35-44 ▪ 45-54 ▪ 55-66 ▪ 67-74 ▪ >75
Sex	▪ Male ▪ Female
Education attainment	▪ Not a high school graduate ▪ High school graduate or equivalent ▪ Some college or associates degree ▪ Bachelor's degree ▪ Graduate/professional degree
Worker status	▪ Full-time ▪ Full-time work from home (WFH) ▪ Part-time ▪ Part-time WFH ▪ Non-worker
Disability	▪ With disability ▪ No disability
Household income (annual)	▪ <$35k ▪ $35-50k ▪ $50-75k ▪ $75-100k ▪ $100-150k ▪ >$150k
Household size (persons in household)	▪ 1 ▪ 2 ▪ 3 ▪ 4+

Table 4: Example population synthesis results

GEOID	PER ID	HH ID	Age	Sex	Education	Worker	Disability	HH Income	HH Size
001	1	1	<17	M	<HS	Non-worker	No	$75-100K	2
001	2	1	45-54	F	Grad/Prof	Full-Time WFH	No	$75-100K	2
001	1	2	25-34	M	Bach	Full-time	No	$50-75K	1

observed data. If simulated totals fell outside of these bounds, the synthesis results were dropped, and the simulation was repeated until the results reflected the conditions revealed in the ACS. For the most part, the large populations of block groups kept simulated demographic breakdowns for individual variables relatively close to the observed breakdowns.

The simulation output is a person-level table defining the home block group and demographic characteristics of individual travelers. It gives a person and household ID that can be used to filter to uniquely identify a person. An example is provided in Table 4. In this example, note that for household ID (HH ID) 1, the household characteristics are the same. This is because two people (Per ID 1 and 2) comprise this household. The other characteristics are unique to the person ID and define individual characteristics. The outputs of the population synthesis is a table representing every person (by household) with their respective demographic characteristics across the entire Richmond region. Population synthesis modeling is completed through the `population_synthesis.R` script.

Destination Aggregation: Destination data come from a variety of sources at different geographic scales. Zone data are assembled from block and block group features to provide detailed granularity within the City of Richmond and moderate granularity elsewhere across the region. For each zone, the total number of destinations is tabulated using raw destination data, which come in polygon (blocks) or point form. The zone consolidation, spatial analysis, and summarization of activity by zone are executed in the script `prepare_destinations.py`, with rules governing feature selection, summarization, and output column names specified in the project configuration file. The output of this process is a feature class containing a distinct feature for each geographic zone and columns providing a distinct ID and summaries of total destination activities in each zone.

Destination Relevance: Destination relevance models estimate an individual's probability of traveling to a general destination type during a given day based on their demographics. This was ultimately intended to help understand how many relevant destinations are reachable and how many competing travelers can also reach these destinations. When evaluating competitiveness if a person is not likely to travel to a certain destination, they are not a competitor for this destination (or are at least less of a competitor). Trip records for modeling were taken from 2017 National Household Travel Survey (NHTS), and six destination types were modeled:

1. **Work:** work or work-related trips
2. **Shopping:** general errands or purchase of goods, services, or meals
3. **Social:** recreation, exercise, and visits to family or friends
4. **Health:** health care or adult care
5. **Community:** volunteering or religious/community activities
6. **School:** school or childcare

Individual logistic regression models were fit for each destination type. In each model, all variables included in the population synthesis were considered (in the same classes as defined by the synthesis itself), as well as the urban/rural status of the trip origin. Although the urban/rural status was not explicitly a part of the population synthesis, it could easily be inferred by identifying if the block group was in a US Census urban area or cluster. Because each model was logistic, the response could be interpreted as the probability that an individual would take a trip of the model-specific purpose given their demographic characteristics and known home location.

Model specifications are provided in Table 5. The following bullets offer high-level interpretative guidance for understanding the values in the table.

- For non-intercept coefficients, positive values indicate an increased probability of taking a trip of that purpose associated with that demographic class, and negative values indicate a decreased probability.
- The magnitude of the non-intercept coefficients reflects the size of this change in probability: larger absolute values of the coefficients indicate greater probability swings associated with that demographic class.
- Increases and decreases in probability for classes of a given variable can only be judged against the baseline for that variable, and assumes all other variables are held constant.

Table 5: Destination relevance parameters by demographic group and travel purpose

	Work	Shopping	Social	Health	Community	School
Intercept	0.013	0.488	10.412	0.045	0.105	0.585
Age (baseline <17)	8-24: 0.058 25-34: 0.039 35-44: 0.030 45-54: 0.033 55-66: 0.026 67-74: 0.009 >75: -0.001	18-24: 0.143 25-34: 0.267 35-44: 0.294 45-54: 0.305 55-66: 0.312 67-74: 0.327 >75: 0.311	18-24: 0.040 25-34: 0.068 35-44: 0.056 45-54: 0.033 55-66: 0.028 67-74: 0.025 >75: -0.025	18-24: 0.018 25-34: 0.043 35-44: 0.046 45-54: 0.055 55-66: 0.062 67-74: 0.074 >75: 0.085	18-24: -0.022 25-34: -0.021 35-44: -0.005 45-54: 0.008 55-66: 0.015 67-74: 0.048 >75: 0.074	18-24: -0.297 25-34: -0.462 35-44: -0.482 45-54: -0.492 55-66: -0.505 67-74: -0.524 >75: -0.530
Sex (baseline F)	M: 0.018	M: -0.018	M: -0.006	M: -0.016	M: -0.016	M: 0.002
Education (baseline: <HS)					HS: 0.010 Assc: 0.020 Bach: 0.035 Grad: 0.043	HS: -0.059 Assc: -0.042 Bach: -0.052 Grad: -0.045
Disability Status (baseline: worker)	With: -0.019		With: -0.108	With: 0.099	With: -0.034	With: -0.016
Worker Status (baseline: non-worker	35-50: -0.004 50-75: -0.006 75-100: -0.013 100-150: -0.023 >150: -0.041	35-50: 0.014 50-75: 0.018 75-100: 0.022 100-150: 0.026 >150: 0.034	35-50: 0.036 50-75: 0.065 75-100: 0.081 100-150: 0.105 >150: 0.139			
HH Size (baseline: 1)	2: 0.001 3: -0.003 4+: -0.006	2: -0.060 3: -0.106 4+: -0.143	2: -0.065 3: -0.104 4+: -0.118	2: 0.005 3: 0.004 4+: 0.003		
Urban/ rural status (baseline: urban)		Rural: -0.005	Rural: -0.032		Rural: 0.004	Rural: -0.006

An example interpretation of the "work" model might consist of the following (this is not intended to be comprehensive, but rather give a general idea of how these models should be interpreted):

> *The work model is heavily controlled by worker status. The large positive coefficients for full-time and part-time workers indicate that workers who do not work from home are much more likely to take a work trip than non-workers. Age and income contribute to the probability of taking a work trip in predictable ways but have a lower impact than worker status. Holding all other demographic information constant, a person becomes less likely to take a work trip as they get older (except for children, who have a low probability of work trips). Additionally, holding all other variables constant, the higher income a household has, the less likely any one person in that household is to take a work trip*

For travelers likely to make work trips, jobs are the relevant type of destination. However, not all jobs are equally relevant to all workers. For this analysis, traveler educational attainment was used as the basis for assessing job relevance, where workers with a given education level are more likely to value access to jobs at that education level and less likely to value access to jobs at other education levels. The relative relevance values of jobs by education level are shown in Table 6. These estimates are based on professional judgment, and further analysis would be needed to calibrate precise numbers based on observed relationships between educational requirements and the educational credentials of individual workers. Traveler educational attainment is derived from the results of the population synthesis, while job education level is based on shares reported in LEHD. Destination relevance parameters are produced by the `destination_choice_modeling.R` script.

Travel Time Budgets: Travel time budget models estimate an individual's probability of making a trip given the expected trip duration and traveler demographics. Generally, the further away a person is from a destination, the less likely they are to travel to that destination. This affects the assessment of destinations reachable as well as the assessment of competing travelers who have access to the same destinations. Trip records for modeling were taken from the 2017 NHTS. Models were fit for two travel purposes and three modes, as outlined in Table 7 and Table 8.

Table 6: Job relevance by education level

Traveler education level	Job education level			
	Less than high school	High school or equivalent	Associates degree/some college	Bachelors degree or higher
Less than high school	1.0	0.8	0.5	0.2
High school or equivalent	0.8	1.0	0.8	0.2
Associates degree/ some college	0.2	0.8	1.0	0.5
Bachelors degree	0.2	0.5	0.8	1.0
Graduate or professional degree	0.1	0.2	0.5	1.0

Table 7: Travel Time Budget Purposes and Associated Accessibility Destination Sets

Travel Budget Purpose	Accessibility Destination Set
Home-based work (HBW)	Jobs
Home-based other (HBO)	Community Health care School Shopping Social

Table 8: Travel Time Budget Modes and Associated Accessibility Modes

Travel Budget Mode	Accessibility Mode
Motorized	Automobile
Transit	Transit
Non-motorized	Walk Bike

Table 9: Demographic Characteristics Affecting Travel Time Budgets

Travel Budget Demographics	Groupings	Interpretation
Age	<17 18-66 >67	The <17 age group has the shortest travel time budgets. The <67 class tends to have shorter travel time budgets than the 18-66 class. Within the 18-66 class, all ages appear to have similar travel time budgets.
Worker status	Full-time Part-time Non-worker	The full-time class takes longer trips than both the part-time and non-worker classes. Part-time workers and non-workers have similar travel time budgets, but those for part-time workers are slightly longer.
Urban/rural status	Urban Rural	Travelers in urban areas tend to have shorter travel time budgets than those in rural areas.

Exploration indicated that demographics are less influential in defining travel time budgets than in defining destination relevance, with only a few demographic characteristics demonstrably influencing trip duration. As with destination relevance modeling, all variables in the population synthesis were considered, as well as urban/rural status of the trip origin. Of these variables, only three indicated notable differences in travel time distributions between their classes, regardless of mode and purpose. Furthermore, these differences were often only seen amongst combinations of classes. The demographic characteristics and key groupings influencing travel time budgets are outline in Table 9.

For both purposes, all modes, and all combinations of demographic characteristics, observed travel times generally follow lognormal distributions. Consequently, travel time budgets were estimated by fitting a lognormal distribution to the observed times. To estimate the likelihood of a person with fixed demographics and home location taking a trip of a given purpose by a given mode, the "survival function" – defined as one minus the distribution's cumulative distribution function (cdf) – was used. This guarantees the following properties:

- The probability of taking a [theoretical] 0-minute trip is 100%.
- The probability of taking a [theoretical] infinitely long trip is 0%.
- For a given purpose, mode, and set of demographics, the probability of taking a trip with duration equal to the median observed trip for those specifications is 50%.

An example interpretation of these properties can be seen in the image below, which compares the HBW travel time survival functions for urban-residing, full-time, aged 18-66 workers across the three modes described above. For short travel times, there is a high probability of trip making, regardless of mode. As travel times increase, it becomes clear that non-motorized trips are less probable – an expected result – while transit riders with these demographic characteristics are accustomed to longer travel times.

Parameters of the estimated distributions are provided in Table 10 below. Note that some combinations of demographic characteristics are precluded, such as full time workers aged 17 and younger. Moreover, there were not enough trip records for part time workers 17 and younger in rural areas using transit to calculate a travel time budget curve, so we generally assume these travelers have no transit accessibility from rural residential locations. In the table, meanlog and sdlog are the two parameters of the lognormal distribution. Mathematically, meanlog and sdlog are estimates of the mean and standard deviation of log-transformed travel times (respectively). This means that a higher meanlog indicates a tendency for longer trips (note that exp(meanlog) = median travel time), and (holding meanlog constant) a higher sdlog produces a steeper decline in the travel time budget curves.

Travel time budget parameters are produced by the `travel_budget_modeling.R` script.

Figure 16: Example Travel Time Budget by Mode for HBW Trips for Urban Traveler Aged 18-66, Full-Time Worker

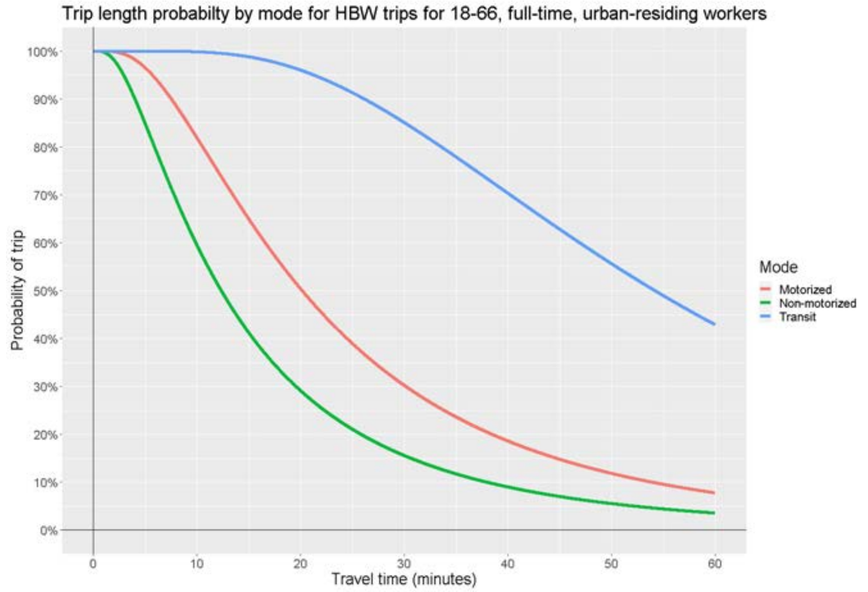


Table 10: Travel budget decay parameters by travel purpose, mode, and demographic characteristics

Purpose	Mode	Age	Work Status	Urban/Rural	meanlog	sdlog
HBW	Motorized	17 or younger	Part-time	Rural	2.703	0.766
HBW	Motorized	17 or younger	Part-time	Urban	2.454	0.647
HBW	Motorized	18-66	Full-time	Rural	3.081	0.814
HBW	Motorized	18-66	Full-time	Urban	3.002	0.769
HBW	Motorized	18-66	Part-time	Rural	2.882	0.797
HBW	Motorized	18-66	Part-time	Urban	2.749	0.750
HBW	Motorized	67 or older	Full-time	Rural	2.952	0.874
HBW	Motorized	67 or older	Full-time	Urban	2.902	0.786
HBW	Motorized	67 or older	Part-time	Rural	2.830	0.838
HBW	Motorized	67 or older	Part-time	Urban	2.754	0.769
HBW	Non-motorized	17 or younger	Part-time	Rural	1.968	1.125
HBW	Non-motorized	17 or younger	Part-time	Urban	2.340	0.815
HBW	Non-motorized	18-66	Full-time	Rural	1.487	1.099
HBW	Non-motorized	18-66	Full-time	Urban	2.512	0.878
HBW	Non-motorized	18-66	Part-time	Rural	1.859	1.136
HBW	Non-motorized	18-66	Part-time	Urban	2.435	0.935
HBW	Non-motorized	67 or older	Full-time	Rural	1.115	0.978
HBW	Non-motorized	67 or older	Full-time	Urban	1.994	1.336
HBW	Non-motorized	67 or older	Part-time	Rural	1.427	1.181
HBW	Non-motorized	67 or older	Part-time	Urban	2.013	1.169
HBW	Transit	17 or younger	Part-time	Rural	NA	NA
HBW	Transit	17 or younger	Part-time	Urban	3.988	0.400
HBW	Transit	18-66	Full-time	Rural	4.258	0.653
HBW	Transit	18-66	Full-time	Urban	3.992	0.569
HBW	Transit	18-66	Part-time	Rural	4.031	0.464
HBW	Transit	18-66	Part-time	Urban	3.881	0.667
HBW	Transit	67 or older	Full-time	Rural	4.726	0.661
HBW	Transit	67 or older	Full-time	Urban	4.057	0.474
HBW	Transit	67 or older	Part-time	Rural	3.723	0.543
HBW	Transit	67 or older	Part-time	Urban	3.886	0.580
Other	Motorized	17 or younger	Non-worker	Rural	2.619	0.896
Other	Motorized	17 or younger	Non-worker	Urban	2.487	0.844
Other	Motorized	17 or younger	Part-time	Rural	2.630	0.805

Table 10: Travel budget decay parameters by travel purpose, mode, and demographic characteristics (Continued)

Purpose	Mode	Age	Work Status	Urban/Rural	meanlog	sdlog
Other	Motorized	17 or younger	Part-time	Urban	2.466	0.809
Other	Motorized	18-66	Full-time	Rural	2.651	0.930
Other	Motorized	18-66	Full-time	Urban	2.555	0.876
Other	Motorized	18-66	Non-worker	Rural	2.685	0.939
Other	Motorized	18-66	Non-worker	Urban	2.536	0.861
Other	Motorized	18-66	Part-time	Rural	2.616	0.912
Other	Motorized	18-66	Part-time	Urban	2.506	0.852
Other	Motorized	67 or older	Full-time	Rural	2.694	0.920
Other	Motorized	67 or older	Full-time	Urban	2.600	0.874
Other	Motorized	67 or older	Non-worker	Rural	2.666	0.895
Other	Motorized	67 or older	Non-worker	Urban	2.529	0.815
Other	Motorized	67 or older	Part-time	Rural	2.664	0.905
Other	Motorized	67 or older	Part-time	Urban	2.512	0.830
Other	Non-motorized	17 or younger	Non-worker	Rural	1.920	1.170
Other	Non-motorized	17 or younger	Non-worker	Urban	2.180	1.040
Other	Non-motorized	17 or younger	Part-time	Rural	1.958	0.968
Other	Non-motorized	17 or younger	Part-time	Urban	2.527	0.947
Other	Non-motorized	18-66	Full-time	Rural	2.132	1.266
Other	Non-motorized	18-66	Full-time	Urban	2.199	1.088
Other	Non-motorized	18-66	Non-worker	Rural	2.325	1.339
Other	Non-motorized	18-66	Non-worker	Urban	2.407	1.114
Other	Non-motorized	18-66	Part-time	Rural	2.219	1.257
Other	Non-motorized	18-66	Part-time	Urban	2.293	1.061
Other	Non-motorized	67 or older	Full-time	Rural	2.285	1.038
Other	Non-motorized	67 or older	Full-time	Urban	2.251	1.052
Other	Non-motorized	67 or older	Non-worker	Rural	2.322	1.373
Other	Non-motorized	67 or older	Non-worker	Urban	2.393	1.186
Other	Non-motorized	67 or older	Part-time	Rural	2.370	1.118
Other	Non-motorized	67 or older	Part-time	Urban	2.232	1.264
Other	Transit	17 or younger	Non-worker	Rural	3.683	0.802
Other	Transit	17 or younger	Non-worker	Urban	3.675	0.703
Other	Transit	17 or younger	Part-time	Rural	2.807	2.198
Other	Transit	17 or younger	Part-time	Urban	3.825	0.744

Table 10: Travel budget decay parameters by travel purpose, mode, and demographic characteristics (Continued)

Purpose	Mode	Age	Work Status	Urban/Rural	meanlog	sdlog
Other	Transit	18-66	Full-time	Rural	3.684	1.031
Other	Transit	18-66	Full-time	Urban	3.728	0.758
Other	Transit	18-66	Non-worker	Rural	3.751	0.981
Other	Transit	18-66	Non-worker	Urban	3.716	0.768
Other	Transit	18-66	Part-time	Rural	3.301	1.219
Other	Transit	18-66	Part-time	Urban	3.680	0.757
Other	Transit	67 or older	Full-time	Rural	3.635	0.504
Other	Transit	67 or older	Full-time	Urban	3.693	0.724
Other	Transit	67 or older	Non-worker	Rural	3.566	1.145
Other	Transit	67 or older	Non-worker	Urban	3.608	0.816
Other	Transit	67 or older	Part-time	Rural	3.574	1.624
Other	Transit	67 or older	Part-time	Urban	3.686	0.735

Network Embellishments: Accessibility analyses require estimating "least-cost" paths from each zone to all other zones over a travel network. The least-cost path is the route over the network that imposes the lowest cost on the traveler. In most cases, this is simply expressed as the shortest travel time, but network cost estimation can be much more complex. The network embellishments undertaken for this study aim to account for the presence and quality of bicycle and pedestrian facilities in determining the least-cost paths for non-motorized travelers.

There are two key aspects of network analysis that can enrich accessibility evaluations. First, route choice models focus on which facilities a traveler is likely to utilize given the costs (time, monetary, safety/security risks, etc.). This implies understanding how facility attributes influence (the perception of) these costs, ideally with respect to traveler demographics. Secondly, travel budget specifications should align with the cost estimation parameters that inform route choice. Given the limitations of NHTS data and the scarcity of conclusive literature on these topics, this study focuses on how facility characteristics can be assumed to influence the perception of time when walking or biking. It does not account for how different travelers perceive travel costs based on their demographics. This is an area for additional research and development in subsequent efforts.

Since NHTS data only allow for the specification of travel time budgets (with limited information on any other expression of "cost"), travel time remains the primary factor informing route choice decisions in this study. However, facility attributes were used to enrich walking and biking networks to estimate accessibility by non-motorized modes. For example, when walking or biking, a traveler may be interested in safety of solo travel, aesthetic quality of the walk, presence and quality of non-motorized only facilities, etc. In some cases, travelers may choose a longer route to utilize a preferred facility or avoid an unsafe stretch of road. In the accessibility scoring process, we can think of this as making the route choice decision based on an "effective time": the true travel time weighted by the presence of various beneficial and detrimental facility characteristics along the path.

To this end, embellishments were added to the Richmond walking and biking networks to calculate "effective time" for each edge in the network. The goal was to achieve a more realistic understanding of how people travel in the city and ultimately observe how facility characteristics impact travel behavior and accessibility. This was of particular interest for the walking and biking modes, where non-distance factors are expected to play a large role in route choice. Network embellishments were sourced from the City of Richmond's sidewalk, bicycle facilities, and transportation surfaces inventories. The facility characteristics listed in Table 11 were used to enrich the pedestrian and bicycle networks for accessibility scoring.

Table 11: Facility Characteristics that Influence "Effective Time" by Walking and Biking

Non-Motorized Faciliy Charateristics	Influence on travel time/route choice
Sidewalk presence	Pedestrians prefer routes with sidewalks to routes with no sidewalk
Sidewalk quality	Pedestrians prefer sidewalks with street trees and minimal cracking, vertical uplift, and ponding. Pedestrians avoid sidewalks in poor condition.
Bicycle facility presence	Cyclists prefer travel on shared use paths, bike lanes, wide shoulders, and other designated bicycle facilities.
Parking lot presence	Pedestrians avoid facilities adjacent to parking lots (implying vehicle access/egress and separation from land uses).
Alleyway presence	Cyclists and pedestrians avoid alleyways.
Bridge presence	Cyclists and pedestrians avoid traveling along bridges.

Of course, there are many other characteristics that could influence perceived costs and route choice. Future developments could consider additional factors as supporting data are identified.

The calculation of effective time occurred on the network edge level and used a compounding approach to adjust total time based on the prevalence of various benefits/detriments. First, for each edge, the proportion of the edge exhibiting a beneficial or detrimental facility characteristic was assessed. This guaranteed an edge would not, for example, experience the full benefit of a sidewalk if that sidewalk only covered 10% of the edge. Next, each proportion was multiplied by a "factor weight"; for both benefits and detriments, this weight was 0.3. This weight was chosen in conjunction with research suggesting that weighting reductions/increases in perceived cost by a factor of 30% "elicit[s] differences in the agents' behavior without affecting the plausibility of the routes,"[7] and that the presence of sidewalks is associated with a 33% reduction in perceived distance.[8] Compound benefits and detriments were then calculated according to the following formula:

$$C = s * \sum_{k=1}^{n} \left(\prod_{i=n-k+1}^{n} v_{(i)} \right)$$

Where:

- C is the compound benefit or detriment
- n is the number of benefits or detriments considered
- $v_{(i)}$ is the ith order statistic of all weighted proportions for benefits or detriments
- s is the sign indicating directionality of output factor: -1 for benefits (since benefits reduce time) and 1 for detriments (which increase time)

Finally, the compound benefit and compound detriment are averaged to produce a final "effective time factor", which is then multiplied by the true time to produce the effective time. Using this construction, the effective time is guaranteed to be within about

7. Filomena, G., Manley, E., & Verstegen, J.A. (2020). Perception of urban subdivisions in pedestrian movement simulation. PLoS ONE, 15(12). https://doi.org/10.1371/journal.pone.0244099
8. Lue, G. (2017). Estimating a Toronto Pedestrian Route Choice Model using Smartphone GPS Data: It's not the destination, but the journey, that matters (Unpublished Master's thesis). University of Toronto.

43% of the true travel time; these extremes would occur in the case of benefits lining the entire length of the edge, and no detriments (or vice versa).

Assigning facility benefits and detriments to the walking and biking networks was accomplished through a coarse analysis of spatial proximity between network edges and facilities. The City's transportation inventories do not perfectly align with the OpenStreetMap network features, and conflation of spatial features is a challenging task with few established reliable automated procedures.[9] All facility attribute data were converted to raster surfaces using a cell size of 50 meters. Any network edge overlapping a 100-meter buffer around those raster cells was assumed to have the attributes of the facility. The cell size and cell buffer parameters can be changed in the network configuration file. Future applications should consider tightening both parameters for greater precision and/or explore more sophisticated approaches to feature conflation.

The assignment of facility characteristics and application of the compounding factor weights yield an estimate of "effective time" for each network edge. Figure 17 shows the effective time at the top and the ratio of effective to true time at the bottom for the Westover Hills area of Richmond. The ratio map, particularly, reveals the edges for which pedestrian travel is enhanced by the quality of facilities in the area (values less than 1.0) or degraded by detrimental features such as parking lots, alleys, and bridges (values greater than 1.0).

When analyzing travel networks for the accessibility scoring process, the effective travel time estimate was used to determine the shortest path among origin-destination (OD) pairs. A true time estimate of travel time among OD pairs was generated from this shortest path. That is, true time accessibility scores reflect the true time accumulated over the path offering the shortest effective time rather than over the path offering the shortest true time. The OD travel time estimates were stored in matrices following paradigms in the `emma`[10] python module.

The creation and enrichment of networks is executed by two scripts: `prepare_networks.py` and `build_networks.py`. The creation of OD matrices with true time and effective time estimates is executed by the script `skim_networks.py`.

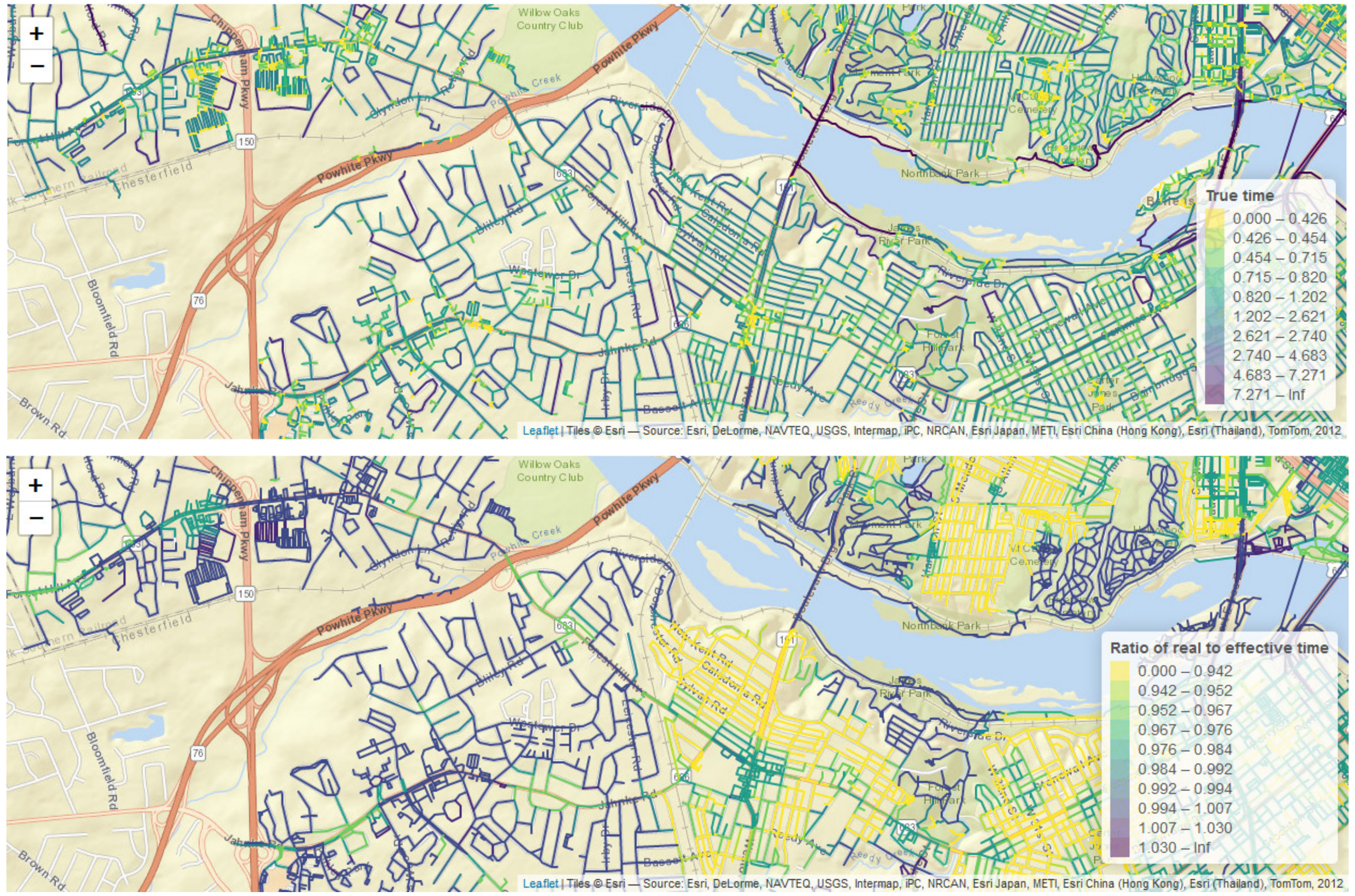
Analyze Competitors: With effective and true time estimates of travel time among OD pairs tabulated, the next step of the accessibility scoring process was to estimate the number of "relevant travelers" that could reach each destination zone and access destination-end activities. This entails estimating the number of travelers with access to each destination location, stratified by type of destination activity (work, shopping, school, etc.). This estimate applies destination relevance weights and travel time tolerance parameters to account for traveler characteristics in assessing each potential traveler's trip-making propensity given the relevance of the destination activity type and the cost of reaching the destination.

This analysis is conducted in a series of nested iterations as described in Table 12. Each analysis phase shown in the table iterates over a vector of analysis components. For example, in "A. Travel mode," each travel mode is analyzed independently in the iterative process, starting with the walk mode and proceeding through the bike, transit, and auto modes. Additionally, each analysis phase in the table nests within the previous phase. Thus, "B. Travel purpose" iterates over each distinct travel purpose, analyzing each purpose for the current mode. Then for each travel purpose, phase "C. Travel time tolerance group" iterates over distinct combinations of demographic characteristics having common travel time budget parameters. Once each item in a nest is processed, the parent nest advances until all destination activities have been analyzed for all modes (phases A through F).

The inputs to this process are the output table generated by the population synthesis, the destination relevance parameters, travel time budget parameters, and travel time skims by mode. The output of this process is a table with a single record for each zone and columns summarizing the number of relevant travelers that can access each destination activity in that zone. The analysis of competitors with access is executed by the `script summarize_competitors.py`.

Analyze Accessibility: With the number of relevant travelers that can reach destination zones tabulated, the next step of the accessibility scoring process is to summarize the number of destinations reachable from each origin zone. This is a two-step process. The first step entails tabulating the number of destinations reachable from each origin zone for each demographic subgroup having common destination relevance parameters.[11] This step uses a sequence of nested iterations like the process used for analyzing competing travelers. The steps of this process are outlined in Table 12. Note that the only differences between these steps and the steps described in Table 12 are found in phases "F. Destination activity" and "G. Competitive vs non-competitive." The nests and flow of the iterations are the same as in the analysis of competitors. This initial step applies destination relevance weights and travel time tolerance parameters to account for traveler characteristics at the origin end to weight destinations at the destination end.

Figure 17: Effective Walk Time (Upper) and Ratio of Effective to True Walk Time (Lower) in Westover Hills Area



The inputs to this process are the output table generated by the population synthesis, the destination relevance parameters, travel time budget parameters, and travel time skims by mode. The output of this process is a table with a single record for each zone and demographic subgroup. Since there are many potential demographic subgroups, it is possible for each origin zone to be listed thousands of times in this table, with each instance reflecting a different traveler characteristic. For this reason, the outputs of this process are very large (many gigabytes). Columns in this table report the number of travelers in the demographic subgroup in each zone and the number of destination activities reachable, weighted by relevance and travel time tolerance for that subgroup. The analysis of access to relevant destinations is executed by the script `summarize_access.py`.

The second step in this stage of the accessibility scoring process summarizes the large tables produced in the first step to yield a composite estimate of accessibility to each activity from each origin zone given the demographic characteristics of that zone's residents. This requires reading in the table produced in the first step and calculating new columns that record the product of each destination activity reachable (both basic utility and decayed destinations formulations) and the number of residents in each population group. The resulting table is then summarized for each origin zone, yielding columns containing the total population of

9. https://gistbok.ucgis.org/bok-topics/geospatial-data-conflation
10. https://renaissanceplanning.github.io/emma-docs/index.html

11. Note that each of these demographic subgroups is part of a larger demographic group having common travel time tolerance parameters, as indicated by the nested of phase D within phase C in Table 12.

Table 12: Analysis of Relevant Competing Travelers: Nested Iterations

Competing travelers analysis nest	Description
A. Travel mode	In this phase, the analysis focuses on a particular travel mode (walk, bike, transit, auto), using data and parameters defined for that mode.
B. Travel purpose	In this phase, the analysis focuses on a particular travel purpose (HBW, HBO), using data and parameters defined for that purpose.
C. Travel time tolerance group	In this phase, the analysis filters the population synthesis table to focus on travelers that have common travel time budget parameters.
D. Destination relevance group	In this phase, the analysis further filters the population synthesis table to focus on travelers that have common destination relevance parameters.
E. Alternative impedance estimates	In this phase, the analysis calculates trip-making propensity factors based on travel time budget parameters and alternative travel time estimates (true time vs. effective time).
F. Destination activity	In this phase, the analysis applies destination relevance parameters for each traveler, summarizes total relevant travelers to the zone level, broadcasts zone-level relevance over the origin-destination-level propensity matrix developed in nest E, and summarizes how many relevant competing travelers can reach this destination type in each destination zone. These results are then stored as a column in the output table.

each zone and the total of each population-activity product. The product fields are then divided by the zone population to generate composite accessibility scores to each destination activity. This is effectively a weighted-average process that accounts for variability in destination relevance and travel time tolerances for the diverse residents of a given zone. This step of the analysis is executed by the script report_access.py.

Analyze Travel Time to Crisis Destinations: The final step of the accessibility scoring process is the analysis of travel times to nearest crisis destinations. The crisis destinations included in the analysis are:

- Emergency services
  - Police stations and sheriff facilities
  - Fire and EMS stations
  - Urgent care facilities
- Other
- Cooling stations
- Shelters for persons experiencing homelessness
  - Food pantries
  - Social services
  - Polling places

This analysis is executed during the summarization of destination accessibility (`summarize_access.py`) since this is convenient during processing. However, it is documented separately since it produces a distinct set of outputs. The process uses the `nearestDest` function from the `emma` python module. This function finds the ith nearest zone with a non-zero value for destination-end activity based on a travel time or cost matrix and a table of zone activities. Thus, the inputs to this process are the destination aggregation results

Table 13: Analysis of Relevant Destinations Reachable: Nested Iterations

Competing travelers analysis nest	Description
A. Travel mode	In this phase, the analysis focuses on a particular travel mode (walk, bike, transit, auto), using data and parameters defined for that mode.
B. Travel purpose	In this phase, the analysis focuses on a particular travel purpose (HBW, HBO), using data and parameters defined for that purpose.
C. Travel time tolerance group	In this phase, the analysis filters the population synthesis table to focus on travelers that have common travel time budget parameters.
D. Destination relevance group	In this phase, the analysis further filters the population synthesis table to focus on travelers that have common destination relevance parameters.
E. Alternative impedance estimates	In this phase, the analysis calculates trip-making propensity factors based on travel time budget parameters and alternative travel time estimates (true time vs. effective time).
F. Destination activity	In this phase, the analysis applies destination relevance parameters for each traveler, summarizes total relevant travelers to the zone level, broadcasts zone-level relevance over the origin-destination-level propensity matrix developed in nest E, and summarizes how many relevant competing travelers can reach this destination type in each destination zone. These results are then stored as a column in the output table.
G. Competitive vs. non-competitive	In this phase, the first analysis iteration looks up the number of competitors that can reach each destination zone, broadcasts these values over the origin-destination matrix, and normalizes the number of destinations reachable (basic utility and decayed destinations) by the number of competitors. The second analysis iteration does not execute the step above, leaving simple totals of destinations reachable in the origin-destination matrix. The resulting matrix is then summarized to yield the number of relevant destinations reachable from each origin zone for the current demographic group being analyzed. The competitive and non-competitive results are stored in separate columns and the combined results are then stored as rows in the output table. Each row also includes a column recording the number of residents in the demographic group being analyzed.

and travel time skims by mode. The output of this process is a table with a single record for each zone and columns summarizing the shortest travel time to each crisis destination activity from that zone.

Additional Research

The accessibility scoring process described above enhances prevailing approaches to measuring accessibility to better reflect traveler needs and preferences in describing the accessibility offered by different travel modes. The various formulations of accessibility reveal how different factors influence the geography of accessibility in the City of Richmond and offer nuanced understanding of how accessibility varies for different population groups when destination relevance, network attributes, and the presence of competing travelers are accounted for. These enhancements will help the City better understand issues and identify opportunities for improving the usefulness of the multimodal transportation system for all travelers.

However, accessibility evaluation could be enhanced further to generate even richer insights in future studies. Some potential items for additional research are listed below.

- Defining more robust and precise data and procedures for enriching networks with key attributes that affect traveler perceptions of travel costs. This could also imply a need to attune network attribute cost effects to traveler preferences. For example, the presence of a bike lane may be very important to inexperienced or risk-averse cyclists but less important to experienced cyclists in route choice. This would require substantial literature review and data analysis to align network attributes with user preferences.
- The transit accessibility analysis conducted in this study focuses on walk access to transit. When evaluating shortest paths between OD pairs on the combined walk/transit network, only paths that spend part of the trip on a transit vehicle were retained, meaning destinations reachable only by walking were not considered "transit accessible." Rather than dropping shortest paths consisting only of walking, the analysis could be modified to find the shortest path that does use a transit vehicle. This approach is more computationally intensive but would enhance transit accessibility results, especially for the analysis of minimum times to crisis destinations.
- The large tables produced in the analysis of destinations reachable (see Table 13, e.g.) produces very large tables replete with detailed traveler information and destination accessibility summaries. While the current process proceeds to summarize the table to yield a single composite accessibility score, selections from the table could be summarized to yield separate accessibility estimates for detailed subgroups, such as the access to jobs for workers with high school or less education versus workers with bachelors degree or higher. This kind of reporting is currently only supported for collections of zones, such as the citywide averages described in the Equity of Access section above. The proposed enhancement would develop procedures to express these comparative accessibility findings within individual analysis zones for richer insight into the inequalities of access.
- The accessibility scores produced in this study assume continuous linear growth in the value of accessibility as the number of destinations reachable increases. For example, consider three separate neighborhoods, A, B, and C. Residents of neighborhood A can reach only one grocery store; residents in neighborhood B can reach three grocery stores; and residents in neighborhood C can reach nine grocery stores. In this example, neighborhood B has three times the access to grocery stores of neighborhood A, and neighborhood C has three times the access of neighborhood B. However, it is unclear whether each additional grocery store accessible offers the same value to travelers. Future research could examine the value of surplus destinations in accessibility scoring to better calibrate results to align with traveler needs and correspond to the adequacy of access provided to all users.

3 - TRANSPORTATION TECHNOLOGY ACCESSIBILITY

Introduction

This chapter describes the prevalence of technologies that are required for or facilitate access to multimodal transportation options under the Multimodal Network Equitable Access Study conducted for the City of Richmond under the Growth and Accessibility Planning Technical Assistance (GAP-TA) program. This work is part of in alignment with Task 3: Method and Metric Development. This technical memo describes Richmond residents' access to four technologies: broadband internet access, smartphones, credit and debit cards, and bank accounts. These technologies provide for access to multimodal transportation by facilitating transactions, running required mobile applications, and furnishing information on options and routes. Two primary analyses are described in this memo: a location analysis showing the census tracts and neighborhoods where residents most lack access to one or more of these technologies, and a demographic analysis revealing the racial / ethnic, gender, income, and age characteristics of Richmond residents most frequently lacking access to one or more of these technologies.

This chapter has four sections including this 'Introduction.' The 'Methodology' section describes how the analysis was conducted, including details of data sources and processing steps. The 'Results' section provides maps, figures, and tables showing the use these technologies by location and associations with economic and sociodemographic characteristics. Finally, the 'Orientation to Deliverable' section describes the data files that accompany this memo.

Methodology

Data Sources

The primary data sources used for this analysis are the U.S. Census Bureau's 2019 five-year American Community Survey (ACS) results and the Paths to Equity (PTE) survey conducted by the City of Richmond in 2021. The ACS provides census tract-level estimates of access to these technologies, which serve for the location analysis of broadband access and smartphone ownership. ACS does not have data about access to credit or debit cards, or bank accounts.

The PTE survey was used for location analysis of credit and debit card access, and bank accounts, with data at the neighborhood level. The PTE survey also allows for associations to be made with demographic characteristics for people who lack access to these technologies since it aligns individual respondents with race, gender, age, and income in a way that ACS data does not. Therefore, PTE survey data is used for demographic analysis, with access to internet at home standing in for broadband internet access, and access to a phone data plan standing in for smartphone ownership.

Table 14 aligns the technologies with the data sources and their uses in this study. Table 15 summarizes key strengths of weaknesses of the two data sets.

Processing Steps

Location Analysis: The location analysis using ACS data involved the following steps.

1. Download ACS data for 2019 from data.census.gov for Virginia census tracts for computers and internet access (Table S2801: Types of Computers and Internet Subscriptions). Retain fields for broadband (field number 014E), smartphones (field number 005E), and total household (field number 001E). Calculate the share of households in each census tract in Richmond without access to broadband and without access to smartphones.
2. Download a shapefile of U.S. Census tracts for 2019 from the U.S. Census Bureau's TIGER/Line website. Retain census tracts within the city of Richmond.[12]
3. Join the processed ACS data to the census tracts file using the 'GEOID' field.
4. Map the results.

12. [1] https://www.census.gov/geographies/mapping-files/time-series/geo/tiger-line-file.html.

Table 14: Technologies and Data Sources

Technology	Geographic Units	Data	Purpose in This Study
Broadband	Census Tract	U.S. Census Bureau, ACS 2019 five-year	Location analysis
Access to Internet at Home	Neighborhood	Paths to Equity (PTE)	Demographic analysis
Smartphone Ownership	Census Tract	U.S. Census Bureau, ACS 2019 five-year	Location analysis
Access to Phone Data Plan	Neighborhood	Paths to Equity (PTE)	Demographic analysis
Credit and Debit Cards	Neighborhood	Paths to Equity (PTE)	Location analysis and demographic analysis
Bank Accounts	Neighborhood	Paths to Equity (PTE)	Location analysis and demographic analysis

Table 15: Strengths and Weakness of Data Sets

Data Set	Strengths	Weaknesses
ACS	▪ Replicable over time since ACS is updated annually, and questions related to technology are unlikely to change in the near future. ▪ Where the data is available, it matches the technologies under examination very precisely (e.g., broadband instead of just internet).	▪ A sample with some margin of error, even if the sample is large and the margin of error relatively small. ▪ Does not include demographic data linked with individual responses, making demographic analysis of this data set impossible.
PTE Survey	▪ Followed high-quality survey solicitation procedures that aimed to make the survey responses as representative of the city population as possible. ▪ Very recent data. ▪ Combines demographic data about respondents with technology access, allowing for demographic analysis.	▪ Small sample size in many neighborhoods, and no responses in some neighborhoods. ▪ High number of responses without a valid neighborhood. ▪ Respondents not perfectly representative of Richmond residents. For instance, respondents have higher average income than Richmond residents on average.

The location analysis using PTE survey data involved the following steps.

1. Manually clean neighborhood names entered in the survey so that they match the neighborhood names in Richmond neighborhoods shapefile provided by the city.
2. Remove survey responses without a valid neighborhood name or where the respondent lives outside of Richmond. Table 16 shows that 43.5% of the 1,860 responses to the survey included a neighborhood name that was within city limits.

Table 16: Responses in PTE Survey

Conditions	Count of Responses
All Responses	1,864
With neighborhood names	860
With neighborhood name and city of Richmond	811

3. Calculate the share of respondents in each neighborhood without access to a credit or debit card, or without a bank account.
4. Join the processed data to the shapefile by neighborhood name.
5. Map the results.

Demographic Analysis: The demographic analysis involved first filtering responses to only retain those with valid neighborhood names inside Richmond. Keeping only responses that are known to be from Richmond residents ensures that the results reflect the characteristics of Richmond's population. Next, the share of respondents without access to one of the technologies being assessed in the demographic analysis (described in Table 14) is calculated. In some cases, raw age or income categories from the survey were consolidated to enhance readability.

Results

PTE Responses

Figure 18 shows the number of responses by neighborhood and by district. There are 811 responses associated with a neighborhood within Richmond (Table 16). Of the 148 neighborhoods, 106 have at least one response in the PTE survey.

Prevalence of Technology by Location

Broadband Internet: Households in the East End of Richmond are more likely than households on the West End to not have broadband internet access, as shown in Figure 19. The maximum share of households without broadband internet access is 66.2% in census tract 204 where I-64 and I-95 intersect in the Mosby, Brauers, Fairmount, Whitcomb, and Upper Shockoe Valley neighborhoods. The other census tracts with the highest share of households without broadband internet access include in decreasing order census tracts 301, 202, 201, and 207, which are all adjacent to or very near census tract 204. These census tracts include neighborhoods such as Eastview, Fairfield, Creighton, Woodville, Peter Paul, Church Hill North, Union Hill, and Gilpin. Census tract 503 in the Mary Munford neighborhood has the lowest share of households without broadband internet access, at 4.2%.

Smartphones: Smartphone access is more evenly spread throughout the city than broadband internet access. The maximum share of households without smartphone access is 47.7% in census tract 204 (Mosby, Brauers, Fairmount, Whitcomb, and Upper Shockoe Valley neighborhoods), which is also the census tract with the highest share of households without broadband access. This is followed by census tracts 301, 608, 102, 208.02, and 201 in the Gilpin, Commerce Road Industrial Area, Jeff Davis, Windsor, Bryan Park, Bellevue, Rosedale, British Camp Farms, Cottrell Farms, and Whitcomb neighborhoods. The census tracts with the smallest share of households without smartphone access are 403 (VCU), 205 (Shockoe Bottom, Upper Shockoe Valley, Union Hill, Church Hill), and 410 (The Fan). Figure 20 shows the share of households without smartphone access for all census tracts in Richmond.

Figure 18: Map of Number of Responses to Path to Equity Survey

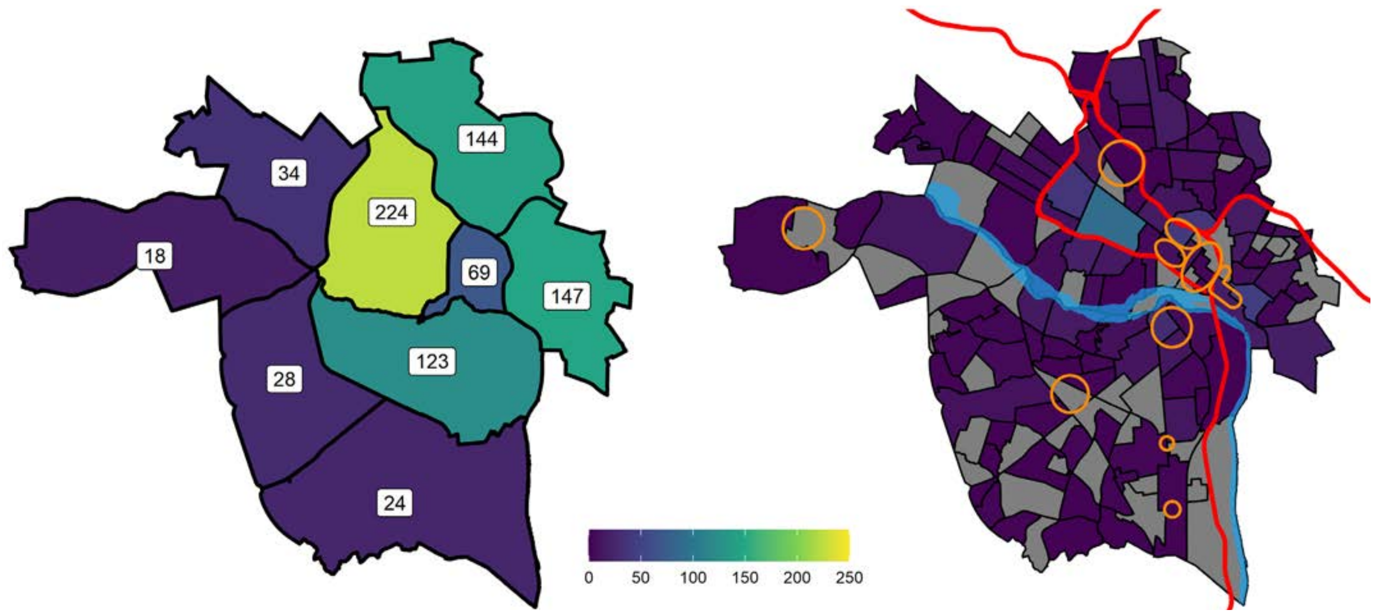


Figure 19: Map of Share of Households with Access to Broadband Internet

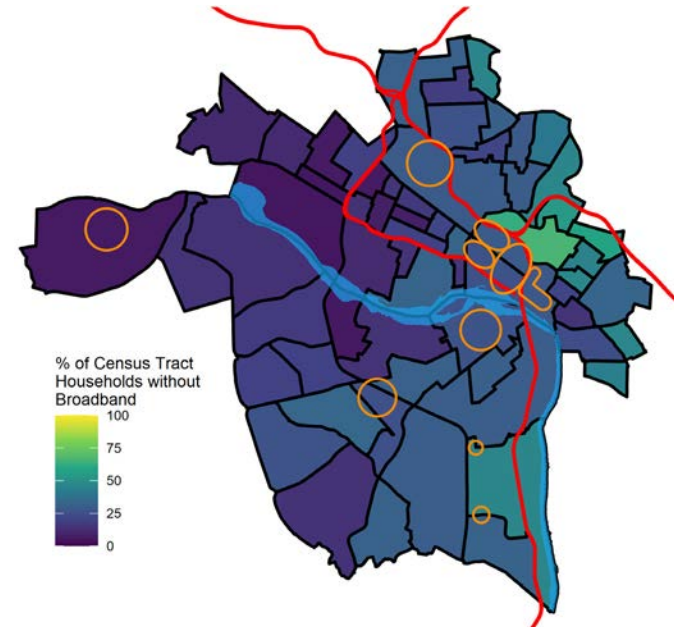
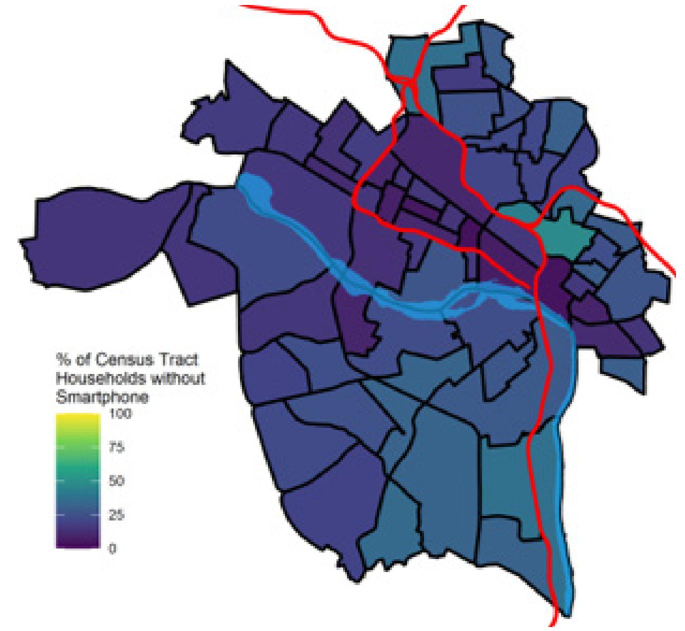


Figure 20: Map of Share of Households with Access to a Smartphone



Credit and Debit Cards: Credit and debit card access is generally widespread in Richmond with fewer geographical patterns than are visible for broadband internet access and smartphones. As shown in the district map on the right side of Figure 21, the East End typically has a greater share of households without credit or debit card access than the West End. While Far West district in the West End shows 12% of households lacking credit or debit card access, this high rates' incongruence with district residents' access to other technologies may result from the small number of PTE survey responses in the district, totaling just 34.

Bank Accounts Lack of access to bank accounts is more common in the East End than in the West End. The district where bank accounts are most commonly inaccessible is the Downtown district, where 16% of respondents lack access to a bank account, followed by the North and East districts at 12%. The districts where bank accounts are most accessible are Far West, Huguenot, and Near West. Figure 22 shows the share of households without access to bank accounts.

Figure 21: Map of Share of Households without Credit / Debit Card Access by Neighborhood (Left) and by District (Right)

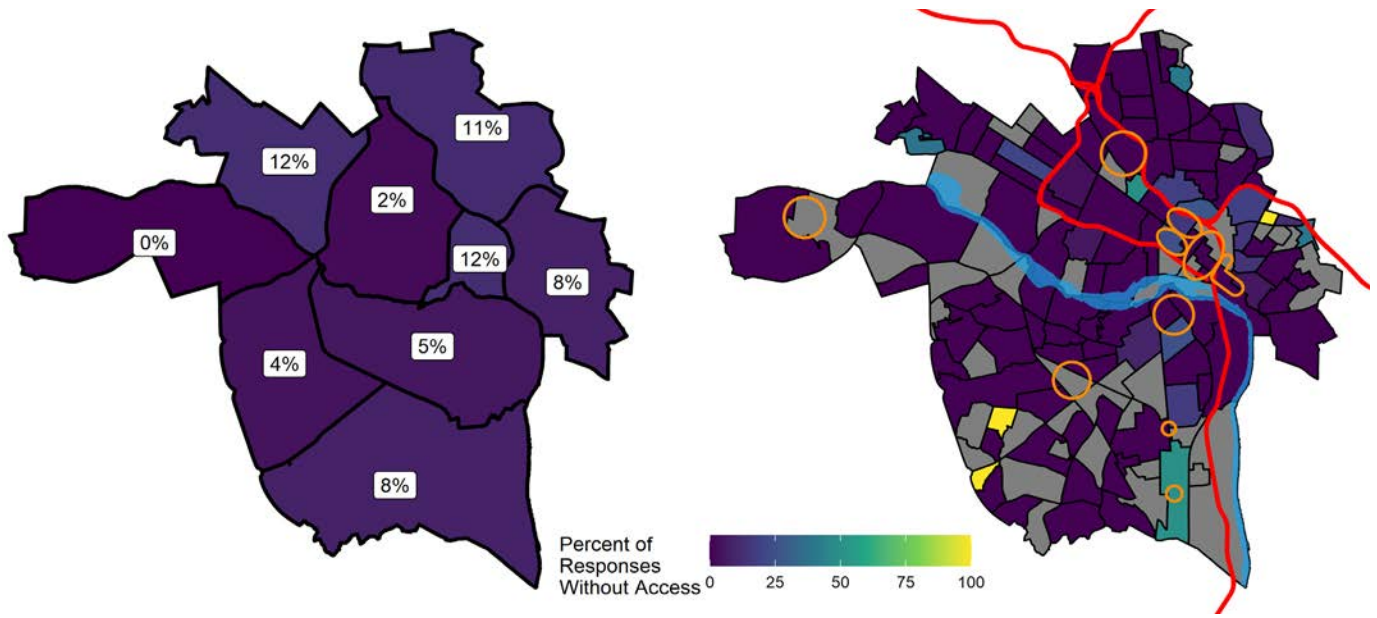
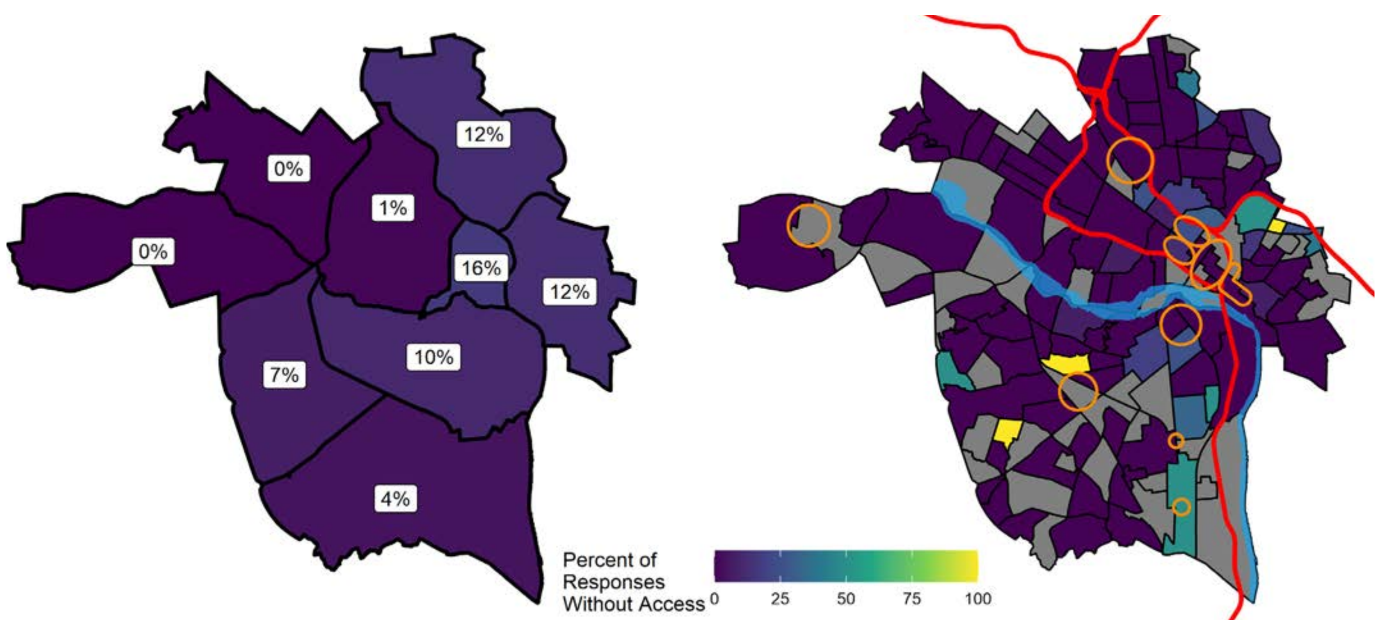


Figure 22: Map of Share of Households without Access to Bank Accounts by Neighborhood (Left) and by District (Right)

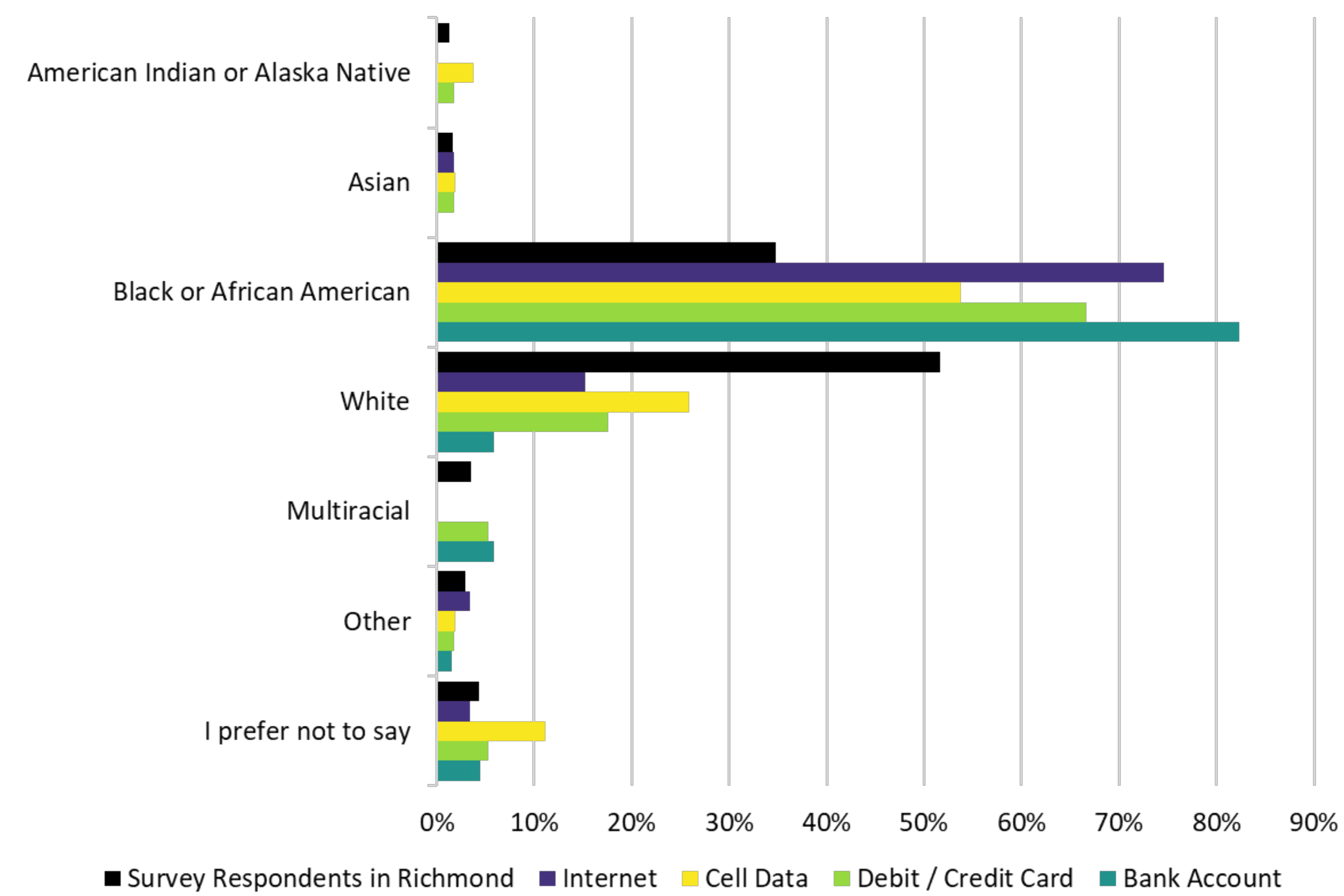


Sociodemographic Associations with Technology

By Race: Figure 23 shows the share of PTE survey respondents without access to a given technology by race. To interpret the graph, compare the black bar representing the share of survey respondents who identify as a certain race with the bars for each of the technologies. When the black bar exceeds the bars for a given technology, respondents of that race experience fewer barriers to accessing that technology on average. When the bar for a given technology exceeds the black bar, respondents who report belonging to that race experience more barriers to accessing that technology on average. Black / African American Richmond residents disproportionately experience barriers to accessing the technologies and belong to the only racial group that reports above average barriers across all four technologies.

Table 17 shows the share of respondents the PTE survey who live in Richmond by race who report not having access to internet, cell data, credit / debit cards, or a bank account. Only respondents who could be confirmed to live in Richmond based on provision of a neighborhood name are included in results. While between 6% and 8% of respondents report not having access to one of these technologies, among African American Richmond residents the rates of households without access are between 3 and 10 percentage points higher than the citywide average depending on the technology. Respondents who do not report their race also have greater barriers to access related to cell data and marginally greater barriers related to credit/debit cards. While only 11 American Indian or Alaska Natives responded to the survey, those who did respondent also more frequently reported not having access to cell data and credit / debit cards than respondents as a whole. Black or African American Richmond residents are more than twice as likely as the city population as a whole to not have access to internet (115% more likely) or a bank account (138% more likely), and are nearly twice as likely not to have access to credit / debit cards (93% more likely). Black or African American Richmond residents are also 55% more likely not to have access to cell data.

Figure 23: Share of Respondents without Access by Race



By Gender: Among survey respondents, men are slightly overrepresented among respondents reporting lack of access to cell data, internet, and debit / credit cards, while women are slightly overrepresented in reporting lack of access to bank accounts. Richmond residents who reported their gender as "other" are slightly overrepresented as lacking access to all technologies, while Richmond residents who reported a non-binary gender are overrepresented in lacking access to internet. Figure 24 shows the share of respondents by gender who lack access to each technology compared with their share of survey responses.

Table 18 shows that there is less variation among gender categories compared with responses as a whole than for racial categories. Although there is a limited number of responses, the highest share of respondents without access to one or several of the technologies is among respondents with gender category "other" or respondents who did not provide a gender category.

Table 17: Technologies and Data Sources

Racial Category	Total Number of PTE Survey Responses	Internet	Cell Data	Credit/ Debit Cards	Bank Account
American Indian or Alaska Native	11	0%	18%	9%	0%
Asian	14	7%	7%	7%	0%
Black or African American	307	14%	9%	12%	18%
White	456	2%	3%	2%	1%
Multiracial	31	0%	0%	10%	13%
Other	26	8%	4%	4%	4%
I prefer not to say	42	7%	17%	7%	7%
Total	887	7%	6%	6%	8%

Table 18: Share of Respondents without Access to Technology by Gender

Gender Category	Total Number of PTE Survey Responses	Internet	Cell Data	Credit/ Debit Cards	Bank Account
Woman	498	6%	5%	6%	8%
Man	329	7%	7%	7%	7%
Non-Binary	23	9%	4%	0%	4%
Other	7	14%	14%	14%	14%
I prefer not to answer	30	10%	10%	10%	10%
Total	887	7%	6%	6%	8%

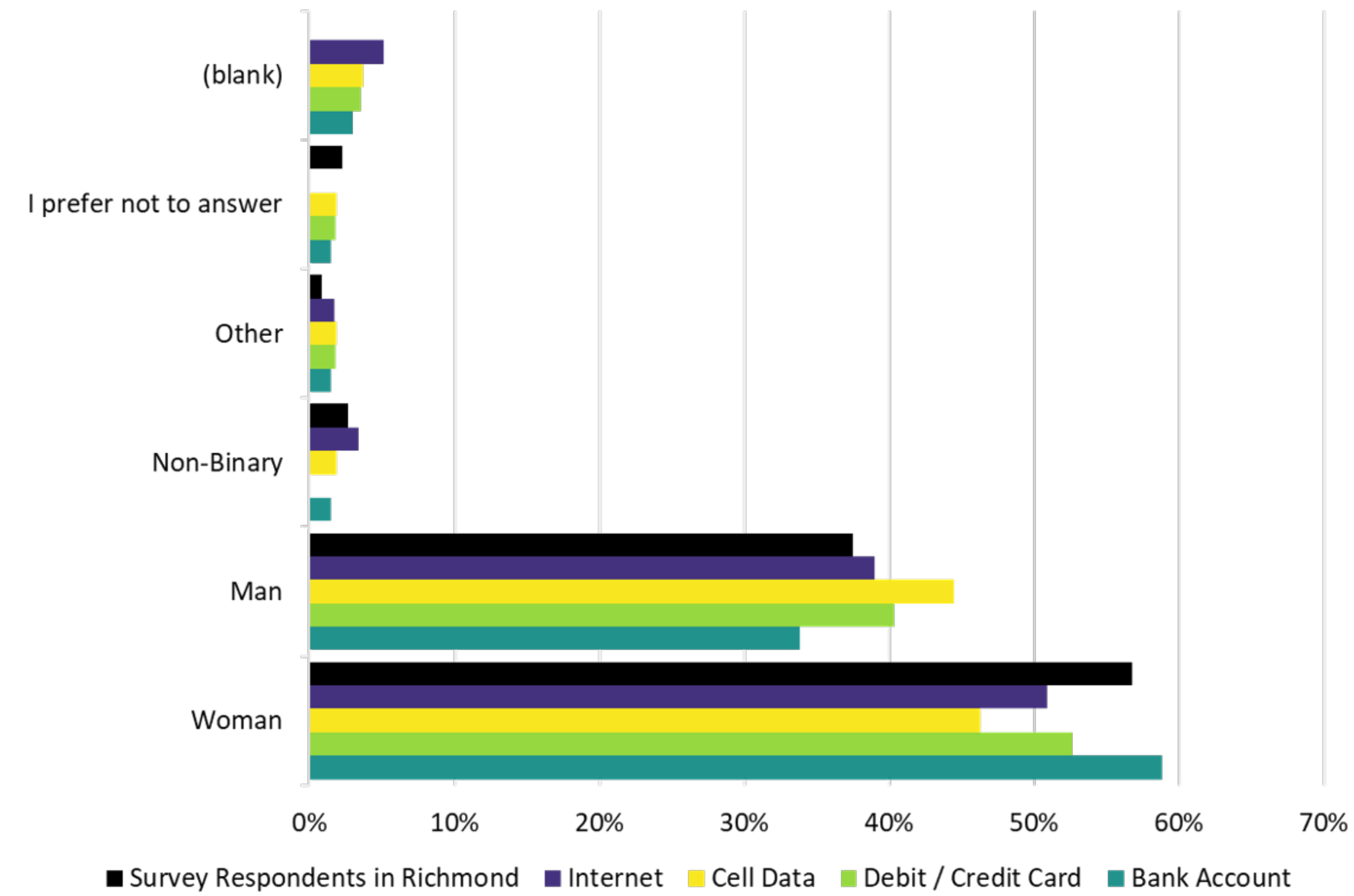
By Income: Figure 25 shows the share of respondents without access to one of the technologies by annual income in U.S. dollars compared with the share of PTE survey responses provided by people in that income category as a whole. It shows that respondents earning less than $14,999 annually report lacking access to the technologies much more frequently than the two highest income categories. Compared to respondents earning between $15,000 and $45,000 annually, those earning $14,999 or less experience lack of access to bank accounts more than twice as frequently, but report lack of access to debit/credit cards slightly more frequently and lack of cell data less frequently.

The PTE survey did not ask respondents about household size, nor did the income categories neatly align with national 2022 poverty guidelines.[13] Thus, it is not possible to draw many definitive conclusions about the rates at which Richmond residents living in poverty experience barriers to technology using the survey. However, the guideline for a single person household is $13,590, which is close enough to the lowest income survey category to conclude that respondents earning less than $14,999 likely live below the poverty line.

Table 19 reinforces the same message, showing that Richmond residents in the lowest income category or those who did not report an income lack access to the technologies at rates between 1 and 14 percentage points above the citywide average. Respondents earning less than $14,999 per year are more than twice as likely not to have access to technologies than Richmond residents as a whole.

13. U.S. Department of Health and Human Services. "Poverty Guidelines." Available at https://aspe.hhs.gov/topics/poverty-economic-mobility/poverty-guidelines.

Figure 24: Share of Respondents without Access by Gender



By Age: Figure 26 shows the percentage of Richmond residents by age group with access to internet, cell data, credit or debit cards, and a bank account. It shows that more senior Richmond residents are much less likely to have internet access than younger age categories, while Richmond residents age 25-54 are much more likely to have access to internet. Additionally, the youngest Richmond residents (age 13-24) are less likely to have bank accounts, credit or debit cards, or cell data access than older Richmond residents. Table 20 shows the share of respondents by age without access to a given technology. It reveals that Richmond residents age 55 and older are 73% more likely not to have internet access than older age cohorts, while Richmond residents from 13 to 25 are twice are 81% and 90% more likely as older age cohorts to not have credit / debit card or bank access respectively, and nearly 50% more likely not to have cell data.

Figure 25: Share of Respondents without Access by Annual Income

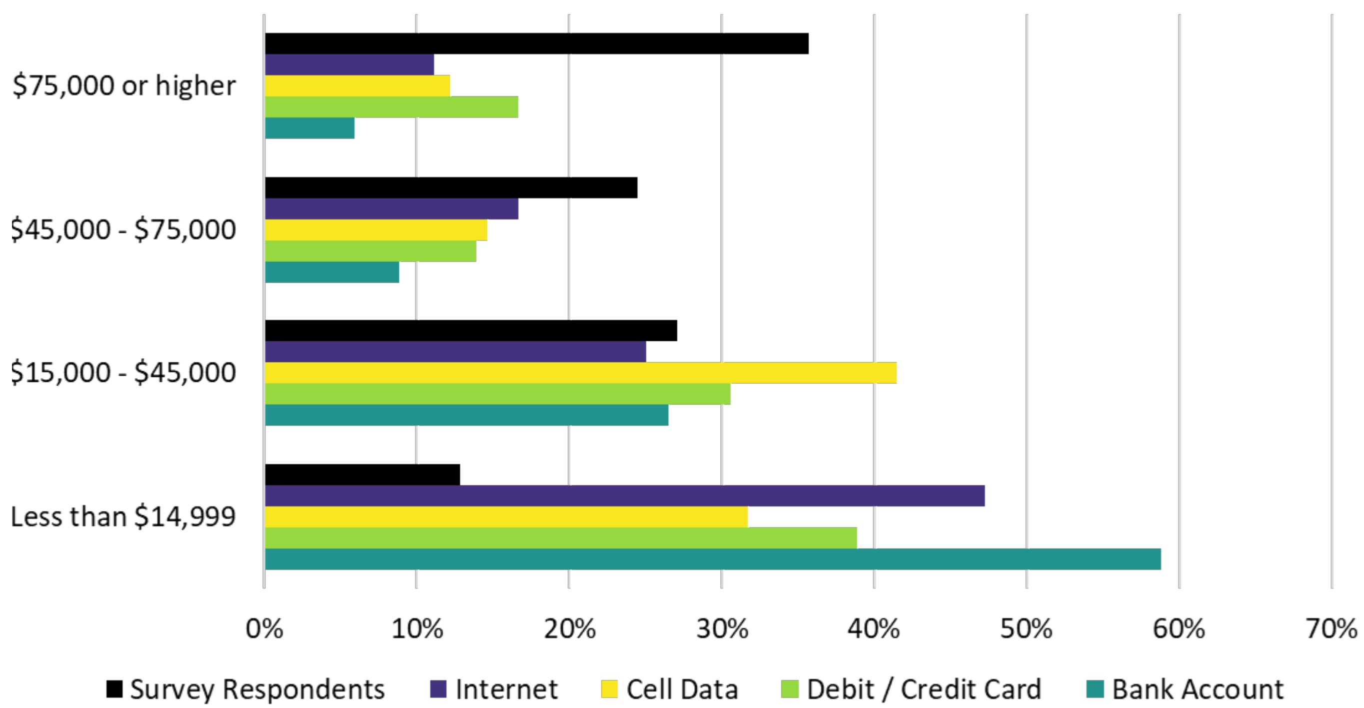


Table 19: Share of Respondents without Access to Technology by Income

Income Category	Total Number of PTE Survey Responses	Internet	Cell Data	Credit/ Debit Cards	Bank Account
75,000 or higher	11	0%	18%	9%	0%
45,000 - 75,000	14	7%	7%	7%	0%
15,000 -45,000	307	14%	9%	12%	18%
Less than 14,999	456	2%	3%	2%	1%
(blank)	31	0%	0%	10%	13%
Total	26	8%	4%	4%	4%

Figure 26: Share of Respondents without Access by Age

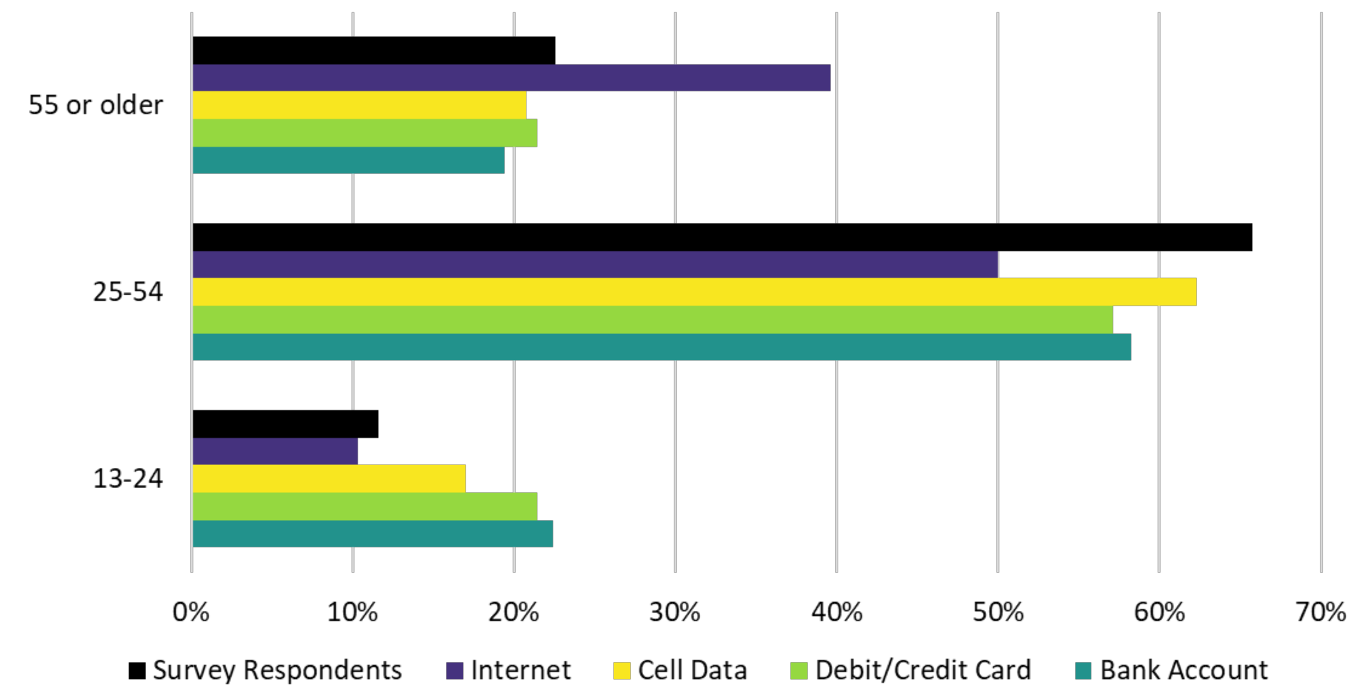


Table 20: Share of Respondents without Access to Technology by Age

Age Category	Total Number of PTE Survey Responses	Internet	Cell Data	Credit/ Debit Cards	Bank Account
55 or older	200	12%	6%	6%	7%
25 - 54	582	5%	6%	5%	7%
13 - 24	103	6%	9%	12%	15%
(blank)	2	50%	50%	50%	50%
Total	887	7%	6%	6%	8%

Next Steps

This data showing Richmond residents' access to technologies that facilitate multimodal transportation can help identify hotspots for inclusion in the city's long-range plan. These hotspots can be determined by creating an index at the neighborhood level that combines access to each technology into a single number, potentially with weighting so that the technologies whose lack presents the greatest barriers to multimodal transportation access have the most influence on the index value. Such an index can be created via the following steps.

1. Convert census tract-level data for smartphone access and for broadband internet access to the scale of neighborhoods by proportional overlap from census tracts to neighborhoods.
2. Normalize access for each technology so that the neighborhood with the least access has a normalized value of 1 and the neighborhood with the greatest access has a normalized value of 0.
3. Determine weights for each technology. These weights can be assessed via qualitative examination of the intensity of each barrier, via a survey or discussion asking members of the public or stakeholders to assign weights based on subjective factors, or via examination of the research related to the height of the barrier erected by lack of access to each technology.
4. Apply the weights by multiplying them by the relevant normalized access score for each neighborhood, and generate the index by summing the products.

The index might also be combined or paired with other equity-related data sources in the final identification of hotspots for inclusion in the city's long-range plan, such as the equity emphasis areas (EEAs) identified by the Office of Intermodal Planning and Investment.[14]

Some neighborhoods do not have enough responses to generate a normalized access value for one or more technologies. These neighborhoods can either be assigned an average score that will prevent that technology from raising or lowering the final neighborhood score. A more computational intense but likely more accurate approach is to develop a regression-based model to predict lack of access to each technology based on economic and demographic characteristics, such as income, ethnic / racial composition, average neighborhood age, population or employment growth rates, and the breakdown of neighborhood employment by industry. It is possible that location-related factors such as proximity to major transportation infrastructure like highways or airports, or proximity to the central business district may also help predict resident access to the technologies. Once models with a high degree of explanatory power have been found, then these models can be used to predict the access to these technologies in neighborhoods with inadequate responses from the PTE survey.

Even though great effort was made during the collection of survey data to include respondents from all parts of the city and with many different demographic characteristics, future versions of the PTE survey may also be able to garner more responses from neighborhoods with few responses in this version or from people who identify with demographic categories with low representation in current PTE survey responses, including Asian / Pacific Island and American Indian / Alaska Native Richmond residents.

Orientation to Deliverable

The GIS files that were produced for the location analysis accompany this technical memo to allow additional mapping and analysis. The files and their attributes are described below.

- richmond-neighborhood-responses.shp
  - This file summarizes PTE survey responses at the neighborhood level and shows the percentage of respondents from each neighborhood without access to a given technology. Table 21 lists and describes the attributes.
- richmond-census-tracts-broadband-smartphone.shp
  - This file summarizes the share of residents without access to a given technology at the level of census tracts. The data is derived from the 5-year 2019 American Community Survey. Standard census tract attributes are described by the U.S. Census Bureau. Table 9 lists and describes the attributes that were added to census tract attributes provided by the U.S. Census Bureau.

14. Equity Emphasis Areas can be downloaded from the Office of Intermodal Planning and Investment's Interact VTrans website: https://vtrans.org/interactvtrans/map-explorer.

Table 21: Fields in richmond-neighborhood-responses.shp

Field Name	Description
OBJECTID	Object Identification Number
Name	Object Identification Number
District	District of Neighborhood
n	Number of Survey Responses
pn_bank	Percent of responses indicating a lack of access to a bank account
pn_car	Percent of responses indicating a lack of access to a personal vehicle
pn_cell	Percent of responses indicating a lack of access to a cell phone
pn_compute	Percent of responses indicating a lack of access to a personal computer
pn_credit	Percent of responses indicating a lack of access to a credit or debit card
pn_webaccs	Percent of responses indicating a lack of access to the internet

Table 22: Fields in richmond-census-tracts-broadband-smartphone.shp

Field Name	Description
Tot_HH	Total number of households
Broadband	Number of households with broadband internet access
Smartpphone	Number of households with smartphone access
No_Smartph	Number of households without smart phone access
No_Broadba	Number of households without broadband internet access
ShareNoSP	Share of households without smart phone access
ShareNoBB	Share of households without broadband internet access

4 - OUTCOME LINKED ACCESSIBILITY METRICS

Introduction

Equitable Accessibility is as much a public health issue as it is a transportation, land use, or technology one. Public health is hindered or helped depending on people's ability to reach jobs, housing, food, services, and care. This section starts by focusing on two measures of public health: the Center for Disease Control (CDC) Population Level Analysis and Community Estimates (PLACES) and Virginia Department of Health (VDH) Health Opportunity Index (HOI). PLACES is a nationally available survey of clinical health conditions at the tract geography, last published in 2020. HOI is a Virginia survey of environmental factors which affect public health outcomes, also available at the tract geography and current to 2020. The latter part of this section describes American Community Survey data important to walk and bike commuting, as well as land use density patterns that can facilitate equitable access within and between neighborhoods. At this stage, the project is identifying area of concern and citywide patterns. The test geographies will be used to focus understanding of these citywide patterns with barriers or pipelines of accessibility within the city of Richmond.

This chapter is organized into the following sections:

- Process 1: PLACES Nationwide Health Outcomes
- Process 2: VDH HOI Virginia Health Outcomes
- Process 3: Household Income Patterns
- Process 4: Residential Multimodal Commute patterns
- Process 5: Development Activity Density

Process 1: PLACES Nationwide Health Outcomes

The purpose of public health data is to identify the spatial relationship of residences, workplaces, land use, and infrastructure that result in different public health outcomes across Richmond. Demographic and economic characteristics are also important to public health outcomes, and barriers to individual and public mobility are important to identify and overcome to achieve equity in Richmond.

The Centers for Disease Control (CDC) provides PLACES as a nationwide public health data at tract resolution for multiple public health factors, including overall health, health access, dental, lung, and mental health, detailed in this memo. The portal for this data is available at PLACES: Local Data for Better Health | CDC (https://www.cdc.gov/places/index.html). The data is available for the 2018/2019 survey year and covers the entire United States.

The data, released in 2021, includes 13 statistics on health outcomes like asthma or obesity, nine statistics on preventative care like dentist visits or regular clinic visits by the elderly, four statistics on health risk behaviors like smoking or lack of sleep, and three statistics on health status. Including physical or mental health. Specific details for survey collection methods, responses, and populations of interest are at Measure Definitions (https://www.cdc.gov/places/measure-definitions/index.html).

Process 1 Methodology

Use the following steps to access PLACES data.

1. **Download:** The data is searchable at the PLACES data portal (https://chronicdata.cdc.gov/browse?category=500+Cities+%26+Places), and is searchable for all geographies from County to Census Tract. To download at the Census tract geography, visit PLACES: Census Tract Data (GIS Friendly Format), 2021 release | Chronic Disease and Health Promotion Data & Indicators (cdc.gov) (https://chronicdata.cdc.gov/500-Cities-Places/PLACES-Census-Tract-Data-GIS-Friendly-Format-2021-/yjkw-uj5s) and select "Export" from the upper right. This will allow the download of KML, Shapefile, or JSON geographic data for all Census tracts in the US.
2. **Clip to study area:** After downloading the Nationwide shapefile, clip the census tracts to the study area, in this case the boundary of Richmond City, with 66 Census Tracts. The data can then be used for analysis or display. The data presents average percent for each health indicator numerically but presents the 95% confidence interval as text.

Process 1 Results

PLACES provides 29 public health statistics at the tract geography. There are 66 tracts within Richmond, showing large scale patterns of health outcomes across the city.

The West End consistently has the best population health outcomes, while the East End and South Side have worse health outcomes. The Gilpin neighborhood, in North Side has the highest incidence of poor PLACES outcomes, with the citywide worst outcomes for smoking (38%), Chronic Obstructive Pulmonary Disease (COPD) (14.8%), sleep deprivation (51%), mental health deficiency (27.4%), dental care (34.7%), physical health deficiency (27.7%), obesity (49.8%), and diabetes (23.7%). For most of the other health outcomes reported by PLACES, the worst outcomes are in the East End. Within the South Side, health outcomes are typically worse in the southeast. This industrial area is sparsely populated, but for those living there are worse health outcomes for smoking, COPD, sleep, mental health, Dental Care, obesity, and high blood pressure than for the rest of the South Side. The Broad Street corridor, connecting the East End Richmond to downtown and including Virginia Commonwealth University, has better than surrounding health outcomes for most of the PLACES metrics.

An advantage of the PLACES data is that each of the metrics is a single clinical or public health outcome, enabling specific linkage between different areas and outcomes.

Health Maintenance: Health insurance coverage for Richmond's working population has the same geographic pattern as many other PLACES statistics. South Side scores are lower with eastern South Side being more severe than the western side. The lowest insurance rates (70%) are found between Hull Street and Midlothian Turnpike and near Gilpin Court and Mosby Court. The West End is in the best condition with health insurance rates over 80%. Figure 27 depicts health insurance rates.

The PLACES Routine Check Ups metric has an unusual distribution, with the lowest scores along the Broad Street Corridor while checkup rates of for most of the rest of Richmond exceed 80%. This could be related to age distribution in these different tracts, with younger populations having a lower participation rate in regular checkups. Figure 28 depicts routine check ups.

There is a wide difference between maximum rates of preventative care for men over age 65 across Richmond, with South Side rates of regular care less than 30% and the West End rates greater than 30%. The lowest rates of care are in the tracts immediately northeast of downtown. Figure 29 depicts preventative care for men. Like men, there is a wide difference between maximum rates of preventative care for women over age 65 across Richmond, with South Side rates of regular care less than 30% and West End rates greater than 30%. Figure 30 depicts preventative care for woment.

Pulmonary Health: Of the PLACES data, smoking rates show some of the greatest variability between maximum (38%) and minimum (8.1%). The distribution across Richmond shows the same concentration of malady to the northeast of downtown, with the Broad Street corridor and west Richmond least affected. There is also an area of concentration to the south, along the I-95 corridor and downstream James River. The South Side generally has smoking rates over 20%. Figure 31 depicts smoking rates.

Asthma rates are best along the Broad Street corridor and to the west of the city, while they are at their worst to the northeast of Downtown. These rates do not correspond directly with the routes of highways through Richmond, though there are several. There is also not much difference between the maximum rate of Asthma (17.1%) and the minimum (7.7%). The most severe Asthma rates are in a tract along the northeast edge of Richmond in Whitcomb Court. Figure 32 depicts asthma rates.

COPD rates are low across Richmond, but the areas with the highest rates in the city are to the south and northeast, consistent with many other PLACES statistics. The distribution of COPD shows better conditions in the Broad Street Corridor most distinctly. Figure 33 depicts COPD rates.

The distribution for mental health is different in some ways than many of the rest of the PLACES statistics. The Broad Street Corridor is not unified as a collection of healthier tracts, with up to a quarter of one tract suffering from a mental health issue. Geographic patterns are otherwise similar to other places data. Figure 35 depicts mental health rates.

Oral Health: The dental care PLACES statistic has similar geography across Richmond as many other PLACES statistics. The range between best and worst condition is substantial (86.7% to 34.7%). The South Side is in worse condition than the West End, and the Broad Street Corridor is in better condition than northeast of downtown and the East End. Figure 36 depicts dental care rates.

There is a wide range of outcomes for this measure of lifetime dental care, with the same geographic arrangement of healthy and unhealthy metrics. The greatest prevalence of this metric (47.2%) is to the northeast of downtown. There is a consistent pattern of dental care for age >18 and retaining teeth past age 65. Figure 36 depicts dental care. Figure 37 depcits total tooth loss rates.

Physical Health: Conditions are generally better across Richmond for this metric, but with the same geographic arrangement of severity as many other PLACES statistics. The worst-off communities are to the northeast of downtown. Figure 38 depicts physical health rates.

Obesity across Richmond shows a similar geographic pattern across Richmond's tracts, with the best conditions in the northwest and along the Broad Street Corridor, worse conditions in south Richmond and the worst conditions in the East End. Figure 39 depicts obesity rates.

For high blood pressure, the only part of Richmond that shows consistently healthy rates is the Broad Street Corridor. North Side and northeast of downtown show the greatest prevalence of high blood pressure, with over half the population of several tracts affected. Figure 40 depicts high blood pressure rates.

The distribution of diabetes in Richmond shows similar geography to many other PLACES statistics. The lowest diabetes rates are remarkably low, but the highest rates in northeast of downtown affect over a fifth of tract populations. Figure 41depicts diabetes rates.

Figure 27: Current lack of health insurance among adults aged 18–64 years

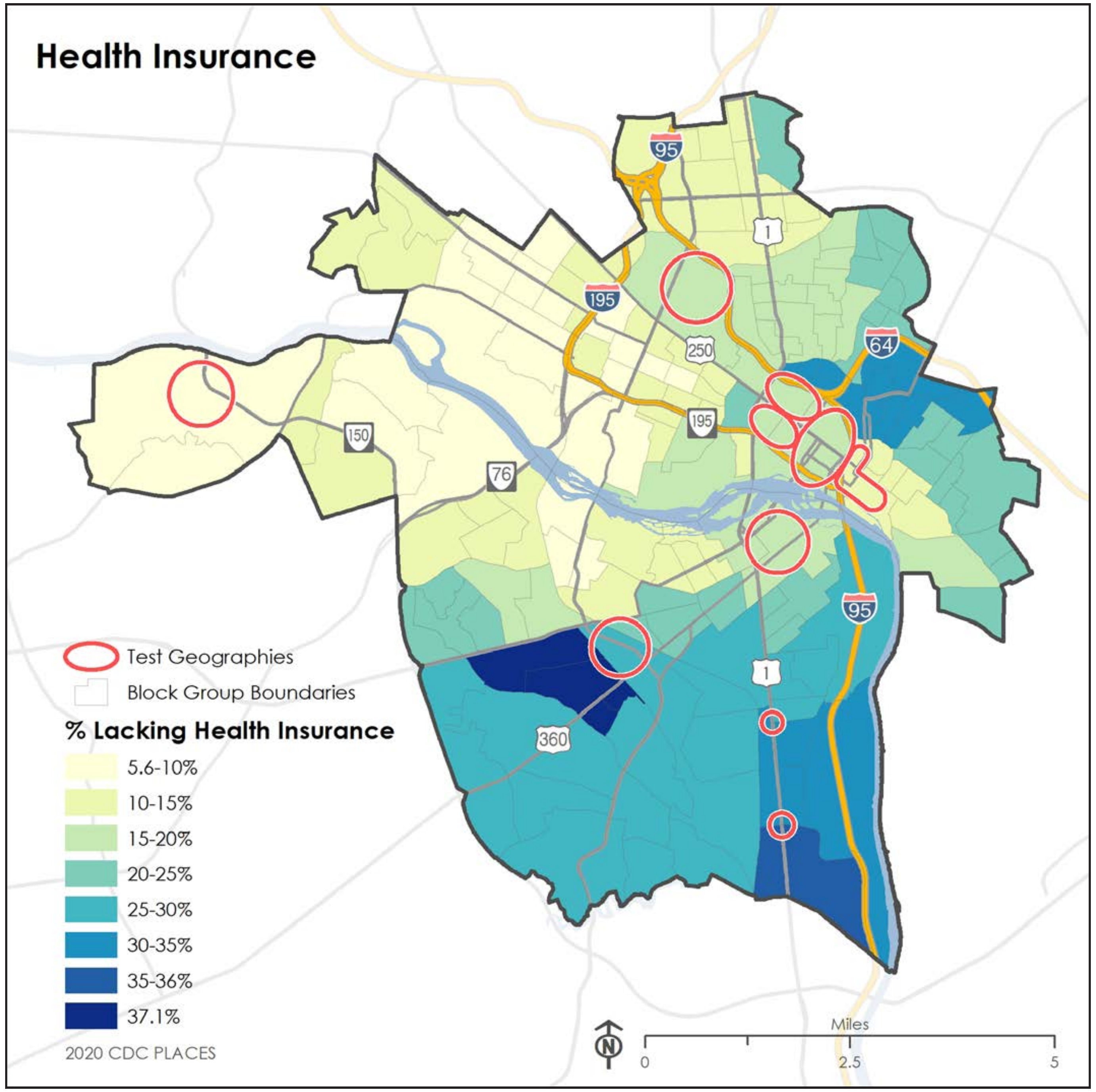


Figure 28: Current lack of health insurance among adults aged 18–64 years

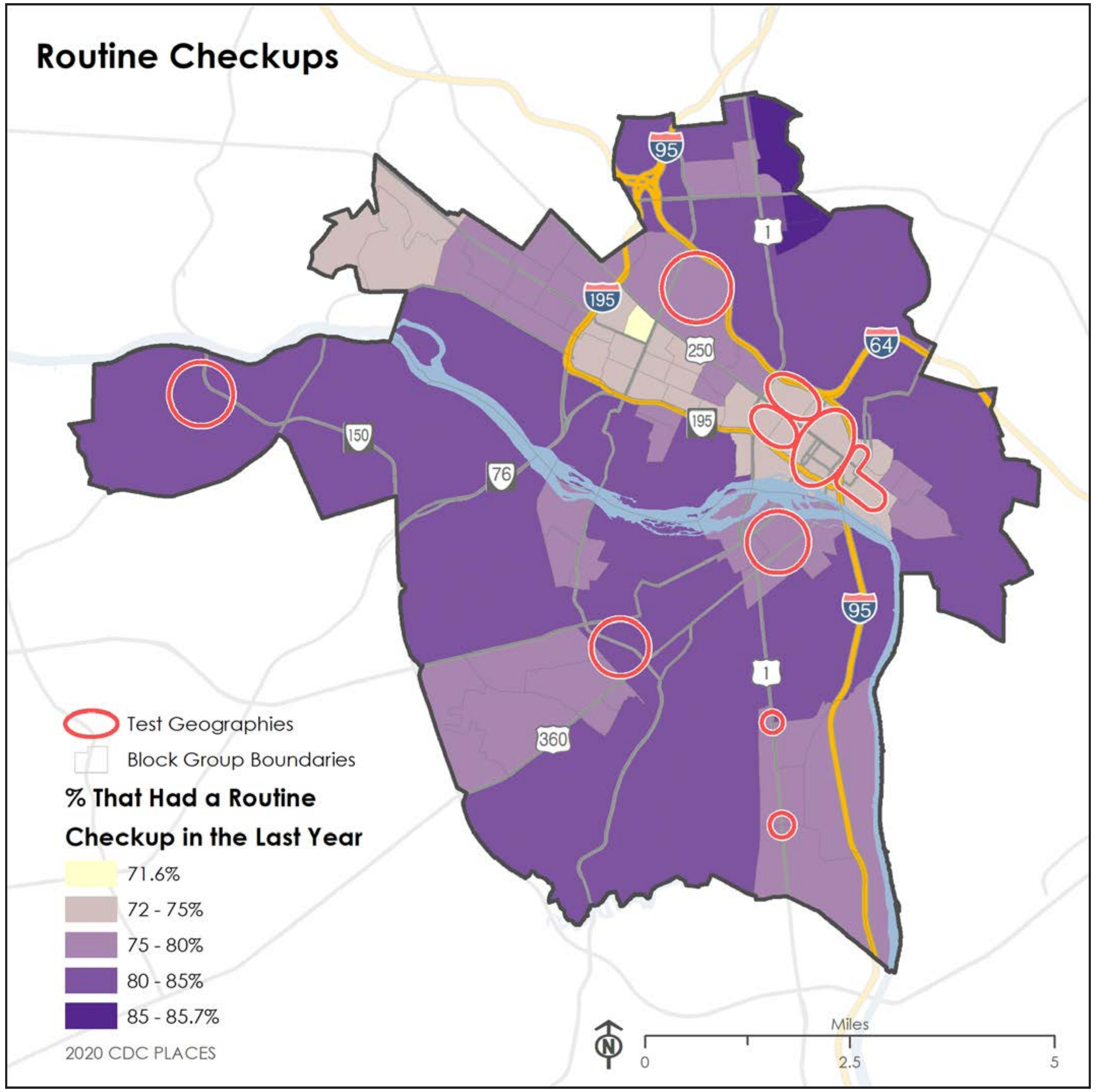


Figure 29: Older men aged ≥65 years who are up to date on a core set of clinical preventive services

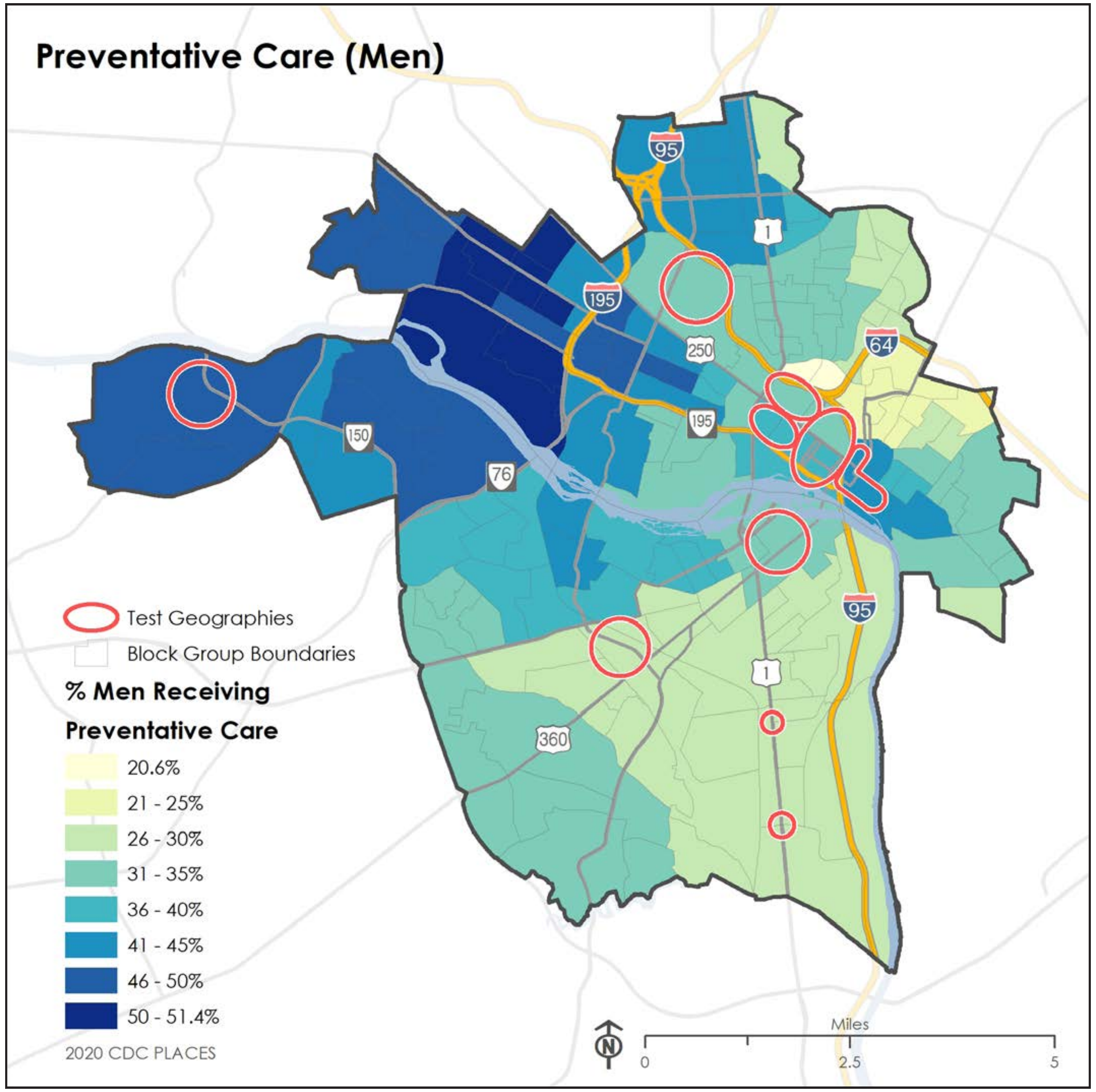


Figure 30: Older women aged ≥65 years who are up to date on a core set of clinical preventive services

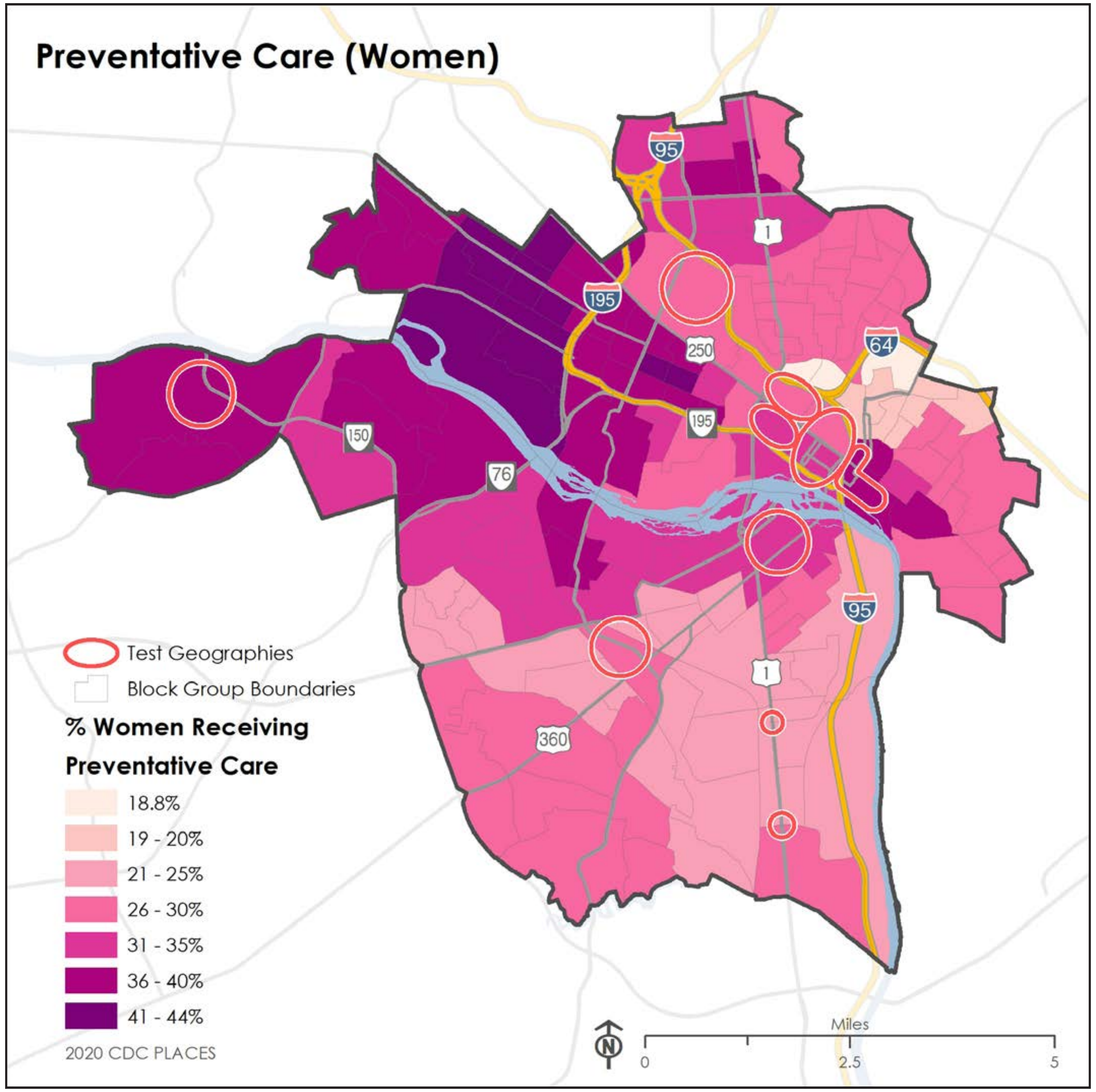


Figure 31: Current smoking among adults aged ≥18 years

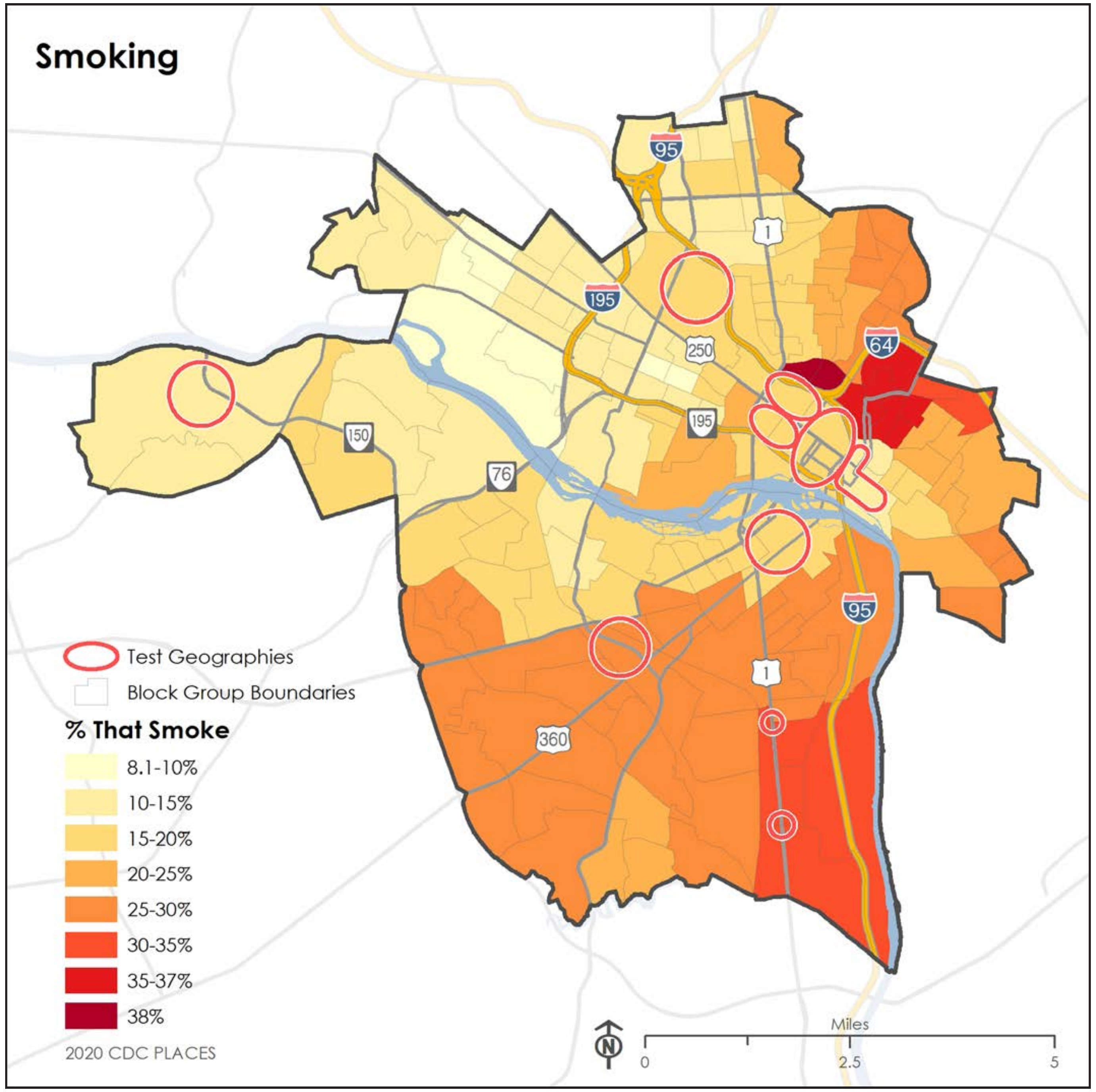


Figure 32: Current asthma prevalence among adults aged ≥18 years

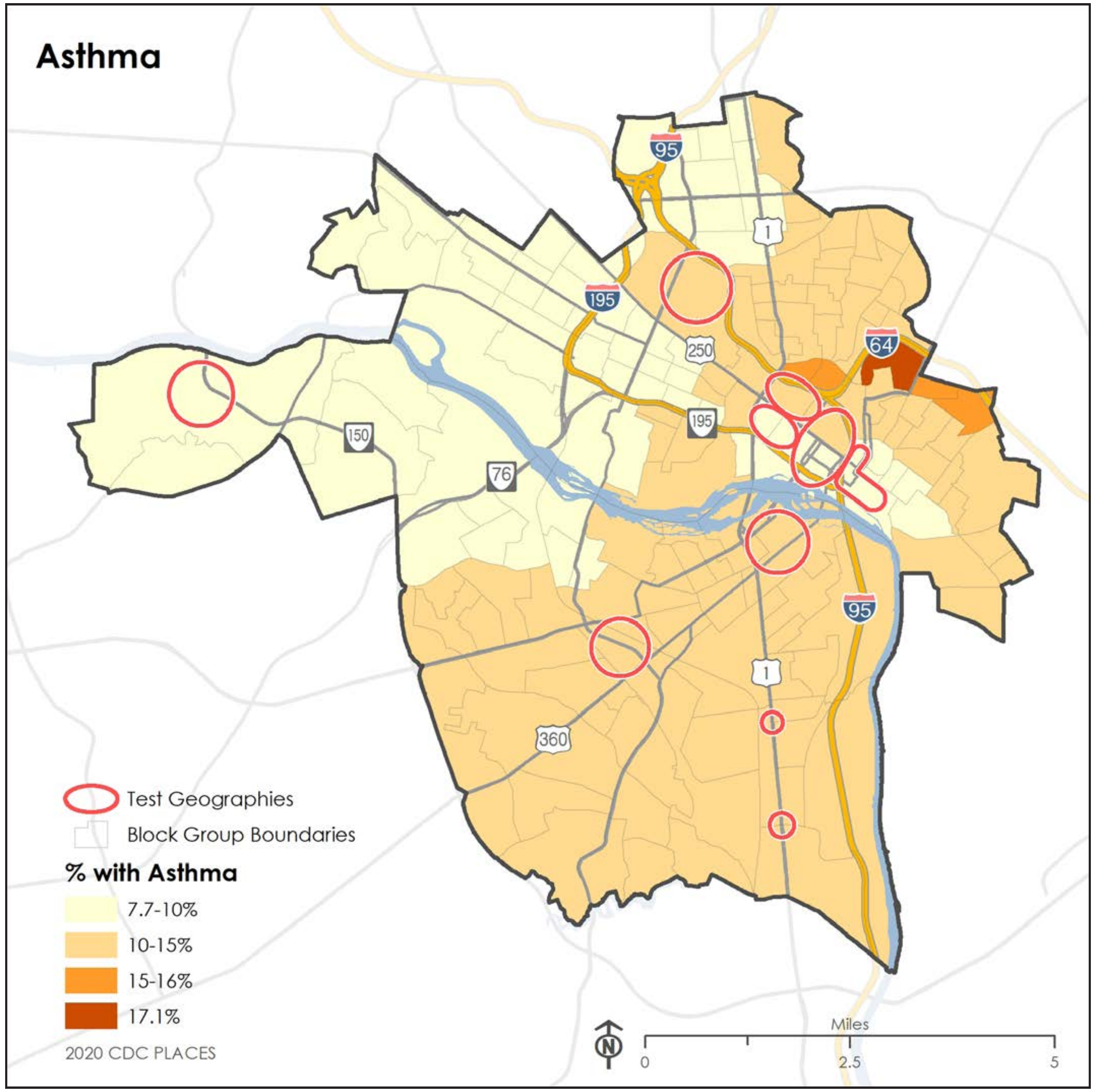


Figure 33: Chronic obstructive pulmonary disease among adults aged ≥18 years

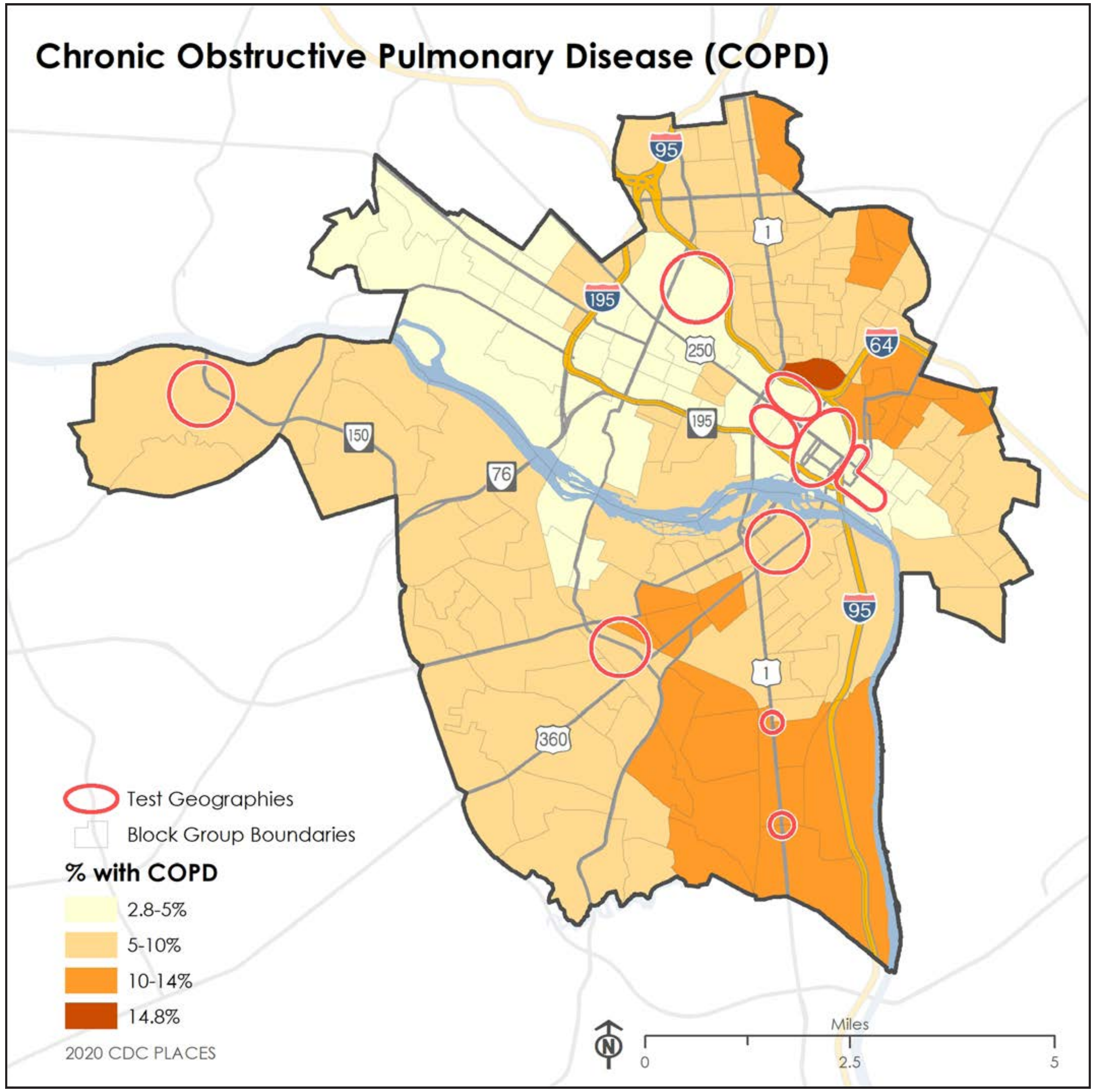


Figure 34: Sleeping less than 7 hours among adults aged ≥18 years

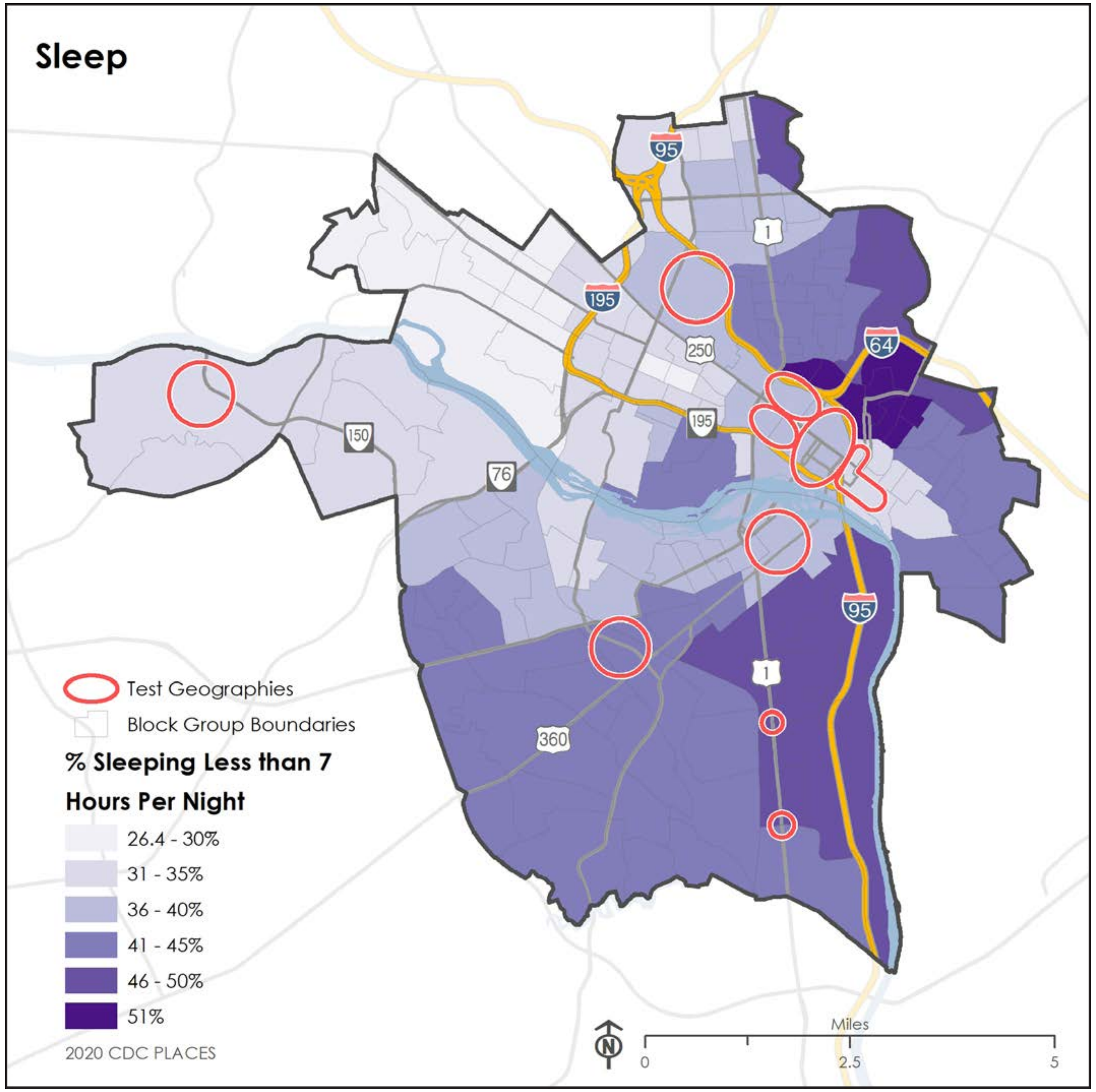


Figure 35: Mental health not good for ≥14 days among adults aged ≥18 years

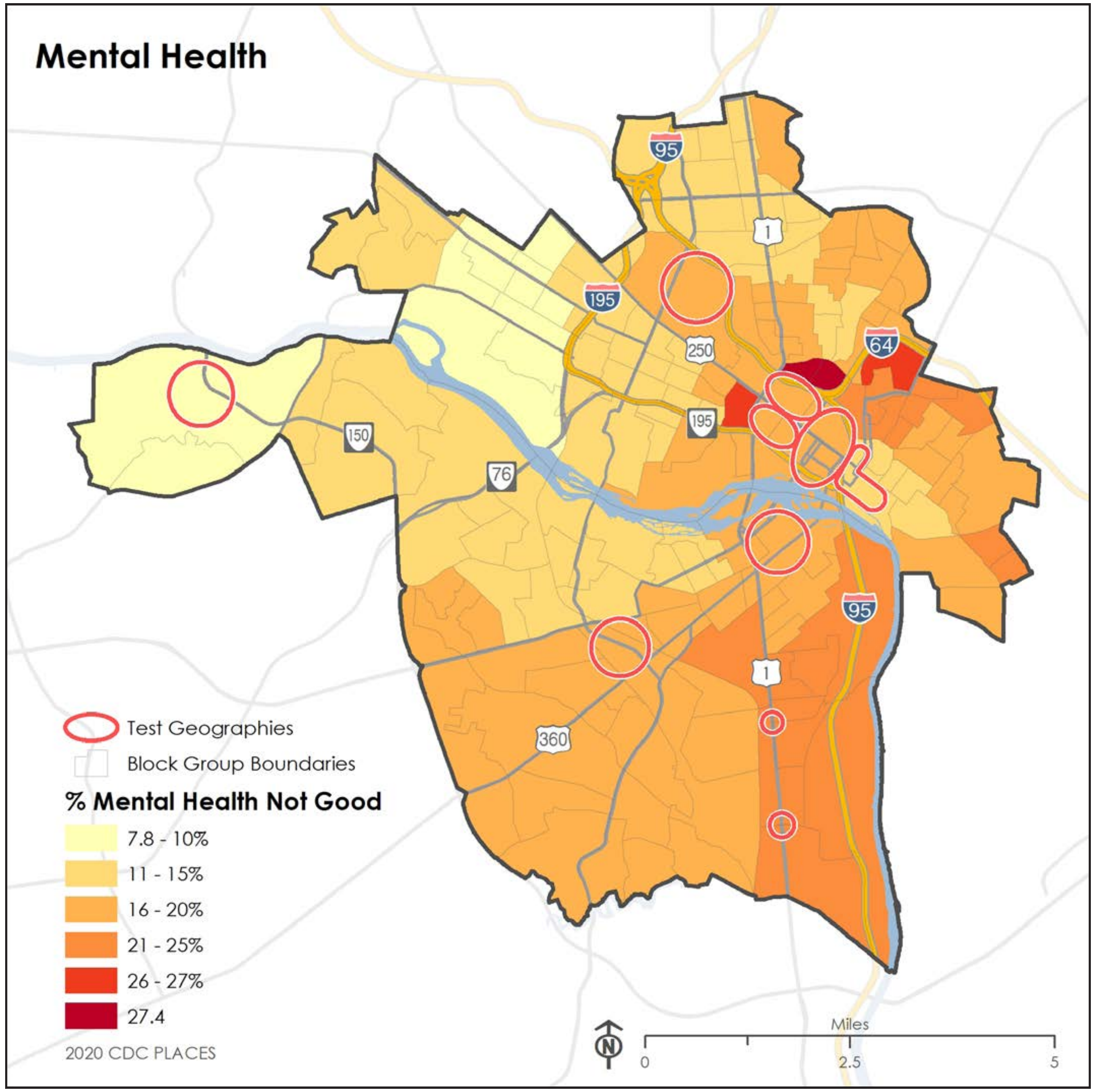


Figure 36: Visits to dentist or dental clinic among adults aged ≥18 years

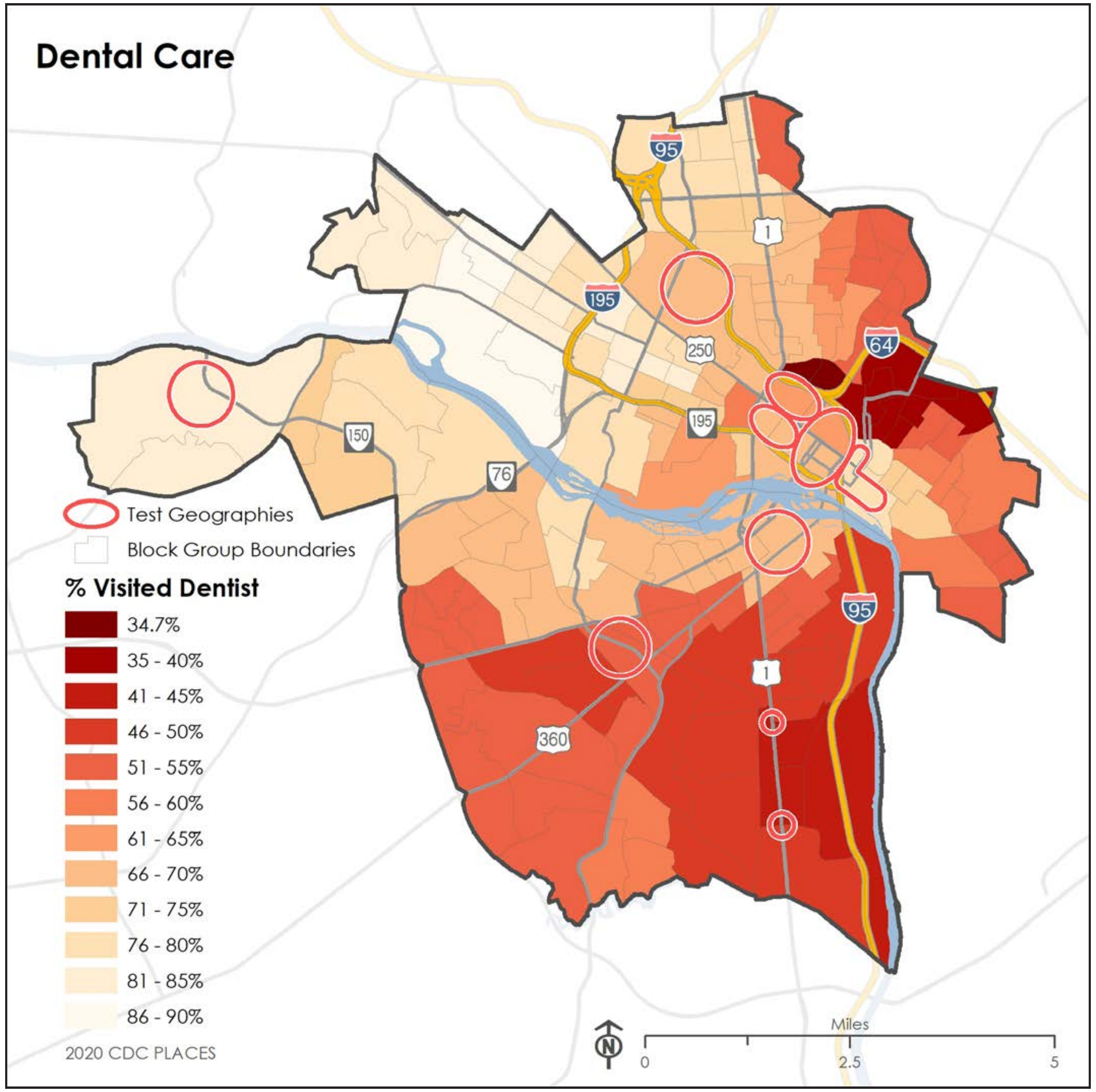


Figure 37: All teeth lost among adults aged ≥65 years

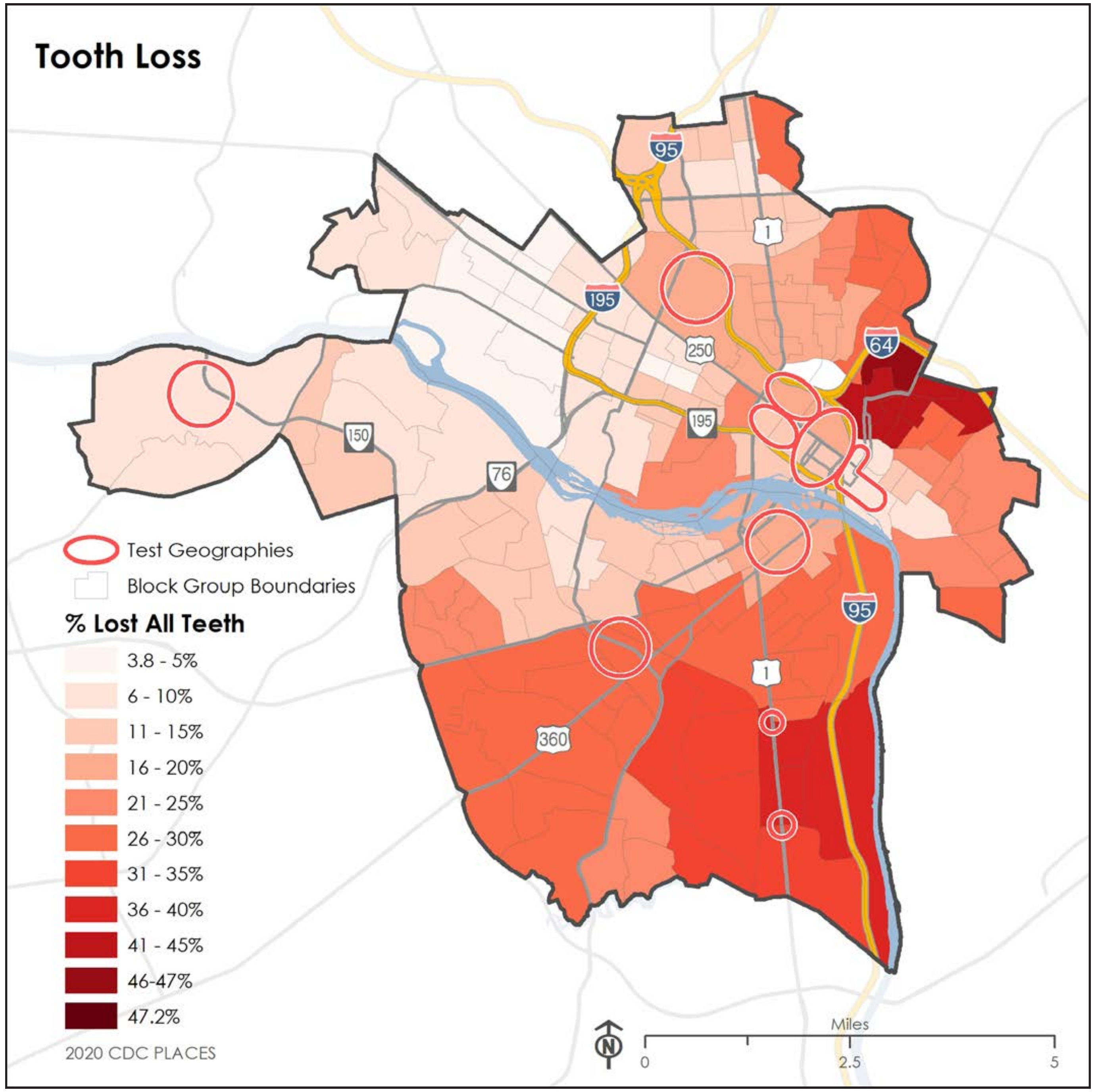


Figure 38: Physical health not good for ≥14 days among adults aged ≥18 years

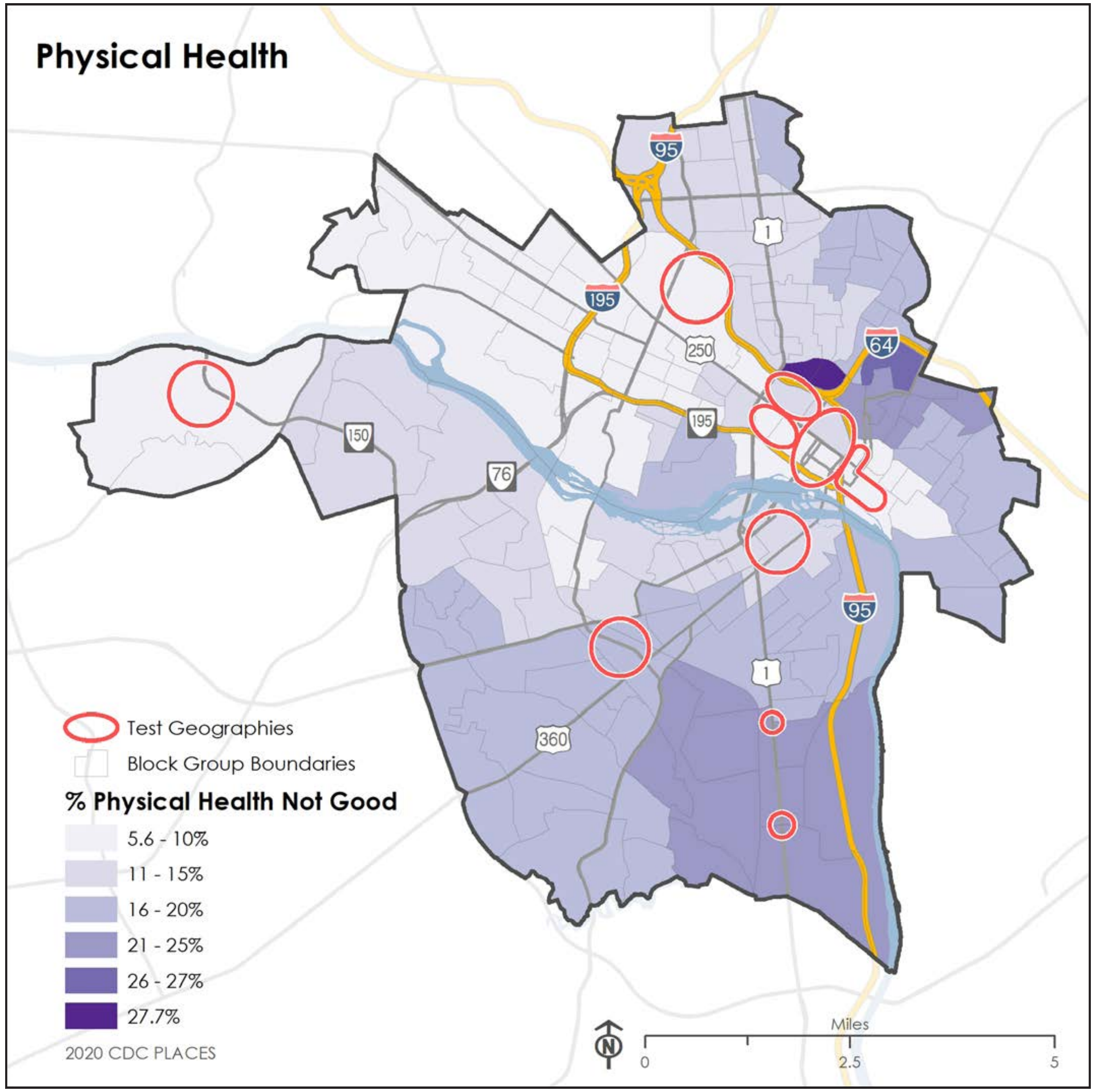


Figure 39: Obesity among adults aged ≥18 years

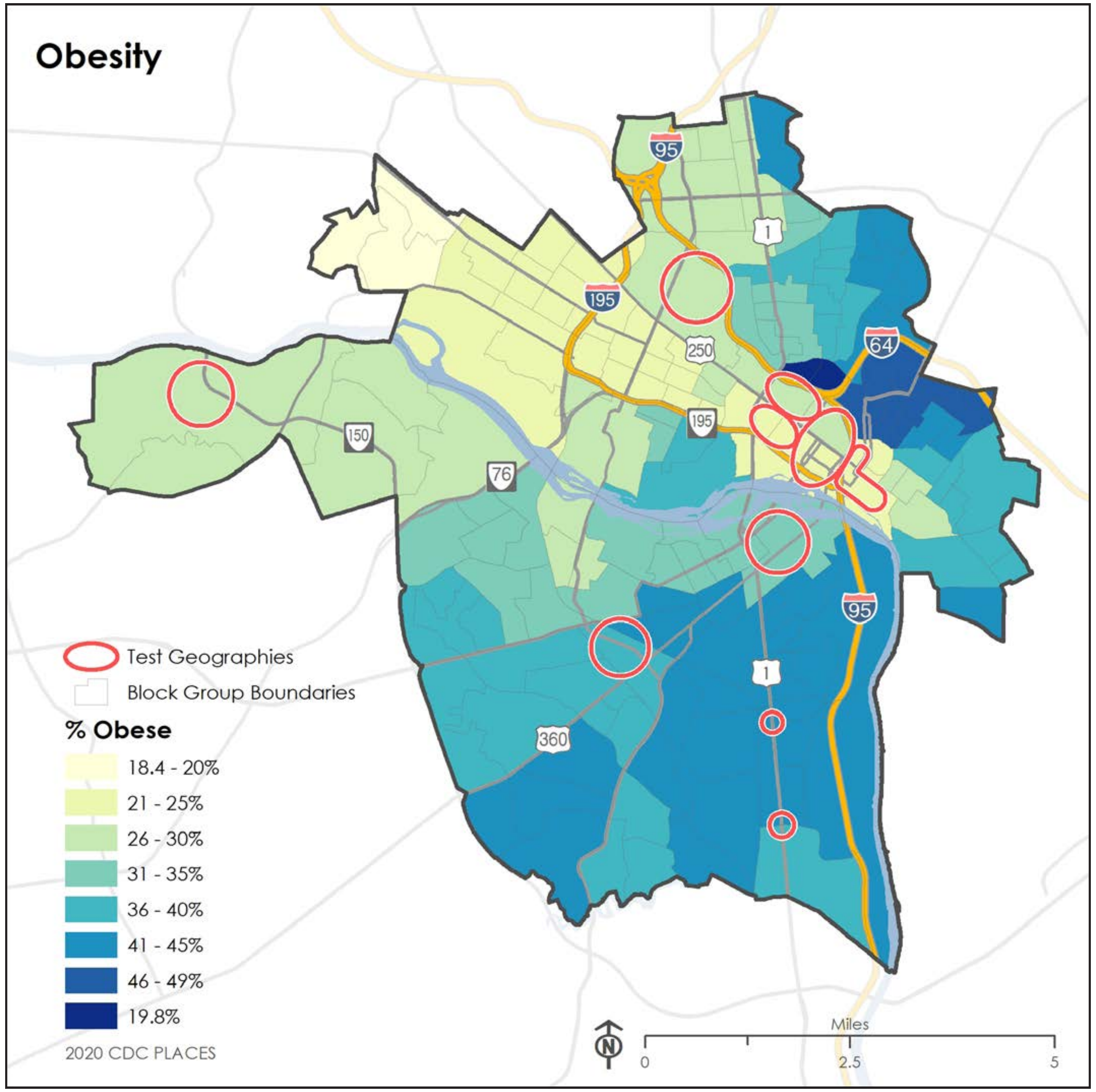


Figure 40: High blood pressure among adults aged ≥18 years

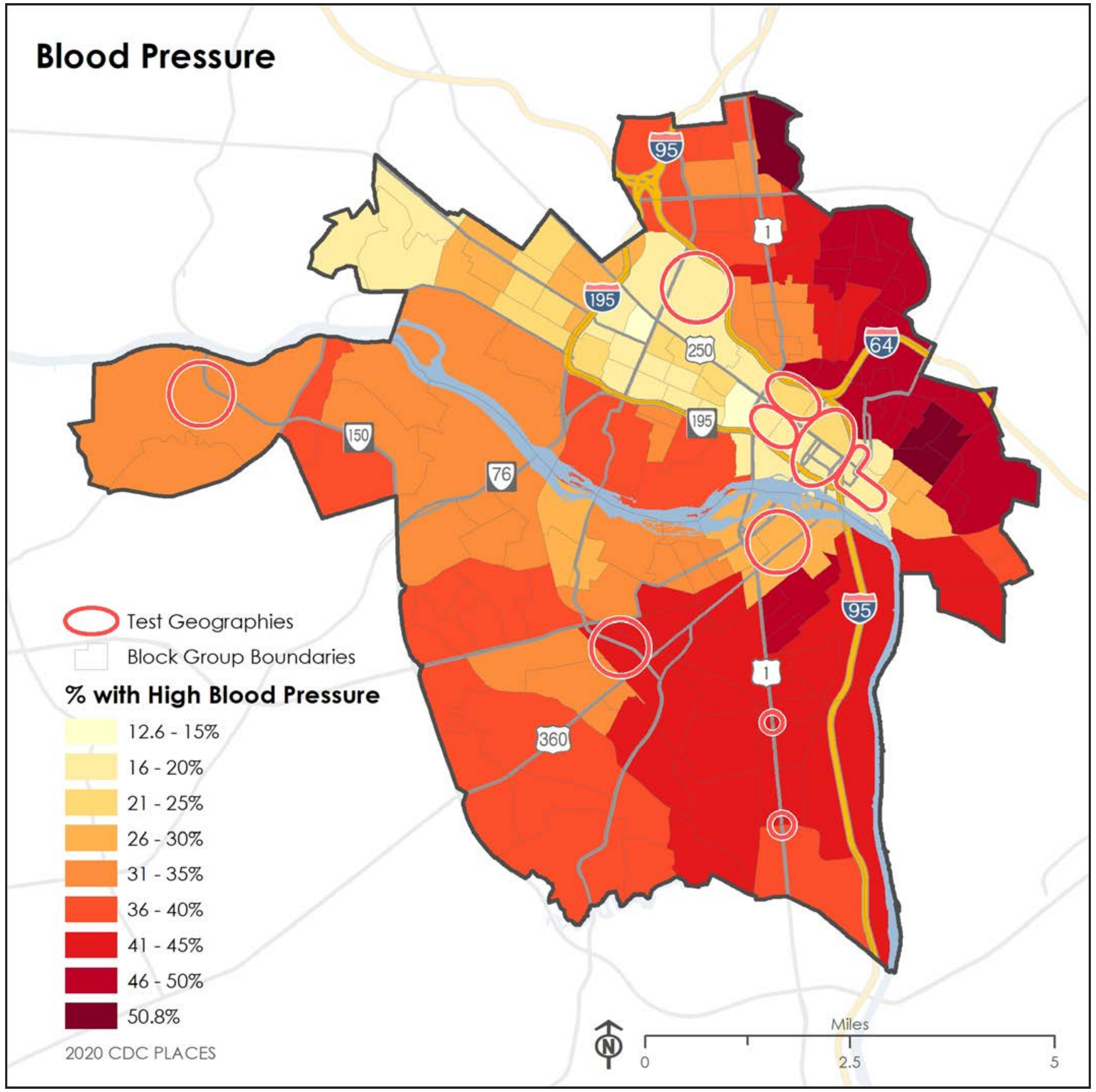
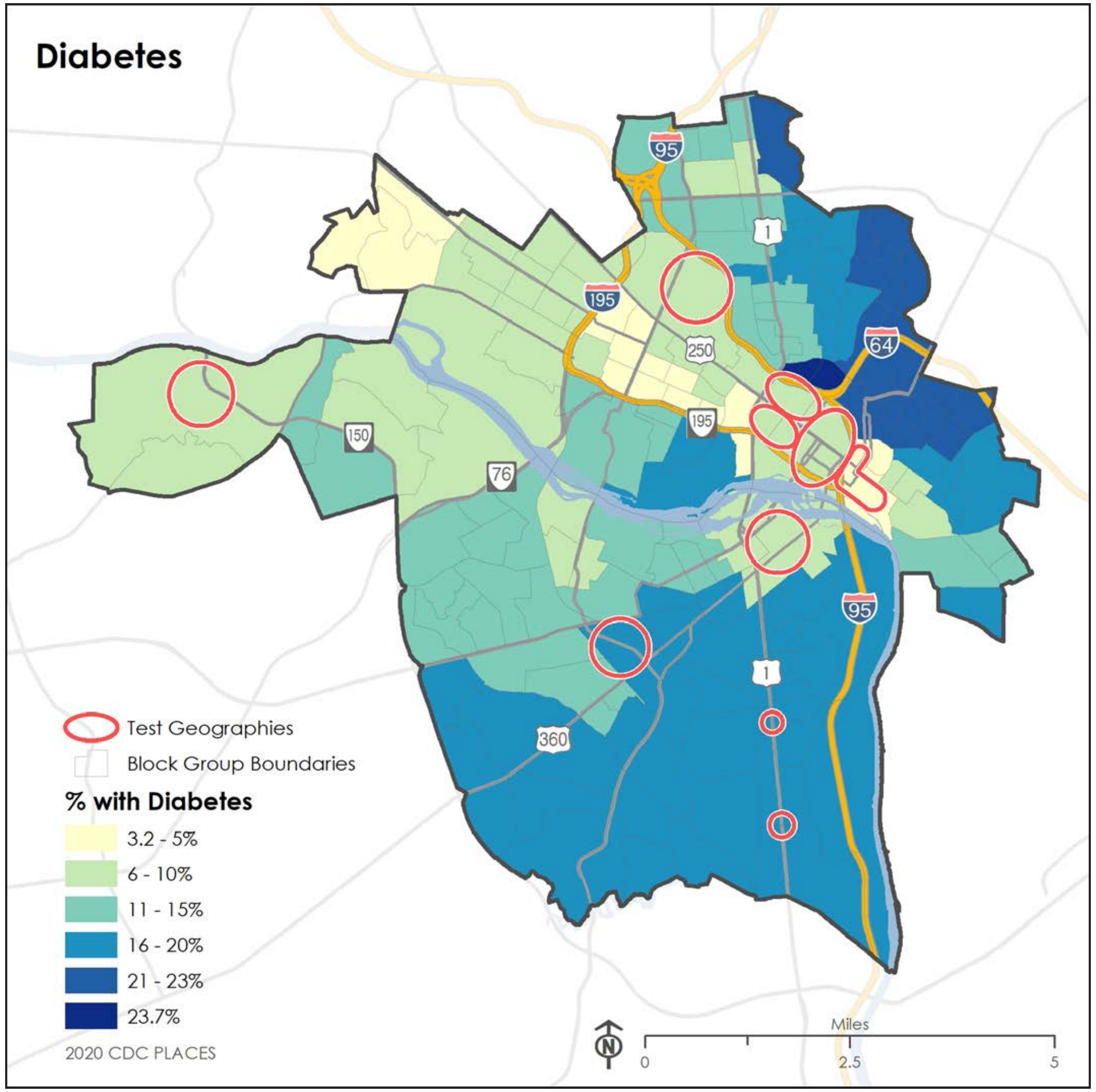


Figure 41: Diagnosed diabetes among adults aged ≥18 years



Process 2: VDH HOI Virginia Health Outcomes

Another public health metric local to Virginia is the Health Opportunity Index (HOI) also available at the tract geography. Unlike PLACES, the HOI indicators are aggregated from available public health and physical condition data and grouped into five overall profiles. These scores are not numeric, but binned into five classes, from high to low condition. Per the Virginia Department of Health (VDH) information site at What is the HOI? (https://apps.vdh.virginia.gov/omhhe/hoi/what-is-the-hoi), the four profiles that make up the HOI are:

1. Community Environmental:
   a. Air quality
   b. Population churning
   c. Population weighted density
   d. Walkability

2. Consumer Opportunity:
   a. Affordability
   b. Education
   c. Food accessibility
   d. Material deprivation

3. Economic Opportunity:
   a. Employment access
   b. Income inequality
   c. Job participation

4. Wellness Disparity:
   a. Access to care
   b. Segregation

The HOI is composed of these four metrics, weighted equally. These 13 variables are described at https://apps.vdh.virginia.gov/omhhe/hoi/what-is-the-hoi/definitions.

The VDH also offers the Youth Well-being Index (YWBI), which catalogs public health threats and assets for youth in particular. The YWBI is composed of fewer, but different, metrics than the HOI as follows:

1. Youth Well Being Index:
   a. Education Index
   b. Crime Indicator
   c. Family Stability Indicator
   d. Housing Indicator
   e. Population Density Indicator
   f. Poverty Indicator
   g. Pre-K Enrollment Indicator
   h. Primary Care Access Indicator
   i. Psychiatrist Access Indicator

Process 2 Methodology

The following steps are needed to import the HOI data for use.

a. **Download:** to download the data visit VDH Heath Districts (https://apps.vdh.virginia.gov/omhhe/hoi/dashboards/health-districts) and see the "A Closer Look" section of the page, at the bottom. In the upper right, select one of five HOI profiles. To the left of the map, select the district of study (in this case Richmond), and the Tableau map will recenter on the selected district. To download data from this interface, click on the download icon in the lower right corner of the Tableau map. Select "Crosstab" to download and "Summary" to download the data as a Comma-Separated Value (CSV) text file. Repeat this selection for each of the five profiles to download all the HOI profiles. To download the YWBI profiles, visit the Youth Well-being Index (https://apps.vdh.virginia.gov/omhhe/hoi/youth-well-being-index) dashboard).
b. **Importing data to GIS:** Geographically, the data are available at the tract geography, but are reported at the vertices of tract by this download method. This data is sorted by class bin, Very Low to Very High. Two steps are necessary to import the VDH profiles into GIS
c. **Editing the profile CSV in Excel:** Open the CSV profile data downloaded in step a,
d. **Changing the Ctfips from numeric to text:** To enable a join in GIS, the tract identifier ("ctfips") needs to be text, not numeric. To the right of the rightmost column in the CSV, in a blank row, fill every cell row with a RIGHT or LEFT excel function selecting the 11 characters in the Tract-level Geo ID. In row A of that column, type "GeoID" for the join to GIS
e. **Recoding profile values to numeric:** The CSV is sorted by profile score. To enable numeric display and calculation in GIS, recode the profile scores in a new column. The profile scores are found in column D of the CSV. Fill the next column to the right of GeoID from step d. with "Very Low" to 1, "Low" to 2, "Average" to 3, "High" to 4, and "Very High" to 5. This can be done with 5 fills, as the CSV is already sorted by profile score. In row A of that column, type the name of the profile for the join to GIS
f. **Save the CSV:** After adding the GeoID and numeric profile scores in two new columns, save the CSV file.
g. **Join data to tract geography:** In ArcMap, join the CSV to a census tract polygon shapefile for your study area in ArcMap using the GeoID column from this CSV to join with the GeoID in the tract shapefile attributes. These HOI or VWBI profile are now associated as attributes with the tracts in your study area.

Process 2 Results

The VDH HOI data are each aggregates of several public health, demographic, and economic factors affecting different aspects of public health outcomes. They are less focused than the PLACES data. They also have different spatial outcomes than the PLACES data, which look more similar in their distributions of poor versus good outcomes across the city of Richmond. The HOI data are better as standalone indicators of public or economic health than the PLACES data. As aggregate measures, they lack the precision that the PLACES data provides.

The Health Opportunity Index (HOI) is scored from Very Low to Very high based on four other metrics, each surveyed at the 2010 Census tract geography. The geographic pattern of the HOI is different from the typical pattern of the places data, as the surveyed data input to the HOI and the following VDH datasets was different than the PLACES data. Figure 42 depicts the health opportunity index.

Community Opportunity- which includes air quality, population churning, population weighted density, and walkability- does not score any of the tracts in Richmond as Very Low or Low, which is why this map only has three values shown. The best conditions in Richmond for this metric are in northeast Richmond. Figure 43 depicts community opportunity.

Consumer Opportunity includes affordability, education, food accessibility, and material deprivation. The arrangement of this data is distinct from Community Opportunity above, with the best conditions found in the West End and western South Side. As with Community opportunity and the PLACES data, the Broad Street corridor is distinct as a higher quality area. Figure 44 depicts the economic opportunity index. Figure 44 depicts the consumer opportunity index.

Economic Opportunity includes employment access, income inequality, and job participation. Unlike the previous two Indices, most of Richmond's tracts are Very Low for the Economic Opportunity Index. There is a distinct east/west divide in this geography that is not evident in the other HOI indices or in the PLACES data. The Broad Street Corridor is not distinct in this data. Figure 45 depicts the economic opportunity index.

Wellness includes access to care and segregation. This is one of the most heterogeneous datasets in Richmond. Overall conditions are worse in the west than they are in the east, opposite of the pattern for economic opportunity. Figure 46 depicts wellness.

Youth Well-Being includes education, crime, family stability, housing, population density, poverty indicator, pre-k enrollment, primary care access, and psychiatrist access. Figure 47 depicts youth well-being.

Figure 42: Health Opportunity Index

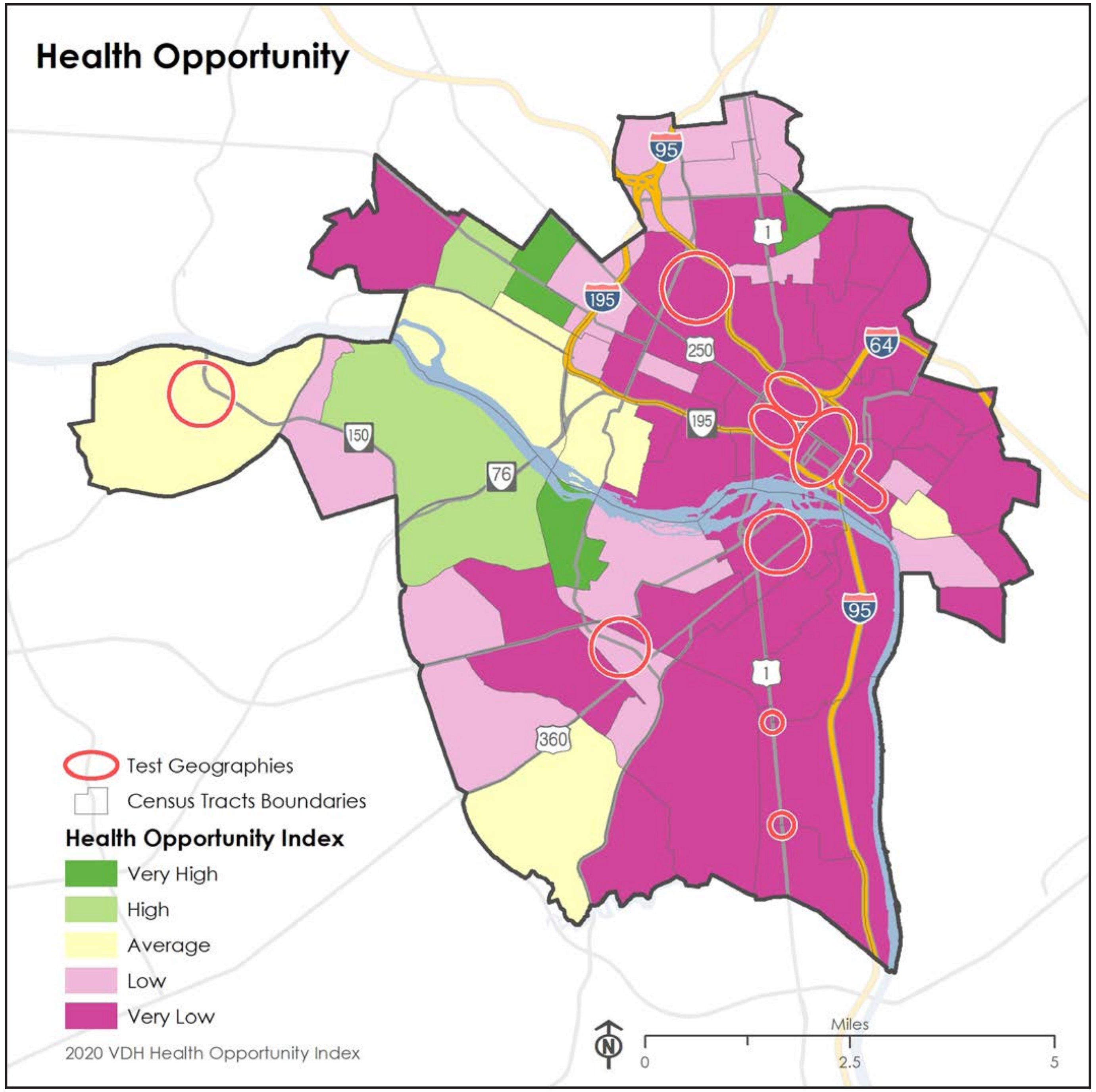


Figure 43: Community Opportunity Index

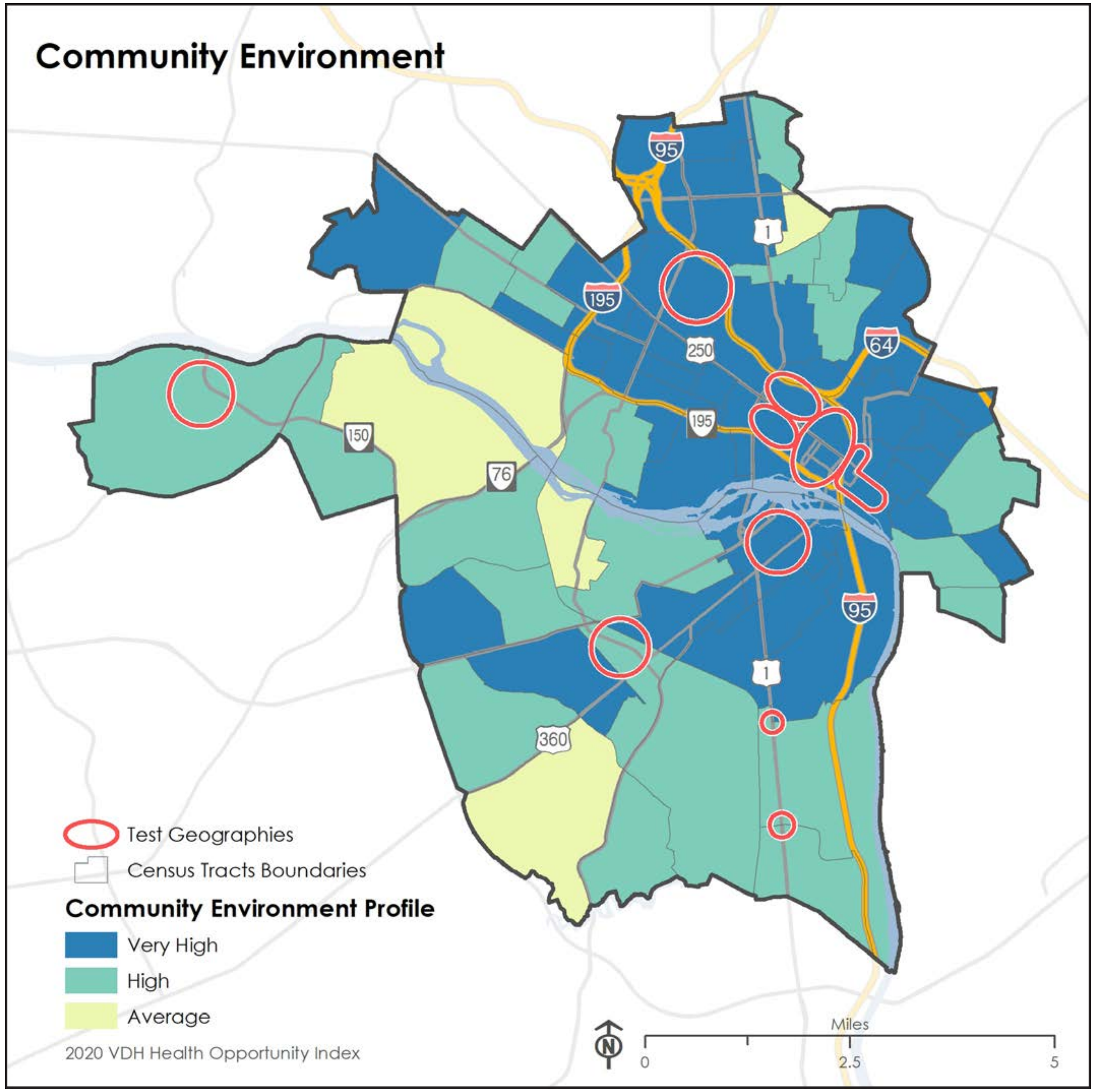


Figure 44: Consumer Opportunity Index

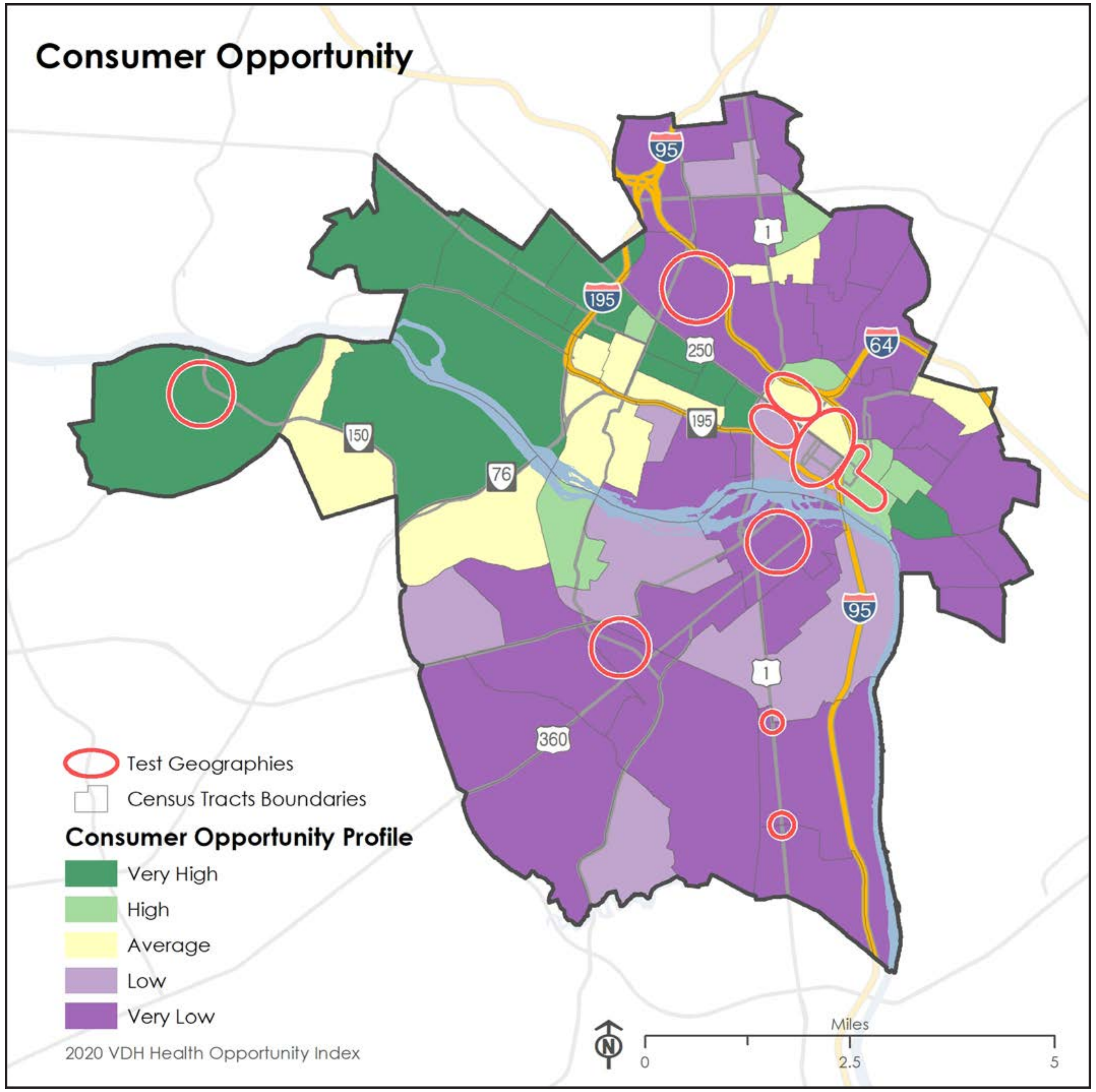


Figure 45: Economic Opportunity Index

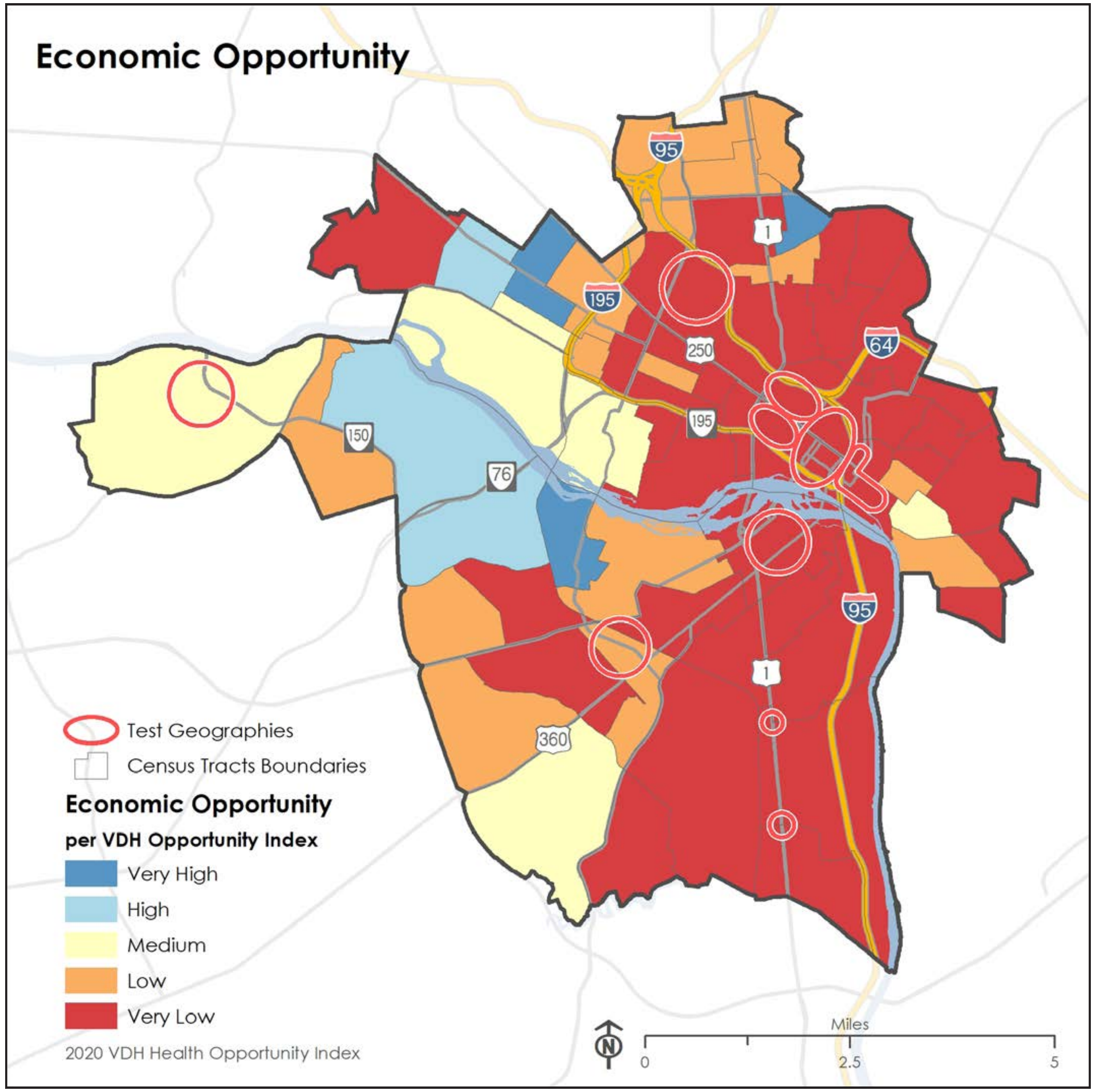


Figure 46: Wellness Index

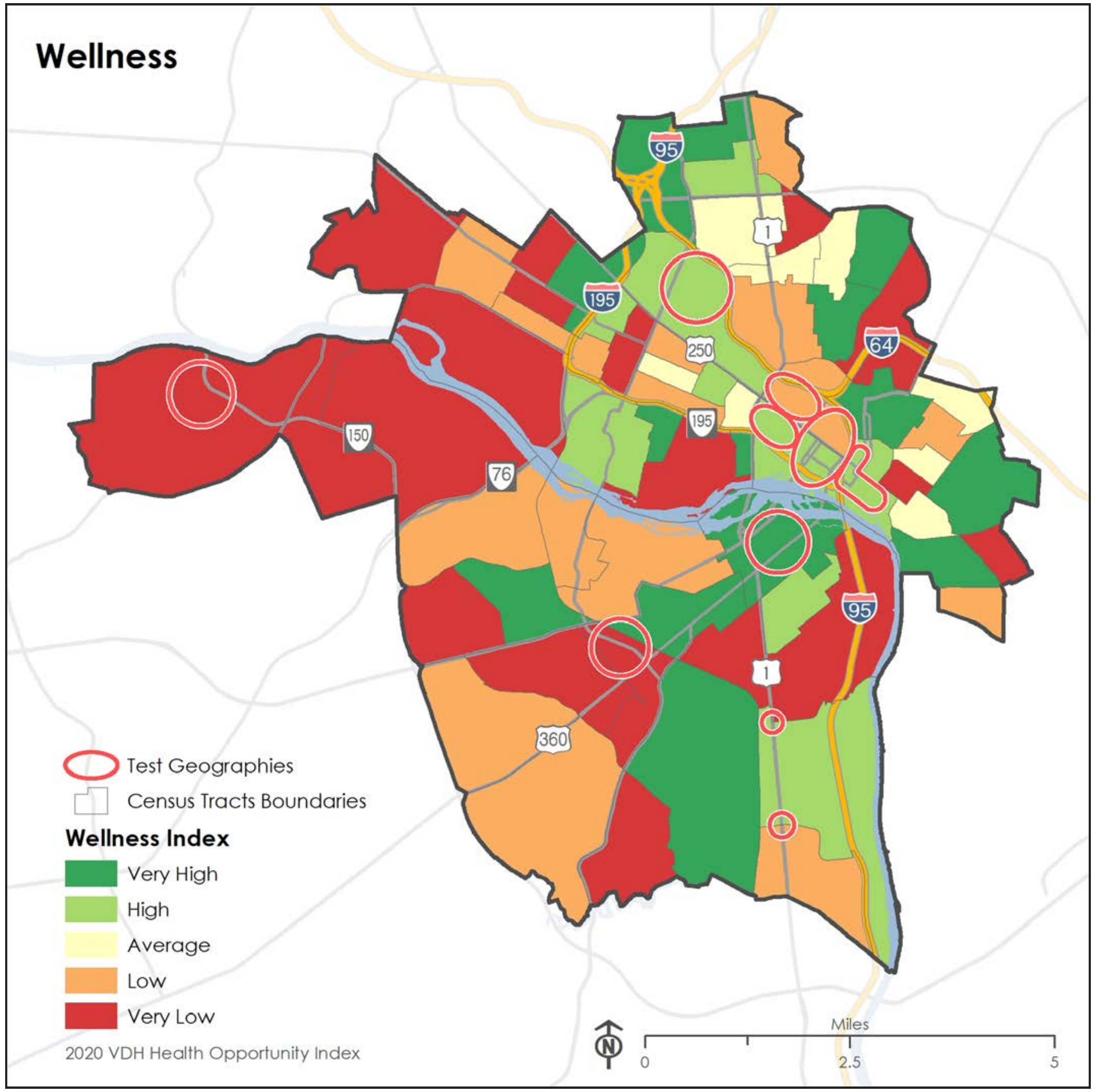
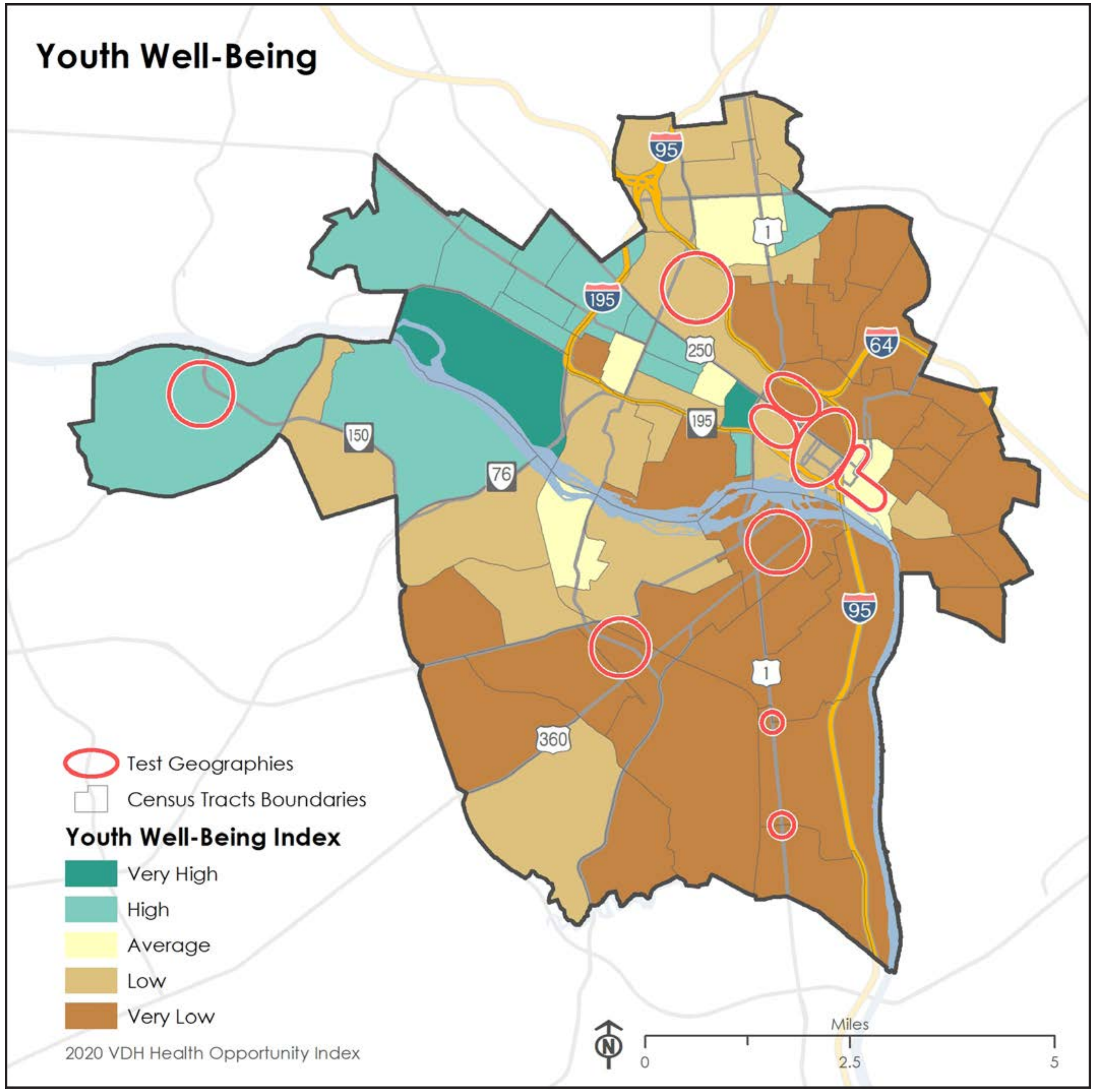


Figure 47: Youth Well-Being Index



Process 3: Household Income Patterns

The American Community Survey (ACS) provides data on household income at the block group geography for income, reported for the 2015-2019 survey period. The ACS survey of Household income for B19001 is counted over 60 monthly surveys, each of a different 0.02% sample of the block group households. This statistic is not exact as a result, but it does allow general comparisons between block groups across Richmond. To protect residential anonymity, the ACS groups household incomes into bands, and does not calculate a median income for each block group. It is possible to approximate a median income from this data

Process 3 Methodology

The following steps are needed to import the HOI data for use.

a. **Download:** Download the table B19001 Household income at the block group geography. This can be downloaded as a CSV from https://data.census.gov/ (https://data.census.gov/cedsci/). This portal can specify study geography, such as Richmond City, VA, block group scale, and download term. As of this document the latest ACS output for this datasets is 2015-2019.
b. **B19001 Approximation of median household income:** This block group data comes as total numbers of households and households grouped by income band, indicating how much households made in the 12 months preceding the ACS survey, as follows:
    a. <10k
    b. 10-15k
    c. 15-20k
    d. 20-25k
    e. 25-30k
    f. 30-35k
    g. 35-40k
    h. 40-45k
    i. 45-50k
    j. 50-60k
    k. 60-75k
    l. 75-100k
    m. 100-125k
    n. 125-150k
    o. 150-200k
    p. >200k

   With no more information than these income groupings and their population of households, the following steps will indicate how to approximate median household income and Gini index for the block groups in Richmond.
c. Open the CSV in Excel
d. **Calculate the proportion of Income for each household income group:** Assume the median income of each household income group in B19001 is the average of the high and low bounds of that group, for the household group with a reported income below $10,000, assume a median household income of $7,500. For the household group with a reported income above $200,000, assume a median household income of $210,000.
e. In the 16 columns to the right of the data, multiply the household numbers in each grouping by the median income of that group. Fill the cells for all the block groups in the study area to calculate the proportion of populations for households in every block group.
f. In the next 16 columns to the right of the cells just calculated, divide the income for each household income group by the total incomes of all household income groups. Fill the cells for all the block groups in the study area to calculate the proportion of populations for households in every block group.
g. **Calculate the proportion of households for each household income group:** In the next 16 columns to the right of the cells just calculated, divide the household numbers in each grouping by the total number of households in each block group. Fill the cells for all the block groups in the study area to calculate the proportion of households in each household income group in every block group.
h. **Calculate the proportion of households that are more affluent for each household income group:** In the next 16 columns to the right of the cells just calculated, sum the household numbers from the original data. For the first household income group, earning less than $10k, sum all household except the first group. For the next group, earning between $10k and $15k, sum all but the first two groups. Continue summing household numbers **more affluent** than each group through the richest group, earning above $200k. Zero households should be **more affluent** than the rightmost group. Fill the cells for all the block groups in the study area to calculate the sum of households that are **more affluent** for every household income group in every block group.
i. In the next 16 columns to the right of the cells just calculated, divide the number of households that are **more affluent** than each household group by the total number of households, to calculate the share of households that are **more affluent** than each group. Fill the cells for all the block groups in the study area to calculate the proportion of households that are **more affluent** for every household income group in every block group.
j. **Determine the rough median household income:** In the next 16 columns to the right of the cells just calculated, use a conditional IF statement and logical AND in Excel to query if the proportion of **more affluent** households is less than 0.5 and proportion of **more affluent** households is greater than 0.5 in the next lowest household income group. If a household income group meets these conditions, use the IF statement to flag it in the Excel spreadsheet. Fill the cells for all the block groups in the study area to flag the median household income groups in every block group.
k. In the next single column of the excel spreadsheet, note the flagged household income group from the step above and note the median income for that income group as assumed in **step d** above. These median incomes are the rough estimates of median income in every block group.
l. **Determine the Gini coefficient of income inequality:** In the next 16 columns to the right of the cells just calculated, for each household income group. Multiply the proportion of **more affluent** households from **steps h and i** by two. Multiply that product by the proportion of total households from **step g**. Multiply that product by the proportion of income, from **steps d through f**. Fill the cells for all the block groups in the study area to calculate the scores for the 16 household income groups.
m. In the next column, sum the 16 cells for each block group to calculate the aggregate score.
n. In the next column, subtract the aggregate score from 1 to calculate the Gini index for each block group.

Process 3 Results

Consistent with the PLACES data, there are distinct differences between prosperous northwest Richmond and less prosperous south and northeast Richmond. The Broad Street Corridor is not distinctly more prosperous than its neighboring block groups to the north and south. Figure 48 depicts median household income.

The income inequality within each block group shows the highest income inequality downtown, in the West End, and on the campus of University of Richmond. While there are some block groups with high household incomes and high GINI indices, there are also others, especially downtown, with the opposite relationship. Figure 49 depicts income inequality.

Figure 48: Median Household Income

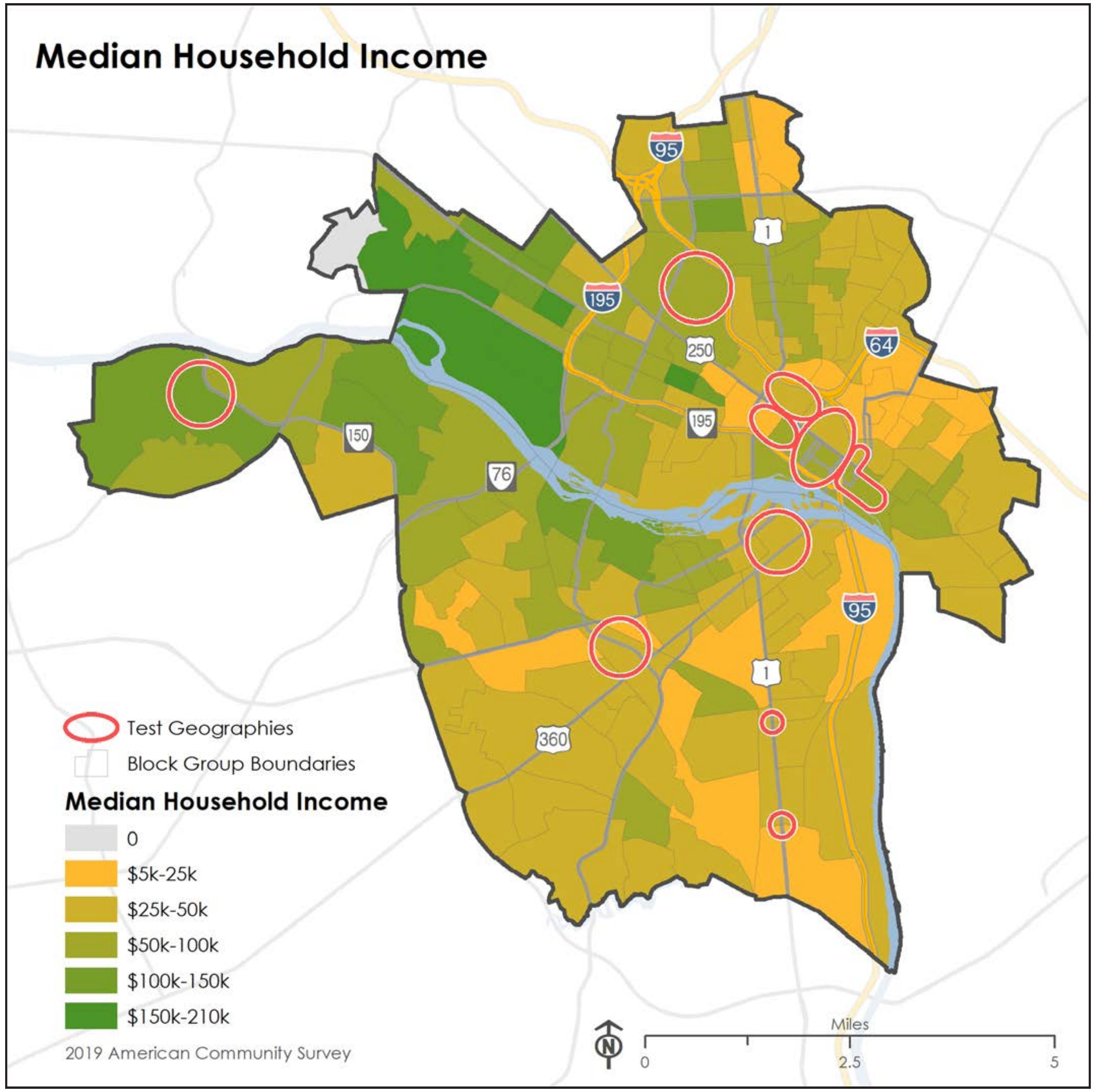
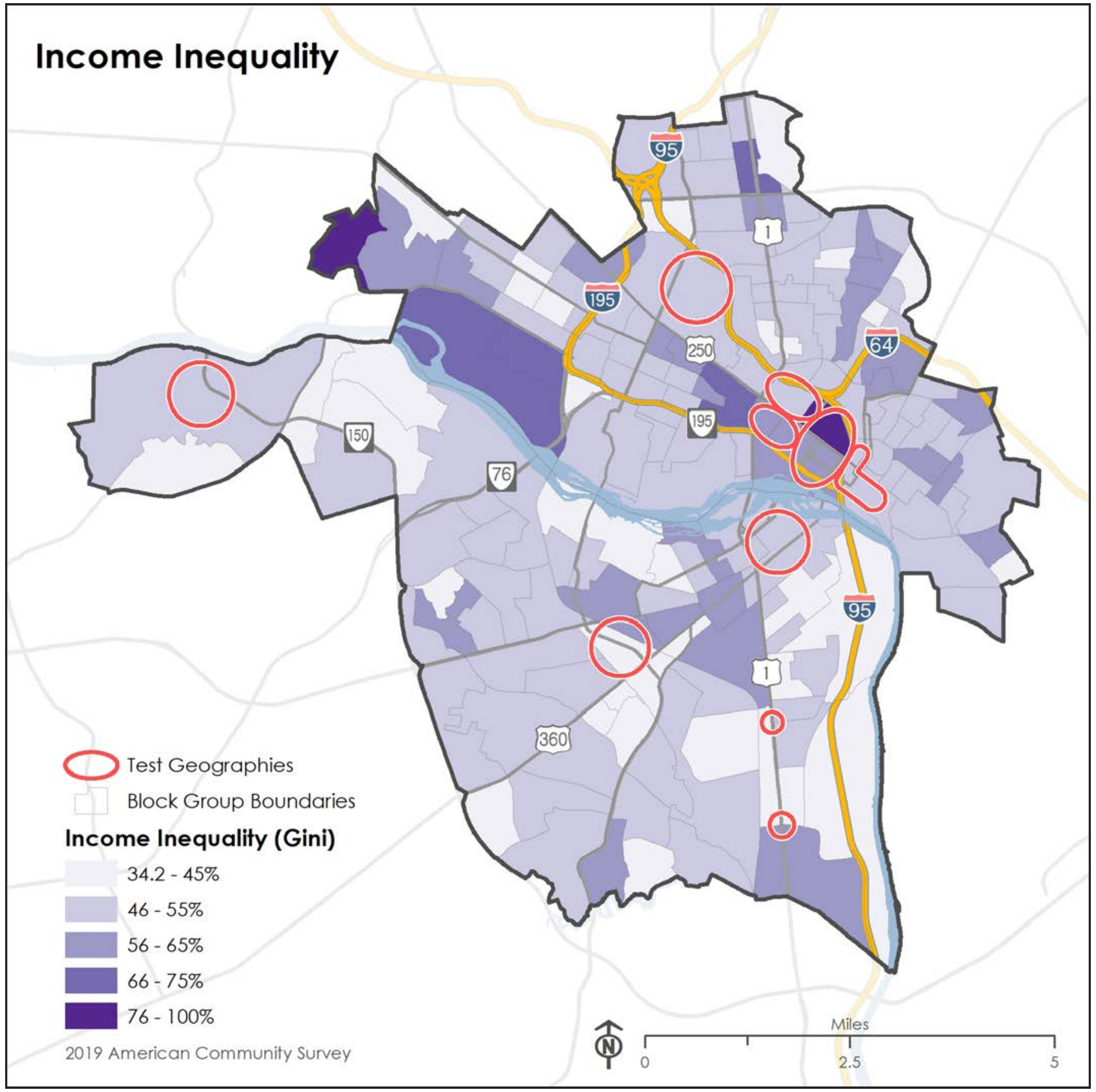


Figure 49: Income Inequality



Process 4: Residential Multimodal Commute patterns

The American Community Survey (ACS) provides data on the commute to work. Commute mode choice and time to commute is relevant to accessibility and job access for populations within Richmond. Walk and bike commutes are of particular interest to the study of equitable access within Richmond, because the scale of the average census tract is similar to the scale of the average bike trip (3 miles), while the scale of the average census block group is like the average walk trip (less than a mile). Unfortunately, the ACS does not yet provide information on bike commute times, but it does provide information on walk commute times. There are not enough bike commutes in most places to allow disclosure of this information for bike commutes.

Process 4 Methodology

The following steps are needed to import the HOI data for use.

a. **Download:** There are two ACS data outputs that can be used for this study at the block group geography: B08301 Means of transportation to work and B08134 Means of Transportation to work x Commute time. Both can be downloaded as CSVs from https://data.census.gov/ (https://data.census.gov/cedsci/). This portal can specify study geography, such as Richmond City, VA, block group scale, and download term. As of this document the latest ACS output for these two datasets is 2015-2019.
b. **B08301 Means of transportation to work:** This provides estimates of commute modes used by the residents of each block group to reach their workplaces, including total commuters, commuters in traffic, carpools, transit, bicycle, walk, and home. The data provided by the ACS is sampled over five years, so the 90% margin of error is provided next to each estimate. For mapping and modeling purposes it is sufficient to use the estimates for each mode. For a study of equitable access, walking and biking commutes are most important as they are the most affordable.
c. **B08134 Commute mode x time to work:** Commute mode by time in commute is not geographically informative for faster modes like traffic or transit, but it is informative for walking commutes. Commuting times are surveyed and reported in 5-minute bins. Given that average walking speed is 3 Miles per Hour (MPH), a 10-minute walk should be a half a mile, while a 15-minute walk would be ¾ mile. This travel distance will vary by route choice and impediments, such as crosswalks or differing sidewalk quality. It remains useful to model walking commutes as moving an average speed of 3 MPH, to understand the range of destinations reachable from the edges or center of each block group. As the ACS only reports commute data at the block group geography, it is not possible to know specific routes or locations of worker residence or workplace locations.

Process 4 Results

The distribution of walk commuting by residents within the 161 block groups of Richmond is sporadic and does not cover all of Richmond. There are many block groups within Richmond that have no residents who walk to work at all. The areas with the highest walk commuting are near downtown, with a high concentration of jobs, and university campuses, where students can and do walk to classes.

Most of Richmond does not commute by walking, indicated by the blank block groups shown in Figure 50. There is a stronger tendency to walk to work in the Broad Street Corridor, with built up commercial and residential density. The highest proportion of walking commuters is on the University of Richmond campus.

Commuting by bike is less common in Richmond than commuting by walk. The Broad Street corridor has some block groups with a bike commute share greater than 10%. Southside Plaza has the highest percentage of bike commutes. Figure 51 depicts bike commutes.

Combining walk and bike commute shares produces a map of active commuters by residential block group. Because walking is more prevalent than biking in active commutes, this looks more like the walking commuter distribution than the biking map, as shown in Figure 52.

To take a close look at walking commutes, Figure 53 shows the distribution of walk commute times for all block groups in Richmond with a walking commute share over 10%. The size of the pie charts over each block group varies with proportion of walking commute. A typical commuter can walk a mile in 20 minutes, The distributions on the pie charts shows that most walk commutes are less than a mile (20 minutes). 50% of the walk commutes on the University of Richmond campus are less than half a mile. The exception Is the one block group in south Richmond with 75% of its walk commutes a mile away, and 25% 2-3 miles away.

Figure 50: Walk Commute

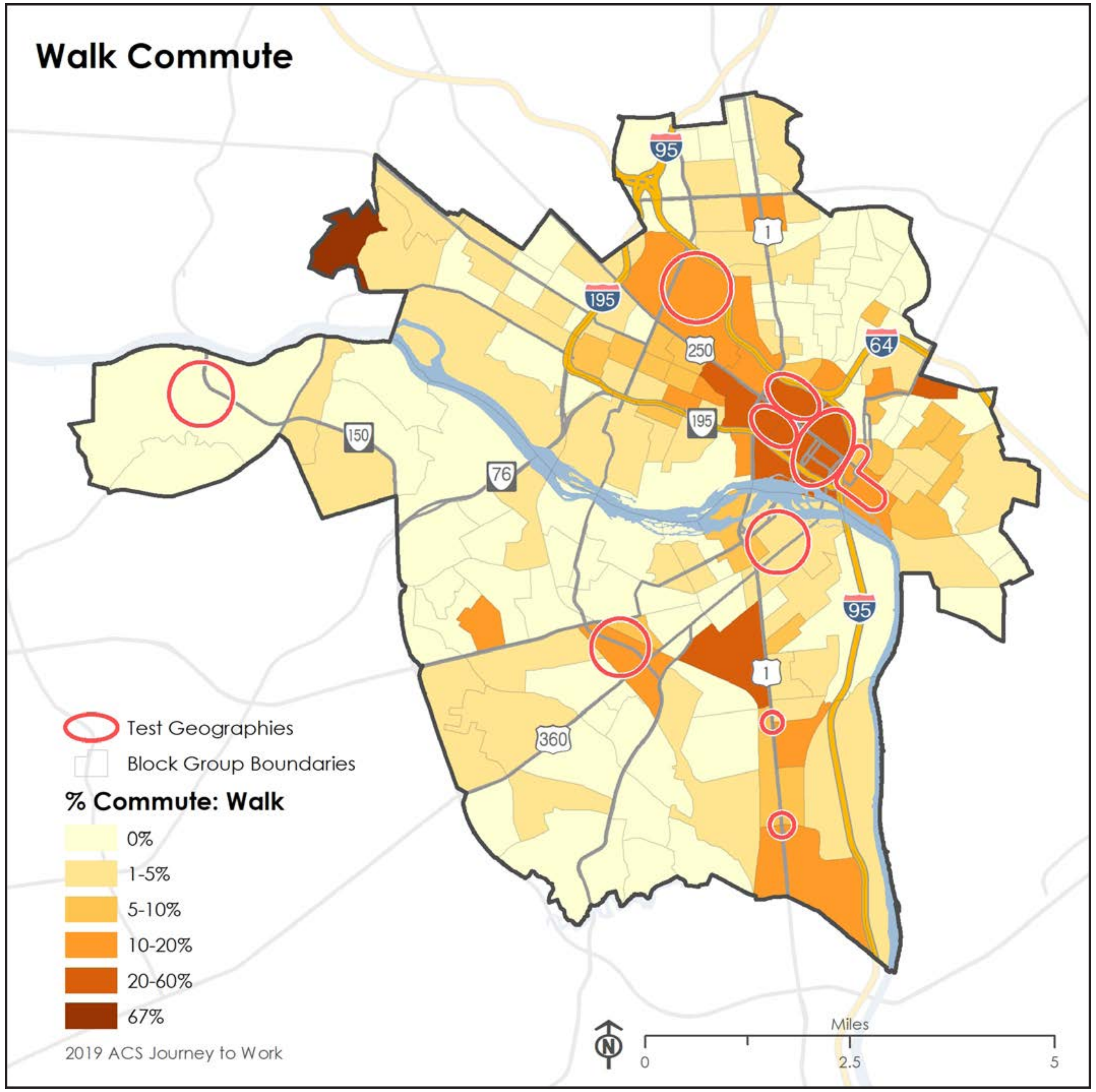


Figure 51: Bike Commute

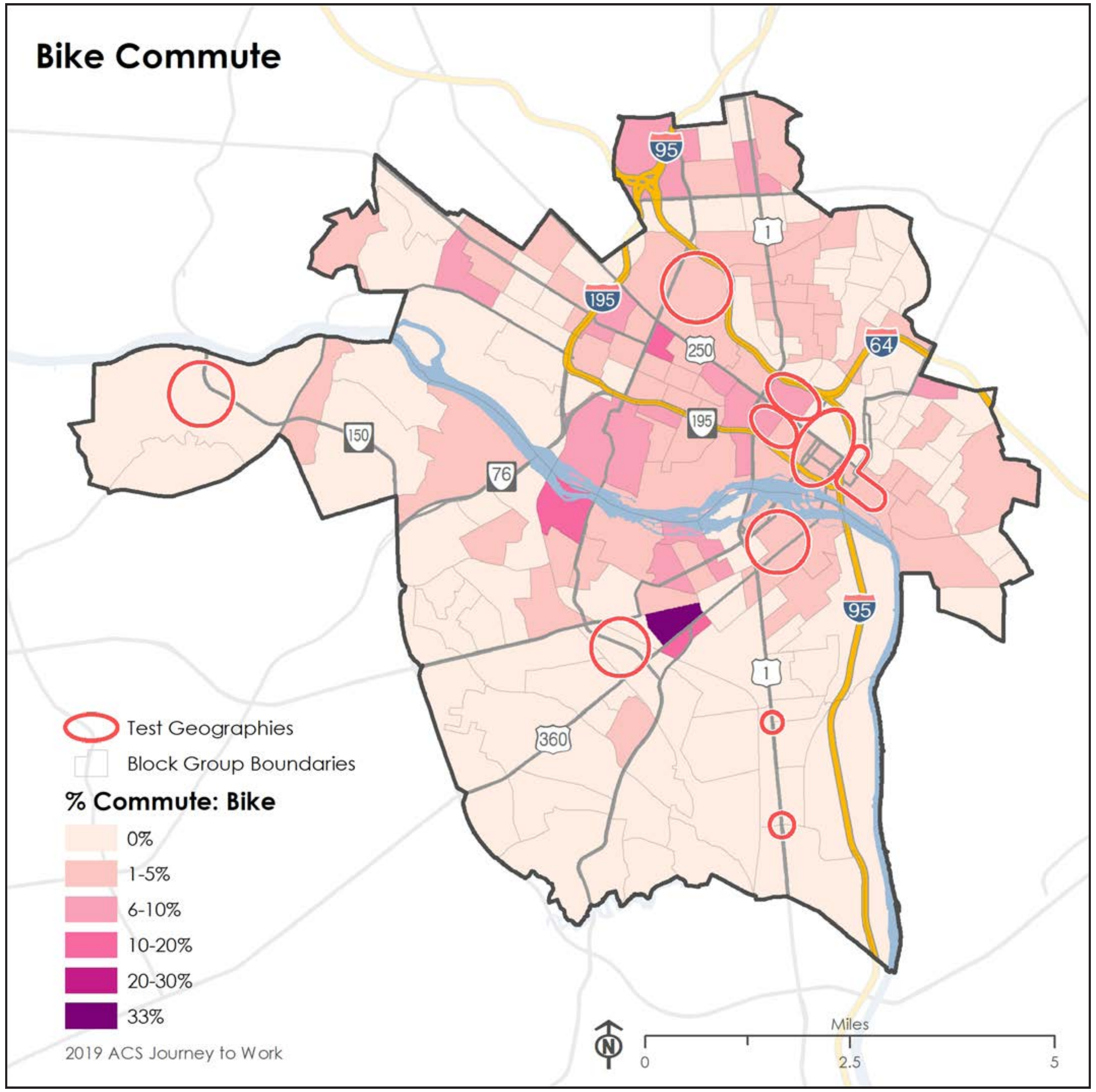


Figure 52: Walk and Bike Commute

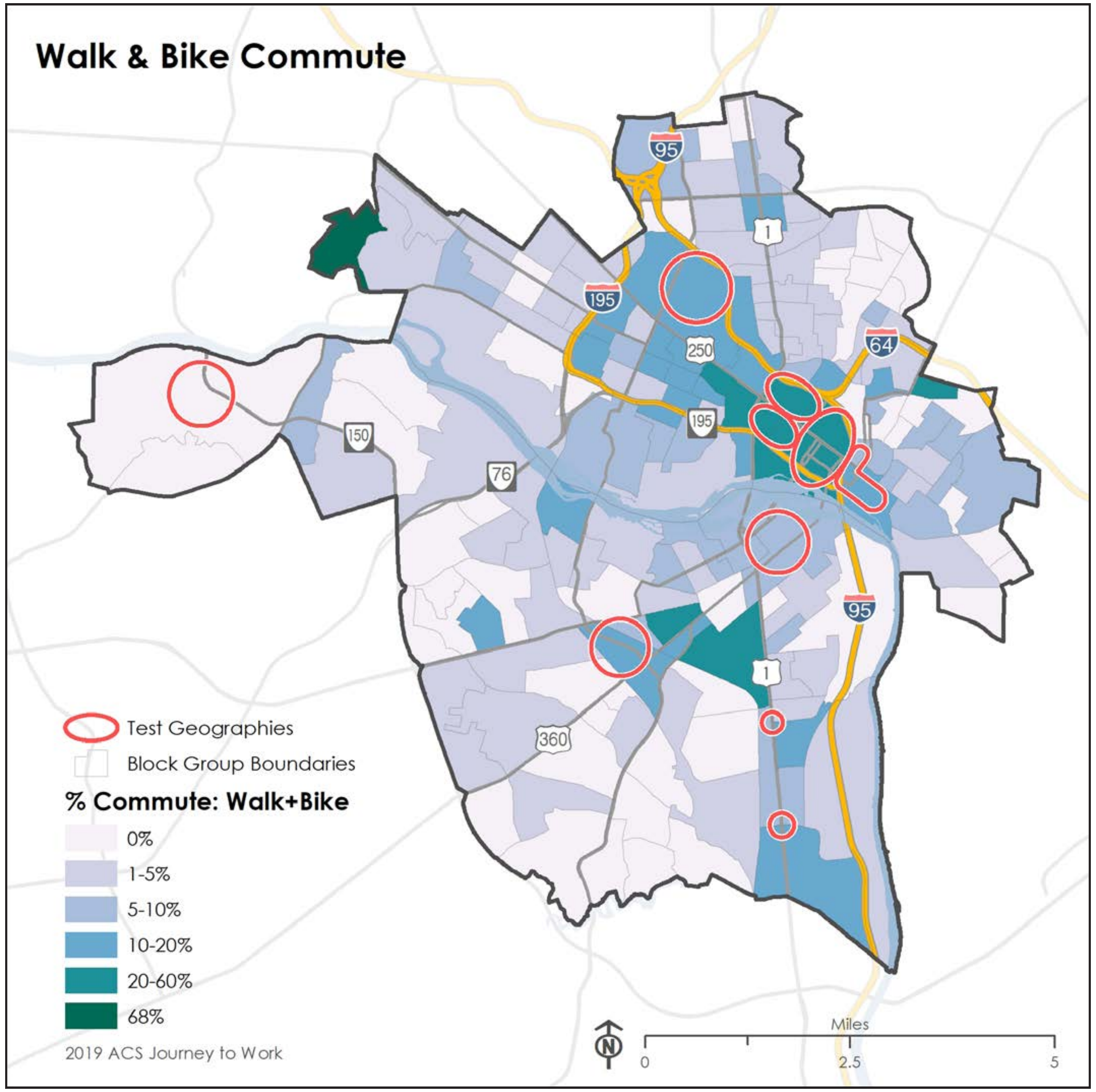
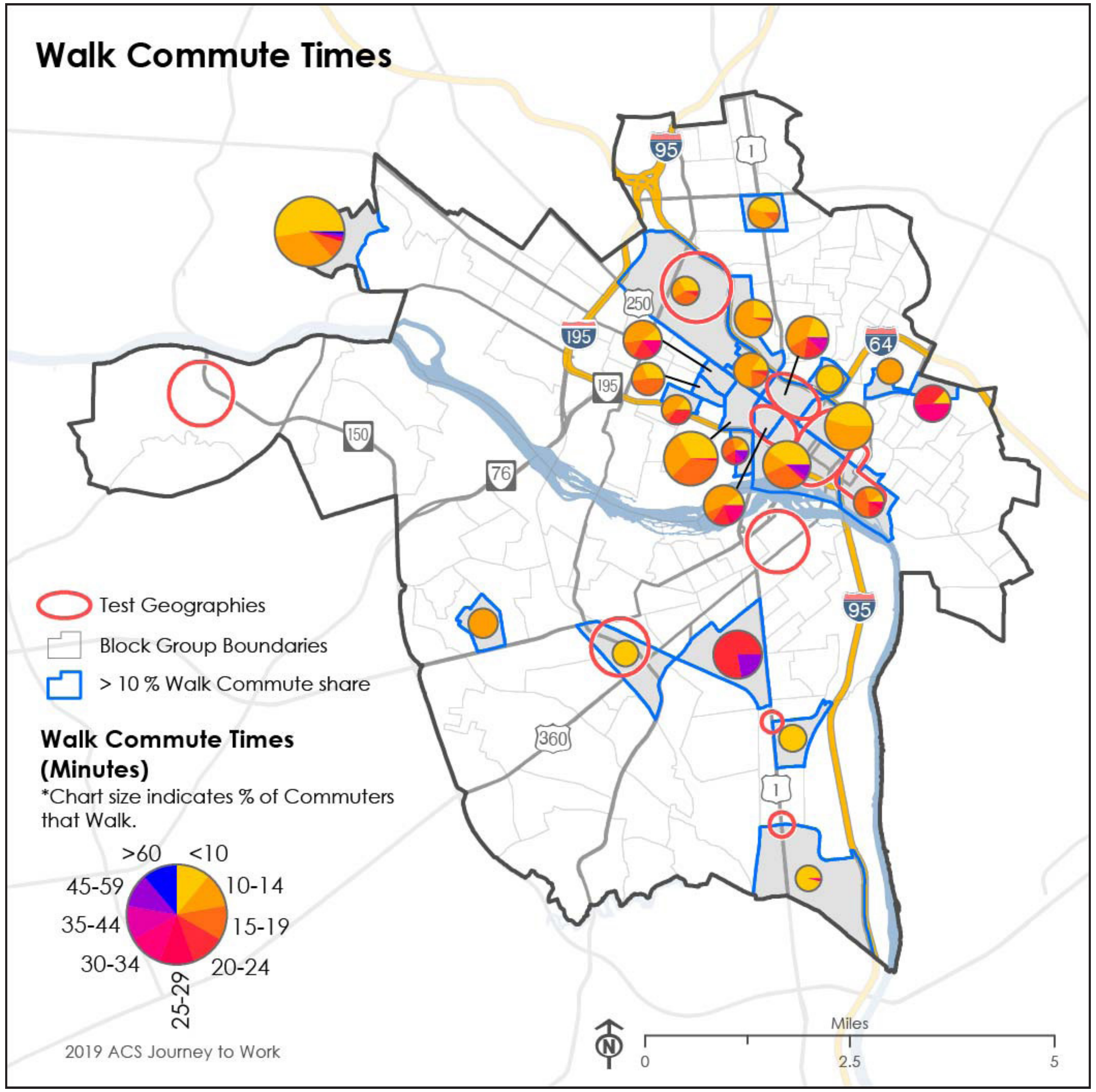


Figure 53: Walk Commute Times



Process 5: Development Activity Density

The Smart Location Database (SLD) was first published by the Environmental Protection Agency (EPA) Office of Smart Growth in 2011 and has since been updated using 2018 data from the ACS, National Employment-Household Dynamics (NEHD), and other sources. It is available for download as nationwide geodatabase of attributed block groups from https://www.epa.gov/smartgrowth/smart-location-mapping#SLD

Process 5 Methodology

a. Download: The SLD is available from https://www.epa.gov/smartgrowth/smart-location-mapping#SLD as a national coverage geodatabase of 2010 block groups with all SLD attributes associated with each block

Process 5 Results

Vehicles Per Household: While some block groups do not have any households without cars, there are fewer than for walking and biking commutes. The University of Richmond campus may not be one of those block groups, considering how many commutes are by biking or walking. 84.3% of Gilpin households do not have cars, which may account for their low public health outcomes. Figure 54 depicts zero car households.

There is a difference between the maps of zero-car households and 1-car or no car households. There are many block groups where every household has at least one car, as shown in Figure 55. zero-car households are rare. One-car households, by comparison, are more common. The highest concentrations of 0 car households are also near the highest concentration of public health issues identified in PLACES.

Activity Density: The threshold activity density for transit service is five people and jobs per acre. Richmond has several block groups that exceed this threshold. This will be compared with existing GRTC transit service levels and networks. Figure 56 depicts activity density.

Intensity: The threshold intensity is 14 people and jobs per acre for walkability, per Newman and Kenworthy's survey of urban and suburban development. Intensity is a slightly different metric than activity density, as it includes both vacant as well as occupied housing units and does not directly measure populations. Figure 57 depicts intensity.

Walkability: The EPA walkability index is an EPA-compiled metric of walkability composed of intersection density, proximity to transit stops, employment diversity, and employment and household mix. It differs from the Intensity distribution because it aggregates these statistics. Figure 58 depicts walkability.

Transit Service: GRTC network does not indicate the density of transit trips offered. Data on buses per hour shows that GRTC service is focused to providing rides to downtown Richmond. Access to jobs and services for residents trying to reach other parts of Richmond is more difficult. Transit service could be used to provide polycentric transportation, but the access needs of populations most likely to use transit need to be identified. Figure 59 depicts transit service.

Infrastructure Density: As important as the land use metrics of walkability above is the provision of walking infrastructure. The distribution of walking infrastructure differs from walkability or intensity,as depicted in Figure 60. This should be compared and corrected against the distribution of roadways in urban Richmond, as most roads in urban Richmond probably have sidewalks on both sides.

Multimodal density does not include sidewalks, but shared use path and bike trails. This block group density exceeds the official GIS on bike routes in Richmond and should be checked against the actual conditions within Richmond. Figure 61depicts multimodal density.

Worker-Job Balance: The distribution of low wage (<$3,333/month) and high wage (>$3,333/month) worker job balance are very similar. Both above maps show the difference between workers and jobs for each block group. This balance is relevant for commutes within block groups, best served by walking and biking commutes. Figure 62 and Figure 63 depict low and high wage jobs respectively.

Figure 54: Personal Vehicle Access (0 Cars)

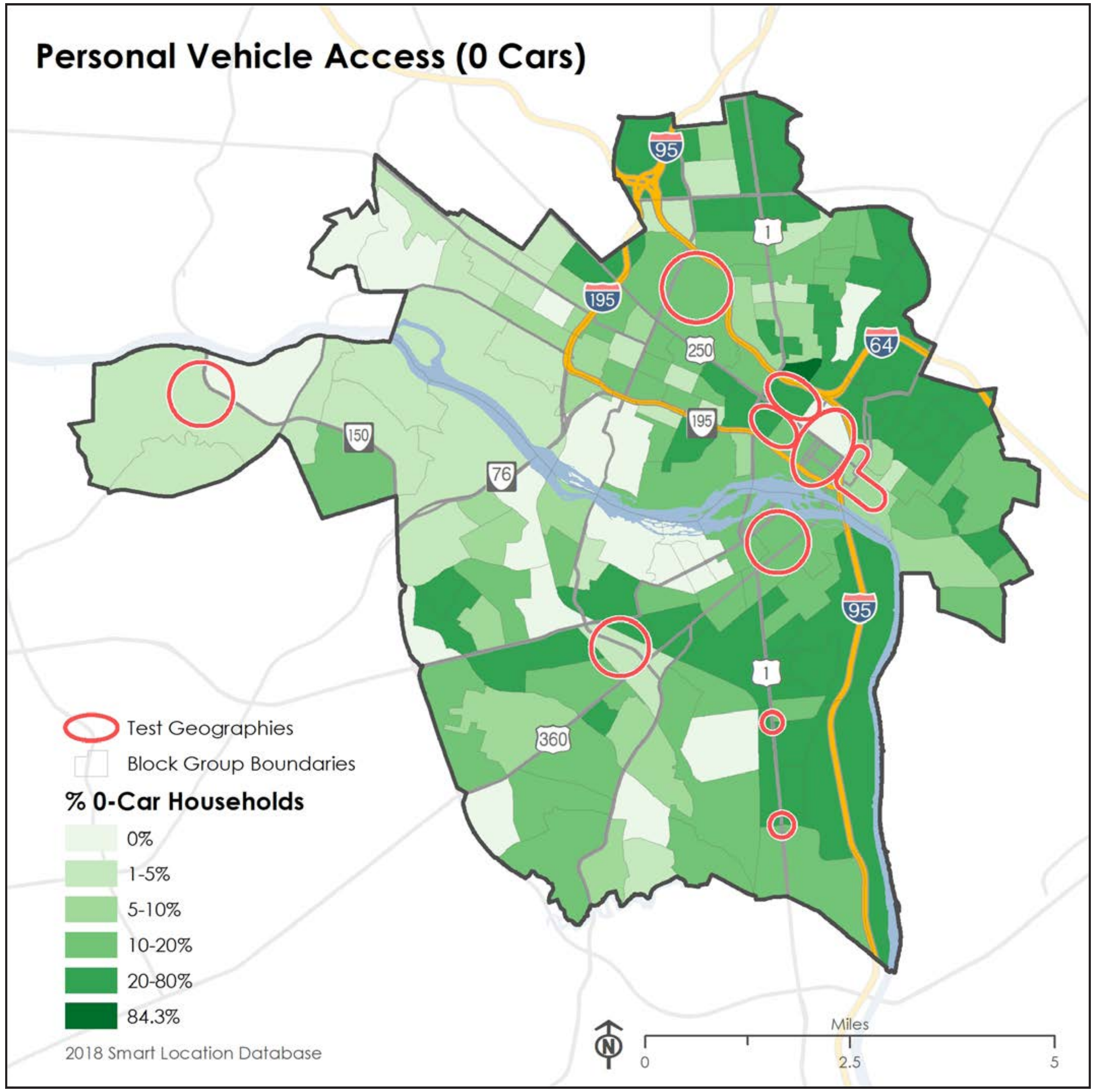


Figure 55: Personal Vehicle Access (0-1 Cars)

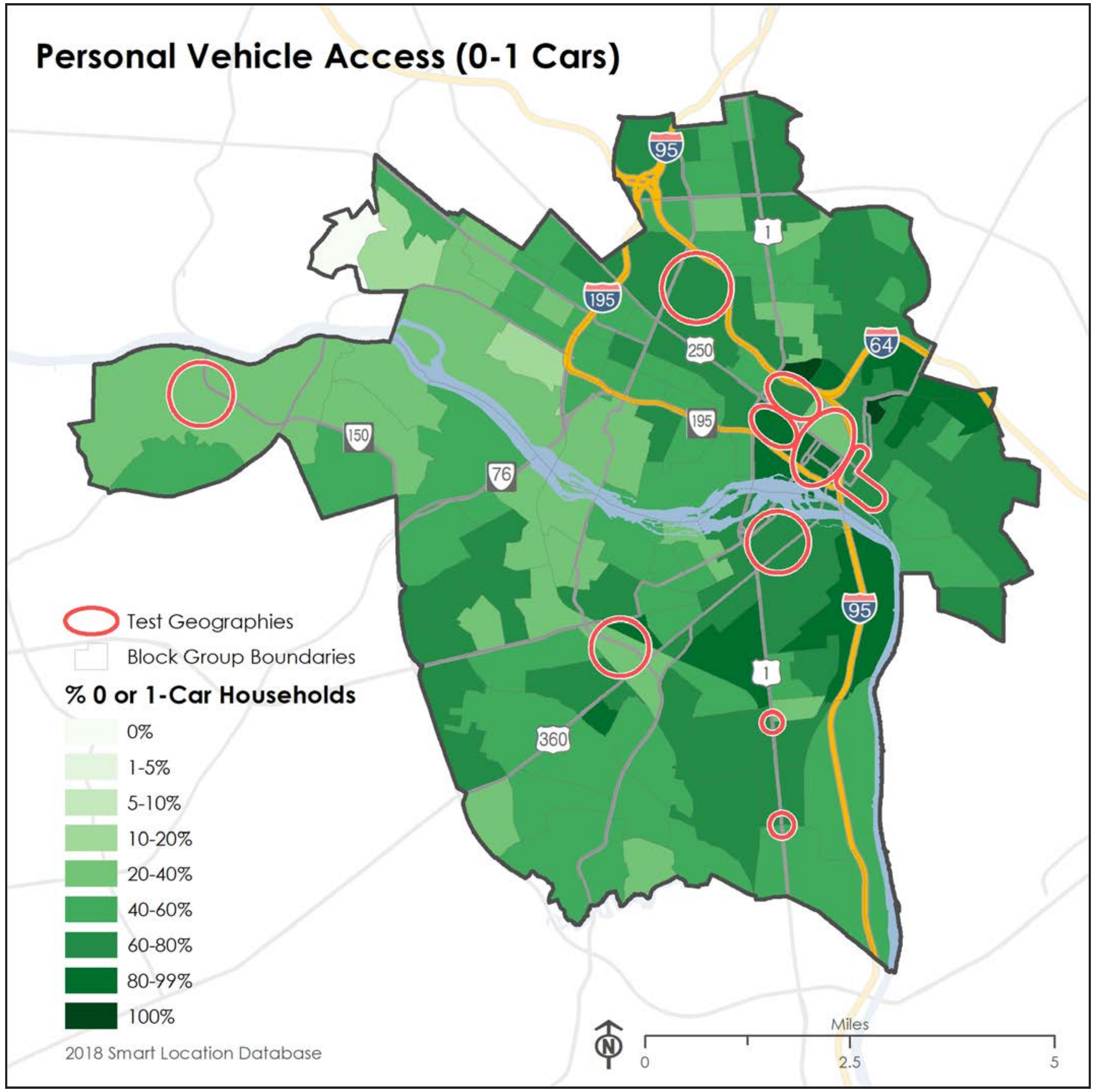


Figure 56: Activity Density

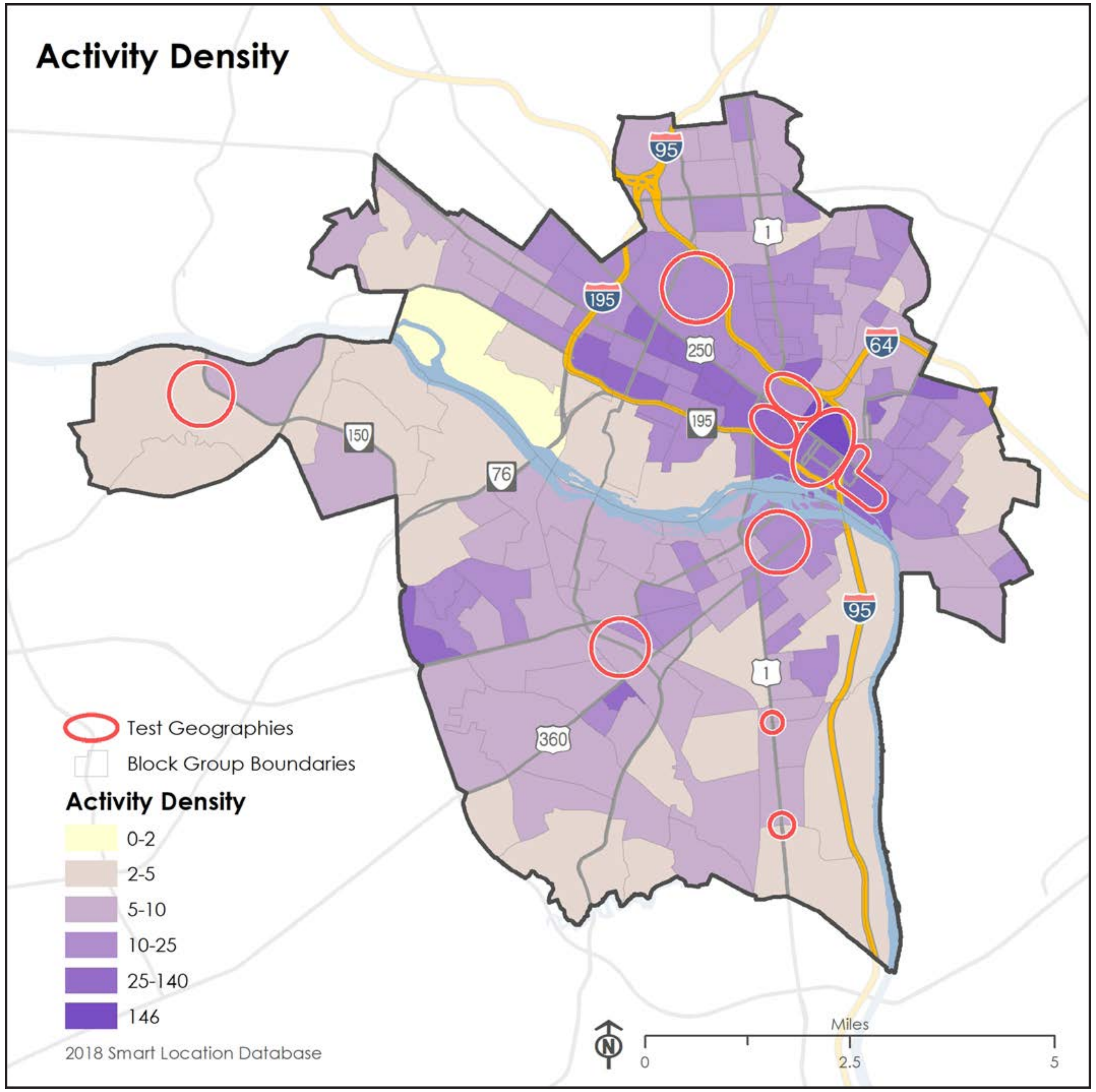


Figure 57: Intensity (Housing and Job Density)

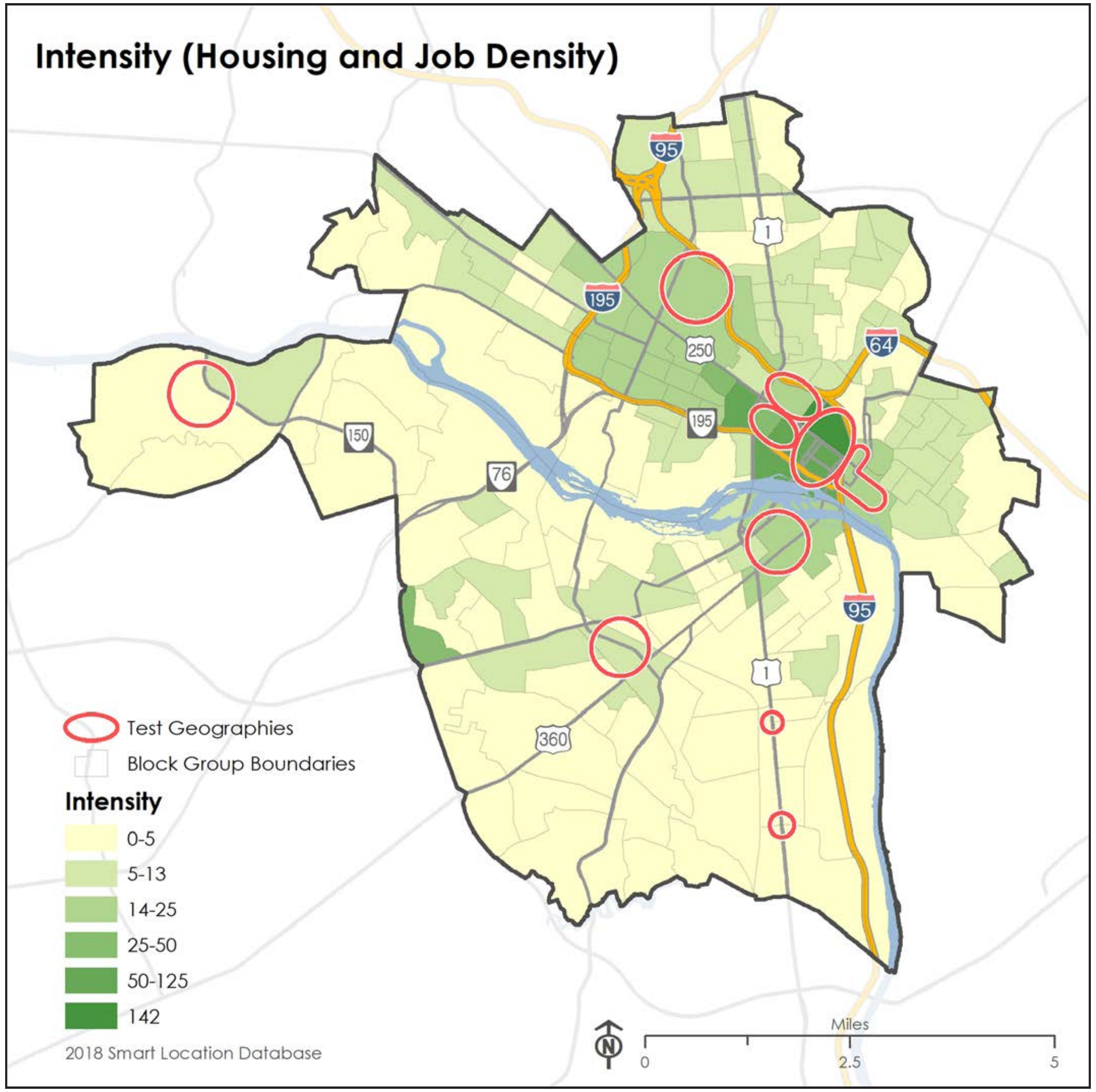


Figure 58: Walkability

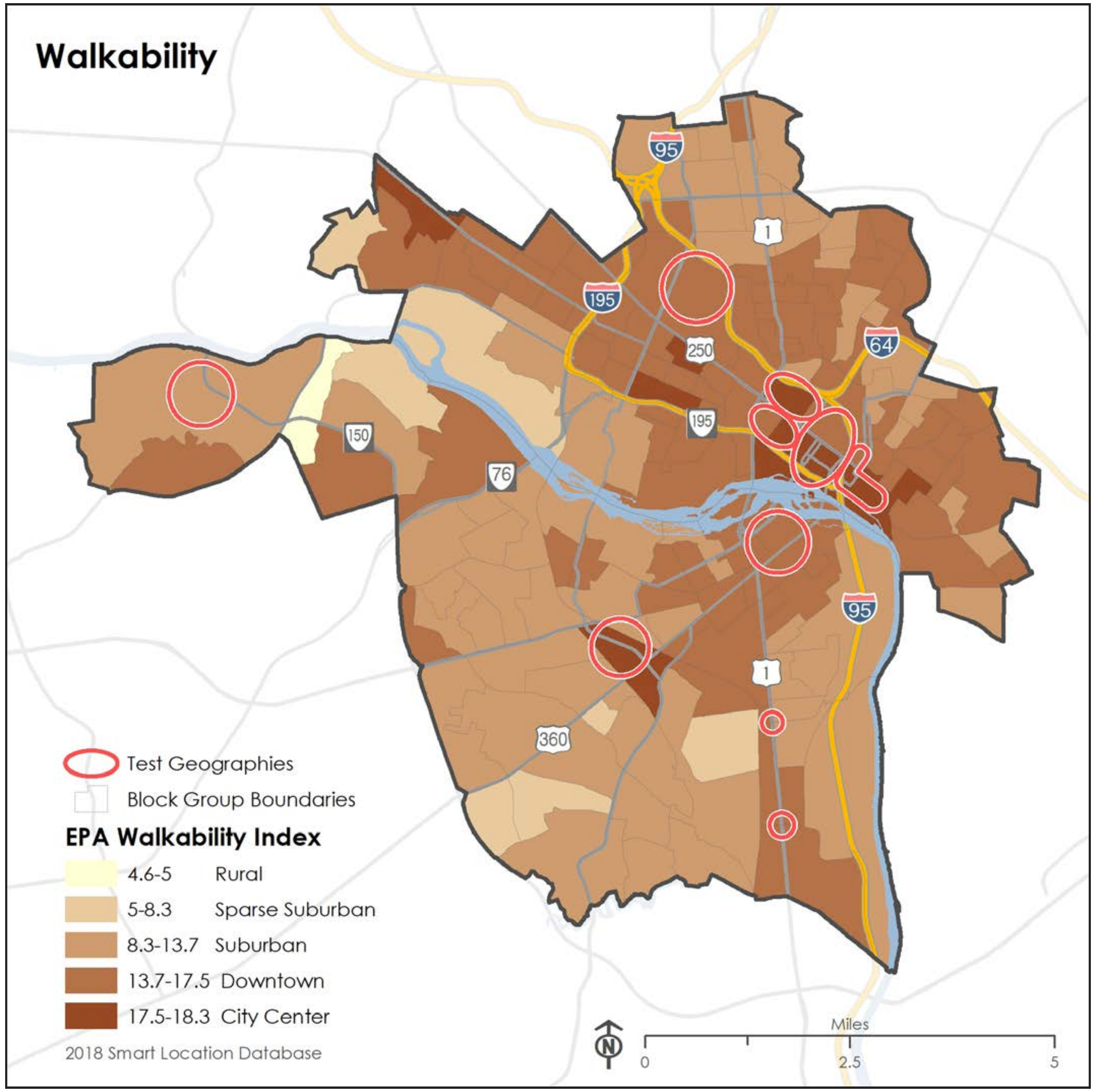


Figure 59: Transit Service

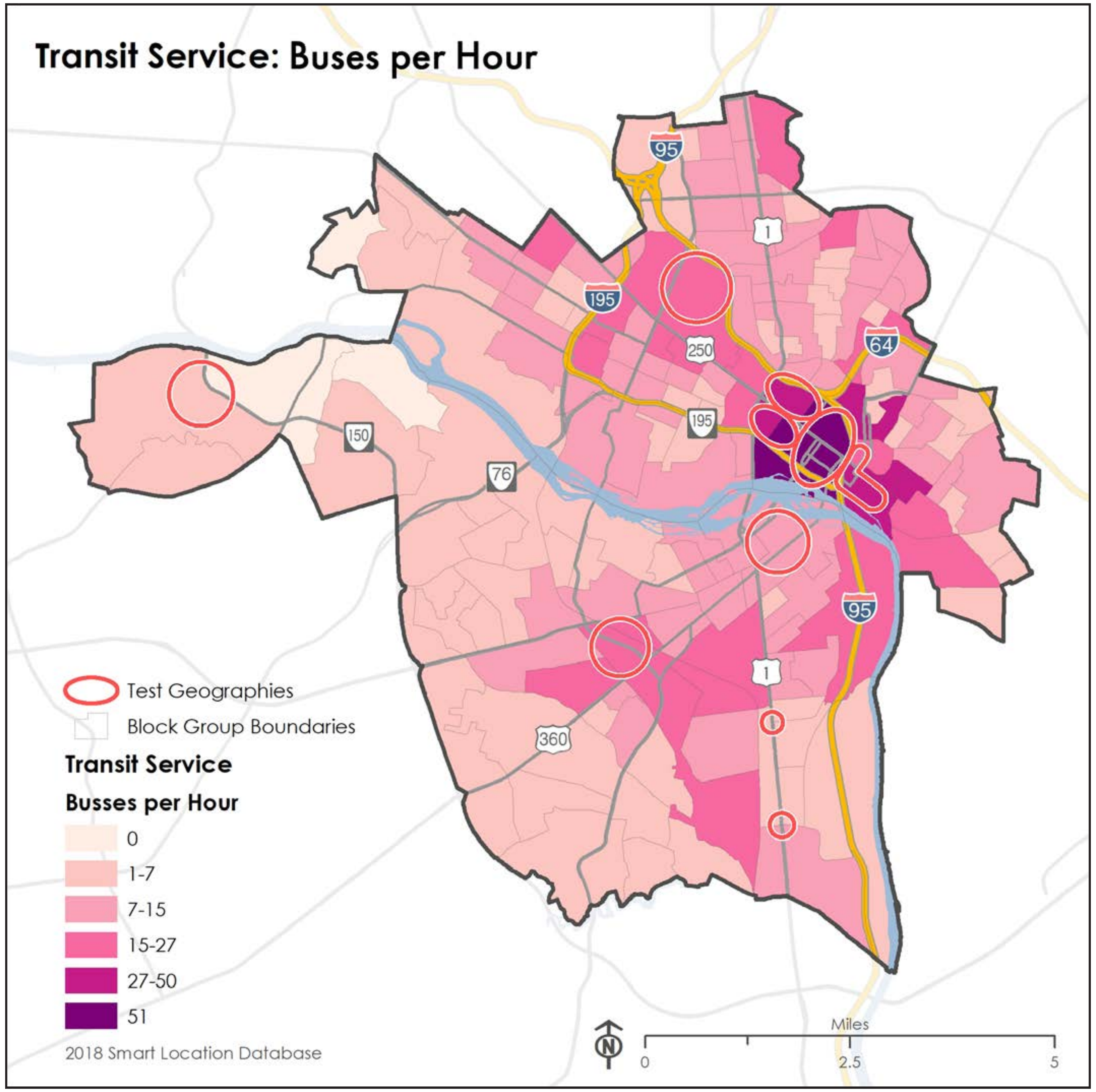


Figure 60: Walker Infrastructure Density

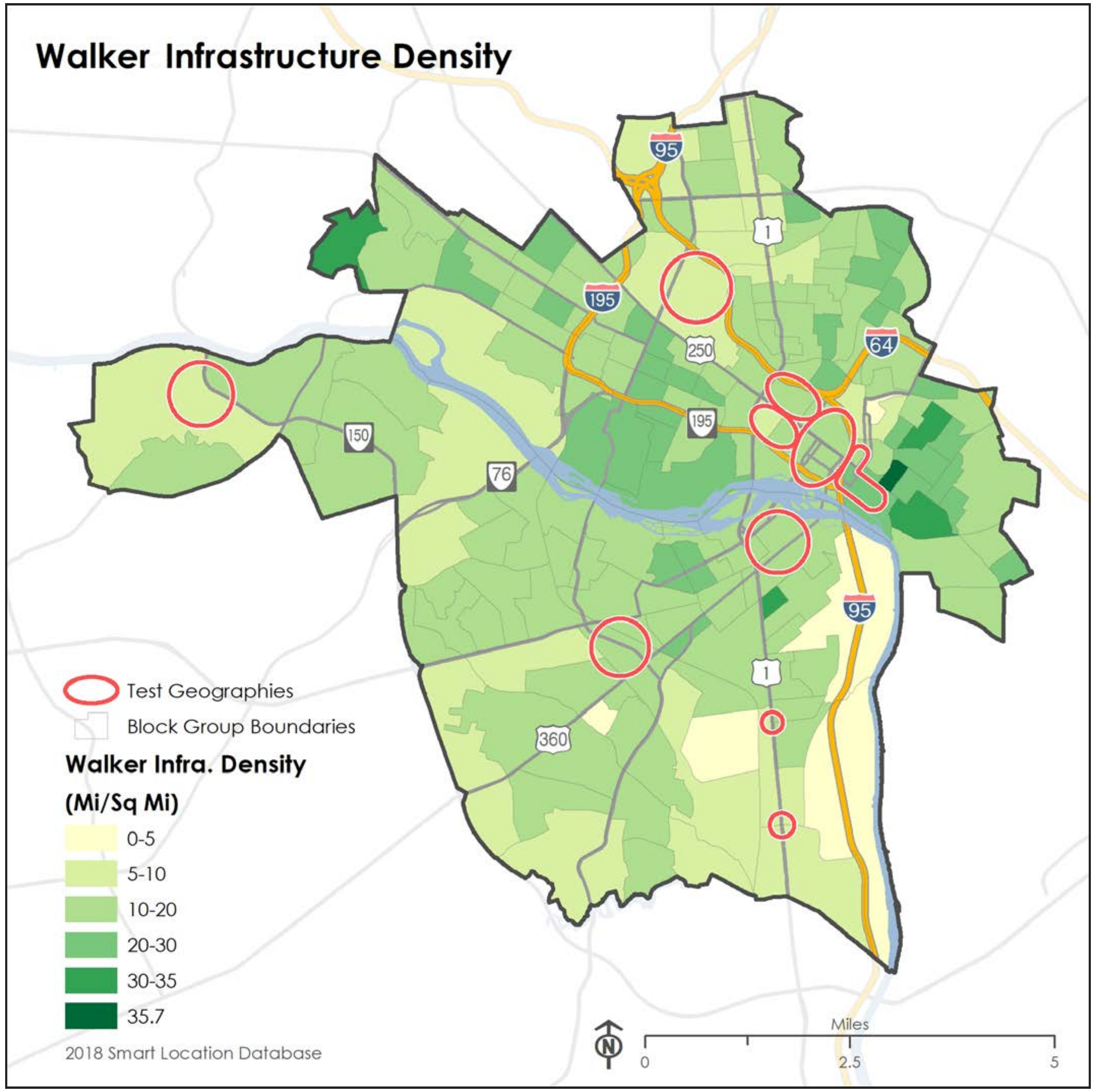


Figure 61: Multimodal Density

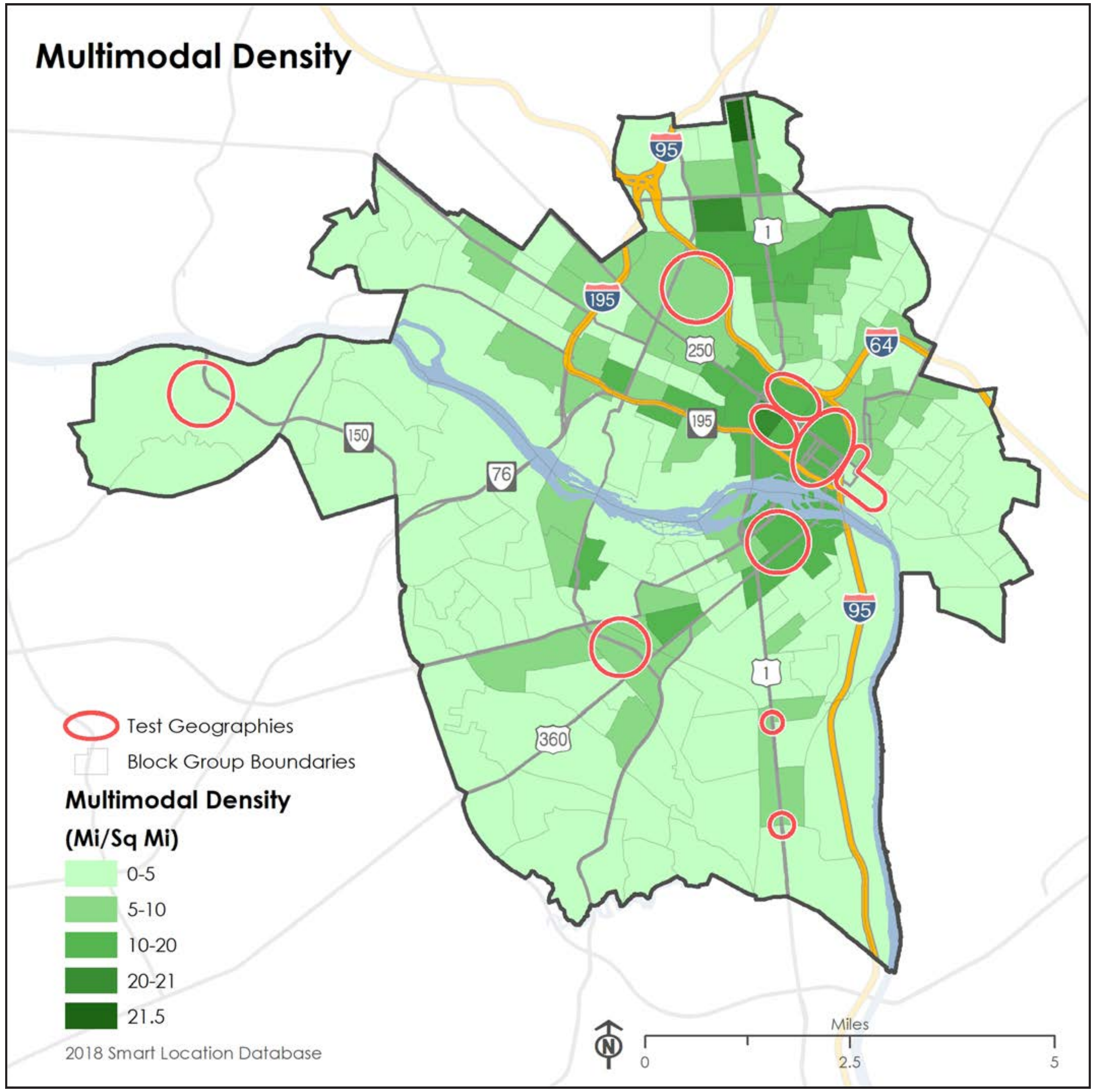


Figure 62: Low-Wage Worker Jobs

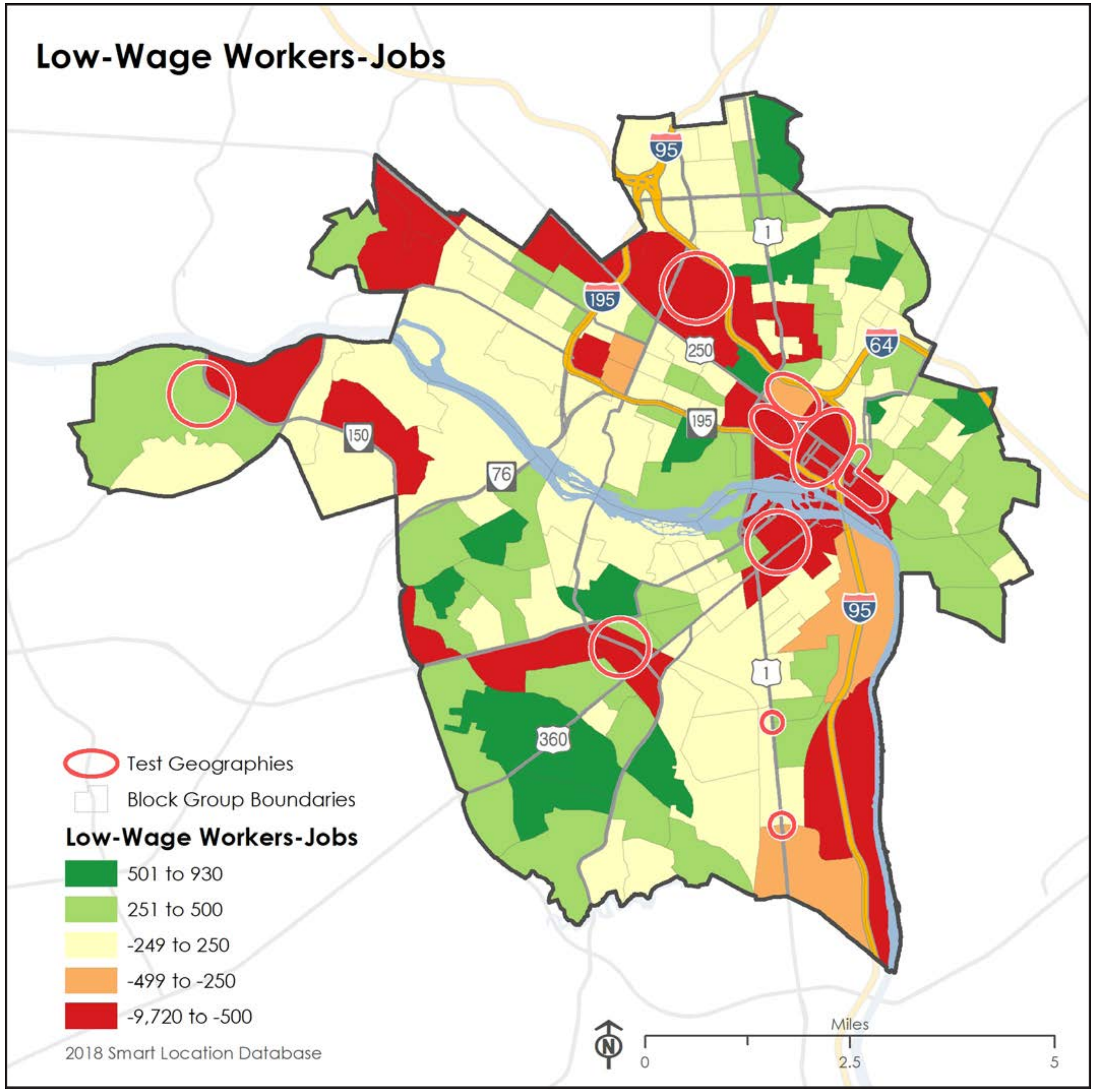
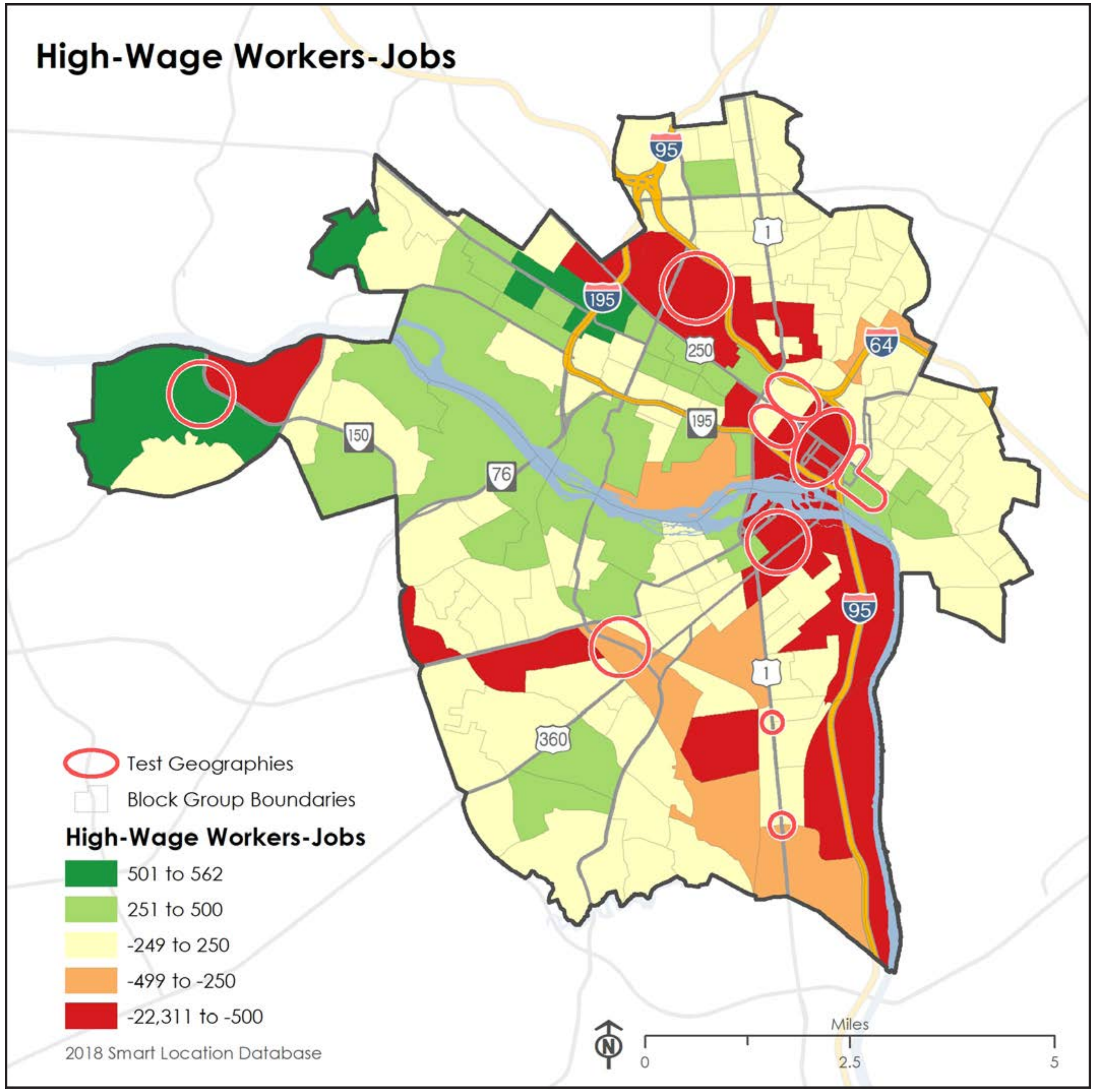


Figure 63: High-Wage Worker Jobs



5 - RICHMOND GENTRIFICATION AND MULTIMODAL ACCESS

Introduction

While the primary focus of the current study has been to examine equitable access in Richmond, the study team has also been asked to consider whether improved accessibility from transportation improvements might have the unintended consequence of accelerating inequality in housing and neighborhood development by creating or magnifying neighborhood gentrification. Several advocacy groups and research organizations have identified Richmond as among the most gentrified cities in Virginia, and some such as the National Community Reinvestment Coalition have even identified Richmond as among the most rapidly gentrifying urban areas in the country. However, there is some disagreement in the literature about what constitutes gentrification, how best to measure it, how it unfolds over time, and what causes it to occur. The literature and practitioners additionally grapple with the extent to which public investments may cause gentrification versus follow after neighborhoods begin to gentrify; to the extent gentrification precedes rather than follows, it can reflect how investments may be directed towards areas with greater political influence as a result of a combination of wealth, racial, and ethnic characteristics. This report seeks to utilize current data to provide additional insight into the gentrification process in Richmond, and to examine its possible relationship to transportation investment and accessibility. It also considers whether different types of transportation improvements are more closely associated with gentrifying areas.

As a corollary to the gentrification process, this report also looks at the suburbanization of poverty. This phenomenon is closely related to gentrification. As low-income populations are priced out of gentrifying neighborhoods, displaced families may move to lower housing cost areas in the periphery of the city. When this process occurs, disadvantaged groups may find that their accessibility declines relative to former central neighborhoods, as suburban areas may have a less dense network of transit services, access to job-rich areas is reduced, and travel times to desired job and social service destinations increase.

Finally, this chapter provides some concluding observations about public policies that can and have been employed in other locales to mitigate the gentrification process and preserve the benefits of more equitable access for target neighborhoods and socioeconomic groups.

Evidence from the Literature

Measuring Gentrification

Recent research shares a concern regarding the availability of comprehensive data to track gentrification, particularly during its early phases when public policy interventions may be more possible. For example, the National Neighborhood Indicators Partnership (NNIP), a leading community development research organization, has noted that "people (often) know from lived experience that their neighborhoods are changing but lack the data to quantify displacement. Further, communities may know which neighborhoods are changing in the present, but do not have systems to anticipate and get in front of future changes."[15] To address this gap in information, the NNIP published the "*Guide to Measuring Neighborhood Change to Understand and Prevent Displacement*" to help communities recognize neighborhood changes with comprehensive qualitative and quantitative data sources, such as the American Community Survey. Table 23 presents four categories of indicators from the NNIP that communities can use to identify and mitigate displacement.

Recent research also uses other data sources, such as proprietary data from Yelp. In "Measuring Gentrification: Using Yelp Data to Quantify Neighborhood Change," the National Bureau of Economic Research joins Census data with Yelp data, such as the numbers of bars, cafes, grocery stores, and restaurants in New York City.[16] This study found that changes in business composition, particularly changes in the numbers of coffee shops, were the leading indicators of gentrification in neighborhoods across New York City. More specifically, a new Starbucks location is associated with a 0.5 percent increase in housing prices in a zip code, which may indicate forthcoming gentrification.[17] The causality of this relationship is not clear, however, as these findings can be explained as restaurants responding to – rather than driving – exogenous changes in neighborhood composition.[18] While the presence of any one type of business such as a Starbucks may not be a comprehensive predictor or indicator of gentrification, the results of this study demonstrate that proprietary business establishment data of particular types can be used to measure real-time changes in neighborhood activities and amenities.

15. Mychal Cohen and Kathryn L.S. Pettit, "Guide to Measuring Neighborhood Change to Understand and Prevent Displacement." National Neighborhood Indicators Partnership. 2021.
16. Edward L. Glaeser, Hyunjin Kim, and Michael Luca. "Measuring Gentrification: Using Yelp Data to Quantify Neighborhood Change." National Bureau of Economic Research. 2018.
17. ibid.

Table 23: Common Indicators of Neighborhood Change

Resident Characteristics	Housing Markets and Conditions
▪ Race and Ethnicity ▪ Income ▪ Education and Age ▪ Household Type and Tenure	▪ Home Values and Sales ▪ Rents ▪ Vacant and Blight Properties ▪ Public and Subsidized Housing ▪ Evictions and Foreclosures
Economic Activity and Investment	**Neighborhood Conditions**
▪ Business Activity ▪ Building Permits ▪ Public and Private Capital Investments	▪ Transit Use ▪ Crime and Safety

Source: Mychal Cohen and Kathryn L.S. Pettit, "Guide to Measuring Neighborhood Change to Understand and Prevent Displacement." National Neighborhood Indicators Partnership. 2021.

Evidence for Transportation-Induced Gentrification

Although municipalities such as Richmond continue to face gentrification, many studies grapple with the role that public investments such as transportation play in the process. Although transportation improvements, particularly active and transit improvements, can provide accessible and affordable mobility options, such improvements are also associated with gentrification.

Among the key questions is how large and what types of investments in public infrastructure are most likely to trigger or accelerate neighborhood change? Additionally, policy analysts question whether and to what extent public investments may cause gentrification or instead follow after neighborhoods begin to gentrify and public policies disproportionately target investments to areas that are more affluent and less racially and ethnically diverse.[19] The sequence of events that cause gentrification as well as the dynamics of the process itself remain disputed in recent research, as most studies conclude that the study of gentrification is a "complex, multi-disciplinary process."[20]

The following sub-sections outline notable research conducted on the relationship between transportation improvements and gentrification, including its implications for transit-oriented development.

Active Transportation Improvements and Gentrification: Active transportation improvements, which entail pedestrian and cycling infrastructure, have often been subjects of investigation regarding the relationships between transportation improvements and gentrification. Recent research has examined the relationships between active transportation improvements and neighborhood change, as many claim that "cycling investment arrives in tandem with incoming populations of privilege or is targeted towards neighborhoods with existing socioeconomic wealth."   Although these studies provide vague conclusions on such relationships, they nonetheless highlight the significance of mobility inequality in cities.

18. ibid.
19. Nicholas N. Ferenchak and Wesley E. Marshall, "Bicycling Facility Inequalities and the Causality Dilemma with Socioeconomic/Sociodemographic Change." Transportation Research: Transport and Environment. 2021.
20. Andey Fomil, "A Systematic Method for Measuring Gentrification Using Building Permits Data: A Washington DC Case Study." West Virginia University. 2021.

Students at the University of Chicago evaluated such inequality by comparing socioeconomic data from the American Community Survey to geospatial data on cycling infrastructure in 46 cities across the United States. This study found that the presence of certain socioeconomic conditions and cycling infrastructure may be linked, as "gentrifying tracts had higher rates of cycling infrastructure relative to disadvantaged, non-gentrifying tracts."[21] Though this study does not pinpoint a causal relationship between active transportation improvements and neighborhood change, this study does highlight the "clear inequity in urban resources that are particularly harmful to underprivileged residents."[22]

As posed by Ferenchak and Marshall, the question becomes, "How well has the recent expansion of bicycling networks advanced transportation justice through appropriate distribution across the [socioeconomic] spectrum?"[23] To address this question, Ferenchak and Marshall evaluated cycling infrastructure and socioeconomic conditions in 29 cities across the United States, noting "inequalities in bicycling facility installation with People of Color (POC) experiencing the lowest rates of overall facility installation."[24] This study found that bicycle facilities did not have a strong causal impact on socioeconomic and demographic change, but that bike facilities were rarely installed in POC communities. This research did reveal that bicycle facilities were more often followed by increases in income than changes in neighborhood racial composition (such as an increase in White population). Ferenchak and Marshall conclude that they do not have evidence to suggest that bike facilities lead to displacement when in fact socioeconomic/demographic changes were more often correlated with later bicycle infrastructure improvements.

This question is also addressed through research conducted by Flanagan, LaChapelle, and El Geneidy, which included indices of both socioeconomic conditions and cycling infrastructure to assess neighborhood changes in Portland and Chicago. This study found that there was significantly more cycling infrastructure investment in neighborhoods with "existing or increasing privilege," as "marginalized communities are unlikely to attract as much cycling infrastructure investment without the presence of privileged populations, even when considering population density and distance to downtown, two motivators of urban cycling."[25]

The findings above provide examples of infrastructure investment *trailing*, rather than *leading*, gentrification, as cycling investment is found to be concentrated in areas of higher wealth. Given the complicated relationships between transportation improvements and gentrification, this research points to the fact that municipalities should also concern themselves with equity in the allocation of mobility-supportive investments among marginalized communities, while also considering the consequences of future transportation improvements.

Transit Improvements, Transit Oriented Development, and Gentrification: Many studies also consider the relationships between transit improvements and gentrification. Often found at the center of transit-oriented developments, light-rail transit improvements may make neighborhoods more desirable for those interested in more accessible and affordable options.

Baker and Lee studied the relationship between light-rail infrastructure and gentrification, finding that the relationship is dependent upon the decisions of local and regional planning agencies. This study provides intriguing insights into how gentrification materializes in different cities across the United States, as Baker and Lee found that, "For San Francisco and Denver, in particular, [results] reveal that light rail station areas have become relatively occupied by whiter, richer, and better-educated residents." Their analysis in Portland, Los Angeles, and Buffalo, however, found that station areas "are characterized by gaining relatively less white and educated populations as well as having relatively greater poverty rates than tracts without stations."[26]

This study concludes that the relationships between light-rail infrastructure and neighborhood change may be uniquely linked, but ultimately require an understanding of politics beyond data analyses. In contrast to light rail, study of the relationship between heavy-rail infrastructure and gentrification has been hampered by the fact that the development and expansion of heavy-rail infrastructure in much of the United States preceded the availability of important socioeconomic data sources that researchers use

21. Gabriel Morrison, "Urban Bicycle Infrastructure and Gentrification: A Quantitative Assessment of 46 American Cities." University of Chicago. 2021.
22. ibid.
23. Nicholas N. Ferenchak and Wesley E. Marshall, "Bicycling Facility Inequalities and the Causality Dilemma with Socioeconomic/Sociodemographic Change." Transportation Research: Transport and Environment. 2021.
24. ibid.
25. Elizabeth Flanagan, Ugo LaChapelle, and Ahmed El-Geneidy. "Riding Tandem: Does Cycling Infrastructure Investment Mirror Gentrification and Privilege in Portland, OR and Chicago, IL?" Research in Transportation Economics. 2016.
26. Dwayne M. Baker and Bumsoo Lee. "How Does Light Rail Transit (LRT) Impact Gentrification? Evidence from Fourteen US Urbanized Areas." Journal of Planning Education and Research. 2017.

today. Nonetheless, some studies suggest that heavy-rail infrastructure and gentrification may be linked. Students at Georgia State University, for example, found that the MARTA System in Atlanta may have induced gentrification over time. This study finds that "low-income groups are sometimes referred to as captive riders because the only form of transit they can afford is public transportation. If rail intra-urban transit stations are a positive amenity, wealthy groups will outbid low-income groups for access."[27]

Another study of the Los Angeles Metropolitan Area, which includes both heavy and light rail, used tax micro-data on household income and location to track household mobility by income with rail station areas.[28] The study found a large decline in households living below 30 percent of Area Median Income (the "Extremely Poor") in rail station areas over the study period from 1994 to 2012. It also found that after a rail station opens, the rate at which the Extremely Poor move into rail station areas decreases. On the other hand, the rate at which households between 30 and 80 percent of Area Mean Income move out of station areas after they open decreased. The authors conclude that changes in area composition are a function of complex mobility rates both inwards and outwards and that contrary to the traditional gentrification narrative the transition in station-area composition can reflect changing inward mobility patterns in addition to that of residents being priced out. Baseline mobility rates further complicate the picture with the study finding that "independent of whether a rail station opens or not...on average, every year approximately 1 in 10 households near rail transit stations move out and a roughly equal share move in."

The construction and opening of the first phase of New York's Second Avenue subway provide additional, albeit informal, insight related to impacts of heavy rail investment on real estate values. Street Easy found, for example, that rents along Second Avenue increased much more rapidly than adjacent avenues in the two years preceding the opening of the initial segment in 2016.[29] This indicates that, not only may heavy rail investments in the most transit oriented big city in the U.S. result in rent appreciation, but that this can occur prior to the opening of such investments, as landlords and real property investors anticipate the gains from increased accessibility.

Transit-oriented development is also often associated with increases in property values, as such development may increase commercial property values through economic activity, such as increased retail sales in the area due to higher foot traffic. Property values in general are a reflection of the capitalized value of a location's desirable attributes. Transportation improvements, like other improvements in quality valued by people or businesses, are reflected in changes in property values.

Bardaka, Delgado, and Florax evaluated the relationship between transit-oriented development and property value, studying neighborhood change along a light-rail line during the development and expansion of the Regional Transportation District (RTD) rail system in Denver. Along the light-rail line, which serves many neighborhoods with incomes lower than the metropolitan statistical area (MSA) average, this study found that the development and expansion of the system was associated with a 25.33 percent increase in residential property values.[30]

Other studies also continue to question the causal relationship between transit-oriented development and gentrification. Padeiro, Louro and da Costa found, for example, that "gentrification is more closely associated with existing local dynamics, built environment attributes, and accompanying policies than transit-oriented development" in over 35 recent studies.[31] Thus, one may conclude that changes in property values may be a significant indicator of gentrification, but that the cause of these shifts can include both infrastructure and other local and regional planning decisions.

27. Christopher K. Wyczalkowski. "Evaluation of the Effect of Rail Intra-Urban Transit Stations on Neighborhood Change." Georgia State University. 2017.
28. Boarnet, et al. "Gentrification Near Rail Transit Areas: A Micro-Data Analysis of Moves into Los Angeles Metro Rail Station Areas." National Center for Sustainable Transportation Research. 2018. https://escholarship.org/uc/item/4p4584w8
29. https://streeteasy.com/blog/second-avenue-subway/
30. Dwayne M. Baker and Bumsoo Lee. "How Does Light Rail Transit (LRT) Impact Gentrification? Evidence from Fourteen US Urbanized Areas." Journal of Planning Education and Research. 2017
31. Miguel Padeiro, Ana Louro, and Nuno Marques da Costa. "Transit-Oriented Development and Gentrification: A Systematic Review." Transport Reviews. 2019.

Measuring Gentrification & Displacement in Richmond

Identifying Gentrification

Gentrification is typically understood as the process through which an urban neighborhood experiences rapid change in the composition of population, businesses, and housing costs. This process can result in the displacement of poor communities as vulnerable populations are pushed out of the local housing market in favor of wealthier occupants.

To understand how this process works and how to avoid harm to existing residents, analysts must develop a framework to identify where gentrification has occurred in the past or could occur in the future. The first step of this process is to identify threshold metrics to identify neighborhoods where conditions make gentrification capable of occurring – that is, to identify areas that are eligible for gentrification (i.e., potentially vulnerable to neighborhood change). Most researchers use an income-based threshold, although some research has leveraged the proportion of older housing as a measure of disinvestment in a neighborhood. However, older buildings in Richmond (as in many other cities such as San Francisco) may be very desirable for wealthy populations, so this measure is less appropriate for use in this analysis.

This report will use a modified Freeman model to evaluate whether census tracts (as a proxy for neighborhoods) in Richmond are eligible for gentrification. To be eligible, a census tract must have a median household income and a median rent level lower than the greater metropolitan area average. Figure 64 illustrates the areas in Richmond that meet these criteria.

After establishing which areas are eligible for gentrification, the next step is to determine if there is any actual evidence of neighborhood change. Gentrification is a long-term, gradual process with no firm start or end dates. However, much analysis typically uses a study period of one decade to determine if a neighborhood has experienced gentrification. Again, many researchers rely heavily on income-based metrics. The Freeman model, which requires an increase in housing prices in addition to a change of income, serves as the most useful framework for application in Richmond.

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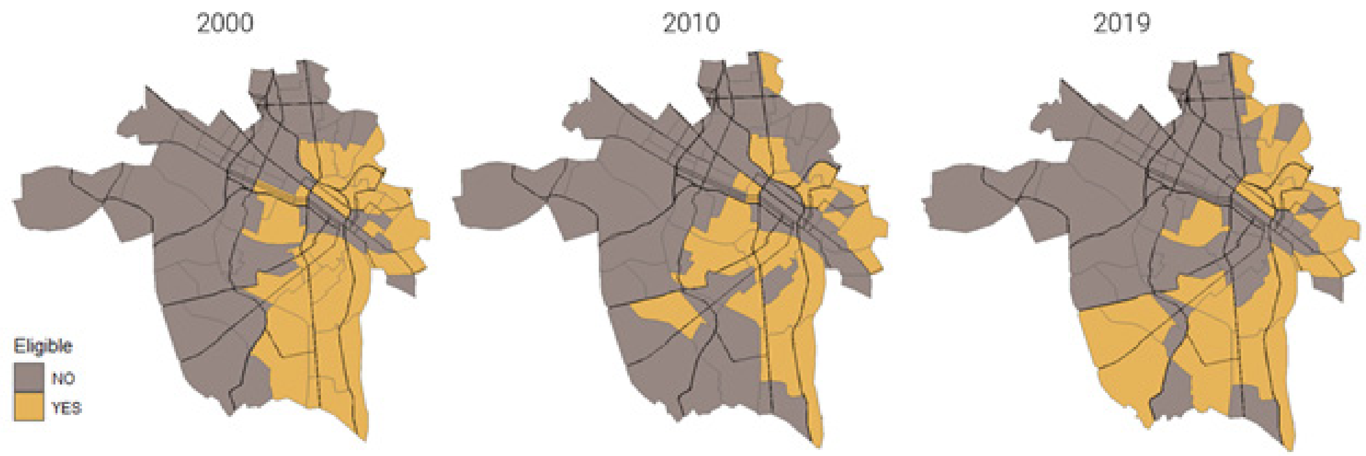
Table 24: Definitions of Neighborhood Eligibility for Gentrification

Researchers	Definition of Eligibility
Freeman[1]	Have a median household income less than the median for the entire metropolitan area AND Have a proportion of housing built within the past 20 years lower than the proportion found at the median for the respective metropolitan area.
Ellen & O'Regan[2]	Ratio of tract to metropolitan area median household income less than 0.7
McKinnish et. al.[3]	Median household income of census tract in the bottom 20% of all urban tracts nationwide.

1. Freeman, L. (2005). Displacement or Succession?: Residential Mobility in Gentrifying Neighborhoods. Urban Affairs Review, 40(4), 463–491. https://doi.org/10.1177/1078087404273341
2. Ellen, I.G., & O'Regan, K.M. (2011). Gentrification: Perspectives of economists and planners.
3. McKinnish, T., Walsh, R., & White, T. K. (2010). Who Gentrifies Low-Income Neighborhoods?. Journal of urban economics, 67(2), 180–193. https://doi.org/10.1016/j.jue.2009.08.003

Figure 64: Definitions of Neighborhood Eligibility for Gentrification



Source: EBP analysis of American Community Survey tables B19013 and B25064 (for 2010 and 2019) and 2000 Decennial Census tables P053 and H060 . Larger maps are included in the Appendix.

Table 25: Measures of Evidence of Gentrification

Researchers	Definition of Eligibility
Freeman	1. Eligible at beginning of study period AND 2. Increase in share of population with at least a college degree greater than the metropolitan area trend AND 3. Any increase in real housing prices
Ellen & O'Regan	1. Eligible at beginning of study decade 2. Increase of at least 10% in the ratio of tract to metropolitan area household income over the study decade
McKinnish et. al.	1. Eligible at beginning of study period AND 2. Real increase in average household income of at least $10,000

For our analysis, we modify the Freeman model as done in the Drexel Urban Health Collaborative (UHC) Measure of Gentrification to categorize neighborhoods into four mutually exclusive groups, as shown in Figure 65:

1. Not eligible for gentrification
2. Eligible at beginning of study period, but no evidence of gentrification.
3. Some evidence of gentrification
4. Evidence of intense gentrification.

To have some evidence of gentrification, a census tract must have experienced growth in educational attainment and housing costs that were above the average for the metropolitan area. Intense gentrification is defined as growth in the top quartile of all tracts in the city. Figure 65 will serve as a spatial framework for later analysis of correlations with transportation investments.

Census tract level data is generally complete in all variables, but it can also encompass multiple neighborhoods at one time. As such, analysis of block groups can be more useful for analyzing dynamics relating to gentrification at a more precise spatial level. However, block group data have a higher incidence of data suppression, which occurs when the Census determines that sample sizes in an area are so small that identifying the number of households in a category might compromise the confidentiality of the survey . Moreover, lower income communities are considered especially hard to access and thus count, and therefore are at a higher risk of being underrepresented in small area census data.[32] Because of this, block level data are often incomplete, rendering analysis of equity impacts in small geographic areas difficult. For example, in 2019, 17/161 block groups in the city of Richmond had no estimate for the median home value, and a different 17 block groups were missing estimates for median rent, compared with only 1/66 census tracts lacking data in either of those variables. Still, this more granular analysis of possible evidence for gentrification at the block group level reveals that several areas in south-west Richmond may have also seen some gentrification, which was not found at the census tract level (Figure 66)

Suburbanization of Poverty & Other Evidence of Displacement

Figure 67 displays the change in the population living below the poverty rate in the greater Richmond area from 2010 to 2019. Although this graphic does not clearly display a strong pattern of suburbanization of poverty in any one county outside of the city, the central area of the City of Richmond now has fewer low-income households than in 2010.

Table 26 displays this measure aggregated by county. Richmond City itself does see a net increase in the number of people living in poverty, even though the map above shows that these people are no longer located in the central parts of the city. Chesterfield County, which is directly south of Richmond, has the largest increase in people living in poverty, with more than 5,000 additional low-income residents. It is possible that some of these people may have relocated from the city in part due to higher housing costs.

Figure 68 displays changes in the BIPOC population across the Greater Richmond Area. Areas that have become whiter are displayed in red, with areas that have become more diverse shown in blue. The BIPOC population in the city of Richmond has decreased, especially in the central parts of the city. Meanwhile, the surrounding counties of Chesterfield and Hanover have had an increase in BIPOC residents over the last 10 years. This could be the result of some displacement from the city center, or simply the result of changing demographics in the region, regardless of gentrification of central Richmond neighborhoods.

The Relationship Between Transportation & Gentrification: Evidence from Richmond

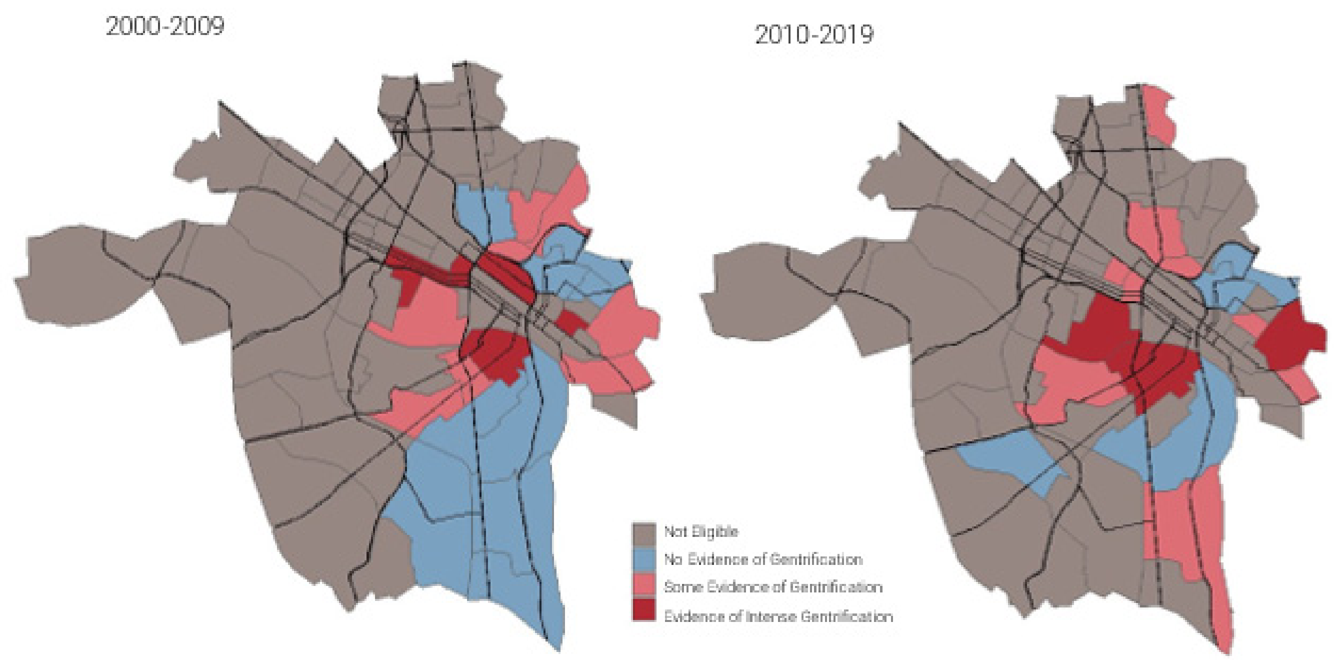
This section uses data on transportation projects in the City of Richmond and the previously presented information on gentrification to examine evidence on the relationship between transportation investments and gentrification. It is divided into two sections – the first looks at transportation projects broadly, while the second focuses on the Pulse BRT.

Richmond Transportation Investments and Gentrification

The study team was provided with data from the City of Richmond's Transportation Engineering Division on projects completed over the last 15 years. The data include 179 projects with a total value of $78 million. Of these projects, 142 were for signal modernization

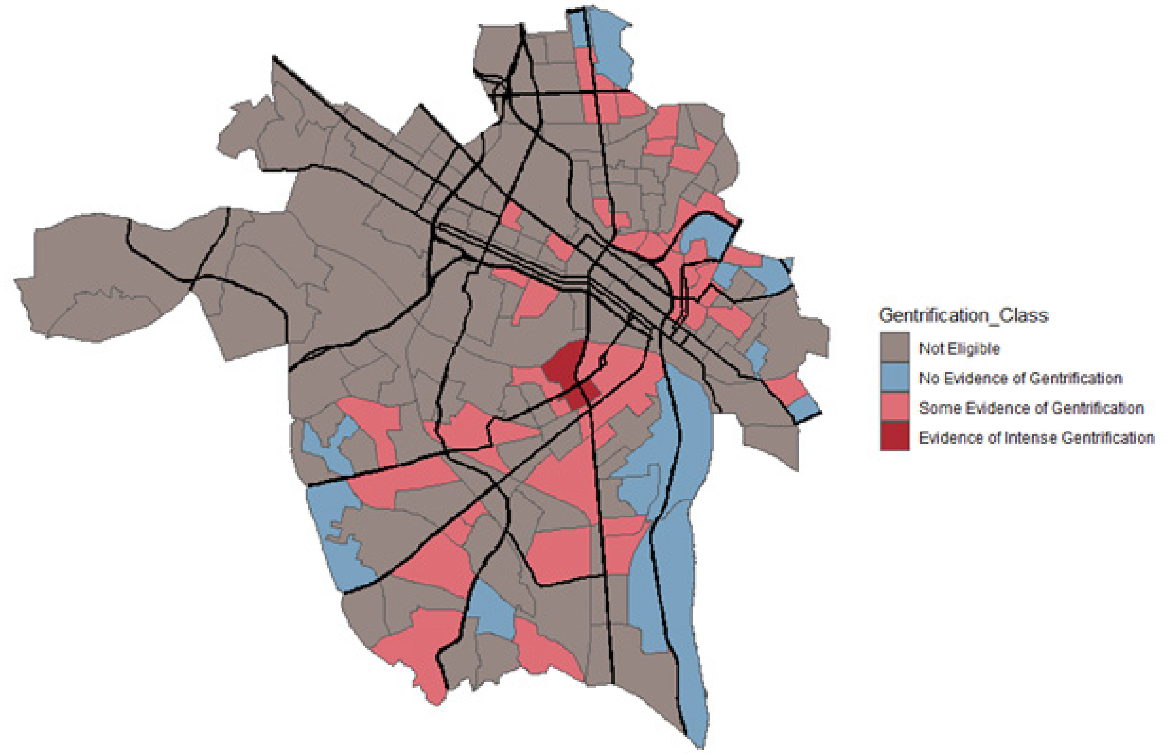
32. http://www.georgetownpoverty.org/wp-content/uploads/2018/08/Low-Income-Families-HTC.pdf

Figure 65: Evidence of Gentrification over the Last Two Decades in Census Tracts in Richmond, VA



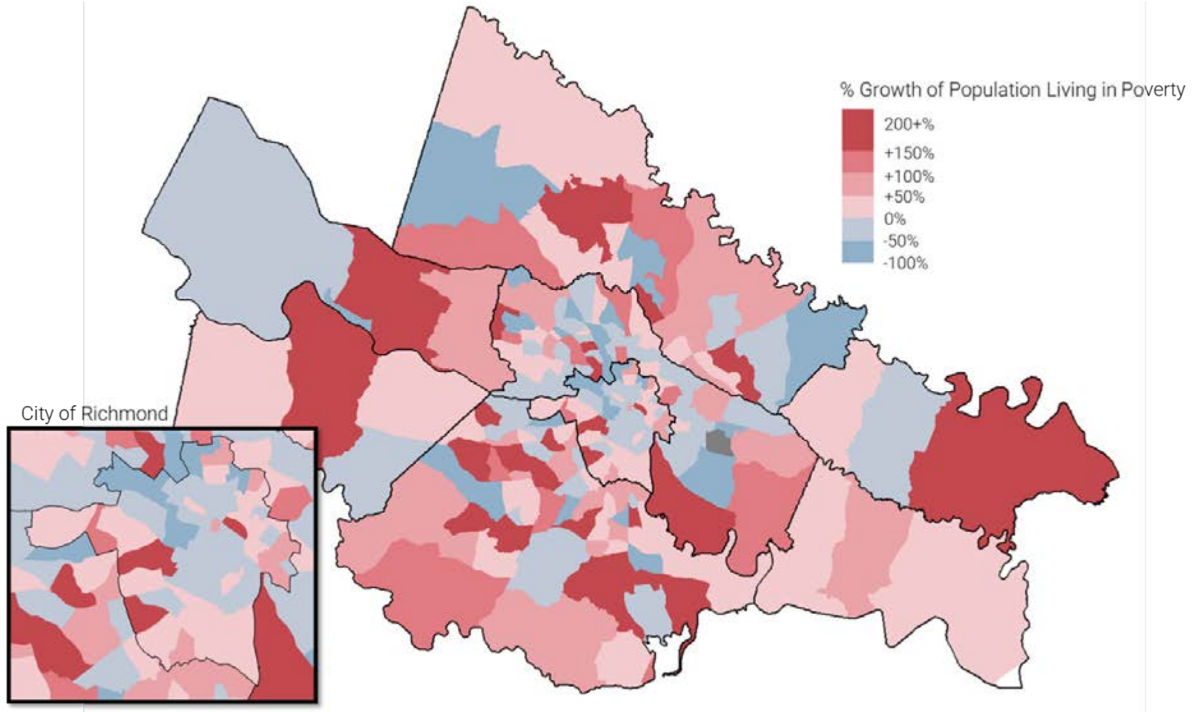
Source: EBP analysis of American Community Survey tables B19013, B25064, B25077 and B15002 and Decennial Census data tables P053, H060, H085 and P037. Larger maps are included in the Appendix.

Figure 66: Evidence for Gentrification in Richmond Block Groups from 2012-2019



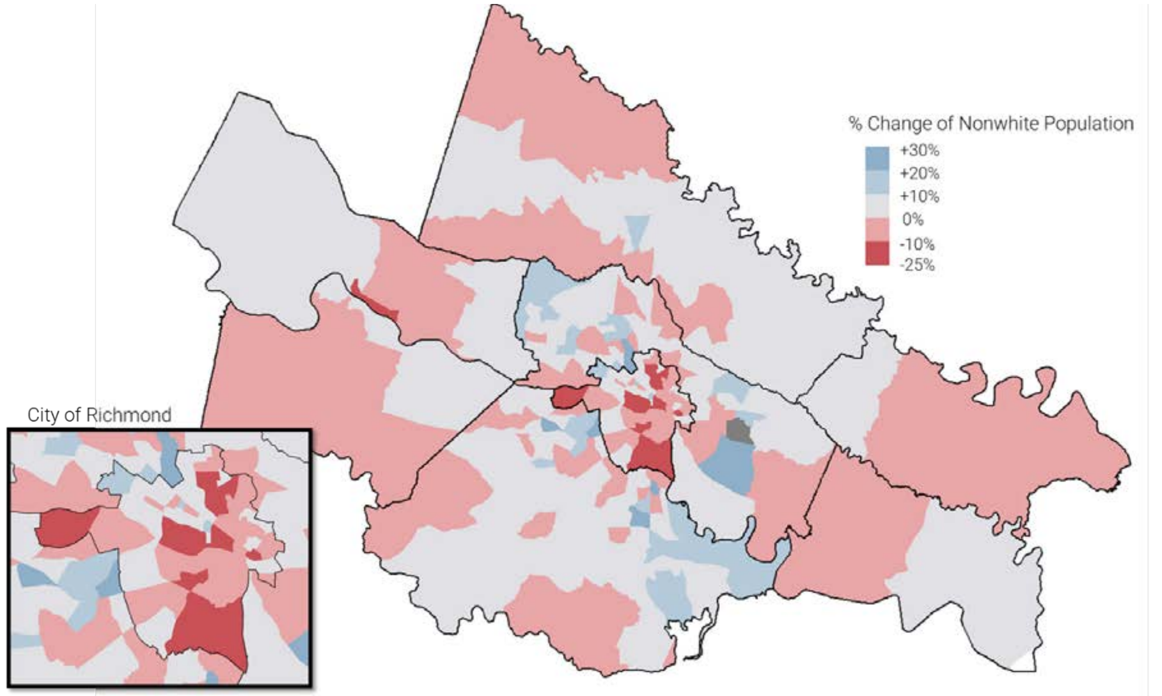
Source: EBP analysis using 2012-2019 5-year Sample American Community Survey Data. As block group level education attainment data is unavailable prior to the year 2012, this analysis cannot be completed for prior historical years at this level of geographic detail. Tract level analysis is provided above. Please note that data suppression and sample bias are significant challenges when analyzing census data at the census block group level.

Figure 67: Increases in the Population Living Below the Poverty Rate in the Greater Richmond Area



Source: EBP analysis with 2010-2019 American Community Survey Data (table B06012) of counties in the RVA region (https://planrva.org/). Note that high percentage changes are more likely to occur in lower population areas, and may not be indicative of significant population influxes.

Figure 68: Increases in the Population Living Below the Poverty Rate in the Greater Richmond Area



Source: EBP analysis using 2010-2019 American Community Survey data (table B02001) .

or other roadway improvements, accounting for over 80% of the value of all projects completed in the last 15 years. Only 13 bicycle infrastructure projects were completed in this time, including the installation and improvement of bike lanes citywide. The 15 pedestrian-oriented projects include projects relating to crosswalks or pedestrian signal improvement or installations.

The study team filtered this list of projects to 40 bike, pedestrian, and roadway improvements that may have had some significant impact on the surrounding area and determined in which neighborhoods they occurred.[33] The costs of these 40 projects totaled $19.6 million, approximately 25% of the total costs of all projects for which data was provided. The geographic location of these 40 projects are detailed below. Please note that some projects included multiple areas of the city and so appear more than once in Table 28.

33. This involved both qualitative and categorical filtering. Signal projects were excluded as were minor projects unlikely to have meaningful impacts on neighborhood development trends.

Table 26: Change in Population Living in Poverty by County

County	People Living in Poverty - 2010	Change in Population of People Living in Poverty, 2010-2019	
Richmond City	48,452	1,748	(+3.6%)
Charles City	699	220	(+31.5%)
Chesterfield	17,905	5,155	(+28.8%)
Goochland	1,178	-45	(-3.8%)
Hanover	4,151	1,336	(+32.2%)
Henrico	28,357	1,316	(+4.6%)
New Kent	738	719	(+97.4%)
Powhatan	1,007	398	(+39.5%)
Total – Richmond's Neighboring Counties	54,035	9,099	(+16.8%)

Table 27: Summary of Transportation Projects in Richmond from the Past 15 Years

Project Category	Total Cost of Projects	Number of Projects
Bike	$5,244,716	13
Other	$1,687,326	9
Pedestrian	$8,517,129	15
Road	$13,868,512	39
Signals	$13,868,512	103
Grand Total	$78,068,273	179

Source: City of Richmond Transportation Engineering Division.

Table 28: Number of Transportation Projects by Type and Area of the City of Richmond (Filtered to Projects Likely to Impact Area Development)

Area	Total # of Projects	Average Value of Projects	Road Improvements	Bike Infrastructure	Pedestrian-Oriented & Other
South Side	15	$441,560	13	1	1
West End	6	$371,418	3	1	2
Central	17	$469,793	4	9	4
North Side	5	$762,843	2	1	2
East End	9	$588,308	5	3	1

Source: Study team analysis of data provided by the City of Richmond Transportation Engineering Division..

The wealthier west end of the city did not see many transportation investments compared to the rest of the city, save for a few, low-cost safety improvement projects. Most bike infrastructure projects occurred in the central and eastern parts of the city. Road improvements were concentrated in the Southside but were also seen throughout the city. Pedestrian-oriented projects were also mostly located in the central district.

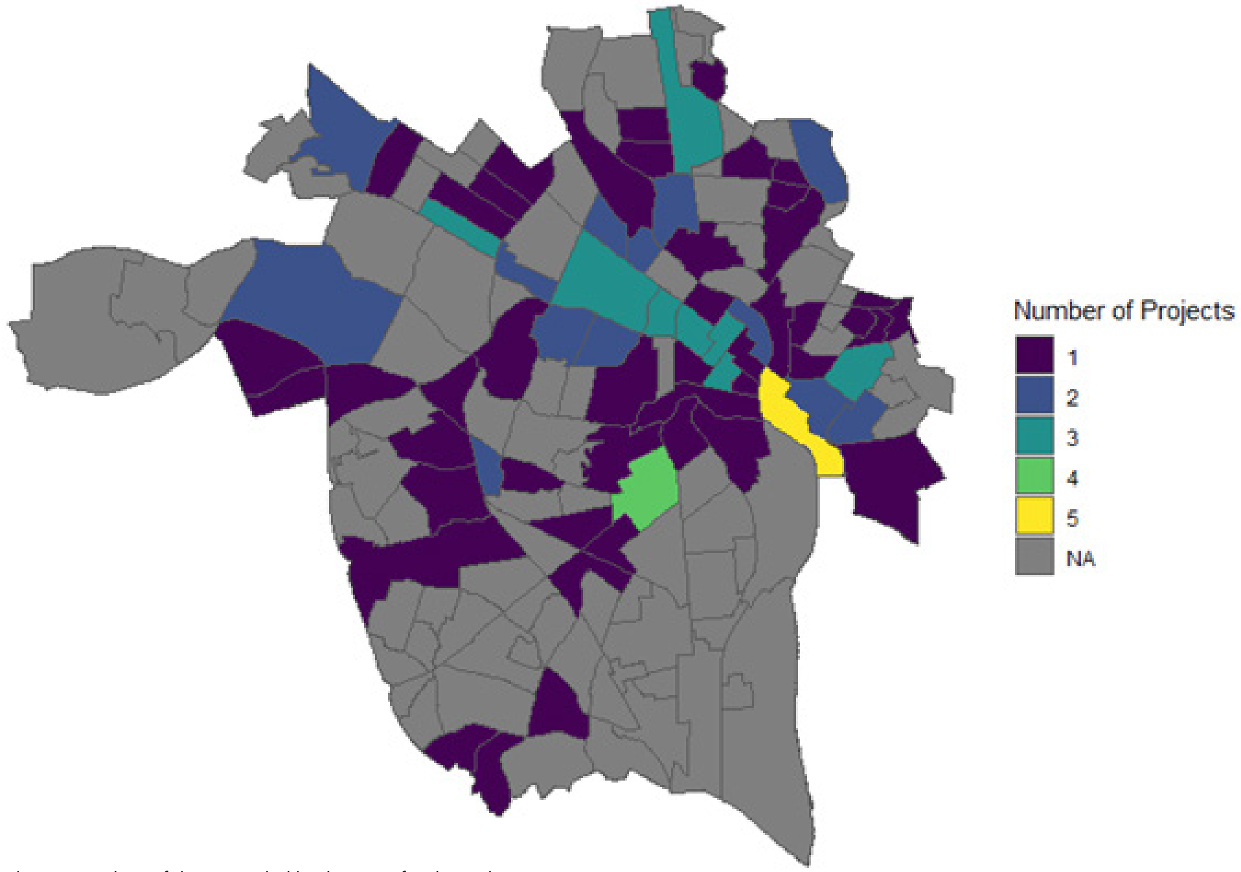
The Shockoe Bottom neighborhood was the site of 5 of these projects, more than any other neighborhood in the City. These included the installation of several bike lanes, the conversion of streets from one-way to two-way, and curb extensions. This neighborhood did show some evidence of gentrification in the 2000-2010 decade. However, the projects identified here all took place between 2012 and 2017, and thus could not have contributed to that process.

Another neighborhood which saw several transportation investments was Swansboro, which was the location of several pedestrian safety and traffic calming improvements and received a new bike lane. These projects occurred between 2009 and 2020. The previously presented analysis found evidence of gentrification in both the 2000s and 2010s in areas around and including this neighborhood. These transportation investments, therefore, may have contributed to gentrification, but there are also likely other factors involved in the rising housing costs of the area.

Potential Gentrification Impacts of Pulse BRT

The GRTC Pulse Bus Rapid Transit project significantly increased connectivity across central Richmond. The formal feasibility study for the project began in 2010, with the official plans announced in late 2014. Construction began in August 2016, with operations of the

Figure 69: Spatial Distribution of Transportation Projects In the City of Richmond (Filtered to Projects Likely to Impact Area Development)



Source: Study team analysis of data provided by the City of Richmond Transportation Engineering Division.

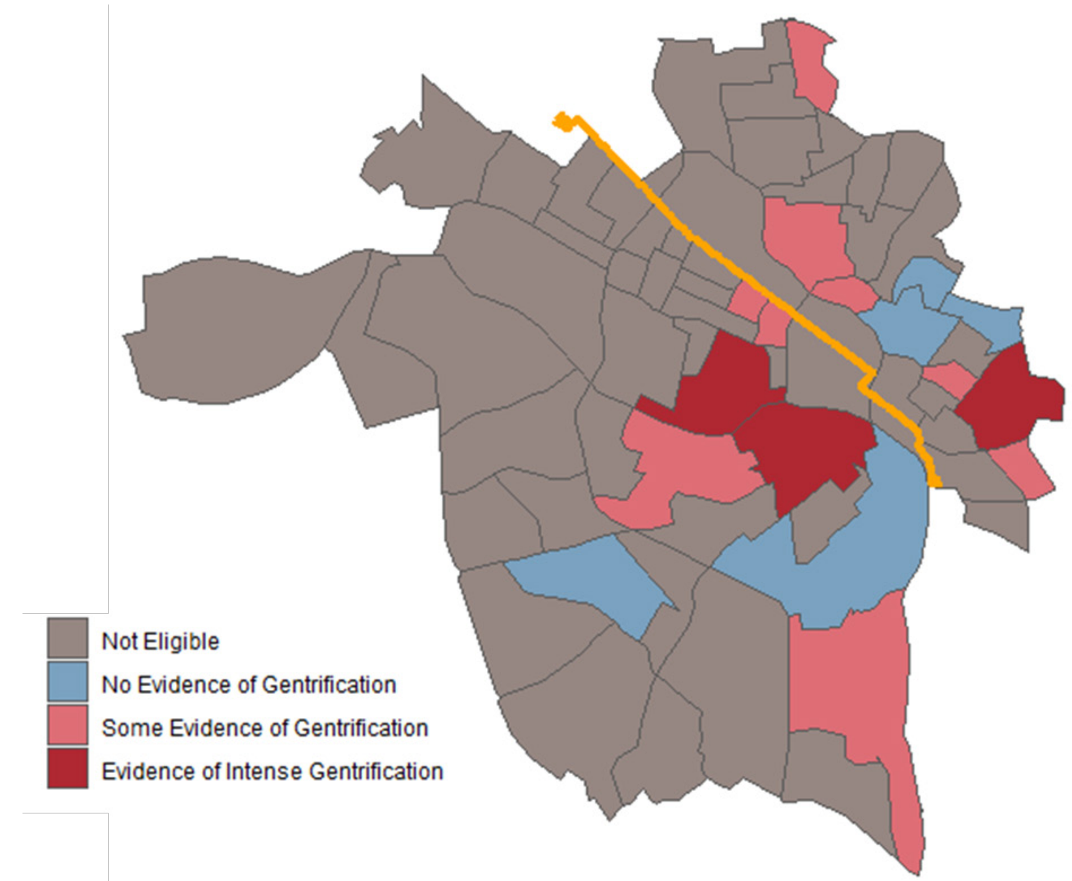
Pulse BRT service commencing in June 2018. It is likely that this project influenced the surrounding housing market before operations began, as real estate developers expected a rise in demand when construction plans were finalized. According to the study team's spatial analysis, the service area of Central Richmond had already experienced significant gentrification in the preceding decade, but there was evidence that it continued well into the 2010s. Figure 70 shows where gentrification occurred in Richmond from 2010-2019, with the Pulse BRT line overlayed in orange. Only two tracts which contained BRT stations were found to have some evidence of gentrification in the 2010s.

Figure 71 shows the trends of several measures in three census tracts that contained BRT stations and were eligible for gentrification in 2010, compared against the metropolitan area average (dashed line) for the years 2010 through 2019.

Of these three tracts, the blue tract has been eligible for gentrification in 2000, 2010 and 2019. This area is largely industrial, with the BRT stop only in the northernmost part of the tract. This large tract contains neighborhoods such as Old Town Manchester and Ancarrow's Landing. Although our analysis did not find clear evidence of residential gentrification in the past decade, rents in this area have been rising at a higher rate in recent years (2017-2019) and the neighborhood of Old Town Manchester has seen notable commercial gentrification, with recent openings of lofts and art galleries. Residents in this area, which is 90+% BIPOC, may be at risk of displacement if these trends continue. The BRT may be contributing to this, as enhanced connectivity to/from downtown may make the neighborhood more appealing to wealthier residents and real estate developers.

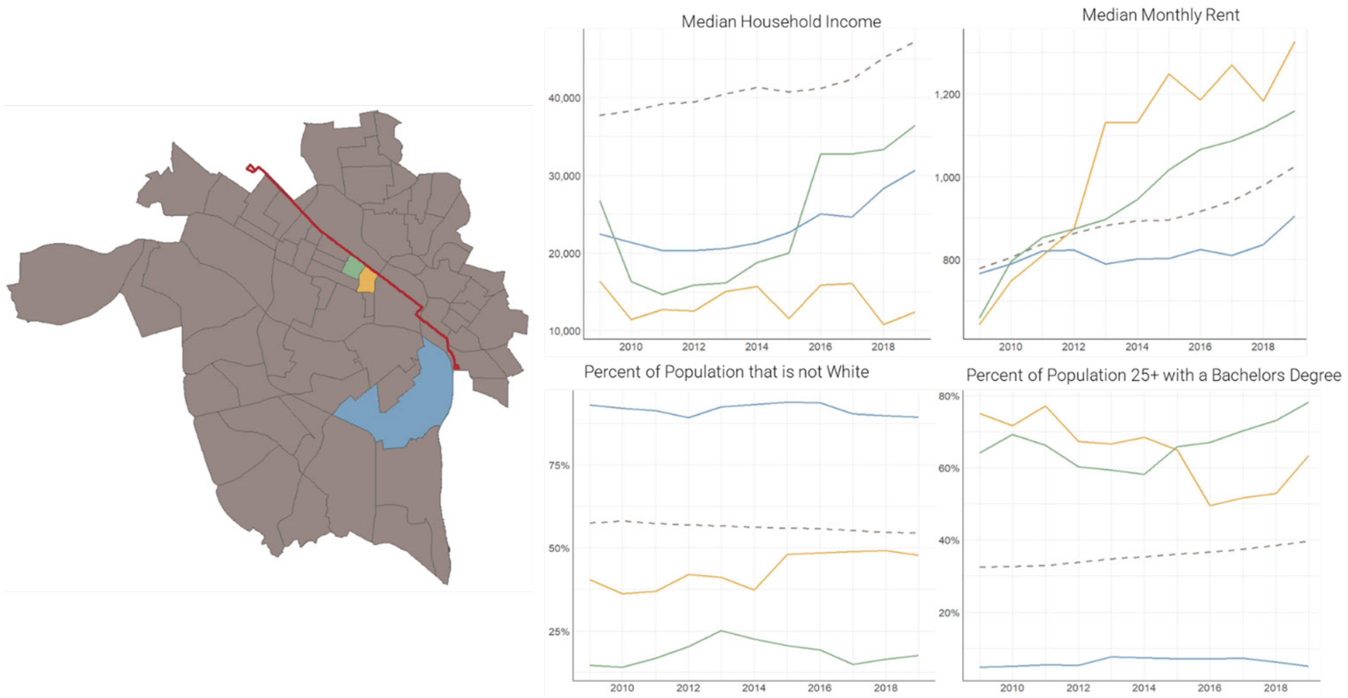
The green and yellow tracts both had evidence of gentrification in the last decade. The green tract, which is in a neighborhood known as the Fan, saw sharp increases in median household income. Rents have been increasing steadily over the decade, but increases were steepest from 2013 to 2016, much higher than the metro average increases. This coincides with the construction of the BRT.

Figure 70: Evidence for Gentrification in Richmond 2010-2019 and the Pulse BRT Line



Source: EBP Analysis of American Community Survey data, Pulse BRT route from Richmond GIS

Figure 71: Socioeconomic Trends of Census Tracts Eligible for Gentrification Near Pulse BRT



However, the Fan is also adjacent to the Virginia Commonwealth University (VCU) campus, located in the yellow census tract. The fluctuations in the percentage of the population that are college graduates and relatively flat median household income could be related to the student population of this area. As such, we cannot conclude that the ongoing gentrification of these areas are solely the result of the BRT line. It is possible that enhanced connectivity has made the neighborhood more attractive for both real estate developers and residents wanting to live in a central district. However, the combination of the VCU campus and the central location are also potential contributors to gentrification of the area.[34]

Conclusions & Recommendations for Tracking Displacement

There is evidence that gentrification has occurred in neighborhoods in Richmond and that low-income and BIPOC populations have over time decreased in the city while increasing in outlying counties. However, additional data would be necessary to determine how much transportation investments may have hastened neighborhood change. Based on the literature review, it is unlikely that individual connectivity improvements, such as bike lanes or bus route redesigns, would have had a significant impact on any neighborhoods eligible to experience gentrification. It is possible that transportation investments were correlated with the presence of a more educated, wealthier population.

Of all transportation investments in Richmond over the last 20 years, the construction of BRT in central Richmond is most likely to have contributed to additional gentrification of neighborhoods such as the Fan. However, our spatial analysis shows that gentrification was underway in this neighborhood well before any specific plans for BRT were announced. Neighborhoods that may have experienced accelerated or extended gentrification because of the BRT are in central Richmond, a dense, well-connected area of the city that has experienced significant housing demand from wealthier populations over the last 20 years, notably from students or employees of the nearby Virginia Commonwealth University.

Additional data is needed to better understand the relationship between transportation improvements and gentrification. Transit agencies increasingly maintain public, historical archives of public transportation service, in the form of GTFS data, has the potential to support studies on the impacts of transit access on surrounding neighborhoods over time. For example, a historical GTFS database could be used to analyze how a major bus network redesign may have correlated with neighborhood gentrification indicators. In addition, improved data on the spatial locations of transportation improvements included in the list provided by the Richmond Transportation Engineering Division would allow for better integration with the existing Richmond GIS assets on topics such as demolitions and property transfers to further enable the analysis of relationships between changes in connectivity or transportation safety and housing market and demographic dynamics. Granular travel data from cell phone records or household travel surveys could also allow for the analysis of changes in individual travel behavior that could be indicative of neighborhood change.

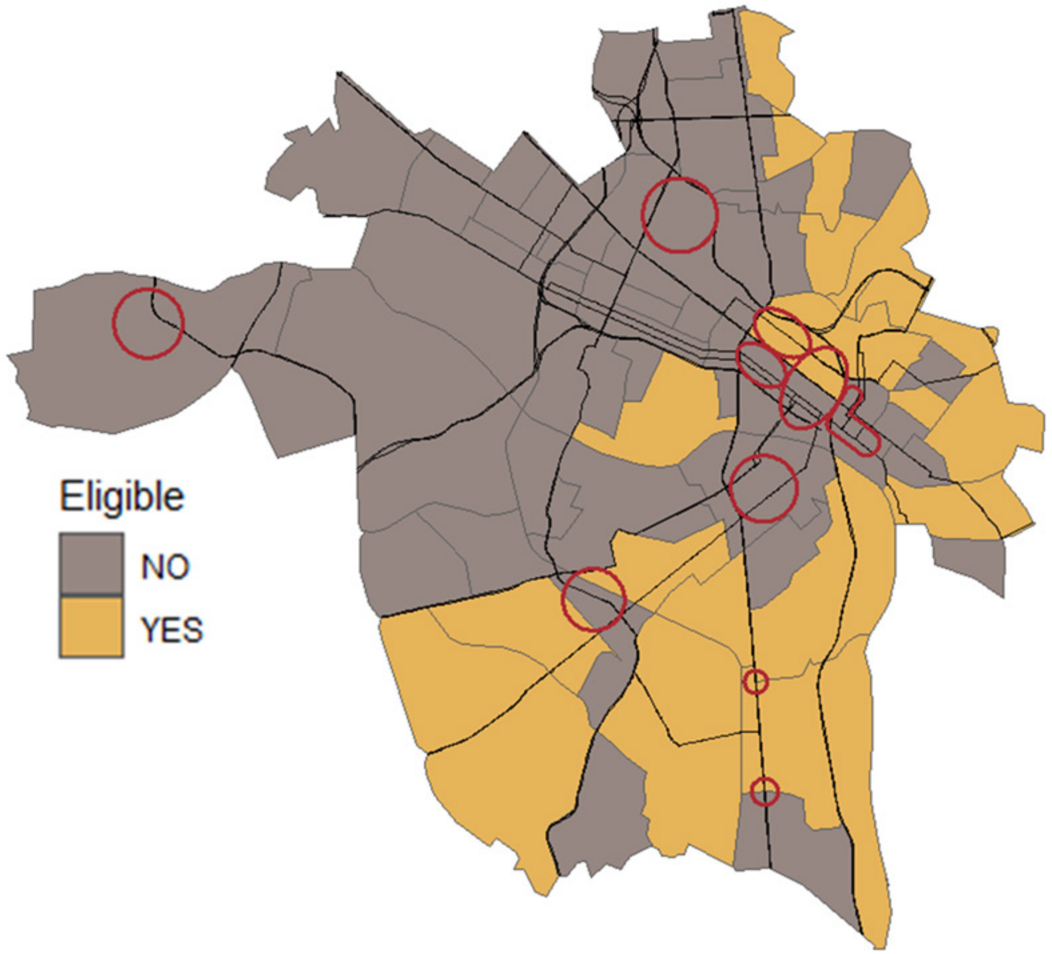
Special attention should be taken to mitigate the potential impacts of transit-induced gentrification in Richmond when planning transportation investments in vulnerable areas. Figure 72 displays neighborhoods which were vulnerable to gentrification as recently as 2019, overlayed with the planned Richmond growth nodes.

Additional metrics, such as evictions and unemployment, which are incorporated into the Urban Displacement Project's Housing Precarity Risk model, may also be valuable for assessing vulnerability to displacement for consideration in future transportation planning decisions.[35]

34. https://commonwealthtimes.org/2020/09/10/vcus-campus-is-only-making-gentrification-worse/

35. https://www.urbandisplacement.org/maps/housing-precarity-risk-model/

Figure 72: Census Tracts Eligible for Gentrification in 2019, with Richmond Growth Nodes



Source: EBP Analysis of 2019 American Community Survey data

Policy Implications

As noted in the foregoing sections, while gentrification has occurred in Richmond (which by some measures is among the most gentrified metropolitan areas of the U.S.[36]), more data is needed to analyze the complexity of the possible causal relationship between transportation investment and gentrification. In Richmond, our analysis shows that transit-induced gentrification is likely to have occurred to some extent in and around the Pulse BRT system. However, the direction of the relationship is partially unclear, as neighborhoods around the BRT began gentrification prior to this improvement.

These findings provide a limited basis for executing changes in transportation investment policies in the City of Richmond to mitigate gentrification. It is nevertheless important for public officials and policy makers to be cognizant of the potential negative effects of gentrification on minority and low-income households and entire communities. Around the country, cities have utilized a variety of mechanisms to mitigate against gentrification and neighborhood displacement. Due to growing concern surrounding the suburbanization of poverty, cities such as Austin[37] and Denver[38] have published reports identifying strategies for mitigating involuntary displacement of marginalized communities.

Among the most effective and widespread is inclusionary housing (also called inclusionary zoning), in which developers are required to provide a certain percentage of affordable units in new buildings. Research from the University of Maryland's National Center for Smart Growth has found that TOD-based affordable housing policies are among the most effective tools for mitigating the possible impact of transit-induced gentrification by supporting housing affordability and helping maintain access to public transportation for low-income households.[39] The Joint Center for Housing Studies at Harvard notes with some caution that "new affordable housing units (inclusionary or government-subsidized) may help retain the income mix of the neighborhood, but those units may or may not prevent displacement of existing residents because the people who move in could be from outside the neighborhood. To increase their efficacy as anti-displacement tools, we would need to offer a neighborhood preference for new tenants. Current fair housing rules, however, often prevent or severely limit such preferences."[40]

Other measures which have met with varying success include:[41]

- Community land and housing trusts, in which non-profit organizations purchase land and homes for resale to community residents
- Tenant right to purchase covenants, which give tenants the right to purchase homes on a right of first refusal basis
- Rent controls or rent stabilization to provide tenants with protections against rapid appreciation in rents
- Limits on big box retailing or other chain retailers, to encourage neighborhood ownership and character [42]

Transportation investment policy should also be conducted with special attention to equity. Past research and the study team's analysis of Richmond suggest that transportation (and other infrastructure) investments, rather than triggering gentrification, may be disproportionately placed in areas where higher income populations are increasing. Conversely, investments may be less prevalent in areas where poverty is increasing, particularly in suburban pockets of poverty, where because of lower densities public transit is less effective or more costly. While further research is still needed in this area, some advocates in other metropolitan locations have observed that active transportation investments, such as bike share programs, tend to have relatively little penetration in poorer, minority neighborhoods.[43]

To counteract these tendencies, locales should be vigilant in the siting of transportation investments to ensure they serve both high and lower incomes, including consideration of flexible public transit services, ride share partnerships, and other mechanisms to provide enhanced transit to lower income suburban areas in an economical manner. Additionally, active transportation facilities, including bike share stations, should be equitably sited, and made affordable in lower income areas.

36. https://ncrc.org/gentrification/
37. https://www.austintexas.gov/sites/default/files/files/Housing/Displacement_Mitigation_Strategy_Blueprint_Chapter__002_.pdf
38. https://www.denvergov.org/content/dam/denvergov/Portals/690/Reports%20and%20Studies/GENT%20STUDY%20052316.pdf
39. https://arch.umd.edu/about-school/news-events/umd-study-targeted-housing-policy-key-preventing-transit-induced
40. https://www.jchs.harvard.edu/blog/strategies-for-responding-to-gentrification
41. https://thenextsystem.org/fighting-gentrification-best-practices
42. https://www.bloomberg.com/news/articles/2021-05-19/small-businesses-are-victims-of-gentrification-too
43. https://bike-lab.org/2020/05/26/assumption-of-equity/

6 - RELATIONSHIP BETWEEN TESTED MEASURES AND ACCESSIBILITY INDICATORS

Summary

This element presents the results of an analysis comparing accessibility scores by the walk, bike, and transit modes to observed mode shares in the Richmond region. Assuming a direct relationship between mode share and access to jobs by each mode, we defined mode usage groups of "less-than-expected," "expected," and "higher-than-expected" for each mode. These usage groups establish geographic areas where mode shares underperform, match expectations, or overperform respectively, given the access provided by each mode. Within each of these geographies, we summarized demographic characteristics and health statistics looking for trends that would indicate barriers to non-auto utilization as well as evidence of demographic disparities in access, mode share, and health behaviors and outcomes.

Through this analysis, we aimed to identify barriers to multimodal travel. We expected areas with relatively high multimodal accessibility scores and low multimodal utilization to face barriers to access that were not accounted for in the accessibility analysis methodology. However, we observed that these areas aligned with neighborhoods characterized by middle- and high-income households and high rates of auto ownership. This indicates that auto ownership is the primary barrier to non-auto utilization. For this reason, we shifted our analysis approach to focus on areas with higher-than-expected mode shares, where we recognized a clear spatial correlation with key demographic groups at the center of equity concerns (e.g., people of color, low-income households).

We found that populations in areas with higher-than-expected non-auto mode shares are generally more diverse and vulnerable than populations in other parts of the region. They also exhibit lower participation in preventative health behaviors and higher rates of adverse health outcomes. As noted above, this indicates that higher-than-expected non-auto utilization is determined largely by socioeconomic status and demographics when the utility provided by a non-auto mode (i.e., its accessibility score) is controlled for. This suggests that the primary barrier to non-auto utilization is access to a car. Most barriers to access experienced by travelers with low rates of vehicle availability are obscured by their need to reach destinations despite not having a vehicle available. It also indicates that, despite a higher utilization of active transportation modes (walking, biking, as well as transit with walk access/egress), any health benefits associated with active travel are swamped by other factors that lead to comparatively poor health among vulnerable populations. Finally, these areas are also more likely to contain lower-income residents, and many are at risk for gentrification.

In general, areas with higher-than-expected use of non-auto modes have less access to the technologies that allow trip-making to be substituted for virtual access. This includes access to broadband internet and smartphones as well as participation in the financial system (i.e., having a bank account or credit card) that is often necessary to maximize the utility of these technologies. This pattern applies for areas with higher-than-expected walk and transit use but is not fully held for biking. Limited access to technology in these areas may heighten dependency on non-auto travel modes to meet accessibility needs and contribute to the higher-than-expected mode shares.

While it is beyond the scope of the current analysis to identify the underlying causes, we see evidence that many neighborhoods in the Richmond region are characterized by vulnerable populations with limited travel choices, relatively poor health outcomes, less access to technology, and higher risk of displacement due to rising demand for housing and affordability crises. These vulnerable groups can be described as generally underserved or at risk with respect to the region's transportation, health care, technology, and housing systems.

Methods

Mode usage groups were defined for three non-auto modes: walk, bike, and transit. "Usage" was defined relative to an expectation: are travelers in a zone using that mode less than expected (low non-auto), about as much as expected (expected non-auto), or more than expected (high non-auto)? Expectation of use was assessed by comparing observed mode share to observed accessibility via that mode. Though accessibility alone is an inadequate predictor of mode share, it is known to have a strong positive relationship with mode share: generally, the more a traveler can get to using a mode, the more likely they are to use that mode.

For this analysis, a proportional relationship was assumed to quantify this theory; mathematically, this constitutes a positive, linear relationship. To avoid the limitations associated with true model fitting in this context (aggregate geographies, known lurking variables), quantiles of accessibility and mode share were compared. The assumed linear relationship then took the form of matching quantiles: if a zone's accessibility for a mode was the 50th percentile of all accessibilities for that mode, its mode share should also be the 50th percentile of all mode shares.

Of course, such a relationship is imperfect because quantiles will never match exactly. But, if a mode share quantile is much lower than the corresponding accessibility quantile, it is safe to say that mode is being utilized less than expected (assuming accessibility and mode share are roughly proportional). Similarly, if a mode share quantile far exceeds the corresponding accessibility quantile, that mode is being used more than expected. A simple difference of the mode share and accessibility quantiles can be used to determine how spread out the two are.

Though this method of grouping is conceptually simple, the "expectation cutoffs" – the difference in quantiles at which mode share is no longer expected – cannot be definitively set based on natural groupings of the data. Rather we defined subjective cutoffs for each non-auto mode through mapping and visualization, selecting cutoffs that produced groups aligning with local knowledge of the city. The cutoffs were:

- Walk: ±0.35
- Bike: ±0.25
- Transit: ±0.15

Thus, for the walk mode, if a zone's quantile difference was less than -0.35, it was considered a low walk area; if the quantile difference was between -0.35 and 0.35, it was considered an expected walk area; and if the quantile difference was greater than 0.35, it was considered a high walk area. This interpretation was used to create the mode-specific usage groups that were used in comparative analysis. The maps below present the geography of each mode's utilization groupings.

Streetlight data representing travel conditions during the spring of 2019 was used to estimate mode shares among census block groups throughout the Richmond region. Accessibility scores were estimated at the block group level across the region except within the City of Richmond, where census blocks were used to provide finer-grained resolution. It was assumed block-group level mode share estimates applied consistently among all blocks within a block group.

Barriers to Accessibility

In general, areas with lower-than-expected non-auto usage are found in parts of the region where high incomes and vehicle availability make travel by car more convenient than other modes, regardless of the access provided by those alternative modes. In this way, wealth and vehicle availability are "barriers" to non-auto utilization. This general interpretation, however, requires further elaboration:

- Some locations with lower-than-expected walk utilization reflect walking conditions that are difficult to fully account for in the accessibility analysis. Several underperforming areas are separated from nearby jobs by highways, the James River, or steep uphill grades. The psychological boundaries imposed by such barriers are not fully accounted for in the current accessibility analysis, though they may be considered in future iterations.
- Lower-than-expected bike shares are observed in downtown Richmond, where jobs access is very high, and the relative convenience of walking to nearby destinations probably mitigates bike utilization. Thus, very high walk accessibility could be considered a barrier to bike utilization.

Figure 73: Expected use of Walk mode

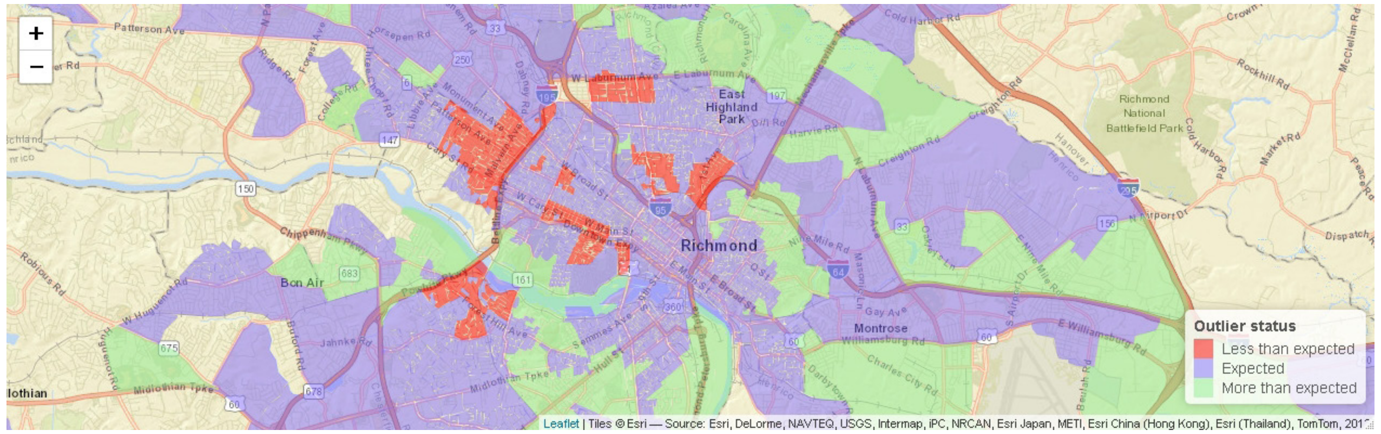


Figure 74: Expected use of Bike mode

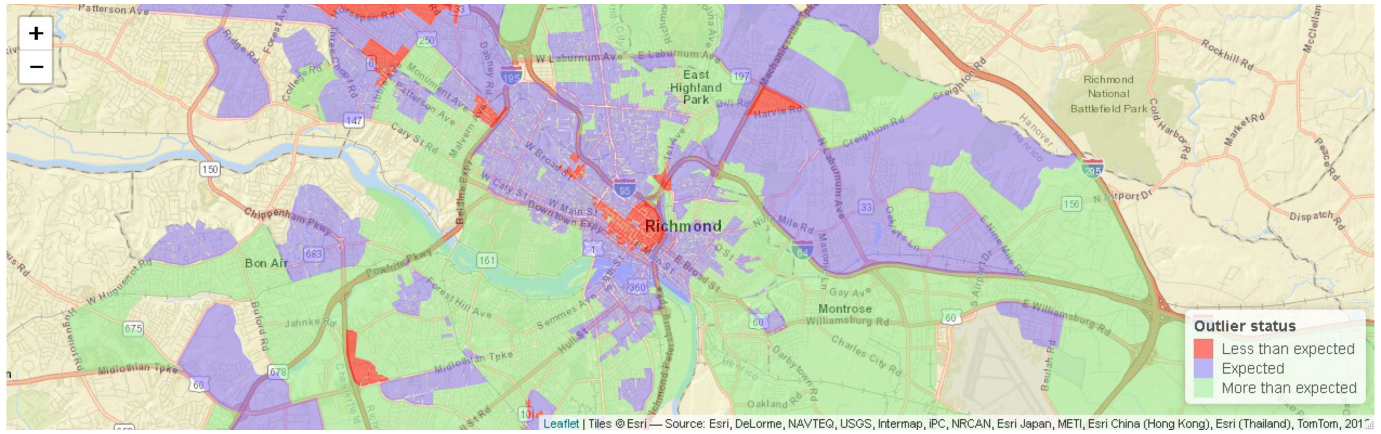
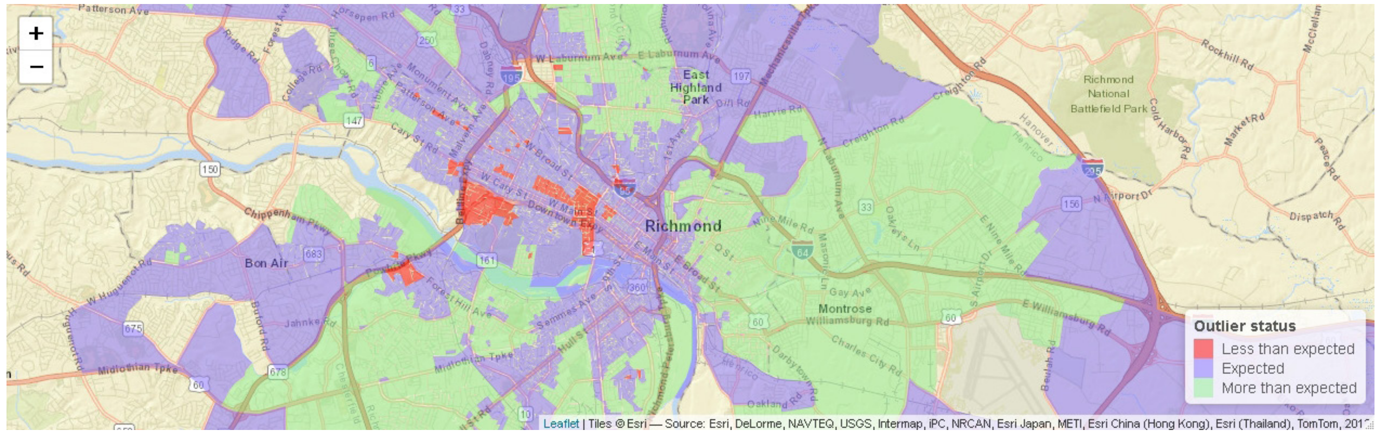


Figure 75: Expected use of Transit mode



- Lower-than-expected transit shares may in some cases be a function of non-optimal access to transit, echoing consideration of psychological barriers impeding walk utilization but with slight variations reflecting the concerns of transit riders. For example, transit shares generally fall in the "expected" range in the Westover Hills area, except around the interchange of Forest Hills Avenue and Powhite Parkway. To the east and west of the interchange are development clusters where bus stops are collocated with destinations, but in the immediate vicinity, stops are located along a wide boulevard cross section surrounded by low density residential development. The access provided by transit may be undermined in this case by a poor access/egress and waiting experience.

In addition to highlighting some potential barriers to non-auto utilization, the mode usage groupings offer geographies within which to examine relationships between accessibility, mode utilization, and key outcome variables. The remainder of this section highlights trends with respect to demographics and health outcomes in the distinct mode usage areas.

Demographics

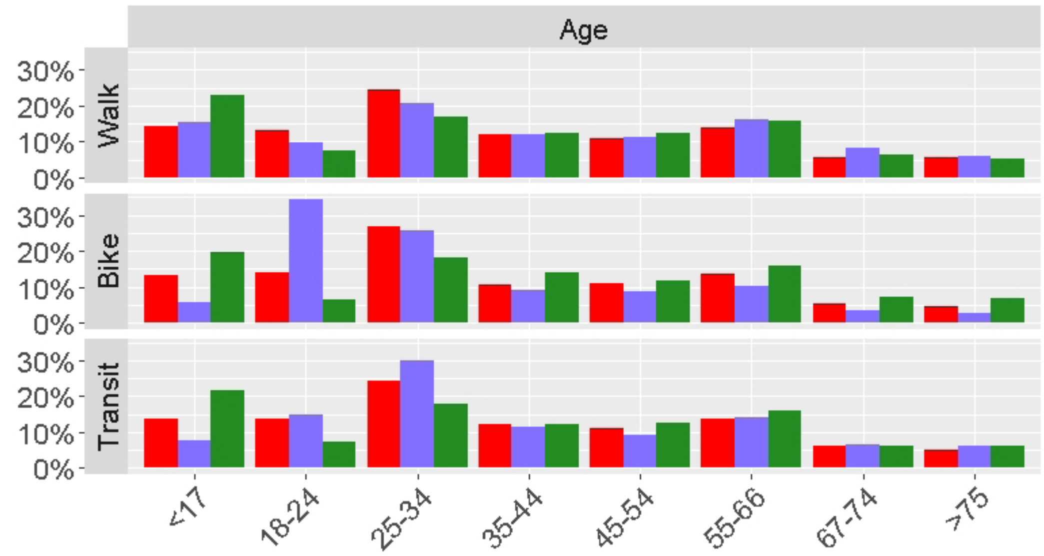
Except for race, demographic data was sourced from our population synthesis of the Richmond metropolitan area (part of the accessibility scoring process). This synthesis combined unique block-group-level 2019 ACS estimates into cohesive descriptions of individuals spanning multiple person- and household-level characteristics. Because race was not a part of the population synthesis, race estimates were pulled directly at the block-group-level from the 2019 ACS. Demographic breakdowns of each characteristic were calculated at the block group level and applied proportionately to block features.

Demographic patterns indicate that populations in high non-auto use areas have higher proportions of vulnerable populations (e.g., minority, low education, low income, disabled). In the case of these vulnerable populations, mode choice is often not a "choice" at all, but rather a function of limited options. Thus, this analysis suggests that higher than expected non-auto utilization reflects lower rates of vehicular availability either due to affordability factors or age and ability factors, calling for investments to improve non-motorized travel options and conditions for these users. A breakdown of residents by demographic characteristic is provided below.

Age

High non-auto use areas tend to have higher proportions of young (<17) and old (>55) populations. Other areas are distinguished by their relatively higher proportions of young adults (the 18-35 population). Young and old populations are more likely to struggle with active modes, so the higher presence of non-motorized usage indicates potential challenges in travel for these populations.

Figure 76: Expected mode use by age



Race

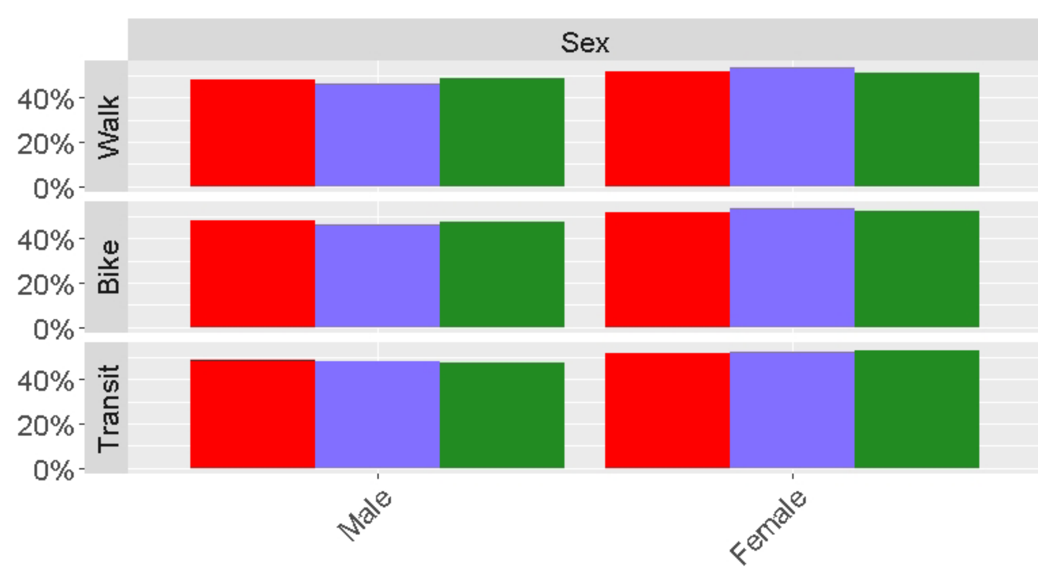
High non-auto use areas are characterized by higher Black populations, while low and expected non-auto use areas tend to have more white populations. Though other races are present, they appear to be much rarer in the Richmond area, making it hard to point to them as distinguishing characteristics of mode utilization groups.

Figure 77: Expected mode use by race

Sex

The sex breakdowns between non-auto use groups are roughly the same. This is an expected result, given that sex distributions tend to be relatively constant across aggregate geographies.

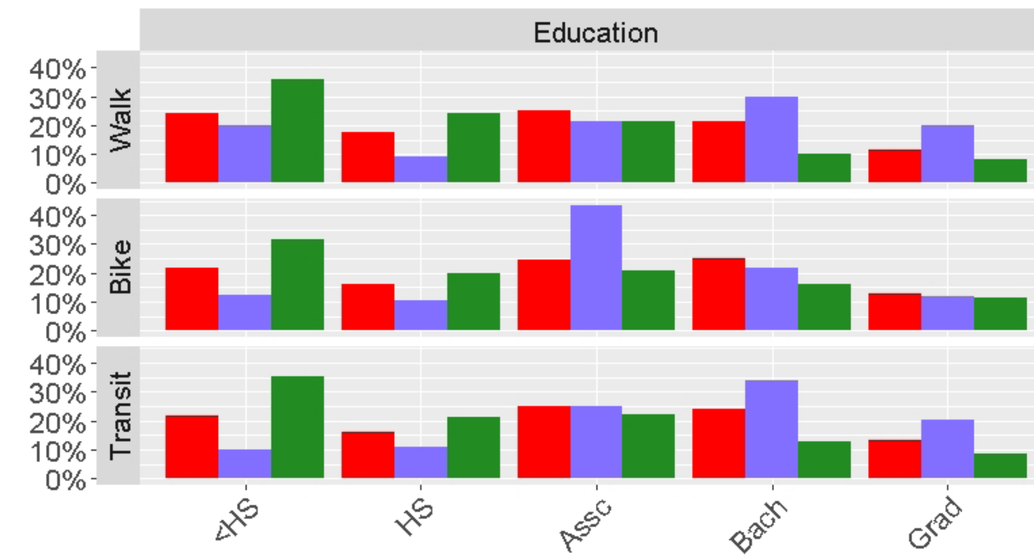
Figure 78: Expected mode use by sex



Education

High non-auto use areas have much higher rates of low educational attainment (high school or less). By contrast, other areas have a more college-educated population. We would expect a less-educated population to correlate with lower employment and income, both of which will be explored in later sections.

Figure 79: Expected mode use by education



Worker Status

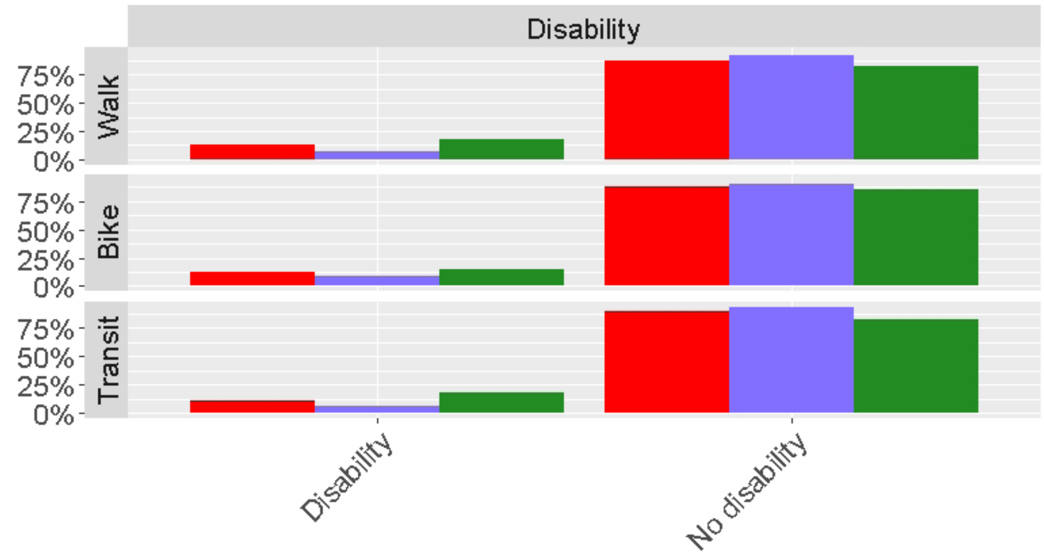
High non-auto use areas have the highest proportion of non-workers, and the lowest proportion of full-time workers; this suggests lower overall employment in these areas. This aligns with our finding of lower educational attainment in high non-auto use areas.

Figure 80: Expected mode use by worker status

Disability

There is a higher instance of disability in high non-auto use areas than in other areas. Depending on the disability, it could pose a serious barrier to non-motorized travel, making the higher-than-expected usage of walking and biking a notable finding.

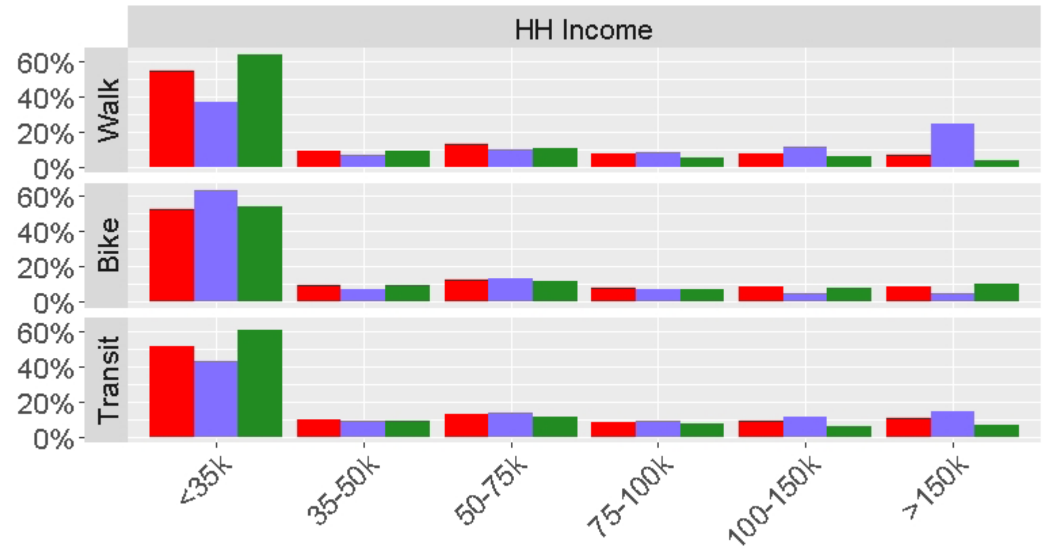
Figure 81: Expected mode use by disability status



Household income

Household income is lower in high walk and transit use areas, but this does not appear to be the case for high bike use areas. In high bike use areas, a larger share of the population appears to be high income. This may be the result of bike usage requiring bike ownership, which is likely higher in high income areas. For the high transit and walk use areas, the higher rates of low-income households align with the lower educational attainment and employment observed in previous sections.

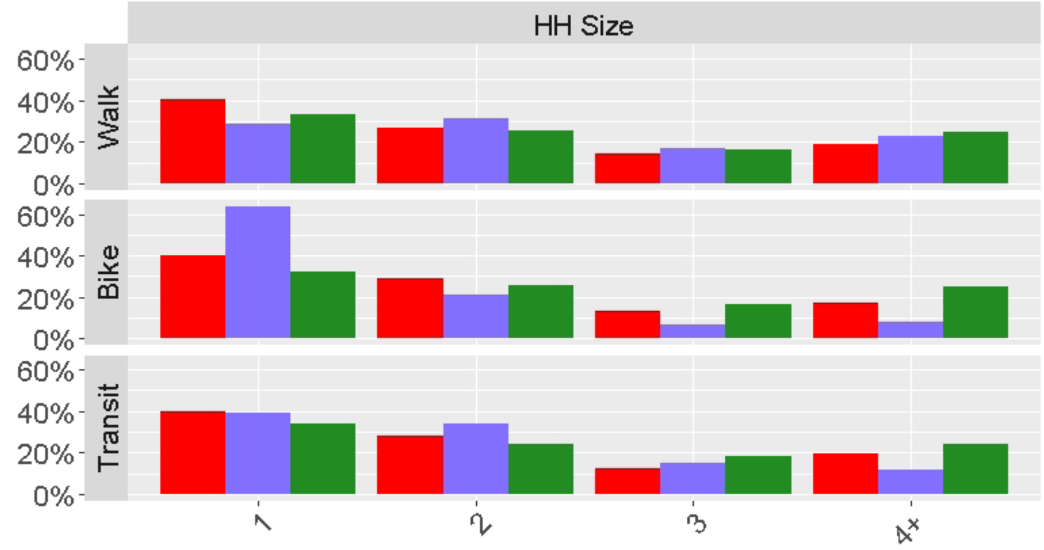
Figure 82: Expected mode use by household income



Household size

Household sizes tend to be larger in high-non auto use areas: there are higher proportions of 3 and 4 person households, and lower proportions of 1 and 2 person households. This indicates that more families with children are likely present in these high non-auto use areas, supporting the previous finding of higher young populations in these areas.

Figure 83: Expected mode use by household size



Health

Health data was sourced from the CDC's PLACES data covering "health risk behaviors, health outcomes, health status measures, and prevention practices". This data was gathered at the census tract level and proportionately to blocks and block groups where appropriate. The data was then overlaid with the areas with lower than expected, expected, and higher than expected use of walking, biking, and transit modes to discern relationships between health outcomes and accessibility.

People in high non-auto use areas tend to have poorer health outcomes, lower participation in preventative care, higher rates of risky behaviors, and generally worse health status than other parts of the region. Despite the higher-than-expected non-motorized mode shares in these areas, these metrics suggest that the people taking these trips are not experiencing the health benefits associated with non-motorized travel or that these benefits are dwarfed by other drivers of health care participation and positive health outcomes. It is important to keep in mind the demographic profile of high non-auto utilization areas (described above) when interpreting these results.

Health outcomes

In nearly all cases, health problems are more common in high non-auto use areas. Though the trend holds for all observed health problems, it is most stark for chronic obstructive pulmonary disease (COPD) and coronary heart disease (CHD) rates.

Figure 84: Health outcomes by expected mode utilization

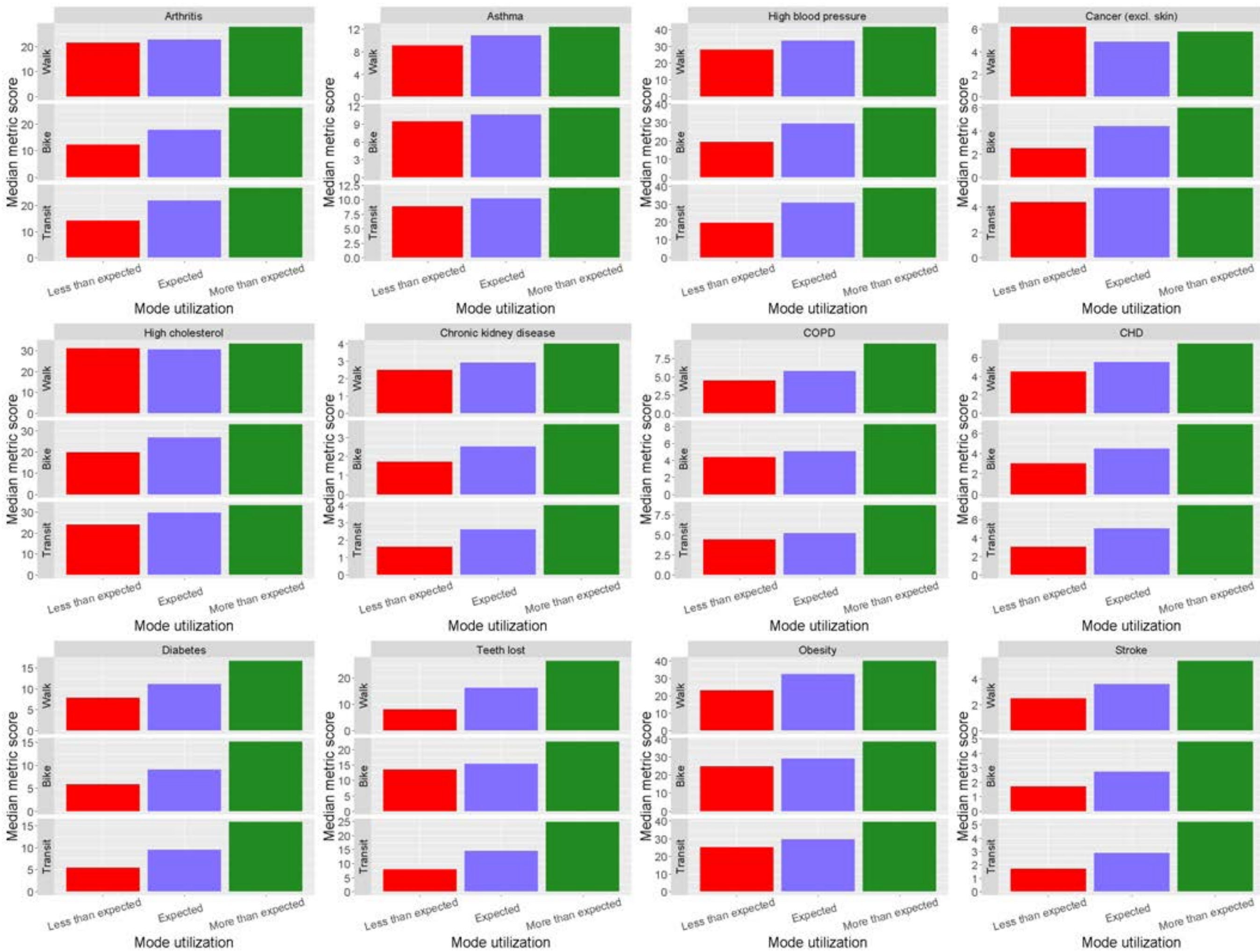


Figure 85: Prevention by expected mode utilization

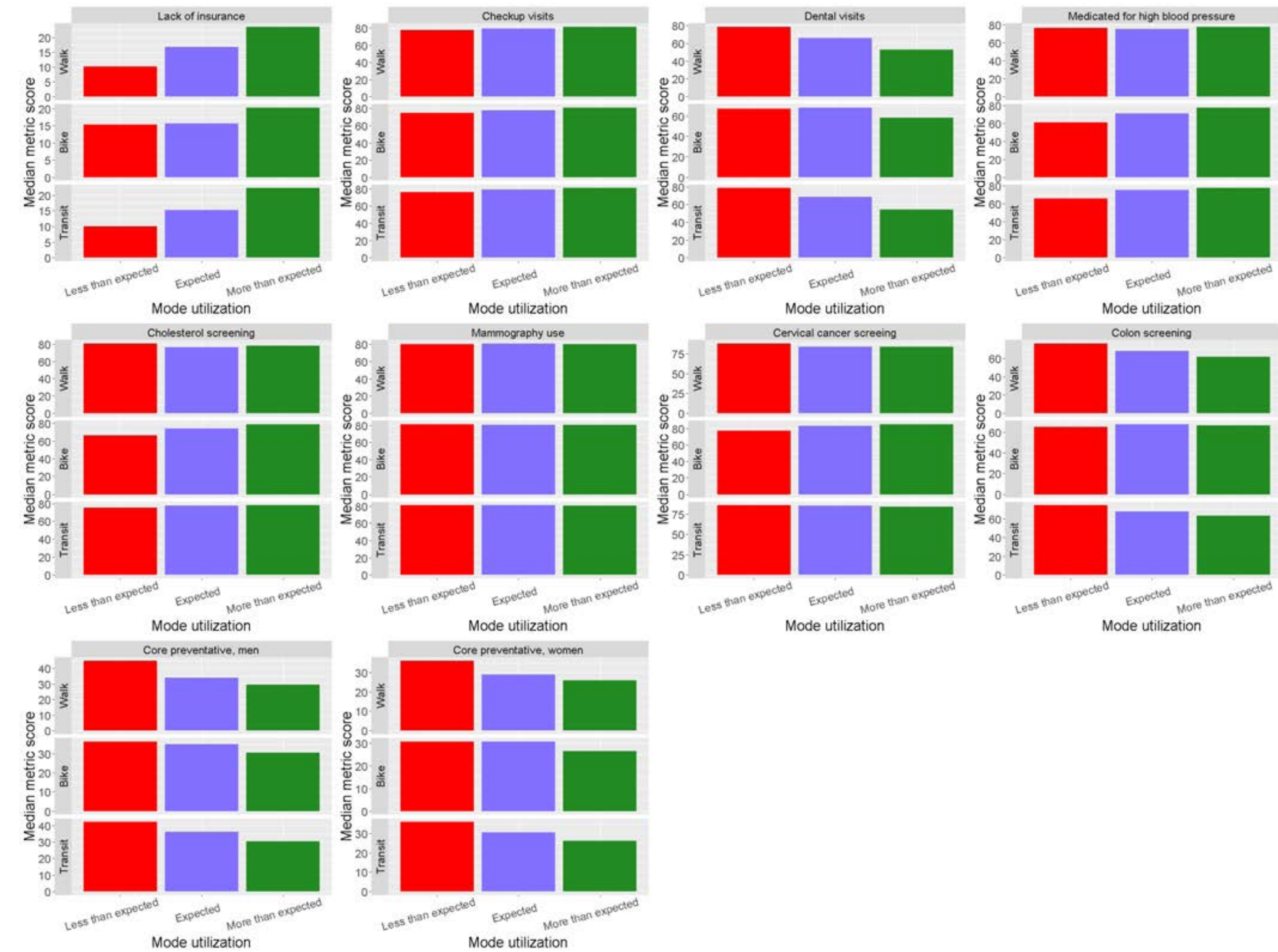
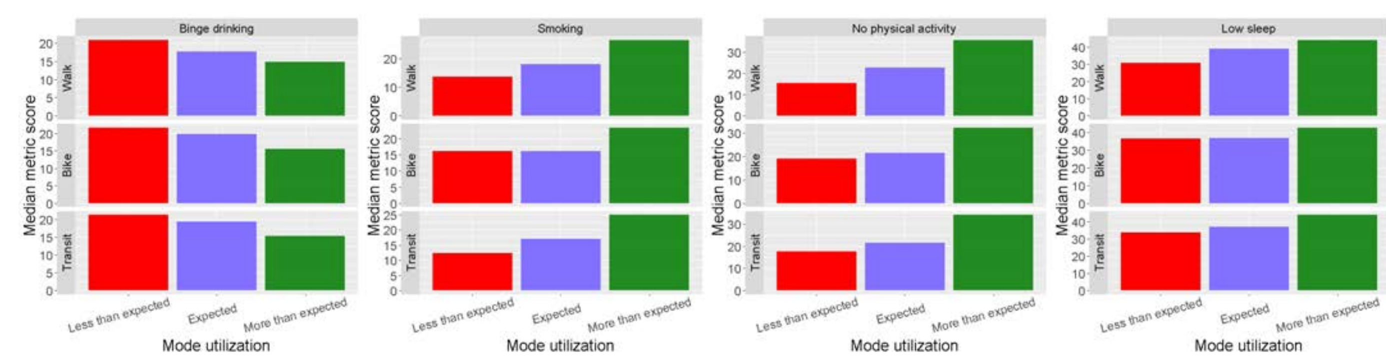


Figure 86: Health risk behaviors by expected mode utilization



Prevention

People in high non-auto use areas tend to participate less in preventative care, with similar trends observed among men and women. They are much more likely to have no health insurance, much less likely to visit a dentist, and notably less likely to have colon screenings. They have modestly higher rates of blood pressure medication and modestly lower rates of cholesterol screening and cervical cancer screening. There is minimal difference in mammography use among the distinct mode utilization areas. Only in higher rates of checkup visits do residents of high non-auto use areas exhibit greater participation in the health care system.

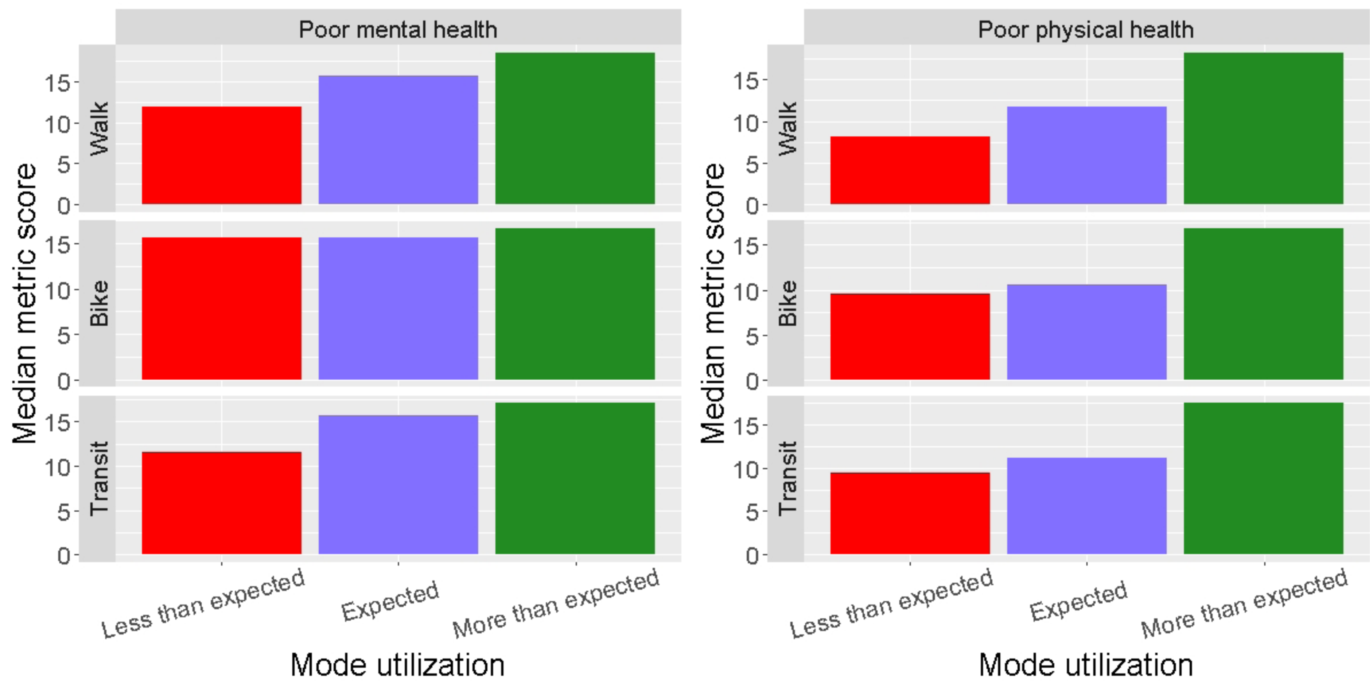
Health risk behaviors

Binge drinking excluded, people in high non-auto use areas participate in more risky behaviors with regard to health. They smoke more often, have less physical activity, and get worse sleep. Binge drinking is notably higher in areas where non-auto utilization is low.

Health status

People in high non-auto use areas are self-described as being in worse mental and physical health, suggesting an overall poorer health outlook.

Figure 87: Health status by expected mode utilization



Technology Access

The team overlaid the data on technology access with the areas with lower than expected, expected, and higher than expected use of walking, biking, and transit modes and calculated the average access to each technology for parts of the city with lower than expected, expected, and higher than expected use of each mode.

Areas with greater than expected walking or transit use more frequently lack access to each of the four technologies shown compared with areas with lower than expected walking or transit technologies (Figure 88 and Figure 89) . Although this analysis does not allow identifying the reasons for the differences in technology access among these areas, it may be that there is another variable related to socioeconomic factors that both make residents in these areas more likely to use walking and transit modes, and also make them have access to these technologies more frequently.

Bicycle access shows this pattern less consistently than walking and transit modes (Figure 90). Broadband shows no meaningful difference among areas with lower than expected, expected, or greater than expected cycling, and areas of lower than expected biking more frequently have credit / debit card access. This suggests different factors driving bicycle mode use than for walking and transit, although their difference is very small. It is possible that lack of credit / debit card access serves as a barrier to accessing biking. Areas with more biking more frequently lack access to bank accounts and smartphones, which may be due to socioeconomic or other variables.

Gentrification and Travel Mode Choice

As discussed above, it is a well-documented fact that lower-income communities are less likely to own cars and more likely to be transit-dependent. As a result, these areas often see higher than expected transit utilization, while also being at risk of gentrification that could displace marginalized communities away from this essential access. Due to the significant reliance on public

Figure 88: Technology Access by Walk Mode Share Compared with Expectations

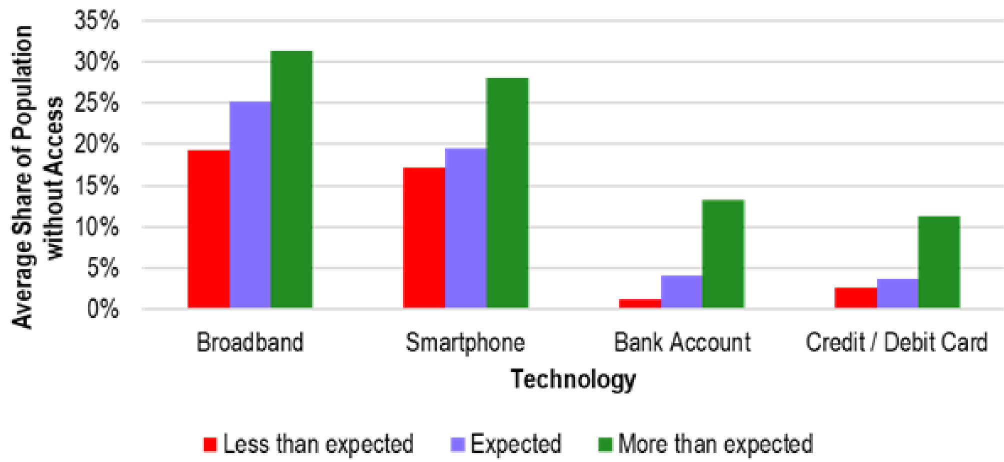


Figure 89: Technology Access by Transit Mode Share Compared with Expectations

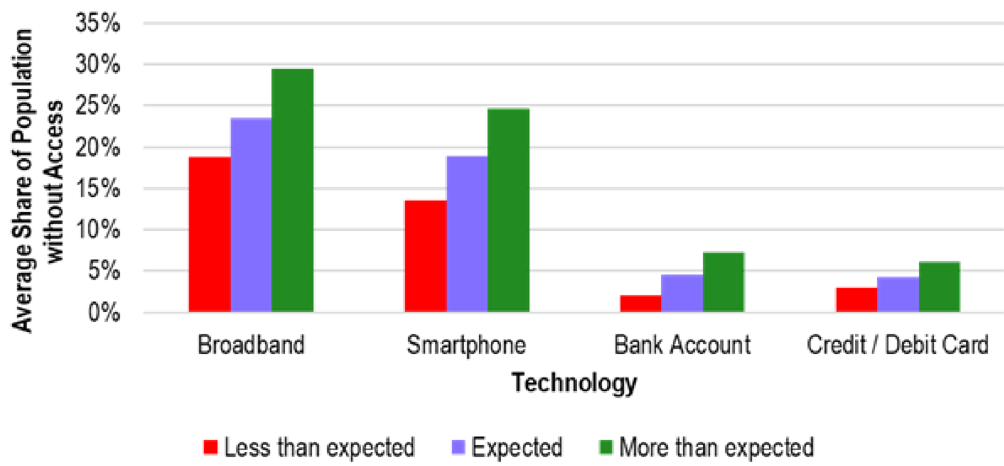
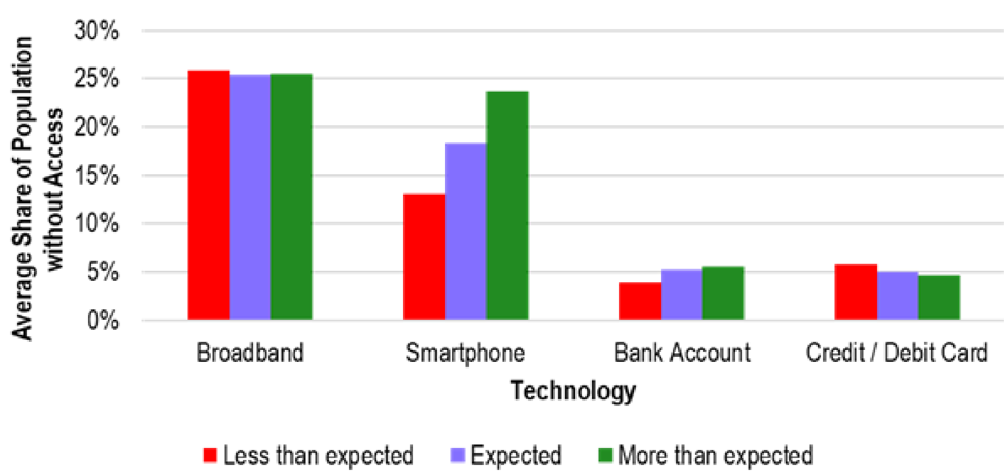


Figure 90: Technology Access by Bike Mode Share Compared with Expectations



transportation, displacement of these communities can have a serious impact on health and other outcomes. Research has consistently found that gentrification can be associated with undesirable health impacts of Black and low-income residents.[44]

Although vulnerability of a neighborhood can often correlate with higher-than expected transit usage, a neighborhood that has already experienced gentrification may see higher usage of non-auto modes. Bike lanes are more frequently installed in higher-income, gentrified neighborhoods than lower-income areas, which could drive bicycle usage. As such, some areas of high bike utilization could be driven by either lack of car ownership for lower income residents, or preference for active modes of wealthier residents.

Conclusion

The accessibility analysis for this effort has affirmed that correlations do exist between levels of modal access and certain indicators. As tested, a strong correlation exists between areas with higher levels of auto-use and well-being. While this report does not identify causes of poor well-being, the results point to a need for improved access and resources in areas with low-levels of auto use. A direct correlation between technology access and transportation access also appears to exist, but the analysis could benefit from additional data to confirm the strength of the correlation. Expanding survey efforts to capture technology access data from neighborhoods with low-representation would greatly support this effort. Correlations between gentrification and mode use proved more difficult to discern, often with areas experiencing gentrification seeing the same mode usage as areas that are not experiencing gentrification.

This study confirms that access is a significant factor impacting a resident's employment, health care, and quality of life. This effort also finds that wealth and auto access are the greatest barriers to non-auto mode utilization. Where low levels of auto access are identified, more work is to be done to improve equity for those reliant on non-auto modes of travel. The findings of this report indicate that additional research into the impacts of access are warranted. The follow-on activities identified throughout this report will help further the understanding of access and equity and should be incorporated in Richmond's multimodal plan update.

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44. Smith, G.S., Breakstone, H., Dean, L.T. et al. Impacts of Gentrification on Health in the US: a Systematic Review of the Literature. J Urban Health 97, 845–856 (2020). https://doi.org/10.1007/s11524-020-00448-4

APPENDIX A - EQUITABLE ACCESS METRICS DATA SOURCES, OPEN SOURCE CODE REPOSITORY, AND DATA DICTIONARY FOR STUDY OUTPUTS

Data Sources

The composite accessibility scores utilize travel survey data to understand travel time budgets and destination relevance for different segments of the population. The 2017 National Household Travel Survey (NHTS) was used to develop factors that weight destinations based on relevance to travelers and travel time from the origin, as described in Table 1.

Table 1: NHTS Weights on Composite Accessibility Score

Aspect of composite accessibility score	Description	Data Source	Process
Destination relevance	How likely is a traveler of a given type to make a trip to each destination type?	NHTS 2017	Estimate choice models (probability of making a trip) for each destination type based on traveler characteristics
Travel budgets	How much does the likelihood of making a trip degrade based on the time (and/or cost) to reach the destination?	NHTS 2017	Estimate distributions of travel times by traveler characteristics, destination type, and mode of travel.

Networks provide insight into travel times by mode. This is necessary to apply the travel time budget and competitive access components of the composite score. Network data used in this study are described in Table 2.

Destinations attract trips. Knowing the geography of destination types is essential to describing the accessibility of any location where trips may begin. Destination types are grouped to keep the analysis manageable, but subtypes within each group may have different weights (see Table 3). Weights may be set based on trip generation rates or normatively (if access to grocery stores is expected to matter more than access to other shopping destinations, e.g.). The weights used in this study are reported in the table below. For non-work destinations, they are based on approximations of expected relative trip generation rates derived from the Institute of Transportation Engineers (ITE) Trip Generation Handbook. For jobs, job relevance is tied to worker education at the residential and workplace locations. Crisis destinations are unweighted since access to these locations are analyzed in terms of the minimum travel time to the nearest one.

Accessibility varies based on traveler characteristics. The population synthesis process estimates traveler characteristics at each origin zone based on ACS data (see Table 4). This allows composite accessibility scores using the "basic utility" formulation to reflect the relevance of destinations reachable given the composition of the population.

Table 2: Network Data used to Determine Travel Times

Mode	Data Source	Description
Auto	Richmond regional travel model loaded highway network	Estimates of travel times by car in congested conditions (AM peak)
Transit	OpenStreetMap	Estimates of travel times by walking for transit access/egress
	GTFS	Estimates of in-vehicle stop-to-stop travel times by transit based on schedules for GRTC and PAT transit agencies.
Walk/Bike	Open Street Map	Estimates of travel times by walking and biking. Includes some basic facility attributes that can be used to modify impedance based on user comfort. The OSM network is queried to exclude facilities that are walk/bike traversable but unlikely to contribute to walk/bike accessibility. The SQL statement is provided below: "highway" IS NOT IN ('track','path','[“track”, “service”]','pedestrian','[“footway”, “service”]', '[“pedestrian”, “unclassified”]','[“footway”, “pedestrian”]', '[“footway”, “path”, “service”]','[“footway”, “path”, “steps”]','corridor', '[“unclassified”, “track”, “residential”]','[“unclassified”, “living_street”]', '[“track”, “tertiary”, “residential”]','[“service”, “living_street”], '[“path”, “steps”],'[“pedestrian”, “footway”]','[“track”, “unclassified”]', 'bridleway','[“footway”, “track”]','services', '[“track”, “service”, “residential”]','[“footway”, “path”]', '[“path”, “service”]','living_steet','[“path”, “track”]')
	CoR Sidewalk Inventory	Enrichment layer to allow presence/absence of a sidewalk and sidewalk condition to influence walk times
	CoR Bicycle Facilities	Enrichment layer to allow bicycle facility type on local roads to influence bicycle times
	CoR Transportation Surfaces	Enrichment layer to allow parking lot adjacency, alleyways, and bridges to influence walking and bicycle times

Table 3: Destination Types, Subtypes, and Weights

Destination Type	Data Source	Description	Suggested weight
Social	HERE POIs – ENTERTAINMENT	Entertainment locations (theaters, auditoriums, clubs, etc.) by block	1.0
	HERE POI – PUBLIC SERVICES	Community assets (libraries, museums, zoos, etc.)	0.20
	HERE POIs – RECREATION	Recreation locations (parks, gyms, etc.) by block	0.10
School	CoR Schools (K12, Colleges)	School building locations by block. Used to disaggregate enrollment estimates from TAZ to blocks.	1.00
Health Care	Hospitals	Hospital locations	1.00
	Urgent Care facilities	Urgent care centers in Richmond	0.30
	Other medical offices	General practitioners, dentists, therapists, etc.	0.20
Community	Religious Centers	Houses of worship in Richmond	0.50
	Community Centers	Community centers in Richmond	1.00
	HERE POI – PUBLIC SERVICES	Community assets (libraries, museums, zoos, etc.)	0.50
Crisis	CoR national shelter system facilities and facilities for homelessness	Shelter locations for persons experiencing homelessness	N/A
	CoR food pantries	Locations collecting, preparing and distributing food to the hungry	N/A
	CoR cooling centers	Locations offering relief from heat	N/A
	CoR fire and EMS stations	Fire and emergency medical stations	N/A
	CoR police stations and sheriff facilities	Law enforcement facilities	N/A
	CoR urgent care facilities	Urgent care centers in Richmond	N/A
	CoR social services	General support for disadvantaged individuals and families	N/A
	CoR Polling places	Polling places	N/A

Table 4: ACS Data for Traveler Characteristics

Traveler Attribute	Census Data	Description
Age	ACS B01001	Estimates of population by age in 5-10 year increments
Sex	ACS B01001	Estimates of population by sex
Education	ACS B15001	Estimates of population by educational attainment
Income	ACS B19001	Estimates of households by income over last 12 months (in brackets)
Household size	ACS B11016	Estimates of households by number of people
Worker status	ACS B23022 and B23026	Estimates of population by work status (full time, part time, work from home, not working, etc.)
Urban/rural	TIGER	Designation of area contexts based on TIGER urbanized areas and urban clusters
Medical condition	ACS B18101	Estimates of population by disability status

Open Source Code Repository

The Richmond equitable accessibility scoring process is facilitated by a series of scripts, mostly in the Python 3+ programming language. Running the process requires the installation of Conda and cloning the project code repository from github (https://github.com/renaissanceplanning/PROJECT_richmond_equity_access/tree/DELIVERY).

With Conda installed and the code repository cloned locally, open a command prompt window to install the development environment needed run the scripts. Navigate to the folder where the repository was cloned and use the `make env` command to build the environment.

```
>> cd path/to/reponame
>> make env
```

The supported `Make` commands include:

- `make env` - builds the Conda environment with all the name and dependencies from `environment.yml` and installs the local project package `richmond_ea` using the command `python -m pip install -e ./src/src/richmond_ea`. Only run this once.
- `make env_activate` - activates the Conda environment.
- `make env_remove` - removes the environment from Conda.

To run the scripts, the `richmond_ea` environment must be active. Open the Anaconda command prompt (click the Windows start button and type "Anaconda" and open the Anaconda command prompt). In the command prompt, navigate to the local path for the code repository, activate the environment, and run each script in order.

```
>> cd path/to/reponame
>> make env_activate
>> python ./app/script_to_run.py
```

The scripts are run in the following order (when executing from the command prompt, replace `script_to_run` with the appropriate script name).

- R scripts for modeling travel parameters and synthesizing population estimates.
- Prepare_destinations.py
- Prepare_networks.py
- Build_networks.py
- Skim_networks.py
- Summarize_competitors.py
- Summarize_access.py
- Report_access.py

These scripts are found in the `app` folder within the locally-cloned project code repository. Each step is described briefly below. Before running any scripts, update the `data_config` file's `DATA` variable to refer to the root directory where all input, interim, and output data area stored.

R script execution (preparatory step)

The `app/model` folder contains three preparatory scripts required to produce materials referenced in later accessibility calculations. These scripts include `population_synthesis.R` (which creates the population synthesis table), `destination_choice_modeling.R` (which calculates probability of travel to a destination type given population characteristics), and `travel_budget_modeling.R` (which estimates parameters of travel time distributions given population characteristics).

Generally, the user will not have to run these scripts, but they are provided for comprehensive coverage of the process. In fact, these scripts only need to be run if re-estimating travel time budget or destination relevance parameters or recreating the population synthesis data for an alternative ACS data year. These files may be unreliable if executed for a different geographic area of analysis (i.e., outside of the Richmond region) or for different population classifications. Additionally, edits to the travel time budget or destination relevance models themselves would require an understanding of the modeling process, as well as familiarity with coding in R.

Because these files are scripts completing a specific job rather than functions, the user will have to do some minor manual edits to get them to execute properly. These are the necessary steps to execute each script:

- Population synthesis
  - Open `population_synthesis.R`.
  - In the top-most section, change the `DATA` variable to the location of the project data directory.
  - In the top-most section, change the `CENSUS_API_KEY` variable to your Census API key. If you do not have one, you may register for one at: http://api.census.gov/data/key_signup.html
  - Run the script.
    - The output is the `population_synthesis.csv` table stored in the `Processed` data folder and `PopSynth` subfolder.
- Destination choice
  - Open `destination_choice_modeling.R`.
  - In the top-most section, change the `DATA` variable to the location of the project data directory.
  - Run the script.
    - The output is the `destination_choice_probabilities.csv` table stored in the `Ref` data folder.
- Travel time budgets
  - Open `travel_budget_modeling.R`.
  - In the top-most section, change the `DATA` variable to the location of the project data directory.
  - Run the script.
    - The output is the `travel_time_decay_parameters.csv` table stored in the `Ref` data folder.

Prepare destinations (step 1 of 7)

This script defines supporting functions for grouping and summarizing destination activities to a common set of zonal features (blocks and block groups). Parameters for script execution are imported from the `data_config` and `project_config` configuration scripts.

The output from this script is the `loaded_features.shp` feature class stored in the `Interim` data folder and `Networks` subfolder.

Prepare network (step 2 of 7)

This script defines supporting functions for enriching raw bicycle and pedestrian network data from OpenStreetMap with facility attributes recorded in City of Richmond and other GIS datasets. It depends on several functions imported from the `prepare.networks` submodule. Parameters for executing this script are defined in the `data_config`, `net_config` and `project_config` configuration scripts.

The outputs from this script are the edge feature classes stored in the `Interim` data folder and `Networks` subfolder and organized by mode. For walk and bike networks, modification surfaces (rasters) are also created in this step.

Build network (step 3 of 7)

This script defines supporting functions for converting network features from shape files and GTFS schedules into route-able networks for accessibility analysis. This script assumes the `prepare_networks` script has already been run previously. Parameters for executing this script are defined in the `net_config` configuration script.

The outputs from this script are files named `skim.h5` in the `Interim` data folder and `Networks` subfolder, organized by mode. These files are `pandas` data frames representing network edges with their true time and effective time cost estimates. These data frames are ready to be used by the `pandana` package to solve shortest paths over each respective network in the next step.

Skim networks (step 4 of 7)

This script defines supporting functions for evaluating the shortest paths among origin-destination pairs over route-able networks for accessibility analysis. This script assumes the `build_networks` and `prepare_destinations` scripts have already been run previously. Parameters for executing this script are defined in the `data_config` and `net_config` configuration scripts.

The outputs from this script are files named `skim.h5` in the `Interim` data folder and `Networks` subfolder, organized by mode. These files are `emma Skim` objects containing true time and effective time travel cost estimates between all possible origin-destination combinations among analysis zones for each respective modal network.

Summarize competitors (step 5 of 7)

This script defines supporting functions for casting estimates of population (by demographic subgroup by analysis zone) at origin locations over an origin-destination matrix, applying factors reflecting travel time budget and destination relevance parameters, and summarizing all relevant travelers that could potentially "compete" for access to a set of destinations (jobs, shopping, schools, etc.). This script assumes the `skim_networks` script has already been run previously. Parameters for executing this script are defined in the `data_config` and `net_config` configuration scripts.

The outputs from this script are H5 tables in the `Processed` data folder and `Access` subfolder, organized by mode. The H5 tables use the naming convention: `competitors_{travel_purpose_impedancetype}.h5` (see data dictionary). These tables summarize the number of relevant competing travelers that can reach each destination zone's activities given the relevance of those activities to travelers in each origin zone. Separate tables are generated for work and non-work travel purposes and for true time and effective time impedance estimates.

WARNING: If existing H5 tables are in the output folder, these should be deleted or moved to another location. Running `summarize_competitors.py` with those tables in-place will simply add records to the existing tables and undermine the integrity of the analysis.

Summarize access (step 6 of 7)

This script defines supporting functions for casting estimates of destination activities (by subgroup by analysis zone) at destination locations over an origin-destination matrix, applying factors reflecting travel time budget and destination relevance parameters for demographic subgroups, normalizing destinations reachable by number of competitors with access (for "competitive" access scoring formulation), and summarizing all destination activities reachable from each origin zone by each demographic subgroup present in the zone. This script assumes the `summarize_competitors` script has already been run previously. Parameters for executing this script are defined in the `data_config`, `net_config` and `project_config` configuration scripts.

The outputs from this script are H5 tables in the `Processed` data folder and `Access` subfolder, organized by mode. The H5 tables use the naming convention: `access_to_dests_{travel_purpose_impedancetype}.h5` (see data dictionary). These can be very large. They record the number of destinations by group and subgroup reachable from each analysis zone for each distinct traveler demographic implied by combinations of values generated in the population synthesis routine in that zone.

This script also produces tables reporting the minimum travel time from each origin zone to each type of crisis destination. These results are stored in csv files in the same folder. The csv files use the naming convention: `neraest_crisis_pts_{impedancetype}.csv`.

Separate tables are generated for work and non-work travel purposes and for true time and effective time impedance estimates.

WARNING: If existing H5 tables are in the output folder, these should be deleted or moved to another location. Running `summarize_access.py` with those tables in-place will simply add records to the existing tables and undermine the integrity of the analysis.

Report access (step 7 of 7)

This script defines supporting functions for summarizing destination activities (by type and subtype) reachable from each origin zone given the demographic composition of the zone. It processes the large H5 tables created in the previous step to return composite accessibility scores for each origin zone based on its demographic composition. This script assumes the `summarize_access` script has already been run previously. Parameters for executing this script are defined in the `data_config`, `net_config` and `project_config` configuration scripts.

The outputs from this script are csv tables in the `Processed` data folder and `Access` subfolder, organized by mode. The csv tables use the naming convention: `composite_{travel_purpose_impedancetype}.csv` (see data dictionary). These tables summarize the number of destination activities by group and subgroup reachable from each origin zone given the relevance of those activities to travelers in that zone. Separate tables are generated for work and non-work travel purposes and for true time and effective time impedance estimates.

Data Dictionary for Study Outputs

The scripts that execute the equitable accessibility scoring process generate a diverse set of output tables. All outputs are organized in subfolders by mode (auto, bike, transit, walk). H5 files contain detailed OD-level results and are not generally expected to be consumed for reporting. CSV tables contain outputs summarized to analysis zones for mapping and other downstream reporting and analysis. The CSV tables generated utilize the following name convention: {analysis focus}_{travel purpose}_{impedance type}.csv. Analysis focus refers to the type of analytical output generated: composite access scores, nearest crisis destinations, or competitors with access to destination zones. Note that "composite access scores" include competitive formulations of access scores whereas "competitors" simply enumerates the number of competing travelers that can reach a destinations zone. Travel purpose is broken down into work and non-work purposes (this is not specified for crisis destinations tables). Impedance type refers to whether the analysis reflects a naïve travel time estimate (true time) or an enriched travel time estimate based on facility factors (effective time). Table 5 describes each part and value in the names of the output files.

Table 5: Output File Descriptions

Name part	Value	Description
Analysis focus	Composite	Tables where all formulations of accessibility scores (decayed destinations, basic utility x competitive, non-competitive) are compiled by zone of origin
	nearest_crisis_pts	Tables reporting shortest travel time to a "crisis" destination from each origin zone
	Competitors	Tables that store the estimated number of relevant competitors that are able to reach destination zones by POI group
Travel purpose	HBW	Access scores associated with commute trip-making
	Other	Access scores associated with non-work trip-making
Impedance type	time	Access scores are based on a simple assessment of travel time modeled over a given modal network
	gen_cost	Access scores are based on embellished travel times that account for network effects on the bike and walk network (includes walk portions of transit network)

The fields in each table also follow a naming convention. Fields in the composite tables report accessibility result by destination type (composite group and detailed subgroups) for "basic utility" (bu) or "decayed destinations" (dd) scoring formulations with and without normalization based on competing travelers with access. Fields in the competitors tables report the number of competing travelers that can reach each zone for the named destination type. These types always refer to the detailed destination subgroups. Fields in the nearest crisis destination tables report the shortest travel time to each type of crisis destination. Table 6 provides detailed descriptions to interpret the field names reported in each kind of output table.

Table 6: Detailed Descriptions of Field Names

Table Group	Name Part	Description
composite	bu	Basic Utility ("decayed destinations" weighted by destination relevance given the travelers residing in each zone)
	dd	Decayed destinations (cumulative destinations reachable, weighted by cost of travel from origin to destination)
	comp	"Competitive" access - if this isn't in the field name, the values reported do not account for the presence of competitors
	work	Scores reflecting access for commute trip-making (if no specific destination type is listed, the weighted composite score for the "work" category is given)
	health	Score reflecting access to health care destinations (if no specific destination type is listed, the weighted composite score for the "health" category is reported)
	community	Score reflecting access to community destinations (if no specific destination type is listed, the weighted composite score for the "community" category is reported)
	school	Score reflecting access to school destinations (if no specific destination type is listed, the weighted composite score for the "school" category is reported)
	shopping	Score reflecting access to shopping/personal business destinations (if no specific destination type is listed, the weighted composite score for the "shopping" category is reported)
	social	Score reflecting access to social destinations (if no specific destination type is listed, the weighted composite score for the "social" category is reported)
	CD01	Jobs worked by workers with less than High School education
	CD02	Jobs worked by workers with High School Diploma or Equivalent
	CD03	Jobs worked by workers with Some College or Associates Degree
	CD04	Jobs worked by workers with a Bachelors Degree or Higher Education
	BA_HEALTH	Doctor's offices, dentists, therapists, and similar health-related practices ("Health" category)
	BA_HOSPITAL	Hospitals ("Health" category)
	BA_URGENT	Urgent care centers ("Health" category)
	FREE_HLTH	Free health clinics ("Health" category)
	COR_COMCTR	Community centers ("Community" category)
	COR_COMGDB	Community gardens ("Community" category)
	COR_RELIG	Religious institutions/houses of worship ("Community" category)
	HERE_PUBC	Public community assets, like libraries and museums ("Community" category)

Table 6: Detailed Descriptions of Field Names (Continued)

Table Group	Name Part	Description
composite	COR_PRVTSCH	Private schools ("School" category)
	COR_PUBSCH	Public schools ("School" category)
	COR_UNI	Colleges and universities ("School" category)
	COR_SNAP	Businesses that accept SNAP payments ("Shopping" category)
	HERE_FIN	Financial services destinations ("Shopping category)
	HERE_FOOD	Restaurants and eateries destinations ("Shopping" category)
	HERE_GROC	Grocery stores ("Shopping" category)
	HERE_SHOP	Other shopping destinations ("Shopping" category)
	HERE_ENT	Entertainment destinations ("Social" category)
	HERE_PUB	Public community assets, like libraries and museums ("Social" category)
	HERE_REC	Recreational points of interest ("Social" category)
competitors	CD01	Jobs worked by workers with less than High School education
	CD02	Jobs worked by workers with High School Diploma or Equivalent
	CD03	Jobs worked by workers with Some College or Associates Degree
	CD04	Jobs worked by workers with a Bachelors Degree or Higher Education
	BA_HEALTH	Doctor's offices, dentists, therapists, and similar health-related practices ("Health" category)
	BA_HOSPITAL	Hospitals ("Health" category)
	BA_URGENT	Urgent care centers ("Health" category)
	FREE_HLTH	Free health clinics ("Health" category)
	COR_COMCTR	Community centers ("Community" category)
	COR_COMGDB	Community gardens ("Community" category)
	COR_RELIG	Religious institutions/houses of worship ("Community" category)
	HERE_PUBC	Public community assets, like libraries and museums ("Community" category)
	COR_PRVTSCH	Private schools ("School" category)
	COR_PUBSCH	Public schools ("School" category)

Table 6: Detailed Descriptions of Field Names (Continued)

Table Group	Name Part	Description
competitors	COR_UNI	Colleges and universities ("School" category)
	COR_SNAP	Businesses that accept SNAP payments ("Shopping" category)
	HERE_FIN	Financial services destinations ("Shopping category)
	HERE_FOOD	Restaurants and eateries destinations ("Shopping" category)
	HERE_GROC	Grocery stores ("Shopping" category)
	HERE_SHOP	Other shopping destinations ("Shopping" category)
	HERE_ENT	Entertainment destinations ("Social" category)
	HERE_PUB	Public community assets, like libraries and museums ("Social" category)
	HERE_REC	Recreational points of interest ("Social" category)
nearest_ crisis_pts	COR_NSSF	National shelter system facilities
	COR_SHELT	Shelters for persons experiencing homelessness
	COR_PANTRY	Food pantries
	COR_COOL	Cooling stations
	COR_EMS	EMS dispatch locations
	COR_FIRE	Fire stations
	COR_POLICE	Police stations
	COR_SHERIF	Sheriff's offices
	BA_URGENT	Urgent care centers
	COR_SOCSVC	Social services
	COR_POLLS	Polling places

APPENDIX B - GENTRIFICATION CLASSIFICATION METHODOLOGY AND MAPS OF GENTRIFICATION STATUS BY YEAR

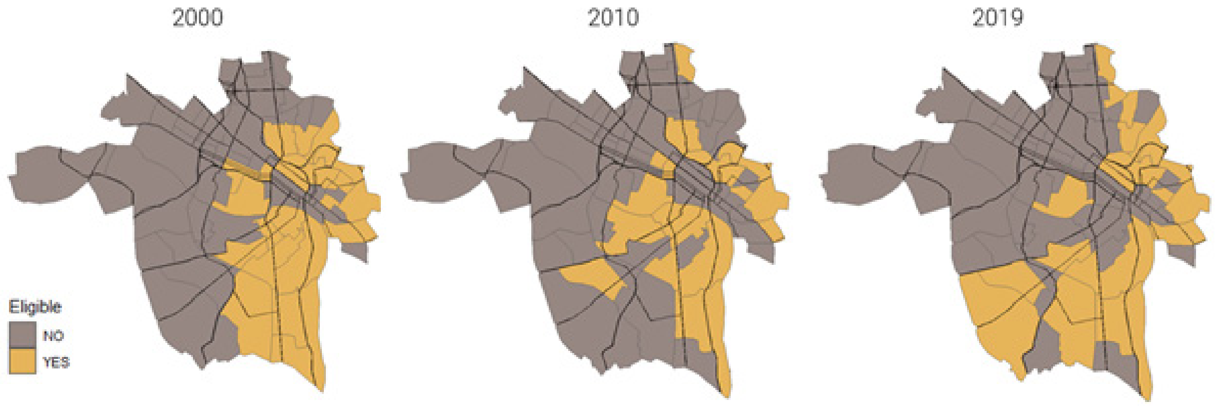
Gentrification is a long-term, gradual process with no firm start or end dates. However, much analysis typically uses a study period of one decade to determine if a neighborhood has experienced gentrification. Our analysis uses an analysis period of one decade. To be eligible for gentrification, a census tract must have a median household income and a median rent level lower than the greater metropolitan area average at the beginning of the decade. Figure 1 illustrates the areas in Richmond that meet this criterion.

Table 1: Gentrification Eligibility Thresholds

Measure	2000	2010	2019
Median Household Income	$31,121	$38,266	$47,250
Median Rent	$442	$805	$1,025
Number of Tracts Eligible for Gentrification	25	17	22

Source: EBP analysis of American Community Survey tables B19013 and B25064 (for 2010 and 2019) and 2000 Decennial Census tables P053 and H060 .

Figure 1: Gentrification Eligibility Thresholds



Source: EBP analysis of American Community Survey tables B19013 and B25064 (for 2010 and 2019) and 2000 Decennial Census tables P053 and H060 . Larger maps are included in this Appendix.

After establishing which areas are eligible for gentrification, the next step is to determine if there is any actual evidence of neighborhood change. We classify all tracts into 4 categories based on whether they were eligible, and how intense their growth in housing costs & education attainment were compared to all other tracts in the city over the analysis decade.

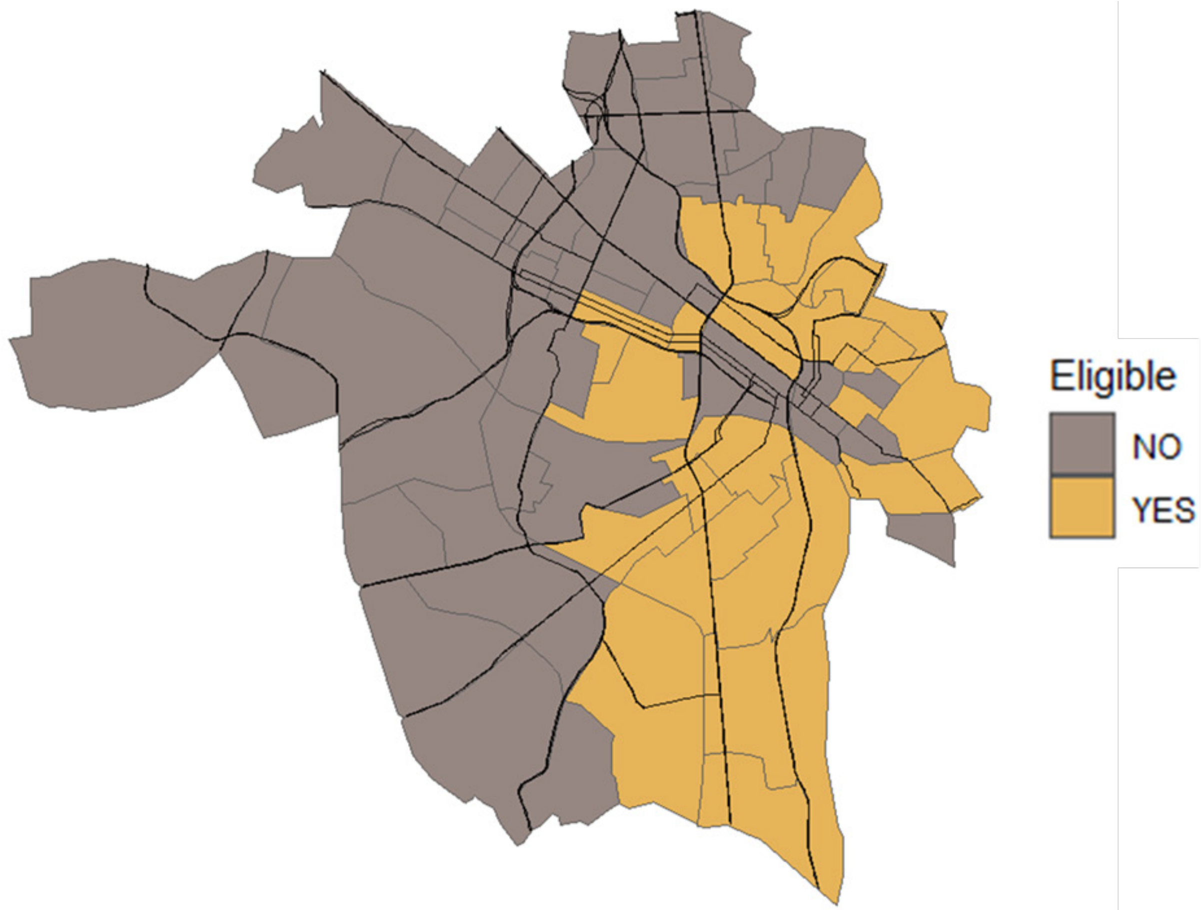
1. Not eligible for gentrification
2. Eligible at beginning of study period, but no evidence of gentrification.
3. Some evidence of gentrification
4. Evidence of intense gentrification.

To have some evidence of gentrification, a census tract must have experienced growth in educational attainment (measured as the percentage of the population over 25 with at least a bachelor's degree) and housing costs (measured by the median home value) that was above the average for the metropolitan area. Intense gentrification is defined as growth in the top quartile of all tracts in the city. This determination was made using the following steps:

Census tracts were assigned into final categories based on the following logic:

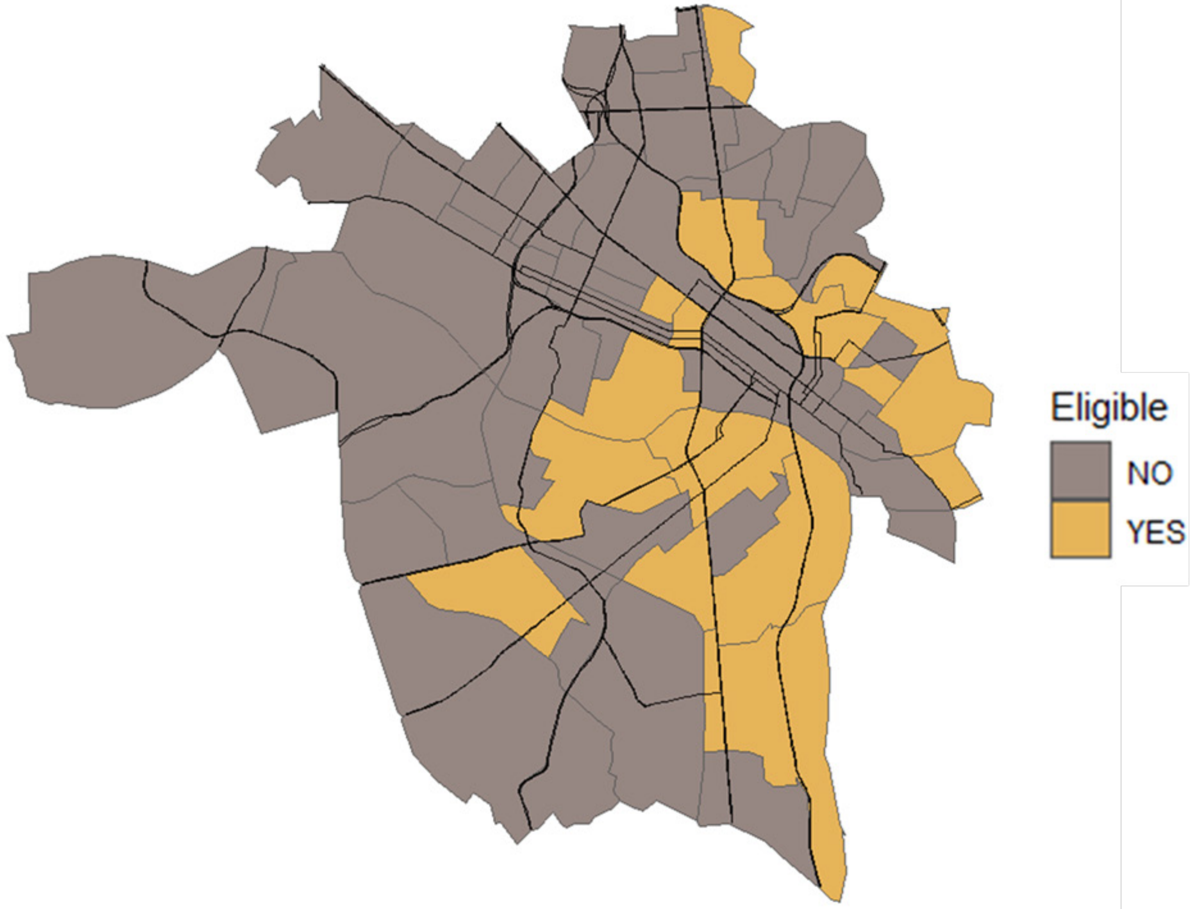
a. Census tracts not eligible for gentrification were noted as such
b. Census tracts who were eligible but did not see above average growth in either home values or education attainment were considered as having no evidence for gentrification.
c. Census tracts which saw above average growth in educational attainment and/or home values were considered to have some evidence for gentrification
d. Only census tracts which saw growth in the highest quantile for both educational attainment and home values were defined as having experienced intense gentrification

Figure 2: Census Tracts Eligible for Gentrification in 2000



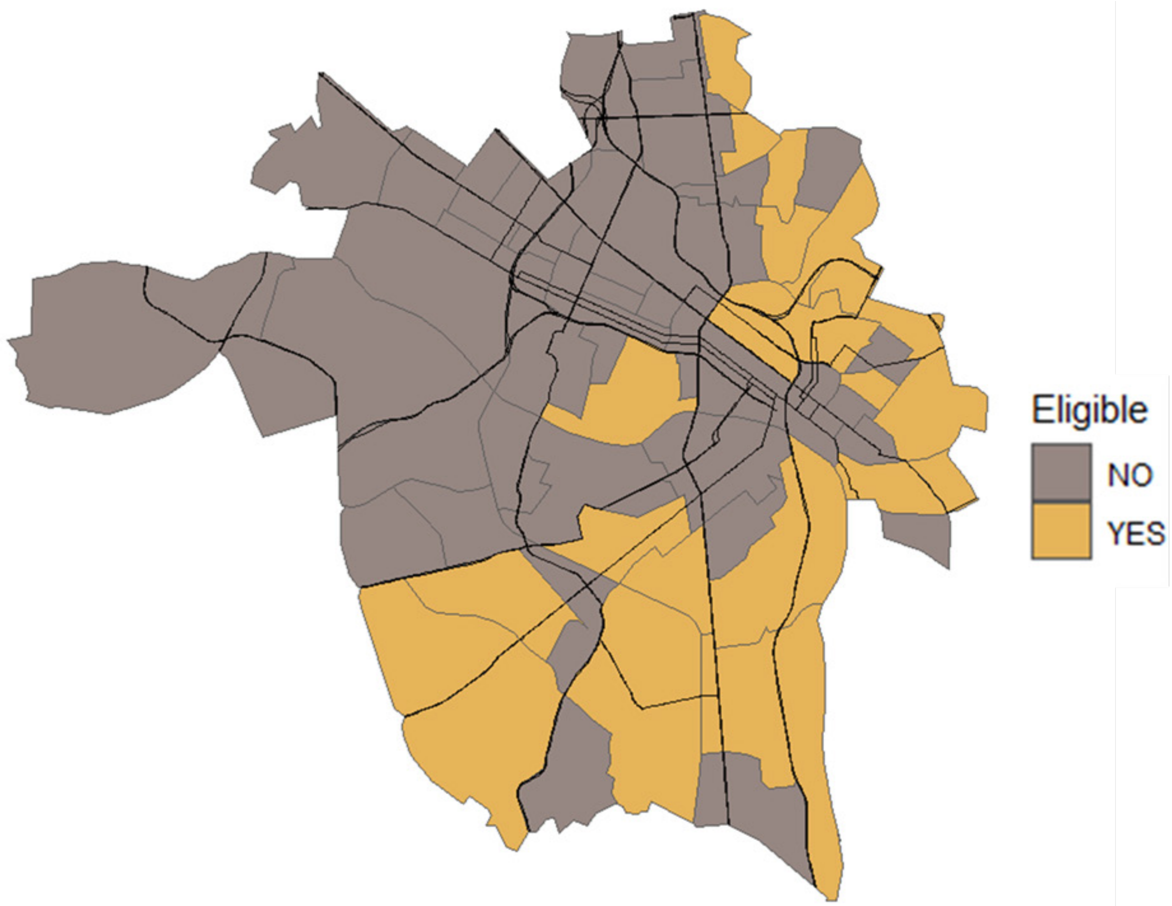
Source: EBP Analysis

Figure 3: Census Tracts Eligible for Gentrification in 2010



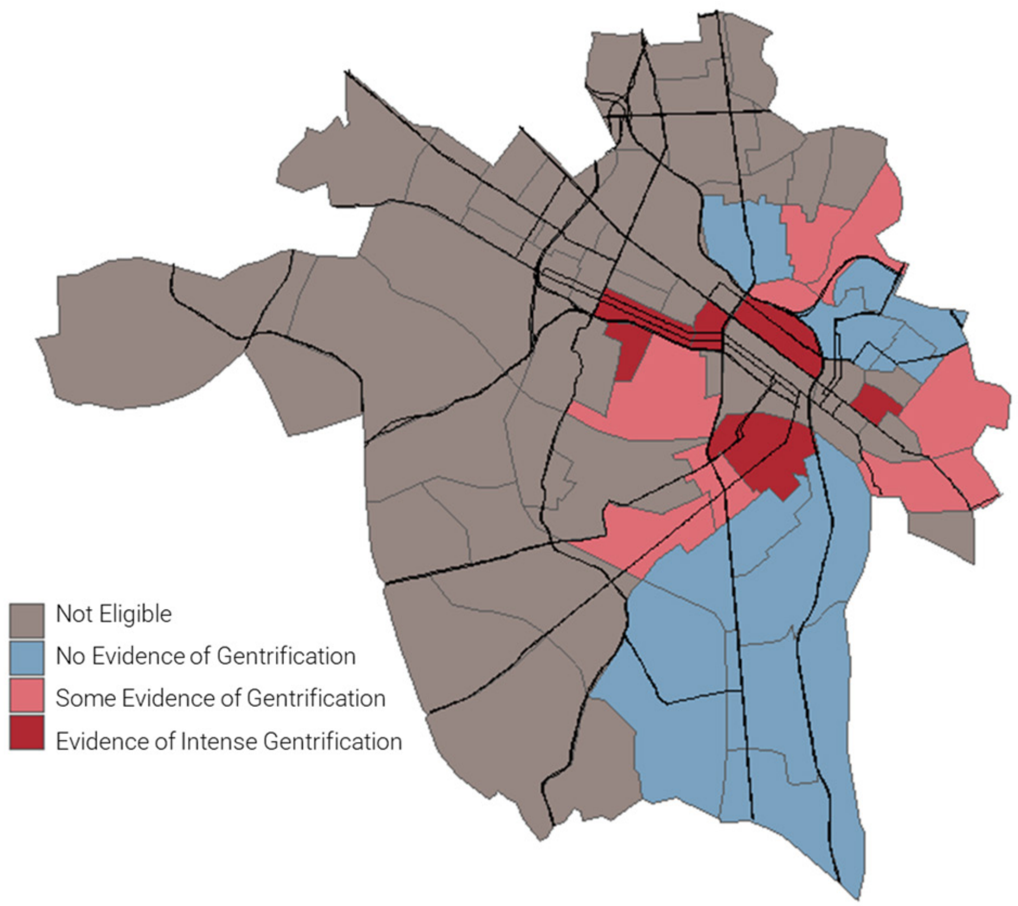
Source: EBP Analysis

Figure 4: Census Tracts Eligible for Gentrification in 2019



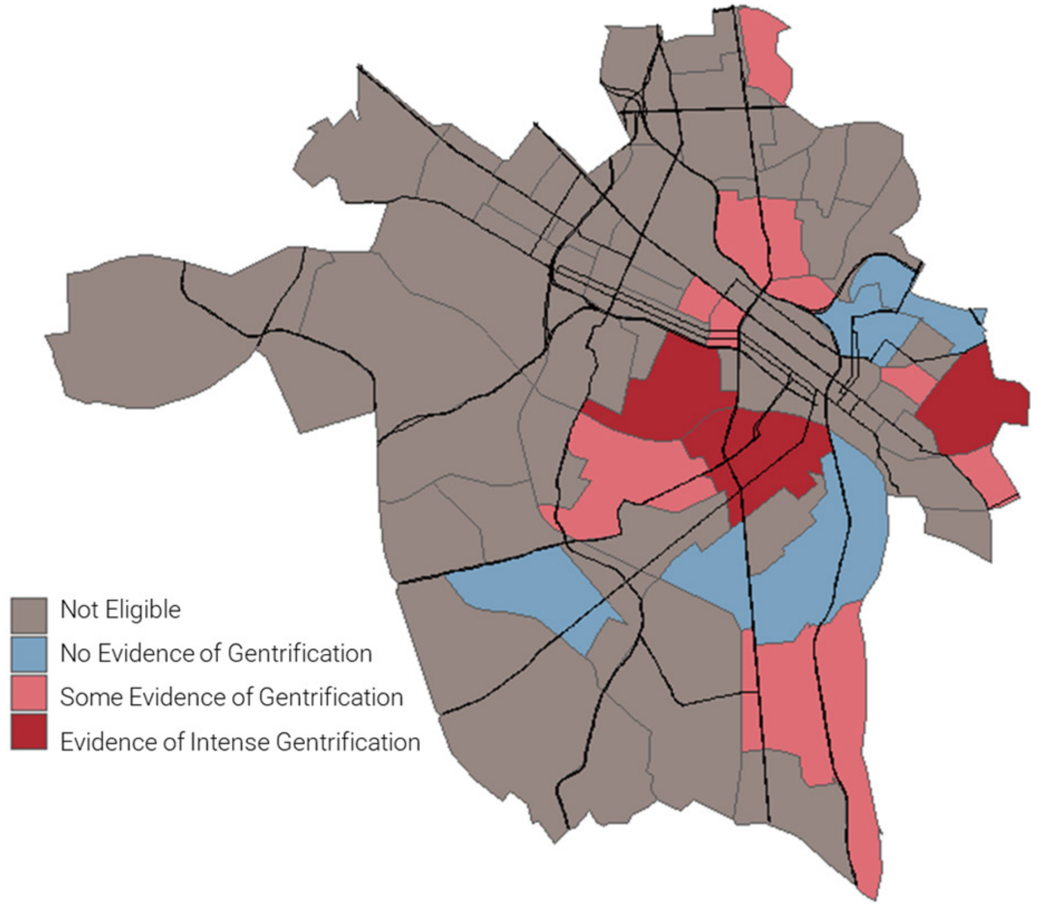
Source: EBP Analysis

Figure 5: Evidence of Gentrification in Richmond 2000-2009



Source: EBP Analysis

Figure 6: Evidence of Gentrification in Richmond 2010-2019



Source: EBP Analysis

BACK COVER PADDING PAGE

**IF ADDITIONAL PAGE IS NEEDED TO ALLOW FOR CORRECT BINDING PATTERN, REMOVE THIS TEXT BLOCK AND ADD THIS PAGE BEFORE
THE BACK COVER PAGE .**

IF AN ADDITIONAL PAGE IS NOT NEEDED FOR CORRECT BINDING PATTERN, DELETE THIS PAGE.