# GEOGRAPHIES OF (DIS)ADVANTAGE IN WALKING AND CYCLING: PERSPECTIVES ON EQUITY AND SOCIAL JUSTICE IN PLANNING FOR ACTIVE TRANSPORTATION IN U.S. CITIES

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## ABSTRACT

Lindsay Maurer Braun: Geographies of (dis)advantage in walking and cycling: Perspectives on equity and social justice in planning for active transportation in U.S. cities
(Under the direction of Daniel Rodriguez)

In recent years, cities across the U.S. have increasingly invested in programs, policies, and infrastructure to support active transportation. Some have suggested that these investments could help to address health disparities observed by race and socioeconomic status (SES) in the U.S., given that walking and cycling are physically active and low-cost modes of transportation. Despite this potential, there is emerging evidence that active transportation investments have been inequitably distributed across communities of varying sociodemographic composition. For instance, cycling advocates have recently argued that low-income and minority populations have disproportionately low access to safe, convenient infrastructure such as bike lanes. At the same time, some active transportation projects have recently faced opposition in several large U.S. cities due to concerns about gentrification.

Limited research has considered the distribution of active transportation infrastructure and potential associations between cycling investment and sociodemographic change. I address this gap through three related analyses. First, I examine how different sociodemographic groups are distributed across space with respect to built environment characteristics in Birmingham, Chicago, Minneapolis, and Oakland. I find that low-SES and minority populations tend to live in more walkable neighborhoods, but are less likely to be distributed across a full range of neighborhood types. Second, I examine cross-sectional associations between bike lane access and area-level sociodemographic characteristics in 22 large U.S. cities. I find that even after adjusting for traditional indicators of cycling demand, access to bike lanes is lower in areas with lower educational attainment, higher proportions of Hispanic residents, and lower SES. Third, I examine longitudinal associations between new bike lane infrastructure and sociodemographic change between 1990 and 2015 in Chicago, Minneapolis, and Oakland. I find evidence

that new bike lanes occurred disproportionately in areas that were either already advantaged or increasing in advantage over time.

These analyses reveal sociodemographic differences in access to environments and infrastructure that support active transportation, often suggesting lower access among disadvantaged populations. Addressing these disparities, however, is complicated by associations between infrastructure investment and sociodemographic change. Efforts to expand active transportation infrastructure should recognize concerns about gentrification and carefully consider the social context of infrastructure investment.

To Danny and Naomi

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## 1.1 Background and motivations

Walking and cycling interventions have become increasingly prominent in efforts to promote health, sustainability, and livability in U.S. cities, reflecting a larger "mobility transition" (Sheller 2015) away from the automobile and toward more active and environmentally friendly modes of transportation. These interventions could be uniquely positioned to address disparities in physical activity and health observed by race, ethnicity, and socioeconomic status in the U.S. (August and Sorkin 2010, Gordon-Larsen et al. 2003, Mokdad et al. 2003), as walking and cycling are relatively low-cost and physically active alternatives to automobile travel (Martens et al. 2016, Rachele et al. 2015). Despite this potential, there is emerging evidence that walking and cycling investments have been unevenly distributed across neighborhoods of varying demographic and socioeconomic composition. This distribution could have important implications for social equity, as access to opportunities for walking and cycling influences access to the diverse health, environmental, and economic benefits that these travel modes can provide for communities and individuals.

In the case of walking, King and Clarke (2015) found that disadvantaged U.S. census tracts (i.e. those with higher poverty, lower median income, higher proportions of black and Hispanic residents) tended to have higher average walkability (i.e. lower median block length, higher street node density)—reflecting what the authors call a "disadvantaged advantage" in walkability. This finding, however, could relate to the authors' use of relatively coarse, nationally available walkability indicators; indeed, other studies focusing on fine-grained indicators such as sidewalk quality, traffic safety, crime, and aesthetics have found these conditions to be inferior in low-income and minority communities (Neckerman et al.

2009, Kelly et al. 2007, Sallis et al. 2011, Cerin and Leslie 2008, Wilson et al. 2004, Boslaugh et al. 2004). More broadly, the co-location of objectively walkable environments and sociodemographic disadvantage could reflect larger patterns of socio-spatial segregation in U.S. cities, in which inner-urban communities are often multiply burdened by environmental health risks, unsafe conditions, inferior transportation options, and other impacts of automobile-centric development (Zavestoski and Agyeman 2015). These socio-spatial arrangements indicate the importance of interpreting "advantage" within a broader social and historical context.

In the case of cycling, advocates have recently argued that low-income and minority populations have lower access to bike lanes than their wealthier, white counterparts—even though these populations have had considerable recent growth in cycling and are disproportionately affected by cycling fatalities (League of American Bicyclists 2014). Based on these claims, as well as the frequent use of income as a positive predictor of cycling demand in the siting of facilities such as bicycle sharing stations, it is possible that a "disadvantaged disadvantage" would be observed in the case of access to cycling infrastructure. Limited research to date has considered this relationship, although early studies have found that disadvantaged communities (e.g., low socioeconomic status, high proportions of minority residents) are less likely than relatively advantaged communities to have plans, policies, and projects that support cycling (Aytur et al. 2008, Cradock et al. 2009) and tend to have disproportionately low access to cycling infrastructure such as bike lanes and bike share stations (Flanagan et al. 2016, Hirsch et al. 2017, Smith et al. 2015, Ursaki and Aultman-Hall 2015). Further quantitative work assessing the location of bike lanes in relation to neighborhood sociodemographic characteristics could complement advocates' contextual observations about disparities in access to bike lanes, potentially providing empirical backing to calls for more equitable infrastructure investment.

At the same time, efforts to expand walking and cycling infrastructure in traditionally underserved areas have recently been met by community resistance, often based on concerns about gentrification (Zavestoski and Agyeman 2015). This type of resistance has been particularly pronounced in the case of bike lanes. In Portland, Oregon, plans to add bike lanes along a pair of one-way streets in the gentrifying Albina neighborhood were stalled by concerns from long-time black residents, who viewed the investment as tailored to white newcomers in the neighborhood (Benesh 2015, Herrington and Dann 2016). In Chicago, similar resistance was expressed by low-income Latino and black residents of Humboldt Park, who initially viewed proposals to add bike lanes in their neighborhood as indicative of the wave of gentrification that had already taken place in nearby Wicker Park (Greenfield 2012, Lubitow et al. 2016). Planners in Chicago were able to successfully engage with this community, however, and the bike lanes are now supported and used by a diverse cross-section of cyclists (Greenfield 2012). Planners in Washington, D.C., are in the midst of a similar effort in the Shaw neighborhood, where residents and community leaders are opposing the installation of a protected bike lane that could remove on-street parking for historically African-American churches—arguments that some have suggested are symptomatic of deeper racial tensions surrounding gentrification in the neighborhood (Freed 2015).

These contrasting claims highlight a key tension in planning for equitable active transportation infrastructure in U.S. cities. On the one hand, advocates often argue that low-income and minority populations have disproportionately low access to safe, convenient infrastructure (particularly bike lanes), and that resolving this disparity could promote health and equity in urban neighborhoods (Martens et al. 2016, Rachele et al. 2015). On the other hand, walking and cycling investments in traditionally underserved neighborhoods are sometimes resisted by community members, with opposition expressed through narratives of race, gentrification, and belonging. Contributing to this tension is the general lack of empirical data about both sides of this relationship—about the existence and extent of disparities in access to walking and cycling infrastructure, and about the potentially simultaneous relationship between gentrification and infrastructure investment.

This dissertation explores the tension between claims about infrastructure access and gentrification from the perspectives of equity and social justice. Using quantitative methods and a combination of cross-sectional and longitudinal data, the dissertation considers whether access to walkable built environments (Chapter 2) and bike lanes (Chapters 3 and 4) varies by individual- and area-level sociodemographic characteristics, and then evaluates the corresponding implications for equity, empirical research, and active transportation planning. The research questions to be addressed in the three papers of the dissertation are, respectively:

- How are different sociodemographic groups distributed across space with respect to built environments traditionally considered to be "walkable"? (Chapter 2)
- Is access to bike lanes associated with area-level sociodemographic characteristics in a cross-sectional sample of 22 large U.S. cities? (Chapter 3)
- Are bike lane investments associated with area-level sociodemographic change (e.g., gentrification) over a 25-year period in three large U.S. cities? (Chapter 4)

In addressing these research questions, the dissertation provides quantitative evidence of potential disparities in access to walking and cycling infrastructure in U.S. cities; considers the implications of these disparities for planning practice and research; and suggests how planners and advocates may move toward a more just and socially sustainable distribution of active transportation infrastructure. In the remainder of this chapter, I review the broad literature base linking the three papers and introduce the research objectives, hypotheses, and methods for each analysis.

## 1.2 Literature review

This review begins with a broad discussion of transportation as a social justice issue and a narrower consideration of how active transportation fits within this framework, then summarizes the connections between active transportation and processes of gentrification. Additional relevant bodies of work relevant to each research question and analysis are referenced in subsequent chapters.

### *1.2.1 Transportation as a social justice issue: Theoretical perspectives*

Transportation infrastructure is unevenly distributed across space. This distribution results from a process that is simultaneously technical and political, with decisions based in part upon where infrastructure is needed or demanded, where growth is projected or encouraged to occur, where physical and social constraints are minimal, and where residents and political actors have either sufficient power to influence the decision making process or insufficient power to push back against it. An uneven distribution of transportation infrastructure is not inherently indicative of social injustice; indeed, building infrastructure uniformly across a region would inevitably fail on metrics of efficiency, effectiveness, and equity. Thus, it is important to consider when distributional in*equalities* become distributional in*equities*, and when the uneven distribution of transportation infrastructure therefore becomes a social justice issue.

Pereira et al. (2016) argue that existing studies of transportation equity tend to lack an explicit ethical framework guiding their conceptualizations of distributive justice. This critique attests to the value of grounding questions about access to transportation infrastructure in foundational theories of social justice, such as those advanced by Rawls (1971, 2001), Walzer (1983), Sen (1983), and Nussbaum (2003). The relevance of transportation to social justice can be seen from a Rawlsian perspective if one considers mobility and accessibility to be among the "primary goods" that are instrumental to the pursuit of individual interests and freedoms (Rawls 1971). While Martens et al. (2016) argue that a Rawlsian framework is not useful for considering the distribution of transportation infrastructure due to Rawls' original conceptualization of primary goods as income and wealth, Rawls' (2001) more recent work has expanded the definition of primary goods "to include personal goods and services provided by the state" (Pereira et al. 2016, p. 17), and Harvey (1976) argues that transportation networks are mechanisms for the redistribution of wealth and income in metropolitan areas. Accepting this broadened definition and Rawls' corresponding "difference principle," a just distribution of transportation infrastructure would be one in which there is "rough equality" and in which "any inequality [is] to the benefit of the least-advantaged member of society" (Fainstein 2010, p. 15).

Walzer (1983) proposes that certain societal goods are sufficiently important to warrant distribution within their own "spheres of justice"; as summarized by Martens et al. (2016), this perspective "argues that goods to which a particular society ascribes a distinct social meaning (e.g. health and education) should be removed from the sphere of free exchange and distributed within their own distributive sphere based on their distinct social meaning" (p. 88). Thus, if one views transportation networks—including the mobility and accessibility benefits they can provide—as having a "distinct social meaning," then the distribution of transportation infrastructure should be evaluated from the perspective of social justice rather than free-market forces. While this framework does not posit an explicit distributional framework, it provides theoretical support for considering transportation as a social justice issue.

Sen (1983) and Nussbaum (2003) argue that the focus of social justice should be not on resources or utilities, but rather on "capabilities," defined as "what [people] have the opportunity to do" (Fainstein 2010, p.55) or "the possibility to achieve basic societal functionings" (Martens et al. 2016, p. 89). Transportation systems are relevant to this framework due to their connections to opportunity; for instance, Pereira et al. (2016) argue that "some minimum level of accessibility to key destinations is a basic capability that is necessary for people to satisfy their basic needs…[and] pursue the life they have reason to value" (p. 22). Thus, through its relationship with access to basic goods and services, transportation infrastructure has instrumental value in facilitating access to opportunity and is therefore an appropriate subject for questions of distributive justice.

Other theorists have considered questions of distributive justice through the lens of power. Harvey (1973) views transportation infrastructure as one of the many spatial arrangements through which real income is distributed and redistributed in metropolitan areas, influencing the costs of accessing jobs, resources, and opportunities to participate in the social and economic life of a community. Transportation is thus one of the "hidden mechanisms" (Harvey 1973, p. 73) that can be leveraged for the redistribution of wealth in ostensibly neutral planning processes. Within this framework, distributional inequalities in transportation infrastructure may be viewed as socially unjust when the "hidden mechanism" of infrastructure investment is consistently co-opted to create and perpetuate imbalanced power structures and social arrangements. Flyvbjerg (1998) takes a similar stance, noting that arguments rooted in technical rationality—and thus apparent neutrality or objectivity—can serve as an important source of power, potentially rationalizing decisions that have already been made by those with power in the planning process. Soja (2010) similarly argues that urban spatial structures are characterized by "deep and unquestioned *structures of privilege and spatial advantage* based on differential wealth and power" (p.

48, emphasis in original), suggesting that decisions about infrastructure can both result from and reinforce geographies of (dis)advantage and opportunity across space.

### *1.2.2 The case of active transportation*

While these theories provide potential justifications for considering transportation broadly as a social justice issue, the specific position of active transportation within the theory and practice of transportation justice remains somewhat unclear. Walking and cycling interventions are often framed as a way to expand mobility and accessibility for diverse travelers (Martens et al. 2016, Herrington and Dann 2016), but some authors have called into question the appropriateness of considering these modes within the three theoretical frameworks outlined above. As previously noted, Martens et al. (2016) question whether transportation in general (let alone specific travel modes) should be viewed as a primary good within the Rawlsian framework, given the primacy of wealth and income as targets for distributive justice. The authors also question whether active transportation—particularly cycling—has gained sufficient prominence and distinct social meaning to warrant consideration within its own sphere of justice, though they concede that accessibility and health meet these criteria. The relevance of walking and cycling within the capabilities approach is also unresolved, given that factors such as physical ability, built environment facilitators, and underlying propensities to travel by these modes are unequally distributed (Pereira et al. 2016, Martens et al. 2016).

Focusing instead on the practice of transportation justice and the specific role of cycling, Golub et al. (2016) draw a distinction between the transportation justice movement and the bicycle movement. The former movement seeks to address distributional inequalities—particularly along racial/ethnic and socioeconomic lines—in the benefits, burdens, and public input opportunities associated with transportation investments (Golub et al. 2013, Sanchez and Brenman 2007). The latter movement instead invokes claims of distributional inequalities by mode, seeking to reclaim public road space for cyclists and to address the longstanding emphasis on the automobile in transportation planning practice; this movement often leverages the minority or "disadvantaged" status of cyclists (relative to drivers) in order to argue for expanded and improved cycling infrastructure (Henderson 2013, Furness 2010). Golub et al. (2016) note that these two movements are not fundamentally opposed and in fact share several potential synergies, as cycling could provide a low-cost mobility option for low-income travelers and is likely to become increasingly relevant to conversations about distributional justice as it experiences growth in both social status and federal funding.

Despite these potential synergies, the two movements are also characterized by tensions that arise in part from a failure to fully account for the social backdrop, or "socio-technical system," upon which infrastructure interventions are placed (Golub 2016, p. 23). Prominent among these tensions include the continued white, middle-class dominance of advocacy practices and representation; the status of cycling as a "second-class mode" rather than a consistent "object of aspiration" for diverse populations; and real or perceived associations between cycling infrastructure investment and rapid sociodemographic change (Golub 2016, p. 25). These conflicts—the latter of which is further discussed in the section that follows—illustrate the importance of considering the social context of infrastructure investment and the corresponding challenges that may be faced in planning for a more "equitable" distribution of active transportation infrastructure.

### *1.2.3 Active transportation and gentrification*

Planners and advocates in several large U.S. cities have recently encountered resistance in efforts to expand active transportation infrastructure—particularly for cycling—in traditionally underserved and disadvantaged neighborhoods. This resistance has commonly centered on gentrification concerns, which may be literal or symbolic (Herrington and Dann 2016, Golub 2016, Hoffman and Lugo 2014). Literal concerns may stem from observed correlations between gentrification and cycling growth (Herrington and Dann 2016) and between cycling infrastructure investment and rapid neighborhood sociodemographic change (Golub 2016), even when causal relationships cannot be established. Symbolic concerns may arise from the ability of cycling infrastructure projects to serve as a platform or forum for the discussion of larger issues of neighborhood change. Indeed, Herrington and Dann (2016) describe gentrification as "exist[ing] at the nexus of historical forces, policy decisions at various scales of governance, public and private investment, the real estate and housing markets, migration patterns, and transformations in the broader political-economy"; within this complex framework, the public engagement processes for infrastructure projects such as bike lanes may represent one of the few decisions "over which residents might have any real expectation of exerting power" in the larger process of gentrification (Herrington and Dann 2016, p. 35).

Concerns about gentrification are also attributable at least in part to the prevailing dialogue surrounding cycling and other contemporary planning interventions, which are often justified from the perspectives of sustainability (Hoffman and Lugo 2014, Lubitow and Miller 2013) and economic development (Fainstein 2010, Lubitow et al. 2016, Hoffman and Lugo 2014, Florida 2012, Hutson 2016). These narratives frame cycling investments and other state-sponsored sustainability and economic development initiatives as *apolitical* or *post-political* (Checker 2011, Lubitow and Miller 2013, Lubitow et al. 2016), relying on appeals to broad, universal values and implying that these initiatives are "too important to be dragged through the political mud" (Lubitow and Miller 2013, p. 122). The upshot of this framing is that issues of race, equity, and displacement are expected to be set aside in the interest of pursuing ostensibly universal public goods, thereby "[disabling] meaningful resistance" (Checker 2011, p. 212) on the grounds of gentrification and social justice. Furthermore, the frequent framing of bike lane investment as a strategy to stimulate local economic development and attract the "creative class" to cities implies a focus on socioeconomically advantaged users and a potential connection to processes of gentrification (Lubitow et al. 2016, Stehlin 2015, Hoffman and Lugo 2014, Florida 2012). Thus, the common justifications and narratives surrounding active transportation projects have implications for how they are perceived by community members, with corresponding implications for social equity.

### 1.3 Overview of dissertation papers

The above perspectives provide a broad rationale for considering the distribution of active transportation infrastructure as a social equity issue. In the three papers of this dissertation, I examine the distribution of walkable built environments and on-street, dedicated bike lanes with respect to sociodemographic characteristics such as race, ethnicity, educational attainment, income, poverty, and composite socioeconomic status (SES). The first paper (Chapter 2) assesses how different sociodemographic groups are distributed across space with respect to objectively "walkable" built environments, while the second and third papers examine the distribution of bike lanes with respect to area-level sociodemographic characteristics using cross-sectional (Chapter 3) and longitudinal (Chapter 4) data. In the sections that follow, I introduce the research objectives, hypotheses, and methods for each of these three analyses. The primary findings and implications arising from this work are summarized and discussed in the conclusion of the dissertation (Chapter 5).

### *1.3.1 Sociodemographic characteristics and walkable built environments*

Research objectives and hypothesis. The first paper of the dissertation (Chapter 2) considers how different sociodemographic groups are distributed across space with respect to built environments traditionally viewed as "walkable" (e.g., high population density, street connectivity, and development intensity). Understanding this distribution is important from both substantive and methodological perspectives, as it can reveal how larger patterns of socio-spatial segregation are related to walkability and as this phenomenon presents persistent challenges (e.g., selection bias) for research on the built environment and travel behavior. Based on the findings of King and Clarke (2015), who observed a "disadvantaged advantage" in walkability, I hypothesize that non-white individuals and those with low SES will tend to live in neighborhoods that are objectively more "walkable." Moreover, I hypothesize that this pattern will create methodological challenges in using traditional regression analysis to estimate associations between the built environment and walking behavior. Specifically, I expect that if sociodemographic differences by neighborhood "walkability" are not fully accounted for in regression models, estimates of the potential relationship between walkability and walking behavior will be biased.

Methods. I use data from the CARDIA study to examine how middle-aged adults in four U.S. cities—Birmingham, AL; Chicago, IL; Minneapolis, MN; and Oakland, CA—are distributed across different types of built environments (i.e. neighborhoods of low, medium, and high walkability). I use a non-parametric matching technique called coarsened exact matching (CEM) to assess and adjust for potential differences in the characteristics of individuals living in different types of built environments. I measure the built environment using a composite "walkability" index derived from indicators of population density, street connectivity, and food and physical activity destinations. The outcome variable is a measure of walking exercise units (EUs). After examining sociodemographic characteristics by neighborhood type, I use CEM to match a subset of participants who have similar characteristics but live in different types of built environments. I then assess the implications of these patterns for empirical research by comparing estimated associations between the built environment and walking EUs before and after matching.

### *1.3.2 Cross-sectional associations between bike lanes and area-level sociodemographic characteristics*

Research objectives. The second paper of the dissertation (Chapter 3) assesses whether access to on-street, dedicated bike lanes varies by area-level sociodemographic characteristics in a cross-sectional sample of 22 large U.S. cities (n=21,846 block groups). This paper fills a critical research gap, as cycling advocates have recently argued that low-income and minority populations have disproportionately low access to bike lanes but limited empirical research to date has examined such disparities. I hypothesize that, in contrast to the case of walkability, there is a "disadvantaged *dis*advantage" in access to bike lanes—that is, the presence and extent of the bike lane network will be greater among block groups exhibiting greater socioeconomic advantage (e.g., higher income and educational attainment, lower presence of racial and ethnic minorities, lower poverty levels).

Methods. Using secondary GIS data from administrative sources in each city, I create four dependent variables describing the presence (yes/no), density, connectivity, and proximity of bike lanes in each block group. Primary independent variables include measures of race, ethnicity, educational attainment, income, poverty, and composite SES. I use linear and logistic multilevel mixed-effects regression models to estimate associations between these sociodemographic characteristics and each bike lane variable, before and after adjusting for other factors that may influence the placement of bike lanes across space (urban form, population age structure, bicycle commute mode shares).

### *1.3.3 Longitudinal associations between bike lanes and area-level sociodemographic characteristics*

Research objectives. The third paper of the dissertation (Chapter 4) examines whether investments in the on-street, dedicated bike lane network between 1990 and 2015 were associated with area-level sociodemographic change (e.g., gentrification) in three large U.S. cities (Chicago, IL; Minneapolis, MN; and Oakland, CA). This paper offers a longitudinal extension to the cross-sectional analysis in Chapter 3, confronting the tension between claims that bike lane investments in disadvantaged communities can promote social equity and claims that such investments are associated with gentrification. I hypothesize that investments in the bike lane network over a given decade disproportionately occurred in areas that either were more advantaged (e.g., higher SES, lower presence of racial and ethnic minorities) at the start of the decade or became more advantaged over time.

Methods. Using the administrative bike lane data collected for the second paper (Chapter 3) and a longitudinal built environment database compiled for a related study, I create a time-varying GIS database of on-street, dedicated bike lanes in each of the three cities at four time points (1990, 2000, 2010, and 2015). I measure two dependent variables describing the density and connectivity of the bike lane network at each time point. Primary independent variables include two categorical indicators of sociodemographic change: a gentrification indicator developed by Freeman (2005) and a more general indicator of change in composite SES. I use linear multi-level mixed effects regression models to estimate longitudinal associations between changes in each dependent bike lane variable and changes in each sociodemographic indicator, adjusting for other factors that may influence the placement of bike lanes across space (urban form, population age structure, bicycle commute mode shares).

Through these approaches, the dissertation offers insights into the distribution of built environments and infrastructure that support active transportation in U.S. cities. This distribution has implications for how communities perceive and experience the impacts of walking and cycling investments, including their potential benefits (e.g., health, environmental, economic) and their potential drawbacks (e.g., connections with gentrification). In quantifying the claims of advocates and providing a nuanced understanding of equity issues in walking and cycling, this dissertation expands upon an emerging evidence base and suggests ways in which planners may strive for a distribution of active transportation infrastructure that is both environmentally and socially sustainable.

## CHAPTER 2. THE BUILT ENVIRONMENT AND WALKING BEHAVIOR: ADDRESSING RESIDENTIAL SELF-SELECTION THROUGH MATCHING IN THE CORONARY ARTERY RISK DEVELOPMENT IN YOUNG ADULTS (CARDIA) STUDY

### 2.1 Abstract

Background: Recent research has found walkable built environments to be positively associated with walking behavior. However, accounting for residential self-selection is an ongoing methodological challenge in this area of research. We examined the nature, extent, and implications of residential self-selection with respect to the built environment using coarsened exact matching (CEM), a non-parametric matching method that accounts for differences in covariates across different “treatment” groups (here, across different types of neighborhood built environments).

Methods: We used data from 2,085 U.S. adults in the 2005–2006 examination of the CARDIA study. To measure the built environment, we created a “walkability index” from indicators of population density, street connectivity, and food and physical activity destinations. The dependent variable was a measure of walking exercise units (EUs). Covariates included sociodemographic characteristics, general health status, and self-reported reasons for choosing one’s neighborhood. We used CEM to match a subset of participants who had similar characteristics but lived in different neighborhood types (i.e. low, medium, and high walkability); unmatched participants were dropped from the final regression models. To examine the implications of residential self-selection, we estimated associations between the walkability index and walking EUs (1) before and after CEM and (2) before and after adjusting for reasons for choosing one’s neighborhood.

Results: We found statistically significant differences by neighborhood walkability level for most covariates prior to CEM. Specifically, non-white individuals and those with low socioeconomic status (SES) tended to live in more walkable neighborhoods. After CEM, 50% of participants were dropped for

not having matches in the other neighborhood types; non-white and low-SES individuals were less likely to be matched. Associations between the walkability index and walking EUs differed by between 11 and 15 percent after using CEM to account for covariate differences by neighborhood type, although these differences were sensitive to the strategy used to divide the walkability index into low, medium, and high categories. Associations between the walkability index and walking EUs were up to 27 percent smaller after adjusting for reasons for choosing one's neighborhood.

Conclusions: The prominence of non-white and low-SES individuals in objectively "walkable" neighborhoods may provide a strategic opportunity for interventions designed to promote health equity. These populations, however, were less likely to be found across the full range of neighborhood types, which could reflect socio-spatial segregation and limits on residential choice. Residential self-selection may lead to biased estimates of the association between walkability and walking behavior under traditional regression analysis, even when sociodemographic characteristics are included as controls. CEM provides a promising method for both examining and controlling for patterns of residential self-selection in research on the built environment and travel behavior.

## 2.2 Introduction

In September 2015, the U.S. Surgeon General issued a call to action that highlighted walkable communities as an important component of health promotion (USDHHS 2015). The call, presented in a report entitled *Step It Up!*, recognizes the value of walking as a focus for planning and health intervention: walking is the most common and accessible form of physical activity among adults (Frank and Engelke 2005), it is positively associated with health independent of vigorous physical activity (Haskell et al. 2007), and it can be incorporated into daily routines through planning strategies that support active transportation (Sallis et al. 2006). Responding to these benefits, *Step it Up!* suggests an important role for planners in creating environments that are safe and convenient for pedestrians of all ages and abilities (USDHHS 2015).

This call follows a growing body of research that has found the built environment to be associated with walking, physical activity, and other elements of travel behavior such as driving, transit use, and cycling (Ewing and Cervero 2010, McCormack and Shiell 2011, Winters et al. 2010). While the evidence base has been fairly consistent, the question of causality remains: the built environment is often *associated* with behavior, but can planning interventions *change* behavior? This question is complicated by residential self-selection, or the tendency for individuals to choose their residential neighborhoods based at least in part on factors related to a behavioral outcome of interest to researchers. This phenomenon is often illustrated through a classic example: those who prefer to engage in a certain activity or to travel by a certain mode (e.g., walking) may choose to live in neighborhoods that allow them to act upon these preferences (e.g., in walkable neighborhoods), making it unclear whether behavior is driven primarily by preferences, by the neighborhood built environment, or by some combination thereof.

While this description of residential self-selection is useful, it tells only a partial story. Individuals and households choose their neighborhoods—or are constrained to live in certain neighborhoods—for a wide variety of reasons, many of which are closely related to sociodemographic characteristics. For instance, a household's economic and social resources may shape, either formally or informally, the set of residential neighborhoods to which it has access. Residential location decisions may also be influenced by larger structural forces such as racial and economic segregation, which tend to guide the distribution of various population subgroups across space. While some scholars have suggested that neighborhood-scale racial segregation in the U.S. has slowly declined since the 1980s (Logan and Stults 2011), others have demonstrated that racial segregation persists and has even increased at the metropolitan scale (Lichter et al. 2015). At the same time, income segregation has grown, particularly among minorities (Bischoff and Reardon 2014, Jargowsky 1996). Within this context, sociodemographic characteristics are likely to be a key consideration in residential location decisions and thus in research that attempts to account for neighborhood selection.

Limited research has considered how these structural patterns of racial and socioeconomic segregation may be correlated with characteristics of the built environment and urban form. Indeed, while many studies of the built environment and travel behavior have controlled for sociodemographic characteristics, few have explicitly examined how different sociodemographic groups are distributed across different types of built environments. Notable exceptions include Shin (2017), Blumenberg and Smart (2009), and Blumenberg and Smart (2014), who collectively find that census tracts in Los Angeles, San Francisco, and San Diego with higher concentrations of immigrant populations tend to be more centrally located and to have higher population, employment, and transit densities. More frequently, sociodemographic characteristics have been framed as control variables rather than variables of substantive interest, despite their potential to reveal how patterns of sociodemographic segregation may influence variations in exposure to the built environment.

In this analysis, we consider residential self-selection as both a methodological challenge and a socio-spatial phenomenon of substantive interest. We use data from the Coronary Artery Risk Development in Young Adults (CARDIA) study to examine residential self-selection with respect to built environment characteristics among middle-aged adults in four U.S. cities. Our research questions are as follows: (1) What is the extent and nature of residential self-selection across different types of neighborhood built environments? (2) What are the implications of these patterns for estimates of the relationship between the built environment and walking behavior in our sample? We use a non-parametric matching method to examine and adjust for covariate differences across different neighborhood types and to consider the implications of these differences for empirical research. This method offers insights into patterns of residential self-selection in several U.S. cities and how these patterns could affect research on the built environment and travel behavior.

## 2.3 Residential self-selection: Descriptions, challenges, and potential solutions

### *2.3.1 Two descriptions of residential self-selection*

Within research on the built environment and walking behavior, descriptions of residential self-selection tend to focus on the role of preferences: individuals may choose to live in neighborhoods that allow them to engage in a preferred activity (e.g., walking for leisure) or to travel for at least some trips by a preferred mode (e.g., walking for transport). While preferred walking behavior is just one of the many competing priorities that characterize residential location decisions, there is evidence that at least some proportion of the population is able to select their preferred neighborhood type. Chatman (2009) found that households who reported seeking access to a particular travel mode at the time of residential relocation were more likely to live in neighborhoods that offered such access, and others have found that approximately 50 to 75% of households live in neighborhoods that match their stated built environment preferences (Schwanen and Mokhtarian 2004, Frank et al. 2007, Cho and Rodriguez 2014). While these associations are not perfect, they suggest that residential self-selection by preferences for travel and other built environment features is a prevalent phenomenon that warrants consideration in empirical studies.

Descriptions of residential self-selection in this area of research less frequently emphasize another phenomenon: neighborhood choice by sociodemographic characteristics such as race, ethnicity, and socioeconomic status (SES), which may also be related to travel behavior. This type of confounding is implicitly recognized in studies that control for sociodemographic characteristics, but it is rarely treated in a substantive way to understand how different sociodemographic groups are distributed across space with respect to built environment characteristics. While past research has examined patterns of racial, ethnic, and socioeconomic segregation in U.S. cities (Logan and Stults 2011, Lichter et al. 2015, Bischoff and Reardon 2014, Jargowsky 1996), fewer studies have considered how these patterns are related to the built environment and thus how they may influence variations in exposure to conditions such as walkability. Given evidence that both physical activity (August and Sorkin 2010, CDC 2014) and access to walkable environments (King and Clarke 2015, Neckerman et al. 2009, Kelly et al. 2007, Sallis et al. 2011, Cerin and Leslie 2008, Wilson et al. 2004, Boslaugh et al. 2004) differ by race, ethnicity, and SES, residential self-selection by sociodemographic characteristics is likely to be relevant to the study of the built environment and walking behavior.

### *2.3.2 Methodological challenges: Selection bias and off-support inference*

Although these two descriptions of residential self-selection could have different implications for equity and planning intervention, their basic upshot is the same: residential self-selection tends to result in different types of individuals living in different types of neighborhoods. This is problematic for causal inference, as individuals living in different neighborhood types may not be sufficiently similar to allow for meaningful comparison. To the extent that these differences are also related to the outcome under study (e.g., walking), estimates of the association between the built environment and behavior may be misstated due to *selection bias*.

Selection bias can result from any characteristic that is related to both the "treatment" (e.g., built environment) and outcome (e.g., walking behavior) of interest (Boone-Heinonen et al. 2011), but most discussions of bias in this area of the literature have focused on travel preferences. The direction of bias exerted by residential self-selection on travel preferences is often expected to be upward, resulting in overstated estimates of associations between the built environment and travel behavior when these preferences are not taken into account; indeed, the majority of studies to date have found this to be the case (Cao et al. 2009, McCormack and Shiell 2011). Others, however, have found that accounting for travel preferences magnifies associations with the built environment (Ewing and Cervero 2010, Chatman 2009), potentially because households that are unable to live in their preferred neighborhood type may still overcome environmental constraints to travel by their preferred mode (Chatman 2009, Cao 2010). Cao and Chatman (2016) further show that the direction of selection bias is a function not only of travel preferences, but also of several other factors—including the responsiveness of travel behavior to changes in the built environment, the relative priority of travel as a residential choice criterion, and the supply of different neighborhood types—that could, in combination, lead researchers to either over- or underestimate associations between the built environment and travel behavior.

While selection bias has been widely investigated, limited attention has been paid to the related challenge of *off-support inference,* which can arise when individuals in different "treatment" and "control" groups (e.g., in different neighborhood types) are so systematically different from one another that there is not enough overlap in their observed characteristics to allow for meaningful comparison. Causal inference relies on the justification of an appropriate counterfactual to treatment—that is, observations in the control group should serve as a reasonable approximation of what would have been experienced by observations in the treatment group in the absence of treatment (Oakes and Johnson 2006). This requirement for meaningful causal inference may be violated when the observed characteristics of treatment and control groups are fundamentally different, making them inappropriate counterfactuals or controls for one another. In such cases, the treatment and control groups are said to be *imbalanced* or to lack *common support*.

For example, a researcher may attempt to account for residential self-selection on walking preferences by including a control variable for these preferences, such as an indicator or index derived from self-reported survey data on attitudes toward travel and physical activity. In theory, this approach can begin to address the threat of selection bias. In practice, however, if few or no individuals expressing a preference for walking are found in non-walkable neighborhoods (or vice versa), comparisons of the effects of this indicator across walkability levels may not be supported by the data. Similar issues of limited support may arise from sampling procedures if few individuals of certain observed characteristics (e.g., low income) are recruited from a given treatment/control group (e.g., from neighborhoods of low walkability), or when interactions between observed characteristics are of interest but these interactions are not sufficiently represented in all treatment/control groups (e.g., if an insufficient number of low-income individuals with a preference for walking are observed in neighborhoods of low walkability).

It is important to recognize that regression analyses can still be conducted in the absence of common support across treatment/control groups. However, such analyses are not supported by actual data, "but rather [are based] on extrapolation, interpolation, regression smoothing, and imputation" (Oakes and Johnson 2006, p. 375). Extending the above example, traditional regression analysis allows one to estimate associations between walkability and walking behavior while holding preferences constant, but if a preference for walking is expressed only in one neighborhood type, holding preferences "constant" across neighborhood types in this way has limited practical or substantive meaning.

While there is often no *a priori* reason to expect a particular degree or direction of bias from off-support inference, the potential for regression analysis to obscure fundamental or structural differences between groups can generate results that are mathematically defensible but potentially misleading (Oakes and Johnson 2006). As traditional regression analysis with statistical controls has been the most common tool used to address residential self-selection in research on the built environment and travel behavior (Cao et al. 2009), and as few studies have directly considered the potential for off-support inference, accounting for this challenge is a critical research direction.

#### *2.3.3 An alternative approach: Coarsened exact matching*

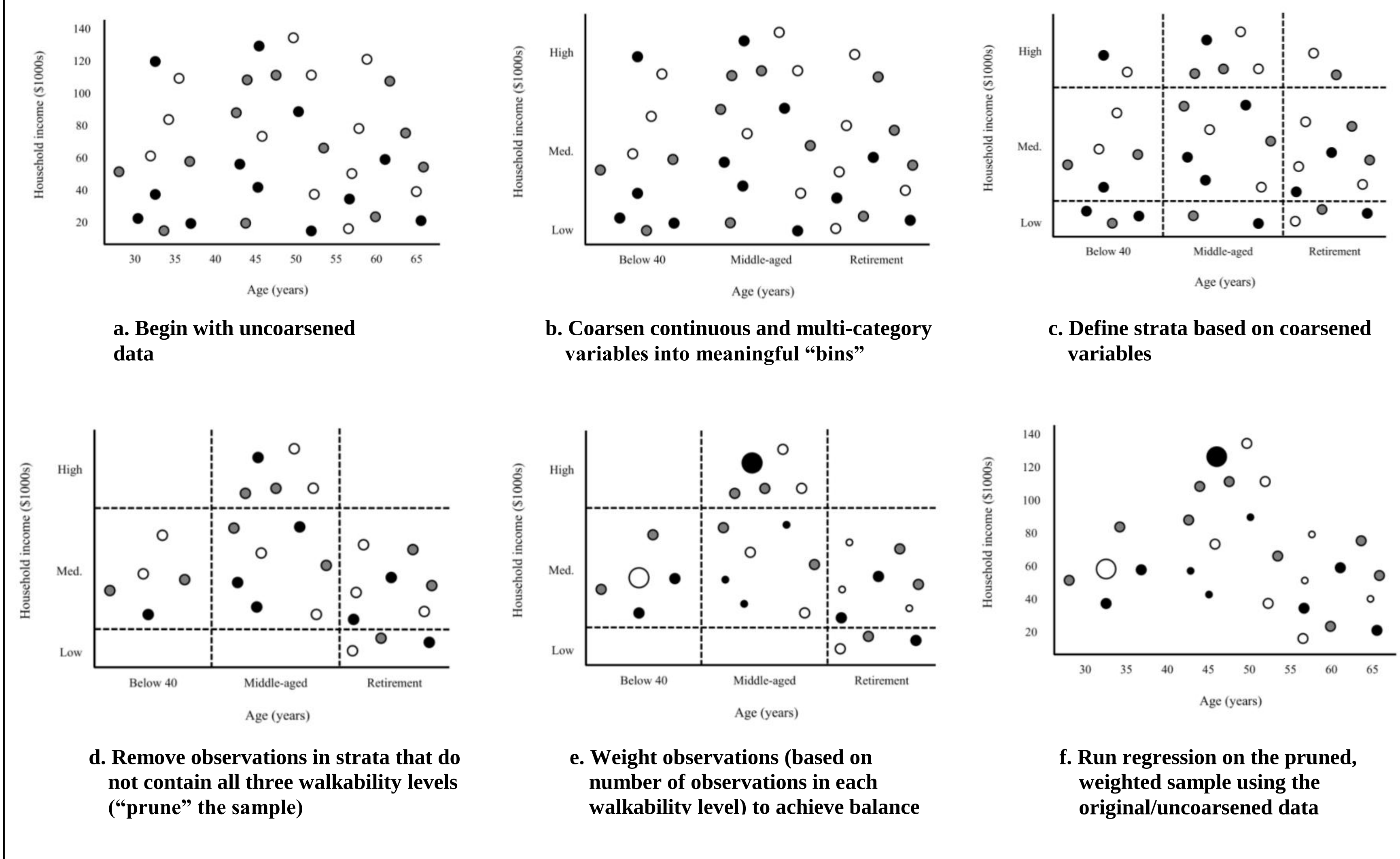
Matching methods seek to avoid off-support inference by restricting the sample to individuals for which similar characteristics can be found in other treatment/control groups. From a research design standpoint, a system of exact matching—in which individuals in different treatment/control groups are considered to be matches for one another if they share the exact same values on all characteristics of interest—represents an ideal approach. Problems of dimensionality arise, however, when individuals must be matched on many covariates, particularly when matching on continuous variables (e.g., income) since it is unlikely that two individuals will have the exact same values.

Parametric propensity score methods seek to address this problem by reducing the information from all covariates into a single value—the propensity score, or an individual's predicted probability of being exposed to a given treatment—that can be used to match, weight, or stratify observations (Rosenbaum and Rubin 1983). Propensity score methods have been widely used in many fields, including several studies of the built environment and travel behavior (Boer et al. 2007, McCormack et al. 2012, Cao 2010, Cao et al. 2010, Cao and Fan 2012, Cao 2015). However, these methods have several limitations, including reliance on parametric assumptions to model probability of treatment, loss of information on individual covariates, and the need for an iterative process to check for covariate balance across treatment/control groups (Iacus et al. 2012, King and Nielsen 2016).

Coarsened exact matching (CEM) is a non-parametric alternative that addresses some limitations of propensity score methods (Iacus et al. 2012). CEM does not require modeling reasons for selection into treatment, but rather matches on observed covariates in a way that more closely approximates exact matching. To address the problem of dimensionality that occurs when matching on continuous and multi-category covariates, CEM temporarily coarsens these types of variables into meaningful bins (e.g., dividing income into poverty levels), creating categorical variables that can be used for exact matching.

After this coarsening process, CEM creates a unique stratum for every possible combination of the coarsened covariate values. Each observation is placed into a single stratum based on all of its covariate values, regardless of treatment/control status. Then, observations in strata that do not contain at least one observation in each treatment/control group (e.g., in each neighborhood type) are removed from the sample; this process is often described as "pruning" the sample to observations with common support. The regression model of interest is then estimated for this reduced or "pruned" sample using the original, uncoarsened data. Estimation weights are applied in the regression model to account for different numbers of observations in each treatment/control group within individual strata, thereby achieving balance across treatment/control groups; specifically, observations in a treatment/control group that is relatively rare within a given stratum receive higher weight, while observations in a treatment/control group that is relatively common receive lower weight. An illustration adapted from King (2013), based on the simple case of a three-level treatment variable and two covariates, is provided in **Figure 2-1**.

**Figure 2-1.** Conceptual illustration of coarsened exact matching (CEM) (adapted from King (2013))




**a. Begin with uncoarsened data**

**b. Coarsen continuous and multi-category variables into meaningful "bins"**

**c. Define strata based on coarsened variables**

**d. Remove observations in strata that do not contain all three walkability levels ("prune" the sample)**

**e. Weight observations (based on number of observations in each walkability level) to achieve balance**

**f. Run regression on the pruned, weighted sample using the original/uncoarsened data**

○ = participant with **low** walkability, ◍ = participant with **medium** walkability, ● = participant with **high** walkability

CEM has several advantages over propensity score matching (PSM) (Iacus et al. 2012, King and Nielsen 2016). First, CEM retains full information on all individual covariates, offering greater transparency and a richer understanding of how different types of individuals are distributed across different treatment/control conditions. Second, CEM does not rely on parametric assumptions about selection into treatment, and it accounts for nonlinearities and all potential interactions between matching variables (which must be explicitly modeled under PSM). Finally, CEM does not require an iterative process of checking for balance after matching; the degree of balance is set in advance by the selected covariates and degree of coarsening. Based on these advantages, we applied CEM to an analysis of the built environment and walking behavior, leveraging its potential to address both selection bias and off-support inference while providing transparent information about patterns of residential self-selection with respect to built environment characteristics.

## 2.4 Data and variables

### *2.4.1 Data source and study sample*

We used data from CARDIA, a population-based cohort study that began in 1985-1986 with 5,115 young adults (ages 18-30) recruited in four U.S. cities: Birmingham, AL; Chicago, IL; Minneapolis, MN; and Oakland, CA. Study enrollment was designed to achieve balance by gender, race (black, white), education (≤ high school, > high school), and age (18-24, 25-30) in each city; specific recruitment procedures have been described previously (Hughes et al. 1987). Seven follow-up exams have been conducted over 25 years. We used data from CARDIA year 20 (2005-2006) in order to incorporate a neighborhood environment questionnaire that was administered only at this exam.

Among the 3,549 participants who completed the 2005-2006 exam, 710 were excluded because they were missing data on one or more variables; the majority of these (n=519) did not complete items of interest from the neighborhood environment questionnaire. The remaining participants were distributed across 205 core-based statistical areas (CBSAs), although the majority (n=2,085) lived in a CBSA corresponding with one of the four CARDIA cities. We restricted our analysis to those who lived in a

CBSA corresponding with one of the four CARDIA cities at the 2005-2006 exam, leaving a final sample of n=2,085.

### *2.4.2 Dependent variable: Exercise units from walking*

As part of a CARDIA physical activity questionnaire, participants responded to the following question: "Did you take walks or hikes or walk to work in the past 12 months for at least one hour total time in any month?" Individuals who responded "yes" were asked how many months they engaged in walking activity, and how many of these months were for at least four total hours. We used these responses to create a combined measure of the frequency and intensity of walking ("exercise units") using the formula $4(m_i + 3n_i)$, where $m_i$ is the number of months of less frequent walking (< 4 hours/month) and $n_i$ is the number of months of more frequent walking (≥ 4 hours/month). The resulting measure ranged from 0 for those engaging in no walking to 144 for those engaging in four or more hours of walking each month.

### *2.4.3 Treatment variable: Walkability index*

Our treatment variable was a walkability index created from measures of population density, street connectivity, and food and physical activity resources within three kilometers of each respondent's residence. We measured these attributes using GIS data linked to participants' geocoded home addresses. The derivation of this index has been described previously (Braun et al. 2016) and is summarized below.

Population density was measured from U.S. Census data. We used road network data from ESRI StreetMap to create two measures of street connectivity: intersection density and link-to-node ratio. As a proxy for overall development patterns, we used Dun & Bradstreet data describing the locations of businesses and facilities related to physical activity (e.g., parks, recreation/community centers) and the food environment (e.g., restaurants, grocery stores). We used these data to create three measures of the density and accessibility of resources: (1) a count of resources within three kilometers, inversely weighted by distance; (2) mean distance to physical activity resources; and (3) mean distance to food resources.

We standardized each measure and created an additive index (**Equation 1**), with item directions and weights based on theory and the results of a meta-analysis by Ewing and Cervero (2010). We added the absolute value of the sample minimum to each observation to put the index on a scale starting at zero (lowest walkability).

$$Walkability_i = \sum(\text{density}_i + 3 * (\text{link to node ratio}_i) + 3 * (\text{intersection density}_i) + 2 * (\text{resource count}_i) - \text{mean distance to PA resources}_i - \text{mean distance to food resources}_i) + |\text{minimum sample value}|$$

It is important to recognize that this indicator captures relatively coarse, structural dimensions of urban form rather than fine-grained dimensions of walkability (e.g., aesthetics, infrastructure conditions). As such, it may be more aptly described as an index of urban form. However, for parsimony and directionality (i.e. higher values are "better") and to remain consistent with past research on the built environment and travel behavior, we hereafter refer to this index as a measure of neighborhood walkability.

#### *2.4.4 Covariates*

The CARDIA neighborhood environment questionnaire included the following question: "Thinking about when you moved to your neighborhood, what 3-4 characteristics were most important in your decision to move there?" Among the reasons from which respondents could choose, two—presence of stores and restaurants and access to public transportation—were related to the built environment and could reflect neighborhood choice for reasons related to anticipated walking behavior. We therefore created a binary variable to indicate whether respondents selected at least one of these reasons. This is not a measure of preferences per se; indeed, an individual who chose to live near public transportation may have done so out of economic necessity rather than an underlying preference for neighborhoods that offer transit service. However, we considered this indicator as a proxy for neighborhood choice on factors related to the built environment and anticipated walking behavior, which could have the same methodological implications as walking preferences (i.e. bias from neighborhood selection on factors also related to the outcome under study).

We used information from other CARDIA questionnaires to measure sociodemographic characteristics (age, gender, race, educational attainment, income, household size, marital status, employment status) and general health status (health problems interfering with physical activity), with definitions described previously (Braun et al. 2016). As a complement to these individual-level measures, we created a deprivation index to describe the SES of participants' neighborhoods. We used principal component analysis to create a single measure from four attributes of the census tracts in which participants resided: percent with less than a high school diploma, percent with at least a college degree, percent with income less than 150% of the federal poverty level, and median household income. For the resulting measure, higher values indicated lower neighborhood SES (i.e. higher deprivation).

## 2.5 Methods

### *2.5.1 Main analyses*

We used CEM to describe patterns of residential self-selection in our sample and to consider the implications of these patterns for the study of the built environment and walking behavior. Analyses were conducted using Stata version 14.0 and R version 3.1.3. First, we examined the characteristics of CARDIA participants living in different neighborhood types to see whether they were imbalanced (i.e. systematically different). To do this, we divided participants into three walkability "treatment" groups (tertiles) based on the sample distribution of walkability index values and labeled these groups as having low (first tertile), medium (second tertile), and high (third tertile) walkability. We used descriptive statistics to assess the characteristics of participants in each walkability tertile, and performed ANOVA and $\chi^2$ tests as appropriate to determine whether differences in covariates across walkability tertiles were statistically significant.

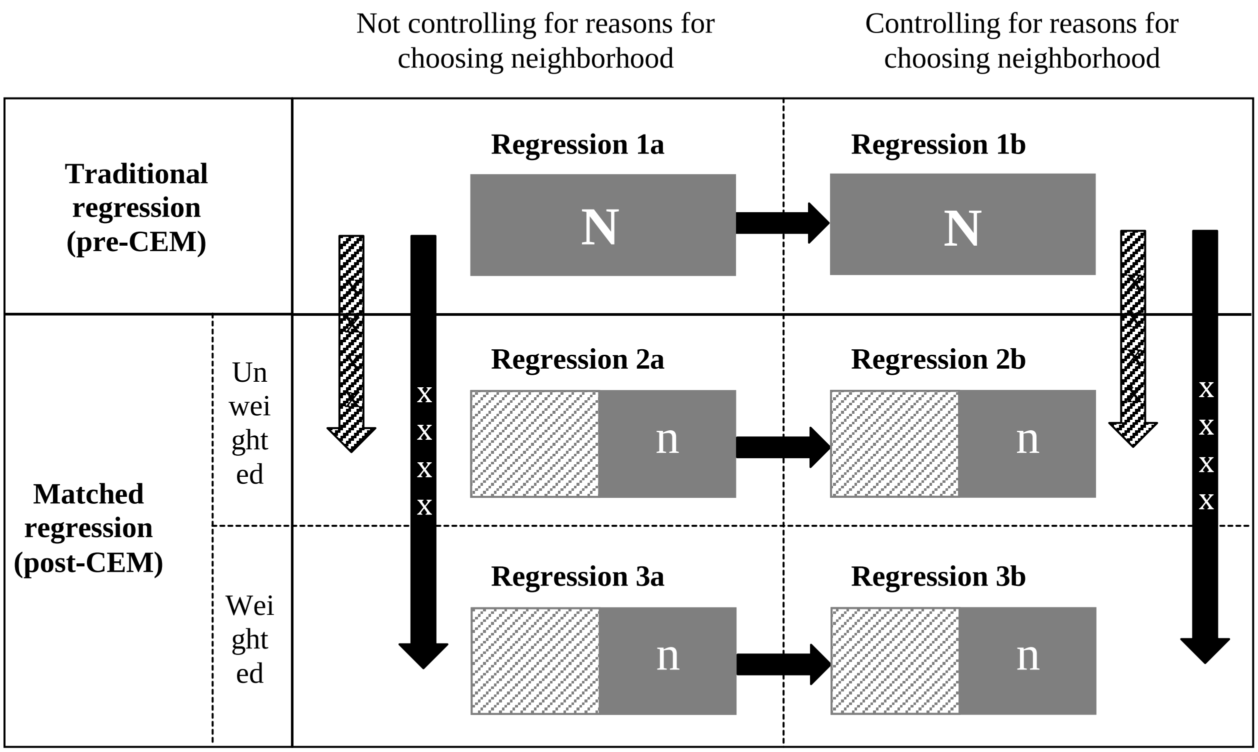
Next, we matched participants on the covariates found in the first step to be significantly different across walkability tertiles, coarsening continuous and multi-category variables as needed to allow for exact matching. This process created a unique stratum for every possible combination of the coarsened covariates, and dropped observations in all strata that did not contain at least one participant from each walkability tertile. We used descriptive statistics to compare the characteristics of matched and unmatched participants.

Finally, we compared estimated associations between the continuous walkability index and walking exercise units (EUs) before and after CEM. The analytical framework for these regression comparisons is presented in **Figure 2-2**. Because our dependent variable had a notable proportion of zero values (28%), we estimated separate coefficients for (1) *any* walking EUs and (2) the *amount* of walking EUs conditional on a non-zero value. In the first set of regressions (1a and 1b; pre-CEM models), we modeled walking EUs as a function of the walkability index in the full, unmatched sample, adjusting for covariates. In Regression 1a, these covariates included all sociodemographic characteristics, general health status, and city; Regression 1b included these covariates as well as the indicator of reasons for choosing one's neighborhood. These models represented the traditional approach of adjusting for residential self-selection using regression controls.

The remaining regressions were estimated for the subsample of participants who were matched using CEM (post-CEM models). As described in Section 2.3.3, CEM consists of "pruning" the sample to participants with common support (i.e. those for whom similar individuals, or matches, could be found in other walkability tertiles) and then weighting these participants to achieve balance within each stratum. To examine the effects of each step, we conducted the post-CEM regressions in two phases: Regressions 2a and 2b showed traditional (i.e. unweighted) estimates for the CEM-matched sample, while Regressions 3a and 3b gave the full effects of CEM (pruning and weighting). This phased approach allowed us to assess the extent to which differences between the pre- and post-CEM coefficients could be attributed to the use of a different subsample and/or to weighting. All post-CEM regressions modeled walking EUs as a function of the walkability index and covariates. In Regressions 2a and 3a, these covariates included all sociodemographic characteristics, general health status, and city; Regressions 2b and 3b included these covariates as well as the indicator of reasons for choosing one's neighborhood.

Comparing the coefficients from Regressions 1, 2, and 3 (vertical arrows in Figure 2-2) showed the combined impacts in our sample of off-support inference and selection bias from sociodemographic characteristics; the dashed (shorter) vertical arrows showed the effects of "pruning" the sample while the solid (longer) vertical arrows indicated the combined effects of pruning and weighting. Comparing each set of "a" and "b" regressions (horizontal arrows) showed the impacts in our sample of selection bias from factors related to the walkability of the neighborhood of choice.

**Figure 2-2.** Analytical framework for regression comparisons




Vertical arrows represent the implications in this sample of (1) off-support inference and (2) selection bias from residential self-selection by sociodemographic characteristics

- Dashed (shorter) vertical arrows show the effects of "pruning" the sample to participants who can be matched
- Solid (longer) vertical arrows show the combined effects of pruning the sample and weighting participants to achieve balance across the three walkability tertiles

Horizontal arrows represent the implications in this sample of selection bias from choosing neighborhood for built

### *2.5.2 Additional analyses*

We conducted three sets of additional analyses to test the robustness of our results. First, we repeated the analysis under alternative strategies for coarsening the walkability index by using different cutpoints to determine the three walkability groups. Second, we repeated the analysis for two alternative samples: one excluding participants in Birmingham (n=1,574) given notable differences in urban form between Birmingham and the three other cities, and one adding participants who no longer lived in the four CARDIA cities (n=2,839). Third, we conducted a similar CEM process in the 2009 National Household Travel Survey (NHTS) to assess whether the patterns of residential self-selection observed in our data may also be evident in other types of surveys. While the NHTS does not include a measure of walkability, it includes a measure of population density that we selected as a relatively comparable treatment variable. We used data from 16,785 NHTS respondents who lived in metropolitan areas and were within the age range of the CARDIA sample, matching them based on their metropolitan area and five covariates from our main analysis that were also available in the NHTS: race, education, income, household size, and employment status.

## 2.6 Results

### *2.6.1 Differences in characteristics by walkability tertile*

Statistically significant differences across walkability tertiles were observed for the majority of covariates (**Table 2-1**). Average income, neighborhood SES, and household size decreased with each increasing walkability tertile, as did the proportions of participants who were white, educated beyond high school, married, or employed. The proportion of participants who reported choosing their neighborhood for reasons related to the built environment increased with each increasing walkability tertile. Participants from Birmingham were overrepresented in the lowest walkability tertile and underrepresented in the highest walkability tertile, while the reverse was true for participants from Chicago and Oakland.

**Table 2-1.** Descriptive statistics for all participants and by walkability level, n=2,085 adults in the 2005-2006 CARDIA exam

| | | **Groups by walkability level** | | | |
|---|---|---|---|---|---|
| **Characteristics** | **All participants (n=2,085)** | Low [a] n=695 | Medium [b] n=695 | High [c] n=695 | p-value for differences |
| *Built environment "treatment"* | | | | | |
| Walkability index | 20.98 (7.99) | 12.15 (3.67) | 21.09 (2.17) | 29.71 (4.36) | — |
| *Walking behavior* | | | | | |
| Participation in walking PA (%) | 71.80 | 67.77 | 73.09 | 74.53 | 0.01** |
| Exercise units from walking PA | 50.37 (53.06) | 41.99 (49.42) | 51.88 (52.68) | 57.24 (55.84) | 0.00*** |
| *Covariates* | | | | | |
| Age, in years | 45.15 (3.66) | 45.04 (3.70) | 45.24 (3.63) | 45.16 (3.65) | 0.59 |
| Female (%) | 57.46 | 54.82 | 56.98 | 60.58 | 0.09* |
| Race (white, vs. black) (%) | 50.31 | 62.73 | 47.48 | 40.72 | 0.00*** |
| Education (more than HS, vs. less/equal) | 58.90 | 63.31 | 57.27 | 56.12 | 0.01** |
| Income, in thousands of U.S. dollars | 71.13 (40.85) | 83.91 (37.59) | 67.93 (41.45) | 61.57 (40.18) | 0.00*** |
| Neighborhood deprivation | 0.00 (1.81) | –0.82 (1.39) | 0.15 (1.84) | 0.67 (1.84) | 0.00*** |
| Household size | 2.98 (1.47) | 3.30 (1.44) | 2.91 (1.42) | 2.74 (1.49) | 0.00*** |
| Currently married (%) | 53.43 | 69.93 | 50.36 | 40.00 | 0.00*** |
| Currently working (%) | 81.49 | 85.90 | 79.71 | 78.85 | 0.00*** |
| Health problems that interfere with PA (%) | 15.44 | 15.83 | 13.96 | 16.55 | 0.39 |
| Chose neighborhood for BE (%) | 41.73 | 20.29 | 42.73 | 62.16 | 0.00*** |
| City | | | | | 0.00*** |
| Birmingham, AL (%) | 24.51 | 44.75 | 26.19 | 2.59 | |
| Chicago, IL (%) | 23.69 | 15.97 | 18.71 | 36.40 | |
| Minneapolis, MN (%) | 25.71 | 21.15 | 28.20 | 27.77 | |
| Oakland, CA (%) | 26.09 | 18.13 | 26.91 | 33.24 | |

PA = physical activity, BE = built environment
Values in parentheses indicate standard deviations (not presented for categorical variables)
[a] For "low," index values ranged from 0 to 17.21
[b] For "medium," index values ranged from 17.21 to 24.90
[c] For "high," index values ranged from 24.90 to 56.04
[d] Based on ANOVA for continuous and $\chi^2$ test for categorical variables; significance: * = 90%, ** = 95%, *** = 99%

These results suggested that residential self-selection into different levels of neighborhood walkability in our sample was significantly (at $p < 0.05$) related to race, educational attainment, income, neighborhood deprivation, household size, marital status, employment status, and city of residence. We therefore identified these eight variables as the matching covariates for CEM. Although significant differences were also observed for the indicator of reasons for choosing one's neighborhood, we did not use this as a matching covariate because, as previously noted, we do not consider it a true indicator of preferences; we assumed that individuals who lived in very different neighborhood types but who cited the same reasons for choosing their neighborhood were describing different constructs and may not share the same underlying built environment preferences. We therefore used this variable as a covariate in the regression analyses, but not for matching.

### *2.6.2 Matching outcomes*

The race, educational attainment, marital status, and employment status covariates identified in the previous step were already binary and did not require coarsening. Each of the four cities was also retained as a separate bin. We coarsened the remaining three non-binary covariates as follows: income was divided into three groups according to the 2014 federal poverty level (FPL) of $24,230 (below 100% of FPL, 100-200% of FPL, and above 200% of FPL), the deprivation index was coarsened into two bins (≤median, >median), and household size was divided into two types of structures (1-2 members, ≥3 members).

Of the 768 possible combinations of these eight coarsened covariates, 410 contained at least one participant in our data while the rest were empty. Among the 410 non-empty strata, 85 contained at least one participant in *each* walkability tertile and were thus considered to be matched; these strata contained a combined total of 1,034 participants (49.6% of original sample). The remaining 1,051 participants (50.4%) could not be matched and were therefore dropped from the post-CEM regressions. Forty-two percent of participants in the low, 54% in the medium, and 53% in the high walkability tertiles were matched.

### 2.6.3 *Comparison of matched vs. unmatched participants*

Compared to those who were matched, unmatched participants had lower average income, neighborhood SES, and household size; lower proportions of participants who were white, educated beyond high school, married, or employed; and a lower proportion of participants reporting health problems that interfered with physical activity (**Table 2-2**). Participants from Birmingham were notably underrepresented in the matched sample while participants from the other three cities were slightly overrepresented. Just over 40% of both matched and unmatched participants chose their neighborhood for reasons related to the built environment.

The pattern of descriptive statistics shown by walkability tertile in Table 2-1 persisted in both the unmatched and matched portions of the sample (Table 2-2). However, for nearly every matching covariate, the values for the matched sample indicated higher SES, larger household size, and a higher proportion of white participants, even within the same walkability tertile. While the differences by walkability tertile in the matched sample suggest residual imbalance, we adjusted for these differences using the CEM weights to achieve balance in the final regressions.

### 2.6.4 *Comparison of pre- and post-CEM regressions*

Estimated associations between the continuous walkability index and walking EUs were consistently positive, and the majority of these associations were statistically significant at 90% confidence or greater (**Table 2-3**). Compared to the traditional regression coefficients for the full sample (Regressions 1a and 1b), unweighted coefficients for the matched sample (Regressions 2a and 2b) were smaller both for any walking EUs (difference of 21-30%) and for the amount of walking EUs conditional on a non-zero value (difference of 4-18%), suggesting that associations between the walkability index and walking behavior were slightly weaker in the subset of participants who could be matched. After weighting (Regressions 3a and 3b), the coefficients for any walking EUs were larger than those for the full sample (difference of 11-15%) while the coefficients for the amount of walking EUs conditional on a non-zero value were smaller (difference of 12-15%).

**Table 2-2.** Characteristics of unmatched and matched participants, n=2,085 adults in the 2005-2006 CARDIA exam

| **Characteristics** | **Unmatched (n=1,051)** | | | | **Matched (n=1,034)** | | | |
|---|---|---|---|---|---|---|---|---|
| | All unmatched | Low (n=401) | Med (n=322) | High (n=328) | All matched | Low (n=294) | Med (n=373) | High (n=367) |
| *Covariates* | | | | | | | | |
| Age, in years | 44.85 (3.76) | 44.80 (3.77) | 44.98 (3.76) | 44.80 (3.75) | 45.45 (3.52) | 45.38 (3.58) | 45.47 (3.49) | 45.48 (3.52) |
| Female (%) | 58.90 | 54.36 | 59.32 | 64.02 | 56.00 | 55.44 | 54.96 | 57.49 |
| Race (white) (%) | 42.44 | 56.36 | 34.78 | 32.93 | 58.32 | 71.43 | 58.45 | 47.68 |
| Education (>HS) (%) | 53.09 | 54.61 | 51.24 | 53.05 | 64.80 | 75.17 | 62.47 | 58.86 |
| Income, 1000s of US$ | 64.02 (40.46) | 79.89 (37.21) | 58.29 (38.56) | 50.25 (39.64) | 78.36 (39.99) | 89.38 (37.47) | 76.26 (42.10) | 71.68 (37.96) |
| NBH deprivation | 0.34 (1.68) | –0.58 (1.28) | 0.68 (1.60) | 1.14 (1.67) | –0.35 (1.87) | –1.14 (1.47) | –0.30 (1.91) | 0.24 (1.89) |
| Household size | 2.99 (1.47) | 3.35 (1.44) | 2.89 (1.44) | 2.66 (1.46) | 2.97 (1.47) | 3.23 (1.45) | 2.92 (1.41) | 2.81 (1.52) |
| Currently married (%) | 49.57 | 70.57 | 44.41 | 28.96 | 57.35 | 69.05 | 55.50 | 49.86 |
| Currently working (%) | 76.12 | 83.79 | 74.53 | 68.29 | 86.94 | 88.78 | 84.18 | 88.28 |
| Health problems (%) | 14.08 | 13.97 | 11.49 | 16.77 | 16.83 | 18.37 | 16.09 | 16.35 |
| Chose NBH for BE (%) | 40.72 | 18.70 | 45.96 | 62.50 | 42.75 | 22.45 | 39.95 | 61.85 |
| *City* | | | | | | | | |
| Birmingham, AL (%) | 38.15 | 68.33 | 38.20 | 1.22 | 10.64 | 12.59 | 15.82 | 3.81 |
| Chicago, IL (%) | 20.46 | 8.23 | 14.29 | 41.46 | 26.98 | 26.53 | 22.52 | 31.88 |
| Minneapolis, MN (%) | 19.12 | 13.22 | 23.60 | 21.95 | 32.40 | 31.97 | 32.17 | 32.97 |
| Oakland, CA (%) | 22.26 | 10.22 | 23.91 | 35.37 | 29.98 | 28.91 | 29.49 | 31.34 |

HS = high school, NBH = neighborhood, BE = built environment
Values in parentheses indicate standard deviations (not presented for categorical variables)
Shaded rows indicate variables that were used as matching covariates in CEM

**Table 2-3.** Estimated (standardized) associations between walkability index and walking EUs, n=2,085 adults in the 2005-2006 CARDIA exam

| | | **a. Not controlling for reasons for choosing neighborhood** [a] | | **b. Controlling for reasons for choosing neighborhood** [b] | |
|---|---|---|---|---|---|
| **Method** | **Outcome** | *Coeff.* [c] *(SE)* | *p-value* | *Coeff.* [c] *(SE)* | *p-value* |
| **1. Pre-CEM** | Any walking EUs (yes/no) | 0.193 (0.070) | 0.01 | 0.161 (0.071) | 0.02 |
| n=2,085 (1,497 non-zero) | Amount of EUs, given any | 5.237 (1.580) | 0.00 | 5.042 (1.623) | 0.00 |
| **2. Post-CEM unweighted ("pruned")** [d] | Any walking EUs (yes/no) | 0.156 (0.101) | 0.12 | 0.119 (0.103) | 0.25 |
| n=1,034 (778 non-zero) | Amount of EUs, given any | 5.021 (2.116) | 0.02 | 4.223 (2.199) | 0.06 |
| **3. Post-CEM weighted (full CEM)** [e] | Any walking EUs (yes/no) | 0.215 (0.102) | 0.04 | 0.187 (0.105) | 0.08 |
| n=1,034 (778 non-zero) | Amount of EUs, given any | 4.503 (2.103) | 0.03 | 4.464 (2.227) | 0.05 |

CEM = coarsened exact matching, EUs = exercise units, SE = standard error

[a] Adjusted for age, gender, race, educational attainment, income, neighborhood deprivation, household size, marital status, employment status, health problems interfering with physical activity, and city

[b] Adjusted for the above covariates as well as the indicator of reasons for choosing neighborhood

[c] All coefficients are standardized, showing associations with a one-SD (7.99-unit) increase in the walkability index

[d] Traditional regression coefficients for the "pruned" sample

[e] Coefficients for the full effects of CEM (pruning + weighting)

In each phase, models that controlled for the indicator of choosing one's neighborhood ("b" regressions) produced consistently smaller coefficients than those that did not include this covariate ("a" regressions). The magnitudes of these differences ranged from 1 to 27% smaller when controlling for the indicator.

### *2.6.5 Additional analyses*

Similar patterns of covariate differences by walkability tertile were observed under both alternative versions of the study sample (i.e. dropping participants from Birmingham, adding participants who no longer lived in the four cities) and all alternative sets of cutpoints used to coarsen the walkability index (data not shown). The regression coefficients in these sensitivity analyses also became consistently smaller after adjusting for the indicator of reasons for choosing one's neighborhood; the magnitude of these differences was particularly strong in the subsample excluding participants from Birmingham (10-79%).

Differences between the pre- and post-CEM regression coefficients were sensitive to the cutpoints used to coarsen the walkability index (data not shown). However, across 14 different combinations of cutpoints, the most common outcome was for the unweighted coefficients in the matched sample to be either smaller than or relatively close to (i.e. within 10% of) the traditional regression coefficients for the full sample, and for the CEM-weighted coefficients to be larger than (for any walking EUs) or relatively close to (for the amount of walking EUs) the traditional regression coefficients for the full sample.

In the subsample excluding Birmingham (n=1,574; 994 matched), unweighted coefficients for the matched sample were smaller for any walking EUs and slightly larger for the amount of walking EUs, relative to the full sample (data not shown). After weighting, the coefficients for any walking EUs were smaller than those observed in the traditional regression, while the coefficients for the amount of walking EUs were larger. In the sample including participants who no longer lived in the four CARDIA cities (n=2,839; 1,022 matched), unweighted coefficients for the matched sample were larger for any walking

EUs and smaller for the amount of walking EUs, relative to the full sample. After weighting, the coefficients for any walking EUs were higher than those observed in the traditional regression, but the differences for the amount of walking EUs were minor.

Finally, similar patterns of residential self-selection were observed in the NHTS (**Appendix Table A-1**). Average income, average household size, and the proportions of participants who were white, educated beyond high school, or currently working generally decreased with increasing levels of density. Approximately 55% of the NHTS sample could be matched on these five covariates and metropolitan area of residence using CEM; compared to matched participants, unmatched participants had lower average incomes and household sizes and lower proportions of participants who were white, educated beyond high school, or currently working.

## 2.7 Discussion

We observed notable differences in the sociodemographic characteristics of individuals living in different neighborhood types among a cohort of 2,085 middle-aged adults in the U.S. Specifically, non-white individuals and those with low SES tended to live in neighborhoods with an urban form that would traditionally be described as more "walkable" (high density, street connectivity, and destination intensity); however, these individuals were also less likely than socioeconomically advantaged individuals to be found across all three levels of neighborhood walkability. We found that such differences could lead to selection bias and off-support inference in traditional regression analyses associating the built environment with walking behavior. These two major themes—the nature and extent of residential self-selection and its implications for the empirical study of the built environment and behavior—are discussed in the sections that follow.

### *2.7.1 Nature and extent of residential self-selection*

#### 2.7.1.1 Differences in characteristics by neighborhood walkability

The pattern of residential self-selection in our sample was such that non-white individuals and those with lower SES (e.g., lower income and educational attainment, higher deprivation, lower rates of employment) tended to live in neighborhoods traditionally viewed as more walkable, a finding that persisted in all sensitivity analyses. These findings are similar to those recorded by King and Clarke (2015), who examined the relationship between walkability and sociodemographic characteristics in 64,885 census tracts across the U.S. The authors found what they call a “disadvantaged advantage” in walkability, in which socioeconomically disadvantaged tracts (i.e. those with higher poverty and lower median income), as well as those with higher proportions of black and Hispanic residents, had lower median block length and higher street node density.

#### 2.7.1.2 Extent of residential self-selection

The extent of these patterns was such that only 50% of participants in our sample were similar enough to participants in other neighborhood types to be matched. Viewed differently, of all the covariate combinations observed in our data, only 21% of these combinations contained at least one individual from each walkability tertile while the remaining 79% lacked observations in at least one walkability tertile. These values reflect the proportion of participants who were not sufficiently comparable to individuals in other neighborhood types to allow for meaningful comparison, suggesting a notable degree of residential self-selection by sociodemographic characteristics.

#### 2.7.1.3 Comparison of matched vs. unmatched participants

Across all analyses, unmatched participants had lower average incomes, lower average household sizes, higher levels of neighborhood deprivation, and lower proportions of participants who were white, educated beyond high school, employed, or married, compared to those who were matched. Thus, the unmatched subsample generally had lower SES and a higher proportion of non-white participants. Only 44% of low-SES participants (low educational attainment, low to medium income) were matched, compared to 67% of high-SES participants (education beyond high school, high income).

To further examine the unmatched portion of the sample, we assessed the characteristics of individual strata, or combinations of the coarsened covariate values, that included a reasonably large number of participants yet remained unmatched because at least one walkability tertile was not represented. Of the 410 strata observed in our data, 19 contained at least ten participants but were not matched because not all walkability tertiles were represented. Given that all of the Birmingham-specific strata in this set (11 strata) were unmatched due to missing observations in the high walkability tertile, we focused on the eight remaining strata that were not in Birmingham. Collectively, the participants in these remaining strata (n=111) accounted for 11% of the unmatched sample. Just under half of these participants (n=51) were black, low-SES individuals who lived in neighborhoods of medium or high walkability, but were absent from neighborhoods of low walkability. Viewed only in terms of race, the vast majority of participants in these eight strata (n=98) were black individuals of any SES who lived in neighborhoods of medium or high walkability, but were absent from neighborhoods of low walkability. While these percentages are fairly small in relation to the unmatched sample in its entirety, they are prominent among the strata that one might expect to be matched due to sheer numbers (i.e. ten or more participants) but that remained unmatched due to significant covariate differences across neighborhood types—specifically, due to the relative scarcity of black and low-SES participants in neighborhoods of low walkability.

On the other hand, four strata in our sample—one in each city containing white, educated, high-income, married, employed participants with large households and high neighborhood SES—collectively accounted for 205 participants, or 10% of the study sample. Three of these strata (all but Birmingham) were matched, collectively accounting for 171 participants (17% of matched sample). With the exception of those in Birmingham, which had a generally low prevalence of participants living in highly walkable neighborhoods, the participants in these four white, high-SES strata were more evenly distributed across neighborhood walkability tertiles than their black and low-SES counterparts.

<u>2.7.1.4 Summary of residential self-selection patterns</u>

Taken together, these results indicate that residential self-selection was prevalent in our data, suggesting that non-white and low-SES individuals were: (1) more likely to live in walkable neighborhoods and (2) less likely to be represented across all three walkability tertiles (particularly less likely to live in neighborhoods of low walkability). There are several potential explanations for this socio-spatial arrangement. First, lower-SES populations may actively choose to live in neighborhoods of greater walkability due to resource constraints (e.g., limited vehicle availability), preferences for built environments that facilitate walking, or preferences for amenities that are often associated with higher walkability (e.g., concentration of job opportunities). Second, non-white and low-SES populations may be systematically excluded from neighborhoods of low walkability, which are often in suburban locations. While overt instances of exclusion in residential markets have become less prevalent through anti-discriminatory legislation and mortgage lending practices (Tootell 1996), the costs associated with housing and private transportation and the disruption of social networks may prove prohibitive for those who would otherwise prefer to live in suburban areas (Katz et al. 2001). Tiebout-style sorting—a phenomenon in which even moderate preferences (e.g., for living in proximity to individuals of similar SES) can lead to notable socio-spatial segregation—may also make certain communities informally inaccessible, despite the absence of formal exclusionary mechanisms (Bayer and McMillan 2012).

The relative scarcity of low-SES and non-white participants in neighborhoods of low walkability could also result from difficulties in recruiting these populations for research, particularly in suburban areas. Efforts were made during the CARDIA recruitment process to overcome barriers to participation among low-SES populations (e.g., work schedules) and thus to represent these populations adequately in the sample (Friedman et al. 1988). However, as our findings were replicated in the national NHTS sample, patterns in which low-SES and non-white individuals are systematically scarce in certain neighborhood types—whether resulting from recruitment challenges or actual socio-spatial arrangements—could be prevalent in a wide range of survey efforts. Finally, the inverse association between walkability and SES in our sample could relate to our measurement of the built environment, which relied on relatively coarse, structural indicators that were nationally available (e.g., population density, street connectivity). Due to our wide geographic scope, we could not capture fine-grained characteristics that are likely to influence walkability, such as infrastructure quality, safety, crime, and aesthetics; past research has found that these conditions are less favorable in low-income neighborhoods, despite high levels of walkability as gauged by conventional measures (Neckerman et al. 2009, Kelly et al. 2007, Sallis et al. 2011, Cerin and Leslie 2008, Wilson et al. 2004, Boslaugh et al. 2004). This underscores the role of our “walkability” index as a measure of larger built environment and urban form characteristics.

Regardless of the explanation, our findings suggest that low-income and minority populations are more likely to live in neighborhoods that tend to be classified as “walkable” based on indicators that are traditionally used to describe the built environment in this area of research (e.g., population density, street connectivity, presence of destinations). While these large-scale indicators may not reflect fine-grained components of walkability (e.g., aesthetics and design, infrastructure quality, perceived safety), they may reflect a basic potential for walking that could be improved upon through more fine-grained walkability interventions. Since low-income and minority populations also tend to engage in lower levels of physical activity (August and Sorkin 2010, CDC 2014), planning interventions that improve walkability for these populations may be at a strategic advantage to address health disparities, due to the basic potential provided by objectively “walkable” urban forms. At the same time, the high degree of socio-spatial segregation in our sample and the underrepresentation of low-SES and non-white populations in certain neighborhood types warrant further investigation, as these arrangements could be indicative of formal or informal spatial exclusion with corresponding implications for social equity.

### *2.7.2 Implications for research on the built environment*

Estimated associations between walkability and walking behavior were consistently positive, even when matching on, and statistically controlling for, sociodemographic and neighborhood selection covariates. These results correspond with a large body of literature that has found walkable built environments to be correlated with higher levels of walking, suggesting that walkability could be a viable point of planning intervention to promote physical activity and associated health outcomes.

While these associations were consistently positive, their magnitude varied both: (1) before and after CEM and (2) before and after adjusting for reasons for choosing one’s neighborhood. First, as previously noted, 50% of observations in our analysis could not be matched because they did not share similar characteristics to participants in other walkability tertiles. A similar reduction in sample size was observed for the NHTS analysis, in which 45% of participants remained unmatched. While dropping this proportion of the sample reduces statistical power and external validity—and may not be feasible in studies with smaller sample sizes—the resulting estimates could have higher internal validity for those who were matched.

Although we had no *a priori* reason to expect a particular direction of bias from off-support inference, comparisons of the traditional and CEM-weighted regression coefficients suggest that, in our main sample, the direction of bias was downward for any walking (i.e. traditional regression coefficients were underestimated) and upward for the amount of walking given any (i.e. traditional regression coefficients were overestimated); the latter direction, however, may have been an anomaly as the traditional regression coefficients were most commonly underestimated in sensitivity analyses that varied the walkability coarsening cutpoints. While the coefficient differences were fairly modest (11-15% in the main analysis), they suggest that traditional regression estimates of the relationship between the built environment and walking behavior—even those which statistically control for relevant covariates—may be misstated by up to 15% when residential self-selection is not fully accounted for. Our findings varied somewhat in sensitivity analyses that focused on different samples, suggesting that CEM is dependent upon the characteristics of a given sample and that the results—particularly in comparison to those from traditional regression analyses—should be interpreted with reference to that sample.

Second, the regression coefficients became consistently smaller after adjusting for reasons for choosing one's neighborhood. Although there are theoretical reasons to expect either upward or downward bias from residential self-selection based on built environment factors (Chatman 2009, Cao 2010, Cao and Chatman 2016), in this particular sample, the direction of bias was upward (i.e. traditional regression coefficients were overstated). Individuals who reported choosing their neighborhood for access to stores, restaurants, and/or public transportation options tended to engage in more walking activity (data not shown), suggesting that at least a portion of the observed associations between walkability and walking behavior could be attributed to neighborhood choice for anticipated walking behavior. In our main analysis, accounting for neighborhood choice led to coefficient reductions of up to 27%, although these reductions generally did not lead to notable declines in statistical significance. The reductions were particularly strong in the sensitivity analysis excluding Birmingham, suggesting that the bias from neighborhood choice on built environment factors may be stronger in the three remaining cities (Chicago, Minneapolis, and Oakland); this could reflect the greater availability of walkable neighborhoods in these three cities, offering more opportunities for individuals to sort into neighborhoods that match their preferences for the built environment.

These findings correspond with the work of Cao et al. (2009), who reviewed 38 studies and found that associations between the built environment and travel behavior were most often attenuated after accounting for residential self-selection, although the majority of adjusted estimates remained statistically significant. While the coefficient reductions do not imply that the built environment is not associated with walking behavior—indeed, the majority of coefficients remained statistically significant after accounting for neighborhood choice—they suggest that research that does not fully account for residential self-selection could misstate these associations.

#### *2.7.3 Limitations*

First, as previously described, our walkability index did not incorporate fine-grained environmental features such as safety and aesthetics that could be relevant to walking behavior; this limitation could partially account for the associations between walkability and SES observed in our sample. Second, we were not able to distinguish between walking for transport and walking for leisure, despite evidence that the built environment has different associations with these travel purposes (Hirsch et al. 2014). Third, the implications of residential self-selection in our sample were sensitive to the cutpoints used to coarsen the walkability index into three groups for matching. This attests to the importance of carefully considering the coarsening approach in CEM; while coarsening should ideally be based on theory rather than distributional properties (Iacus et al. 2011), this was not feasible in our analysis because our composite walkability index was based on standardized values of environmental characteristics across our sample, making it a relative (rather than absolute) measure. Fourth, our indicator of neighborhood choice (e.g., reasons for selecting residential location) was not a true indicator of preferences, as it accounted for why individuals made their location decisions but not what their ideal neighborhood type would be. This distinguishes our work from studies that have developed indicators of neighborhood and travel preferences, and our results—including the direction and magnitude of bias from failing to adjust for the indicator—may not be directly comparable. Finally, we were only able to match on observed covariates. To the extent that unobserved factors, such as underlying preferences and attitudes for walking and the built environment, are relevant to both treatment and outcome, our results could still be subject to bias.

### 2.8 Conclusion

We observed a high degree of residential self-selection by sociodemographic characteristics and by residential choice factors related to neighborhood walkability. These patterns of self-selection were such that non-white and low-SES individuals tended to live in neighborhoods with built environment and urban form characteristics traditionally viewed as more "walkable"—reflecting what King and Clarke (2015) have called a "disadvantaged advantage" in walkability. This arrangement suggests a potential point of intervention for efforts to promote physical activity among diverse populations and thereby address health disparities. However, non-white and low-SES individuals were also less likely to be distributed across the full range of neighborhood types (and were particularly absent from neighborhoods of low walkability), raising potential concerns about residential choice and socio-spatial segregation that warrant further exploration.

Due to residential self-selection, approximately half of participants in our analysis could not be matched because they were not similar enough to participants living in other neighborhood types. We found similar patterns of matching in the NHTS, suggesting that residential self-selection by sociodemographic characteristics may be a prominent and consequential challenge in research on the built environment and travel behavior. In our main analysis, residential self-selection led the estimated associations between walkability and walking behavior to be misstated by up to 15%. These differences are particularly telling given that the traditional regression analyses did account for sociodemographic characteristics and reasons for neighborhood choice, but via the status quo approach of statistical control. While CEM has limitations—including potential sensitivity to coarsening methods and the need for relatively large samples—it offers a promising alternative for examining and accounting for patterns of residential self-selection. The results of our analysis highlight the importance of explicitly considering residential self-selection by sociodemographic characteristics and residential choice factors related to neighborhood walkability, both to understand patterns of socio-spatial segregation in a given data set and to account for the potential impacts of these patterns on estimated associations between the built environment and travel behavior.

Finally, the patterns of residential self-selection observed in this analysis suggest that "selection" into neighborhoods of varying walkability may result from systematic *constraints* and not just active *choices* about preferred environments and behavior. Furthermore, our findings highlight the role that larger patterns of socio-spatial segregation may play in empirical research on the built environment. Within this context, the broader terminology of "residential sorting" (Cao and Chatman 2016) may be an appropriate alternative to that of residential self-selection. This terminology would emphasize a larger conceptualization of sorting into neighborhoods based not only on travel preferences, but also on sociodemographic characteristics, economic and social constraints, and other structural factors that may influence both residential location and behavioral outcomes. Although this would represent a minor change in terminology, it could shift the field toward a more socially contextualized understanding of the relationship between the built environment and travel behavior, and of the socio-spatial arrangements that add both complexity and richness to this area of research.

# CHAPTER 3. SOCIAL (IN)EQUITY IN ACCESS TO CYCLING INFRASTRUCTURE: CROSS-SECTIONAL ASSOCIATIONS BETWEEN BIKE LANES AND AREA-LEVEL SOCIODEMOGRAPHIC CHARACTERISTICS IN 22 LARGE U.S. CITIES

## 3.1 Abstract

Cycling advocates have recently argued that low-income and minority communities across the U.S. have disproportionately low access to bike lanes. To date, however, quantitative evidence of disparities in access to bike lanes is limited to a small number of cities. We address this research gap by examining cross-sectional associations between bike lanes and sociodemographic characteristics at the block group level for 22 large U.S. cities (n=21,846 block groups). Dependent variables include the presence (yes/no), density, connectivity, and proximity of bike lanes, measured using secondary GIS data collected by each of the 22 cities between 2012 and 2016. Primary independent variables include indicators of race, ethnicity, educational attainment, income, poverty, and a combined socioeconomic status (SES) index, measured using data from the 2011–2015 American Community Survey. We use linear and logistic multilevel mixed-effects regression models to estimate associations between these sociodemographic characteristics and each bike lane dependent variable, before and after adjusting for traditional indicators of cycling demand (population and employment density, distance to downtown, proportion of residents between ages 18 and 34, proportion of population commuting by bicycle). In unadjusted associations, disadvantaged block groups (i.e. lower SES, higher proportions of minority residents) had significantly lower access to bike lanes. After adjusting for traditional indicators of cycling demand, access to bike lanes was lower in block groups with particular types of disadvantage (lower educational attainment, higher proportions of Hispanic residents, lower composite SES) but not in those with other types of disadvantage (higher proportions of black residents, lower income, higher poverty). These results provide empirical support for advocates' claims of distributional inequalities in bike lane

access, suggesting the importance of more closely considering social equity in the bicycle planning and advocacy process.

## 3.2 Introduction

Over the past two decades, cycling has gained increasing prominence as a sustainable mobility strategy in cities across the globe. While U.S. cycling mode shares have consistently lagged behind those in other countries, particularly in western Europe (Buehler and Pucher 2012), cycling in the U.S. has nevertheless experienced its own "renaissance" (Pucher et al. 2011) supported by planning and policy at multiple levels of government: federal spending on active transportation steadily increased from $6 million in 1990 to $835 million in 2017 (USDOT 2010, League of American Bicyclists 2016), the number of states with published goals to increase cycling more than doubled over the past decade (Alliance for Biking and Walking 2016), and the average density of cycling infrastructure in the most populous 50 U.S. cities doubled between 2007 and 2016 (Alliance for Biking and Walking 2016). These trends point to a growing national interest in cycling and have coincided with modest but steady increases in cycling mode share over time (Pucher et al. 2011, Alliance for Biking and Walking 2016).

There is growing concern, however, that these efforts and investments have been inequitably distributed. Cycling advocates have recently argued that low-income and minority populations have disproportionately low access to cycling infrastructure such as bike lanes, even though these groups have had considerable recent growth in cycling and experience disproportionately high cycling fatality rates (League of American Bicyclists 2014). This concern is particularly problematic because cycling is often discussed from the perspective of health equity: given that cycling could have health benefits related to physical activity, obesity, diabetes, cardiovascular disease, and all-cause mortality (Pucher et al. 2010, Bassett et al. 2008, Wanner et al. 2012, Hamer and Chida 2008, Andersen et al. 2000, Matthews et al. 2007), and that disparities in these health outcomes have been recorded by race and socioeconomic status in the U.S. (August and Sorkin 2010, Gordon-Larsen et al. 2003, Mokdad et al. 2003), some observers have suggested that cycling—a low-cost and physically active mode of transportation—could be a tool to promote more equitable health outcomes in U.S. cities (Martens et al. 2016, Rachele et al. 2015). Existing health disparities may be exacerbated, however, if cycling supports such as bike lanes are inequitably distributed across communities of varying racial and socioeconomic composition.

Although conversations about equity are becoming more prominent in bicycle planning and advocacy, statements about disparities in access to bike lanes have tended to lack quantitative support. For instance, at least two recent reports (League of American Bicyclists 2014, Dressel et al. 2014) have referred to disparities in infrastructure access across the U.S. without citing specific evidence of such national trends. While this lack of specificity is beginning to change with emerging quantitative research on bike lanes and neighborhood sociodemographic characteristics in several cities (Hirsch et al. 2017, Flanagan et al. 2016), there remains a dearth of empirical evidence about current disparities in access to bike lanes across a broad, national sample of U.S. cities.

In the present study, we address this research gap by examining whether area-level sociodemographic characteristics are associated with the presence and extent of bike lanes in a geographically diverse sample of 22 large cities across the U.S. We hypothesize that census block groups exhibiting greater socioeconomic advantage (e.g., higher income and educational attainment, lower presence of racial and ethnic minorities, lower poverty levels) will have greater access to cycling infrastructure as characterized by measures of bike lane presence, density, connectivity, and proximity. Through this approach, we aim to provide a geographically extensive understanding of where bike lanes are located in relation to neighborhood sociodemographic characteristics in the U.S., offering quantitative evidence that could complement contextual observations about disparities and provide empirical backing to calls for more equitable cycling investments. In addition, it is possible that differences in the placement of bike lanes is the result of differences in cycling demand: places with high demand receive bike lanes, while places with low demand do not. Thus, in our analyses we also adjust for traditional indicators of cycling demand such as measures of urban form, resident population age structure, and the proportion of commuting to work by bicycle.

### 3.3 Perspectives on social equity in cycling

Transportation networks produce both benefits and costs for the communities they serve. The distribution of these benefits and costs has been a central focus of the transportation justice movement (Golub et al. 2013, Sanchez and Brenman 2007), as this distribution can influence access to opportunity, wealth, and power in cities (Harvey 1973, Soja 2010) and is often patterned along class and racial lines (Golub 2016). Recognizing these inequities and supported by a robust legal framework at the federal level, the transportation justice movement has advanced the consideration of social equity in transportation planning and policy over the past several decades (Golub 2016).

Cycling has not featured prominently in U.S. transportation equity analyses to date, which have instead tended to focus on the distribution of impacts from large infrastructure projects and regional plans (Sanchez and Brenman 2007). This limited focus may be attributed in part to the historical position of cycling as a fringe or “second class” travel mode, and is likely to change as cycling continues to gain mode share and attract increasing levels of federal funding (Golub 2016, p. 25). The profile of cycling in these types of analyses could also rise alongside growing recognition of cycling’s potential connections to social equity: low-income and minority populations are the two groups with the highest growth in bicycling in the U.S. (Pucher et al. 2011). These groups also tend to have lower access to automobiles and higher rates of diseases attributable to physical inactivity, putting them in a particularly strong position to experience benefits if cycling infrastructure is equitably distributed (Lee et al. 2016).

In the sections that follow, we first review the limited but growing body of literature that has addressed issues of social equity in cycling. Given that few studies to date have examined the distribution of cycling infrastructure from an equity perspective, we broaden our focus to incorporate several studies about pedestrian infrastructure (e.g., walkability). We then explore two potential sets of explanations for disparities in access to cycling infrastructure and conclude by linking these explanations to the conceptual framework for our analysis.

### 3.3.1 Social equity in infrastructure access: Evidence from cycling

Research on disparities in access to cycling infrastructure is currently limited. To the authors' knowledge, only two studies to date have assessed the distribution of bike lanes with respect to sociodemographic characteristics at the sub-county level. Flanagan et al. (2016) examined trends in cycling infrastructure investment and sociodemographic change in Chicago and Portland, finding that bike lanes and bike share stations in these two cities were more likely to be built in relatively advantaged census tracts (e.g., higher educational attainment, higher homeownership rates) and in tracts experiencing gentrification between 1990 and 2010. Hirsch et al. (2017) similarly found that investments in bike lanes and off-street trails were positively associated with neighborhood-level sociodemographic changes consistent with gentrification between 1985 and 2010 in Birmingham, Chicago, Minneapolis, and Oakland. These recent studies suggest that bike lanes and related infrastructure tend to be built in areas that are either already advantaged or are experiencing increases in socioeconomic advantage over time, providing longitudinal evidence of disparities in access to cycling infrastructure in a combined total of five cities.

Several studies have focused specifically on access to bike share stations, given the proliferation of this transport mode over the past several years and the disproportionately white and high-income profile of bike share users (Buck 2012, Gavin et al. 2016). Smith et al. (2015) examined the distribution of bike share stations for 42 U.S. systems and found that, across all systems, only 12 percent of stations were located in census tracts with a high degree of economic hardship, compared to 75 percent located in census tracts with low economic hardship. Similarly, Ursaki and Aultman-Hall (2015) found that traditionally disadvantaged block groups, as characterized by measures of race, income, and educational attainment, had disproportionately low access to bike share stations across seven large U.S. cities. These patterns stand in potential contrast to those observed in other countries; for example, Fuller et al. (2013) found that areas with low income and low educational attainment had relatively *high* levels of access to Montreal's BIXI program. While U.S. bike share systems are increasingly adopting strategies to expand access and ridership among disadvantaged populations (Howland et al. 2017), current empirical findings suggest that bike share stations are among the types of cycling infrastructure that have been disproportionately built in advantaged neighborhoods.

Other researchers have explored patterns of active transportation planning and project implementation at the county level, recognizing the larger institutional framework within which localized infrastructure investment decisions are made. Aytur et al. (2008) reviewed 67 land use plans for municipalities and counties across North Carolina and found that plans in jurisdictions with low income levels and a high presence of non-white residents were less likely to contain policies and strategies that support physical activity, such as non-automobile transportation improvements and mixed land uses. Moreover, the presence of these plan elements was positively associated with leisure- and transportation-related physical activity, suggesting that an inequitable distribution of supportive planning strategies could exacerbate socioeconomic disparities in physical activity and related health outcomes. Cradock et al. (2009) also conducted a county-level analysis, examining patterns of pedestrian and bicycle spending in 3,140 counties across the U.S. The authors found that counties with high poverty rates and low levels of educational attainment were less likely than their wealthier, more educated counterparts to implement pedestrian and bicycle projects between 1992 and 2004. This finding, which could reflect differences in planning capacity between counties of varying socioeconomic composition, points to an uneven use of federal funding that could lead to distributional inequalities in access to active transportation infrastructure.

### *3.3.2 Sociodemographic characteristics and the planning and advocacy process*

Taken together, the studies in this emerging evidence base suggest that low-income and minority populations may have disproportionately low access to cycling infrastructure such as bike lanes. To understand why these disparities might arise, it is useful to consider how the location of bike lanes is determined through the planning and advocacy process. We focus below on two major elements of this process: objective measurement of cycling demand and institutional issues in planning and advocacy.

First, bike lanes tend to be placed in areas where they are demanded, as determined based in part upon objective data about urban form, population characteristics, existing cycling levels, and existing infrastructure attributes. The demand for cycling—and thus for bike lanes—is generally viewed as higher in dense, urban areas characterized by relatively short distances between origins and destinations (Boarnet and Crane 2001, Cervero 2002); in areas with a large proportion of young adults, who tend to cycle more (Winters et al. 2010; Dill and Voros 2007; Heinen et al. 2013); and in areas where high levels of cycling are observed taking place. The location of bike lanes may also be influenced by the need to fill gaps in network connectivity (Mekuria et al. 2012) and to address observed safety concerns.

Although these indicators of demand may appear to be socially neutral, they are in some ways connected to the arrangement of various population subgroups across space. For instance, cycling investments are among the many planning interventions that have recently been framed and justified in terms of their economic development potential (Lubitow et al. 2016, Hoffman and Lugo 2014, Hutson 2016), encouraging the return of a highly educated "creative class" of young professionals to U.S. cities (Florida 2012). At the same time, recent scholarly work has documented the suburbanization of poverty over the past two decades (Howell and Timberlake 2014). Thus, traditional conceptualizations of cycling demand rooted in objective measures of urban form and population age structure could result in the placement of infrastructure in areas where disadvantaged populations have become progressively less likely to reside over time. These relationships suggest the importance of controlling for objective measures of cycling demand, both as a predictor of where bike lanes are located and as a potential explanation for correlations between bike lane location and sociodemographic characteristics.

Second, disparities in access to cycling infrastructure could stem from institutional issues in bicycle planning and advocacy, including those related to goal setting, representation and involvement, and social norms. Several authors have recently examined social equity goals within U.S. transportation plans, often finding these goals to be either absent or inadequately translated into actionable strategies (Manaugh et al. 2015, Karner and Niemeier 2013, Martens et al. 2012, Golub and Martens 2014, Evenson et al. 2012, Lee et al. 2017). Golub (2016) further notes that despite considerable diversity in cycling, low-income and minority populations tend to be underrepresented in the planning profession, in cycling advocacy organizations, and in traditional public involvement opportunities for transportation planning projects. Others have focused instead on the role of social norms, noting that cycling holds different meanings for different subgroups of the population and may not be universally advocated for as an appropriate target for public investment (Hoffman 2016, Golub 2016, Lubitow and Miller 2013, People for Bikes and Alliance for Biking & Walking 2015). These perspectives suggest that disparities in access to bike lanes could arise because social equity is not adequately incorporated into planning goals, because disadvantaged groups are not adequately represented or involved in the planning and advocacy process, or because these groups do not actively demand or prioritize investment in cycling infrastructure.

### *3.3.3 Conceptual framework*

These potential explanations inform the conceptual framework for our analysis of associations between area-level sociodemographic characteristics and bike lane presence in U.S. cities (**Figure 3-1**). We do not posit a causal relationship, but rather seek to understand whether the presence of bike lanes is associated with measures of race, ethnicity, and SES both before and after adjusting for other observed determinants of bike lane location. Thus, line "A" in Figure 3-1 is the primarily relationship of interest for our analysis.

As noted in the previous section, bike lanes are likely to be placed in locations where they are demanded and advocated for, as determined through objectively measured data (arrow "b1") and through elements of the planning and advocacy process (arrow "c1"). Observed disparities in access to bike lanes, then, could result from how these two factors are associated with area-level sociodemographic characteristics (lines "b2" and "c2"). Although planning and advocacy factors (Institutional Factors in Figure 3-1) are difficult to quantify, particularly in a national-level analysis, we have access to several objective measures of cycling demand factors (i.e. urban form, population age structure, and the proportion of the population cycling to work) and incorporate these measures into our analysis. We begin by measuring unadjusted associations between sociodemographic characteristics and bike lanes (line "A") to determine whether disparities in access to cycling infrastructure exist in our sample. Next, we adjust these associations for objective demand factors (arrow “b1”/line “b2”) to assess the degree to which any observed disparities may be explained by the methods through which the demand for bike lanes is typically estimated. If sociodemographic differences in access to bike lanes persist after adjusting for these factors, it is possible that they stem from elements of the planning and advocacy process (arrow “c1”/line “c2”) or from other unobserved relationships relevant to both bike lane location and area-level sociodemographic characteristics.

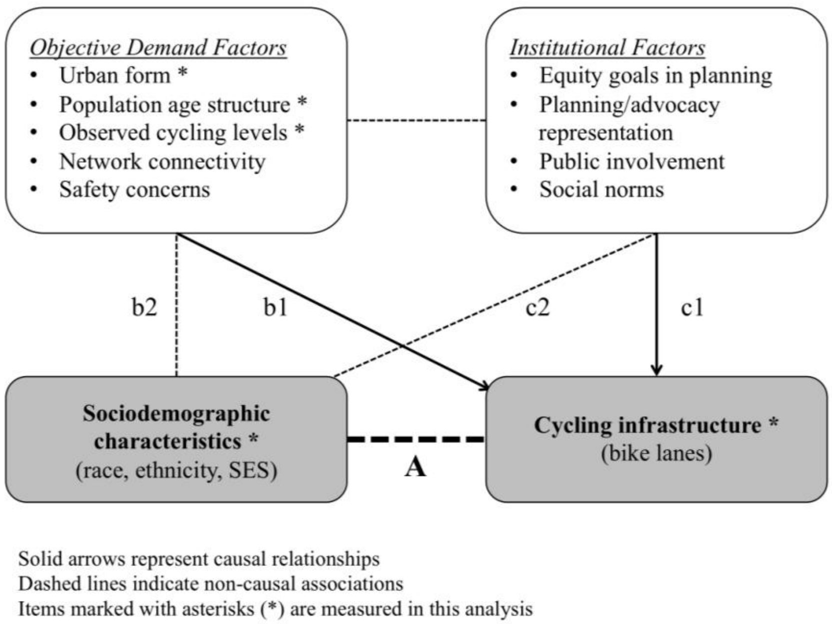



**Figure 3-1.** Conceptual framework

Several other features of this analysis warrant consideration and justification. Lee et al. (2017) note that equity analyses for active transportation must make and articulate decisions about *what* is being distributed, among *whom*, and at what *level of analysis*. In answering the first question, we choose to focus on the distribution of dedicated on-street bike lanes rather than non-dedicated facilities (e.g., shared lanes, signed routes) or off-street facilities (e.g., trails) for several reasons: past studies have found that cyclists prefer at least some separation from motorized traffic (Stinson and Bhat 2003, Hunt and Abraham 2007, Wardman et al. 2007), this separation may be particularly important for attracting female riders and those with less cycling experience (Hunt and Abraham 2007, Garrard et al. 2008), and on-street infrastructure may be more effective than off-street facilities (e.g., trails) in encouraging cycling due to greater connectivity and access to destinations (Krizek and Johnson 2006). For the second question, we examine the distribution of infrastructure by race, ethnicity, educational attainment, income, and poverty, because distributional inequalities in access to cycling infrastructure have been observed by these characteristics in previous studies (Flanagan et al. 2016, Hirsch et al. 2017, Smith et al. 2015, Ursaki and Aultman-Hall 2015). Finally, in answering the third question, we deviate from past work by selecting a smaller geographic unit of analysis—the census block group—that allows for greater spatial resolution and recognizes the importance of close proximity to infrastructure in facilitating active transportation (Krizek and Johnson 2006). The selection of this unit of analysis is likely to have implications for the results, as smaller areas are more likely to be homogeneous than larger areas.

## 3.4 Data and Variables

### *3.4.1 Study sample*

We measured associations between bike lanes and sociodemographic characteristics at the census block group level in 22 large U.S. cities. To derive the study sample, we began with the primary cities of the 25 most populous U.S. metropolitan areas in 2015. We were able to obtain current bike lane data for 22 of these 25 cities (excluding Baltimore, MD; St. Louis, MO; and Riverside, CA); a list of included cities and corresponding number of block groups is provided in **Appendix Table B-1**. The centroids of a combined total of 23,000 block groups fell within the jurisdictional limits of these 22 cities, and among these, 21,846 block groups had complete data for all variables of interest. Thus, the final study sample for this analysis consisted of n=21,846 block groups across 22 cities.

### *3.4.2 Data sources*

Bike lane data were collected in the form of GIS shapefiles from local and regional administrative data sources in each city, including open data repositories, other government websites (e.g., municipal planning websites), and email correspondence with local planners and bicycle coordinators. The dates of these shapefiles ranged from 2012 to 2016, although only two were dated prior to 2014. Each shapefile was thoroughly reviewed to determine how various infrastructure types (e.g., trails, lanes, sharrows, signed routes) and statuses (e.g., planned vs. existing facilities) were coded by individual cities in the shapefile attribute fields; these city-specific codes were clarified and confirmed using Google Earth imagery, and the resulting information was used to consistently classify infrastructure types across all cities. Given the focus of this study on dedicated on-street infrastructure, only the records for existing traditional, buffered, and protected bike lanes were retained for analysis. We used GIS to spatially attribute the resulting bike lanes to the block groups in our study sample, drawing 10-meter buffers around all block groups to allow lanes along boundaries to be attributed to all block groups sharing those boundaries.

Data sources for block group-level sociodemographic characteristics and covariates included the 2011–2015 American Community Survey (ACS), the 2000 Census, and the 2014 Longitudinal Employer–Household Dynamics (LEHD) data.

#### *3.4.3 Dependent variables: Bike lanes*

We created four dependent variables to describe the presence and extent of bike lanes in each block group. First, we created a binary measure of bike lane *presence* to indicate whether a block group contained any bike lanes, regardless of length (0 if none, 1 if any). Second, we calculated a continuous measure of bike lane *density* (in meters per square mile). Third, as a proxy for connectivity, we calculated a continuous measure of bike lane *reach*, defined as the total distance (in meters) that can be traveled solely along continuous bike lanes starting from within each block group. Finally, as a measure of proximity to bike lanes, we calculated each block group's average *distance* (in meters) to the nearest bike lane by measuring the distance to the nearest lane from points spaced at 10-meter intervals within each block group and averaging those values. This measure added information about bike lane access by allowing us to account for (1) the distribution or coverage of bike lanes throughout a block group (widespread vs. spatially clustered) and (2) proximity to bike lanes among block groups that did not contain any lanes within their boundaries, which would have zero values for the other three dependent variables but could still have reasonable access to bike lanes in nearby block groups.

### *3.4.4 Primary independent variables: Sociodemographic characteristics*

The primary independent variables of interest for this analysis were sociodemographic characteristics measured separately and through a composite index, using block group-level data from the 2011–2015 ACS. First, we measured the following five sociodemographic characteristics as separate variables: race (percentage non-Hispanic black), ethnicity (percentage Hispanic or Latino), median household income, educational attainment (percentage with bachelor's degree or more), and poverty (percentage below the federal poverty line). Second, we created a composite socioeconomic status (SES) index to account for possible strong correlations among these separate sociodemographic characteristics (**Appendix Table B-2**). We calculated the SES index by adapting the approach of Christine et al. (2015) to the block group level, performing principal factor analysis on 17 ACS variables related to race and ethnicity, educational attainment, income and wealth, poverty, occupation, employment, and housing. The first factor in this analysis was weighted heavily (i.e. rotated factor loading > 0.4) on nine variables related to income, education, poverty, crowding, occupation, and employment; we standardized these nine variables and applied the rotated factor loadings as weights in an additive index, with higher values indicating higher SES.

### *3.4.5 Covariates: Urban form, age structure, and bike commuting patterns*

Several covariates were measured to account for the objective demand factors presented in our conceptual framework (Figure 3-1). First, we characterized urban form through measures of population density (persons per square mile using data from the 2011–2015 ACS), employment density (jobs per square mile using 2014 LEHD data), and distance to city hall (as a proxy for distance to major employment centers). Second, we characterized the age structure of the population by measuring the percentage of residents between the ages of 18 and 34, corresponding with age groups who demonstrate relatively high levels of cycling. Finally, we measured bike commuting patterns as the percentage of workers who commuted by bicycle in 2000; this time lag was incorporated to address ambiguous temporality between cycling infrastructure and bicycle use when measured at the same point in time.

## 3.5 Methods

### *3.5.1 Descriptive analyses*

Descriptive statistics and corresponding statistical tests (e.g., ANOVA) were used to assess the characteristics of the study sample as a whole and to examine potential differences in the characteristics of block groups by the presence or absence of bike lanes. Additionally, pairwise correlations between each independent variable and the three continuous dependent bike lane variables (i.e. density, reach, distance to the nearest bike lane) were examined as a preliminary measure of unadjusted associations between sociodemographic characteristics and the extent of bike lanes. For bike lane density and reach, these pairwise correlations were measured specifically within the subset of block groups that had any bike lanes, as a high proportion of block groups (57%) had no bike lanes and thus had zero values for these variables.

### *3.5.2 Regression analyses*

Multilevel mixed-effects (ME) regression models were used to estimate the associations of sociodemographic characteristics with each dependent bike lane variable (i.e. presence, density, reach, and average distance to the nearest bike lane), adjusting for covariates. This modeling strategy accounted for the hierarchical structure of the data, in which block groups were clustered within census tracts and census tracts were clustered within cities. Specifically, all regressions were estimated as two-level models (block groups nested within census tracts), with city specified as a factor variable rather than a third-level parameter due to the relatively low number of cities available for clustering at a third level. All standard errors were clustered at the city level.

The specific type of ME regression used varied across the four dependent variables. For the binary *presence* variable, logistic ME regression was used to model the likelihood of having any bike lanes (Model 1). For the *density* and *reach* variables, two-part models for mixed discrete-continuous outcomes were used within the ME regression framework to separately model (1) the likelihood of having any bike lanes (identical to Model 1, estimated using logistic ME regression on the full sample) and (2) the density or reach of bike lanes conditional on having any (Models 2 and 3 for density and reach respectively, estimated using linear ME regression on the subset of block groups that had any lanes). This approach, which is analogous to hurdle models for count data (Belotti et al. 2015, Cragg 1971), was selected due to the large proportion of block groups that had no bike lanes and thus a large proportion of zero values for the density and reach variables, along with the theoretical expectation that different data generating processes may be relevant for determining (1) whether a block group has any bike lanes and (2) the extent of bike lanes among those that have them. Finally, linear ME regression was used to model average *distance* to the nearest bike lane (Model 4); two-part models were not needed for this continuous variable because it did not contain zero values.

Two model specifications were estimated for each dependent variable. First, the five separate sociodemographic characteristics were entered simultaneously into the same regression ("A" models for each dependent variable). Second, the composite SES index was entered in place of the separate educational attainment, income, and poverty variables ("B" models for each dependent variable); the separate race and ethnicity variables were retained in these models because these two sociodemographic characteristics were not included in the final SES index and thus were not redundant with the index. All covariates and the city indicator were included in both model specifications.

### *3.5.3 Additional analyses*

We conducted three additional analyses to further examine the regression results and to test their sensitivity to changes in the study variables and sample. First, we recalculated the SES index to include median housing value, which had a high proportion of missing values (18%) at the block group level and was therefore excluded from the index in the main analysis. This modification led to a reduced sample size of n=18,760, and we re-estimated all models using this reduced sample and the revised version of the SES index that incorporated median housing value. Second, we estimated a series of partially adjusted models in which each sociodemographic variable (i.e. race, ethnicity, educational attainment, income, poverty, SES index) was entered into a separate regression adjusted for covariates; this strategy allowed us to focus on partially adjusted associations for each individual characteristic without adjusting for other sociodemographic measures. Third, we re-estimated all regression models for a subset of the sample that excluded block groups in New York City, Los Angeles, and Chicago (n=11,459 across the remaining 19 cities), and for the complementary subset of block groups in these three cities alone (n=10,387). We conducted this analysis to address the possibility that the regression results in the full sample could be driven primarily by these three large, influential cities due to their substantial number of block groups.

## 3.6 Results

### *3.6.1 Descriptive analyses*

Just over forty percent of block groups in the study sample contained dedicated on-street bike lanes (**Table 3-1**). Among block groups that had any bike lanes, the average length of lanes was approximately 800 meters, the average density was just over 8,700 meters per square mile, and cyclists could travel an average of 55 kilometers without deviating from bike lanes. Among all block groups, the average distance to the nearest bike lane was 1.16 kilometers.

Block groups with bike lanes were significantly different from block groups without bike lanes on all sociodemographic characteristics considered (**Table 3-1**). Compared to block groups that did not have bike lanes, block groups with bike lanes had lower proportions of black and Hispanic residents, higher educational attainment and median household income, lower poverty levels, and higher (i.e. more advantaged) values for the composite SES index. Among covariates, block groups with bike lanes also had higher employment density, higher proportions of young (i.e. ages 18 to 34) residents, and higher levels of bike commuting in 2000, and were located closer to downtown (i.e. to city hall) in their respective cities.

**Table 3-1.** Descriptive statistics for block group-level bike lane characteristics, sociodemographic characteristics, and covariates, total and by presence or absence of bike lanes, n=21,846 block groups in 22 large U.S. cities

| | **All block groups** (n=21,846) | **Block groups by presence of bike lanes** No lanes (n=12,487) | Any lanes (n=9,359) | *p-value for difference* [a] |
|---|---|---|---|---|
| *For block groups considered* | | | | |
| Presence of bike lanes (yes) | 9,359 (43%) | — | — | — |
| Average length of bike lanes (100m) | 3.45 (8.49) | — | 8.06 (11.45) | — |
| Average density of bike lanes (100m/mi$^2$) | 37.59 (78.86) | — | 87.74 (100.59) | — |
| Average reach through bike lanes (100m) | 235.40 (557.57) | — | 549.42 (743.76) | — |
| Average distance to nearest bike lane (100m) | 11.59 (21.08) | — | 2.58 (2.37) | — |
| *Sociodemographic characteristics* | | | | |
| Race (% black) | 23.29 (31.54) | 25.09 (33.04) | 20.89 (29.24) | **0.00** |
| Ethnicity (% Hispanic) | 28.97 (28.83) | 31.01 (29.99) | 26.26 (26.98) | **0.00** |
| Education (% with bachelor's or more) | 33.99 (25.20) | 30.79 (23.87) | 38.27 (26.28) | **0.00** |
| Median household income ($1000s) | 58.54 (36.25) | 56.66 (35.39) | 61.05 (37.23) | **0.00** |
| Poverty (% < federal poverty line) | 21.00 (16.53) | 21.26 (16.43) | 20.65 (16.66) | **0.01** |
| Composite SES index | 0.00 (5.10) | –0.50 (5.00) | 0.67 (5.17) | **0.00** |
| *Covariates* | | | | |
| Population density (1000 persons/mi$^2$) | 27.83 (37.90) | 27.84 (37.14) | 27.80 (38.58) | 0.94 |
| Employment density (1000 jobs/mi$^2$) | 9.40 (51.38) | 6.25 (27.53) | 13.61 (70.97) | **0.00** |
| Distance to downtown (km) | 11.63 (7.31) | 12.51 (6.89) | 10.45 (7.66) | **0.00** |
| Age (% 18 to 34) | 27.88 (12.41) | 26.60 (11.14) | 29.59 (13.68) | **0.00** |
| Bike commuters in 2000 (% bike) | 0.62 (1.49) | 0.46 (1.22) | 0.83 (1.78) | **0.00** |

BG = block group, SES = socioeconomic status
[a] Based on ANOVA; boldface indicates statistical significance at 90% confidence or greater; significance of group differences not estimated for bike lane variables, as bike lanes were used to create groups

In unadjusted pairwise correlations (**Table 3-2**), block groups with higher educational attainment, higher median household income, and higher SES tended to have greater bike lane density and reach and to be closer to the nearest bike lane, while the opposite associations were observed for block groups with higher proportions of Hispanic residents. Block groups with higher proportions of black residents tended to be farther from the nearest bike lane but also tended to have higher bike lane reach, while block groups with higher poverty levels tended to have lower bike lane reach. Among covariates, block groups with higher population and employment density, higher proportions of residents between ages 18 and 34, and higher proportions of bike commuters in 2000 tended to have higher bike lane density and reach and to be closer to the nearest bike lane, while block groups that were farther from downtown in their respective cities tended to have lower bike lane density and reach and to be farther from the nearest bike lane.

**Table 3-2.** Pairwise correlations of block group-level sociodemographic characteristics and covariates with continuous block group-level bike lane variables (density, reach, and distance to nearest bike lane), n=21,846 block groups in 22 large U.S. cities

| | **Density** [a] | | **Reach** [a] | | **Distance to nearest** | |
|---|---|---|---|---|---|---|
| | *r* [b] | *p* [c] | *r* [b] | *p* [c] | *r* [b] | *p* [c] |
| *Sociodemographic characteristics* | | | | | | |
| Race (% black) | 0.00 | 0.87 | 0.03 | **0.01** | 0.07 | **0.00** |
| Ethnicity (% Hispanic) | –0.07 | **0.00** | –0.22 | **0.00** | 0.05 | **0.00** |
| Education (% with bachelor's or more) | 0.18 | **0.00** | 0.17 | **0.00** | –0.13 | **0.00** |
| Median household income ($1000s) | 0.08 | **0.00** | 0.12 | **0.00** | –0.02 | **0.00** |
| Poverty (% < federal poverty line) | –0.00 | 0.92 | –0.06 | **0.00** | –0.00 | 0.48 |
| Composite SES index | 0.09 | **0.00** | 0.15 | **0.00** | –0.07 | **0.00** |
| *Covariates* | | | | | | |
| Population density (1000 persons/mi$^2$) | 0.52 | **0.00** | 0.16 | **0.00** | –0.19 | **0.00** |
| Employment density (1000 jobs/mi$^2$) | 0.13 | **0.00** | 0.14 | **0.00** | –0.06 | **0.00** |
| Distance to downtown (km) | –0.21 | **0.00** | –0.14 | **0.00** | 0.27 | **0.00** |
| Age (% 18 to 34) | 0.15 | **0.00** | 0.11 | **0.00** | –0.10 | **0.00** |
| Bike commuters in 2000 (% bike) | 0.10 | **0.00** | 0.06 | **0.00** | –0.11 | **0.00** |

BG = block group, SES = socioeconomic status
[a] Correlations calculated among block groups with any bike lanes, given the high proportion of zero values for these variables
[b] Pearson's correlation coefficient
[c] Boldface indicates statistical significance at 90% confidence or greater

### *3.6.2 Regression analyses*

In adjusted regression models that considered all five separate sociodemographic characteristics (**Table 3-3**), higher educational attainment and higher poverty levels were associated with a greater likelihood of having bike lanes (Model 1A). Educational attainment and the proportion of black residents were positively associated with bike lane density, while median household income was inversely associated with bike lane density (Model 2A). Educational attainment, median household income, and poverty levels were positively associated with bike lane reach, while the proportion of Hispanic residents was inversely associated with bike lane reach (Model 3A). Additionally, higher educational attainment was associated with closer proximity (i.e. smaller distance) to the nearest bike lane (Model 4A).

Comparatively few statistically significant associations were observed for adjusted regression models that considered race and ethnicity alongside the composite SES index (**Table 3-3**). Higher SES was associated with greater bike lane density (Model 2B) and reach (Model 3B), while higher proportions of Hispanic residents were associated with lower bike lane reach (Model 3B).

Across both sets of regression models, the coefficients on measures of urban form, population age structure, and bike commuting were generally in the expected direction; specifically, access to bike lanes was greater in block groups with higher population and employment density, higher proportions of young residents, and higher proportions of bike commuters in 2000, and lower in block groups that were farther from downtown. The patterns of statistical significance for these covariates, however, varied across dependent variables.

### *3.6.3 Additional analyses*

A similar overall pattern of results was observed when including median housing value in the composite SES index (thus restricting the sample size to n=18,760) (results not shown). When each sociodemographic characteristic was entered into a separate regression model adjusted for covariates, a similar overall pattern of results was found; however, the direction of the coefficients for race, income, and poverty were no longer in the unexpected direction in these models (**Appendix Table B-3**). Some differences in coefficient size and statistical significance were found when re-estimating the regression models without block groups in New York City, Los Angeles, or Chicago (n=11,459 in the remaining 19 cities) and within these three cities only (n=10,387) (results not shown). Most commonly, the coefficients in the three largest cities were larger in absolute value than those in the remaining 19 cities, suggesting stronger associations and occasionally leading to corresponding changes in statistical significance.

**Table 3-3.** Adjusted associations of block group-level sociodemographic characteristics (separate variables and composite index) with block group-level bike lane characteristics using multilevel mixed-effects regression, n=21,846 block groups in 22 large U.S. cities

| | **1A. Presence (y/n)** [a] | | | **2A. Density (m/mi²)** [b] | | | **3A. Reach (m)** [b] | | | **4A. Dist. to nearest (m)** [c] | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *OR* | *SE* | *p* [d] | *Coeff.* | *SE* | *p* [d] | *Coeff.* | *SE* | *p* [d] | *Coeff.* | *SE* | *p* [d] |
| **A. With Separate Variables** | | | | | | | | | | | | |
| *Sociodemographic characteristics* | | | | | | | | | | | | |
| Race (% black) | 1.00 | 0.00 | 0.28 | 11.04 | 6.08 | **0.07** | –19.32 | 66.57 | 0.77 | –0.26 | 0.37 | 0.47 |
| Ethnicity (% Hispanic) | 1.01 | 0.00 | 0.24 | –0.03 | 8.62 | 0.99 | –124.74 | 53.89 | **0.02** | 0.21 | 0.32 | 0.52 |
| Education (% with bachelor’s or more) | 1.02 | 0.01 | **0.00** | 46.43 | 18.99 | **0.02** | 74.76 | 31.32 | **0.02** | –0.46 | 0.18 | **0.01** |
| Median household income ($1000s) | 1.00 | 0.00 | 0.36 | –9.77 | 4.06 | **0.02** | 33.57 | 11.07 | **0.00** | 0.29 | 0.21 | 0.17 |
| Poverty (% < federal poverty line) | 1.01 | 0.00 | **0.00** | 7.02 | 7.44 | 0.35 | 63.29 | 21.80 | **0.00** | –0.23 | 0.16 | 0.15 |
| *Covariates* | | | | | | | | | | | | |
| Population density (1000 persons/mi²) | 0.99 | 0.00 | 0.14 | 78.85 | 8.51 | **0.00** | 9.47 | 10.16 | 0.35 | –0.15 | 0.05 | **0.00** |
| Employment density (1000 jobs/mi²) | 1.00 | 0.00 | **0.00** | 2.46 | 2.05 | 0.23 | 17.84 | 3.39 | **0.00** | –0.02 | 0.04 | 0.63 |
| Distance to downtown (km) | 0.97 | 0.06 | 0.57 | –134.45 | 67.74 | **0.05** | –1561.07 | 1984.83 | 0.43 | 110.89 | 52.88 | **0.04** |
| Age (% 18 to 34) | 1.01 | 0.00 | **0.00** | 21.97 | 7.91 | **0.01** | 82.17 | 27.14 | **0.00** | –0.62 | 0.31 | **0.05** |
| Bike commuters in 2000 (% bike) | 1.06 | 0.02 | **0.02** | 126.84 | 67.35 | **0.06** | 145.05 | 180.79 | 0.42 | –0.51 | 1.66 | 0.76 |

| | **1B. Presence (y/n)** [a] | | | **2B. Density (m/mi²)** [b] | | | **3B. Reach (m)** [b] | | | **4B. Dist. to nearest (m)** [c] | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *OR* | *SE* | *p* [d] | *Coeff.* | *SE* | *p* [d] | *Coeff.* | *SE* | *p* [d] | *Coeff.* | *SE* | *p* [d] |
| **B. With Composite SES Index** | | | | | | | | | | | | |
| *Sociodemographic characteristics* | | | | | | | | | | | | |
| Race (% black) [e] | 1.00 | 0.00 | 0.69 | 6.09 | 6.39 | 0.34 | –20.96 | 65.55 | 0.75 | –0.19 | 0.35 | 0.59 |
| Ethnicity (% Hispanic) [e] | 1.00 | 0.01 | 0.79 | –7.60 | 8.33 | 0.36 | –122.83 | 50.68 | **0.02** | 0.34 | 0.35 | 0.33 |
| Composite SES index | 1.05 | 0.03 | 0.14 | 97.48 | 53.90 | **0.07** | 380.68 | 224.47 | **0.09** | 1.17 | 1.84 | 0.53 |
| *Covariates* | | | | | | | | | | | | |
| Population density (1000 persons/mi²) | 1.00 | 0.00 | 0.25 | 81.22 | 7.92 | **0.00** | 11.06 | 10.34 | 0.29 | –0.15 | 0.05 | **0.00** |
| Employment density (1000 jobs/mi²) | 1.01 | 0.00 | **0.00** | 2.61 | 2.07 | 0.21 | 18.03 | 3.37 | **0.00** | –0.02 | 0.04 | 0.60 |
| Distance to downtown (km) | 0.95 | 0.06 | 0.46 | –153.52 | 74.61 | **0.04** | –1605.23 | 1993.79 | 0.42 | 111.21 | 52.90 | **0.04** |
| Age (% 18 to 34) | 1.02 | 0.00 | **0.00** | 37.07 | 7.93 | **0.00** | 93.40 | 25.46 | **0.00** | –0.74 | 0.33 | **0.03** |
| Bike commuters in 2000 (% bike) | 1.07 | 0.03 | **0.01** | 157.18 | 72.04 | **0.03** | 163.89 | 177.86 | 0.36 | –0.61 | 1.66 | 0.72 |

OR = odds ratio, SE = standard error, SES = socioeconomic status

For all models: two-level clustering (block groups nested within tracts), city specified as a factor variable (coefficients not presented), standard errors clustered at the city level

[a] Modeled using multilevel mixed effects (MLME) logistic regression on full sample (n=21,846)

[b] Modeled using two-part models: first part modeled likelihood of having any lanes among full sample (n=21,846) using MLME logistic regression (identical to Models 1A/1B), second part modeled density/reach of bike lanes among block groups with any (n=9,359) using MLME linear regression (presented in Models 2A/2B and 3A/3B)

[c] Modeled using MLME linear regression on full sample (n=21,846)

[d] p-values in bold indicate statistical significance at 90% confidence or greater

[e] Race and ethnicity variables entered along with composite SES index in “B” models, as the final SES index did not incorporate race and ethnicity variables

## 3.7 Discussion

### *3.7.1 Overview of findings*

We found moderate evidence of disparities in access to bike lanes by race, ethnicity, and socioeconomic status (SES) at the block group level across 22 large U.S. cities. In descriptive analyses that did not adjust for covariates, block groups with higher proportions of black and Hispanic residents and those with lower SES (i.e. lower income and educational attainment, higher poverty levels, lower values on a composite SES index) were less likely to contain bike lanes, tended to be further from the nearest bike lane, and, with some exceptions, tended to have lower bike lane density and reach. Although these associations were not adjusted for other factors that could influence the placement of bike lanes across space, they provide preliminary evidence of disparities in access to cycling infrastructure.

As anticipated, block groups that were closer to downtown and those with higher population and employment density, higher proportions of young residents, and higher proportions of bike commuters in 2000 generally had greater access to bike lanes. After adjusting for these demand covariates, several associations between sociodemographic characteristics and bike lanes persisted. Educational attainment, ethnicity, and the composite SES index were most consistently associated with the presence and extent of bike lanes in adjusted regression models. Specifically, higher educational attainment was associated with a greater likelihood of having bike lanes, closer proximity to the nearest bike lane, and higher bike lane density and connectivity; higher proportions of Hispanic residents were associated with lower bike lane connectivity; and higher composite SES was associated with higher bike lane density and connectivity. These findings are consistent with claims of socioeconomic disparities in access to bike lanes, suggesting a lower presence and extent of on-street, dedicated cycling infrastructure among minority and low-SES populations even after adjusting for other determinants of bike lane location. These associations tended to be stronger in the largest cities in our sample, suggesting that disparities in access to bike lanes may be particularly relevant in large urban areas.

Our results are consistent with previously described studies that have found associations between sociodemographic advantage and cycling infrastructure such as bike lanes and bike share stations (Flanagan et al. 2016, Hirsch et al. 2017, Smith et al. 2015, Ursaki and Aultman-Hall 2015). More broadly, this work fits within a small but growing body of research that has considered disparities in access to other types of active transportation supports, including walkable built environments. For instance, Neckerman et al. (2009) found that high-poverty tracts in New York City were less likely than lower-poverty tracts to contain urban design features supportive of walking, including street trees, sidewalk cafes, clean streets, and landmarked buildings. Kelly et al. (2007) examined signs of physical disorder among block groups in St. Louis, finding that predominantly African-American block groups were more likely to have uneven sidewalks and sidewalk obstructions, and that high-poverty block groups were more likely to show signs of physical disorder. Related studies have examined perceived rather than objective measures of walkability, finding that residents of low-income and minority neighborhoods tended to rate their environments low on metrics of aesthetics and pleasantness (Sallis et al. 2011, Cerin and Leslie 2008, Wilson et al. 2004, Boslaugh et al. 2004). Although there are fundamental differences between the processes of creating walkable built environments and siting cycling infrastructure, the findings for walkability complement those observed in our analysis of bike lanes, together providing a multifaceted understanding of disparities in access to active transportation.

Several other adjusted associations in our analysis, however, suggested *greater* access to bike lanes among disadvantaged block groups. Higher poverty levels were associated with a greater likelihood of having bike lanes and higher bike lane connectivity, and higher proportions of black residents were associated with higher bike lane density. Additionally, although higher median income was associated with higher bike lane connectivity, this socioeconomic characteristic was also associated with lower bike lane density.

The unexpected findings for race, income, and poverty could have both statistical and substantive explanations. From a statistical standpoint, the separate sociodemographic measures included in this analysis had fairly strong correlations with one another, with Pearson's correlation coefficients ranging in absolute value from 0.29 to 0.73 (**Appendix Table B-2**). When we accounted for these correlations through the composite SES index and through partially adjusted regression models (**Appendix Table B-3**), the coefficients for these variables, when significant, were consistently in the expected direction. From a substantive standpoint, the finding that access to bike lanes was higher in areas with higher proportions of black and impoverished residents and lower income levels could reflect sociodemographic transitions such as gentrification. Recent opposition to bike lanes in several U.S. cities has focused on their perceived associations with gentrification (Benesh 2015, Herrington and Dann 2016, Greenfield 2012, Lubitow et al. 2016, Freed 2015), particularly given the frequent framing of bike lanes as an economic development strategy (Lubitow et al. 2016, Hoffman and Lugo 2014, Hutson 2016). As gentrification is a gradual process that can result in pockets of advantage within traditionally disadvantaged neighborhoods, gentrifying areas that receive bike lanes could still have a notable presence of minority and low-SES residents. Although this cross-sectional analysis is not equipped to assess longitudinal phenomena such as sociodemographic change, the potential connections between gentrification and bike lane investment provide one possible explanation for the results observed in the present study.

The coefficients for educational attainment, ethnicity, and composite SES—which were fairly consistently significant and in the expected direction—have interesting interpretations and implications within the context of social equity in cycling. First, areas with higher educational attainment tended to be closer to downtown and to have higher job density, higher proportions of younger residents, and higher rates of bicycle commuting (**Appendix Table B-2**). These correlations with cycling demand factors could account for the positive associations observed between educational attainment and access to bike lanes, which in turn could reflect the framing of bike lane investments as a method to attract highly educated members of the "creative class" to the urban core (Florida 2012). Second, we observed disparities in access to bike lanes among block groups with a high proportion of Hispanic residents. These disparities are particularly notable given that rates of bicycle commuting are highest within the Latino population (Golub et al. 2016); indeed, the prevalence of bicycle commuting among Hispanic and Latino workers in 2015 was nearly 50 percent greater than the prevalence among white and black commuters (U.S. Census

Bureau 2015). The results of the present analysis therefore suggest that the infrastructure needs of Hispanic residents are not being adequately met despite relatively high levels of cycling, corresponding with recent claims by cycling advocates (League of American Bicyclists 2014). Finally, the consistently significant and positive associations observed between SES and bike lane presence could suggest that populations with greater socioeconomic advantage have greater access to the institutional arrangements within planning and advocacy that influence bike lane location, as explained in the section that follows.

### *3.7.2 Institutional explanations: Planning, advocacy, and social norms*

While the disparities observed in this analysis could reflect directly discriminatory practices, it is perhaps more likely that they result from institutional issues within the planning and advocacy processes that guide public decisions about cycling investments. Key issues relevant to both the conceptual framework and the results of this analysis include transportation planning goal setting, representation and involvement in planning and advocacy, and social norms and attitudes toward cycling.

First, goals related to social equity have not been comprehensively integrated into the transportation planning documents that guide infrastructure investments. In a recent review of the transportation plans of 18 large U.S. metropolitan planning organizations, Manaugh et al. (2015) found that while social equity goals were often articulated, they tended to lack specific objectives, strategies, and measures that would allow for meaningful implementation. This shortcoming may be attributable to a lack of specific guidance for equity analysis and the prioritization of other plan goals; furthermore, the limited attention paid to the distribution of infrastructure may be due to the traditional focus of equity analyses on costs (e.g., pollution exposure) rather than benefits (e.g., access to social and economic resources) (Karner and Niemeier 2013, Martens et al. 2012, Golub and Martens 2014). Some have explored this tendency specifically for active transportation plans. Evenson et al. (2012) found that only one-quarter of 46 pedestrian and bicycle plans across North Carolina contained goals related to social equity, and Lee et al. (2017) identified a wide range of approaches—from no mention of social equity to explicit prioritization and measurement of social equity objectives—among the pedestrian and bicycle plans of 13 large U.S. cities. These limitations suggest that goals related to social equity have neither clearly nor consistently been integrated into active transportation plans, potentially leading to inequitable patterns of infrastructure investment as these plans have been implemented.

Second, sociodemographic disparities in access to bike lanes could result from the disproportionately white and high-income composition of the planning profession and cycling advocacy organizations (Golub 2016). This imbalance in representation is particularly notable in light of the considerable diversity of cycling: while it is often viewed as a primarily white, middle- to upper-class mode of travel, cycling is in reality much more diverse with a strong presence of low-income riders, high rates of cycling among the Latino population, and high growth in cycling rates among the African American population (Golub 2016, League of American Bicyclists 2014, People for Bikes and Alliance for Biking & Walking 2015). Despite this diversity, the planning and advocacy institutions that influence the locations of bike lanes tend to be dominated by white, middle- to upper-class actors, resulting in arrangements that could exclude relevant perspectives from the planning process and thereby create imbalances in access to infrastructure and other cycling supports. This issue is exacerbated by the tendency of low-income and minority populations to be underrepresented in traditional public involvement opportunities (Golub 2016), which may further remove the perspectives of these groups from the decision making process.

Third, disparities in access to bike lanes could arise because disadvantaged populations choose not to advocate for this form of transportation investment. While cycling investments are often framed as universal public goods (Lubitow and Miller 2013), the perceived value and appropriateness of these investments may vary across different social and cultural contexts. Indeed, cycling can hold different social significance and meanings for different groups (Hoffman 2016) and is often viewed as a "second class" travel mode (Golub 2016, p. 25) that is reserved for either very rich or very poor travelers (People for Bikes and Alliance for Biking & Walking 2015). Similarly, Golub et al. (2016) argue that cycling can range along a continuum from emancipatory to oppressive for different groups, depending in part upon whether cycling is an autonomous choice or one made out of economic necessity. These perspectives not only provide a potential explanation for sociodemographic differences in access to bike lanes, but also indicate the importance of considering bike lane interventions as taking place upon and interacting with a complex socio-cultural landscape.

### *3.7.3 Study strengths and limitations*

While the majority of past research has considered cycling infrastructure as an independent variable in analyses of travel behavior, the present analysis is among only a handful of studies that have instead framed cycling infrastructure as a dependent variable, considering the various factors that may influence the allocation of bike lanes across space and how these factors may be related to the racial, ethnic, and socioeconomic composition of neighborhoods. Key features that distinguish this study from past work include a smaller unit of analysis (i.e. census block group) that more closely characterizes access to infrastructure and a relatively large sample of cities across the U.S.

This analysis relies on cross-sectional data, which limits its ability to make causal inferences and assess the temporal relationship between bike lane investment and area-level sociodemographic characteristics. This limitation points to the need for a longitudinal analysis that evaluates whether changes in sociodemographic characteristics are associated with changes in infrastructure investment over time. The research design for this analysis is also ecological, focusing on area-level associations rather than individual-level access to infrastructure; however, past work has found that neighborhood SES is significantly associated with health-related behaviors independent of individual-level SES (Turrell et al. 2010), suggesting the value of considering sociodemographic characteristics from an ecological perspective. However, area-based measures suffer from the modifiable areal unit problem, which leads to increased homogeneity with smaller areas and thus a higher likelihood of finding disparities. An additional limitation of this analysis relates to the data used to characterize bike lanes, reflecting a persistent challenge in research on cycling infrastructure (Lee et al. 2017). Because our bike lane data were collected from individual cities, they were created using different methods and systems of classification. While we worked to reconcile inconsistencies through a thorough review of the individual

GIS shapefiles alongside Google Earth imagery, it is possible that some inconsistencies across cities remained in the data. Additionally, due to the large geographic scale of this analysis, we relied on data that were readily available for a large number of cities and thus could not measure certain characteristics of interest to social equity, such as the safety and quality of bike lanes and the accessibility that they provide to social and economic resources (Lee et al. 2017). Future work should consider these attributes of the bike lane network, potentially leveraging finer-grained infrastructure and destination data within individual metropolitan areas. Such analyses could also consider the distribution of cycling supports beyond urban form, such as bike parking and storage, shower facilities at destinations, and characteristics of public safety (e.g., crime rates). The present study, however, provides an important starting point for this type of investigation by providing preliminary evidence of disparities in access to bike lanes.

Finally, we approached the question of disparities in access to bike lanes using a multi-city analysis. Although this approach is useful for understanding broad trends, it is also likely to mask variation across cities. We began to account for this by estimating separate regressions for three very large cities in our sample (New York City, Los Angeles, and Chicago) and for the remaining 19 cities; these groupings, however, are still relatively coarse. The present paper should therefore be seen as a complement to place-based analyses that focus on the planning processes and outcomes of individual cities, where the actions that lead to disparities—and could also lead to their resolution—take place. While the locus of action is within individual cities rather than across them, this multi-city analysis still reveals systematic disparities in access to bike lanes that warrant further attention, both in future place-based research and in planning practice.

### 3.8 Conclusions and policy implications

The results of this study suggest that the development of the cycling network in large U.S. cities to date has been uneven, disproportionately serving areas with higher socioeconomic status, higher educational attainment, and lower proportions of Hispanic residents. As U.S. cities continue to invest in cycling infrastructure, it will become increasingly important to address these disparities and to consider whether bike lanes are serving diverse neighborhoods and populations. Planning and policy approaches that address disparities in access to bike lanes could be beneficial from the perspective of active transportation promotion and health equity; for instance, past work has found that planning strategies that support walking and cycling, such as pedestrian-oriented zoning ordinances, can moderate socioeconomic disparities in active commuting (Chriqui et al. 2017). Promising strategies to address disparities in access to bike lanes could include improved consideration of equity goals and objectives in the plan development process; recognition of the ways in which traditional, objective estimation of cycling demand can lead to distributional inequalities in infrastructure access; and meaningful engagement of traditionally disadvantaged and underserved communities in the planning and advocacy process. At the same time, planners and advocates should remain cognizant of the social context of cycling and open to the possibility that disadvantaged communities may not prioritize bike lanes as a public investment strategy. These approaches could bring distributional equity to the forefront of the planning process, ensuring that public investments in cycling infrastructure serve a diverse set of users and have the potential to support greater health equity in U.S. cities.

# CHAPTER 4. ASSOCIATIONS BETWEEN BIKE LANE INVESTMENT AND AREA-LEVEL SOCIODEMOGRAPHIC CHANGE: LONGITUDINAL EVIDENCE FROM THREE U.S. CITIES BETWEEN 1990 AND 2015

## 4.1 Abstract

Emerging research suggests that low-income and minority communities may have disproportionately low access to cycling infrastructure, leading some observers to argue that investing in bike lanes in disadvantaged communities could promote social equity. However, recent bike lane projects in several large U.S. cities have encountered resistance due to concerns among some community members that bike lanes are associated with (and potentially even cause) gentrification and displacement. Limited quantitative research to date has considered how bike lane investment may be associated with gentrification and other types of sociodemographic change. To address this research gap, we considered whether changes in the bike lane network were associated with area-level sociodemographic change between 1990 and 2015 in Chicago, IL; Minneapolis, MN; and Oakland, CA, using census block groups as the unit of analysis. Dependent variables included the density and connectivity of on-street, dedicated bike lanes. Primary independent variables included two categorical measures of sociodemographic change: (1) a gentrification indicator created from measures of income, educational attainment, new housing construction, and housing value, and (2) a more general indicator of change in composite socioeconomic status. We used linear multi-level mixed effects regression models to estimate associations between changes in each sociodemographic indicator and changes in each dependent bike lane variable, adjusting for covariates that may influence the location of bike lanes (i.e. population density, distance to employment centers, percent of residents between ages 18 and 34, percent of commuters who bike to work). While the results varied by city, we found evidence that higher increases in bike lane density between 1990 and 2015 tended to occur disproportionately in block groups that were either already

advantaged or increasing in advantage (e.g., gentrifying) over time. These findings add empirical support to claims that bike lane investment is positively associated with gentrification and suggest that efforts to expand access to bike lanes—particularly in disadvantaged and traditionally underserved subpopulations—should be pursued with an awareness of this association and its implications for social equity.

## 4.2 Introduction

> *The Great Urban Rebound.* After 40 years of being synonymous with decay, inner cities have come alive and are booming with new development and residents. Twenty years of falling crime rates have helped make urban life desirable again, especially for young adults. As successful city centers fill with people, city leaders find that building high-quality bicycle networks is an efficient and appealing way to move more people in the same amount of space.
> – *Protected Bike Lanes Mean Business*, People for Bikes and Alliance for Walking & Biking, 2014

During the past decade, bike lanes have featured prominently in conversations about urban transformation. Planners and cycling advocates have touted the potential for bike lanes to support local economic development, citing evidence that cyclists tend to spend more money at local businesses than drivers, that bike lanes are associated with higher property values, and that young professionals increasingly prefer to live in urban environments that offer viable alternatives to the automobile (Clifton et al. 2012, People for Bikes and Alliance for Walking & Biking 2014, Carpenter and Zaccaro 2017). Investing in bike lanes has thus been framed as a strategy to revitalize urban cores and to attract and retain a “creative class” of highly educated workers in U.S. cities (Florida 2012, Stehlin 2015, Hoffman and Lugo 2014). These arguments, combined with claims of wider economic benefits ranging from reduced healthcare expenditures and pollution costs to gains in worker productivity (People for Bikes and Alliance for Walking & Biking 2014), convey a clear message: that bike lanes offer a cost-effective way to promote the economic health and vitality of urban centers.

The economic case for bike lanes has been widely leveraged during the past decade as a way to encourage cities and regions to invest in cycling infrastructure (Carpenter and Zaccaro 2017). These arguments, however, have led to criticism on the grounds of social equity. Indeed, the economic justifications for bike lanes tend to focus on socioeconomically advantaged users and to emphasize processes of sociodemographic change and rising property values that are frequently associated with gentrification. These concerns have been raised in high-profile cases of pushback against recent cycling projects in cities such as Portland, Washington, DC, and Chicago (Benesh 2015, Herrington and Dann 2016, Greenfield 2012, Lubitow et al. 2016, Freed 2015), where opposition to bike lanes in traditionally underserved neighborhoods has centered on racial, socioeconomic, and cultural differences between newcomers and long-standing residents.

These criticisms are particularly problematic given that bike lanes are often framed as a strategy to *promote* social equity. Cycling advocates and an emerging empirical evidence base, including Chapter 3 of this dissertation, have suggested that low-income and minority populations have disproportionately low access to bike lanes (League of American Bicyclists 2014, Flanagan et al. 2016, Hirsch et al. 2017). Because these populations are also disproportionately at risk of physical inactivity and related adverse health outcomes (August and Sorkin 2010, Gordon-Larsen et al. 2003, Mokdad et al. 2003), some have argued that investing in bike lanes in disadvantaged neighborhoods could lead to more equitable health outcomes and, more broadly, to a more equitable distribution of the diverse benefits that cycling can provide (Martens et al. 2016, Rachele et al. 2015).

Thus, conversations about social equity in cycling are characterized by a key tension. On the one hand, investing in bike lanes in disadvantaged neighborhoods could address observed disparities in infrastructure access and thereby promote public health and social equity. On the other hand, these efforts may be opposed by the communities they are intended to serve due to concerns that bike lanes are associated with sociodemographic advantage, gentrification, and displacement—concerns that arise at least in part from the narratives commonly used to justify bike lane investments. The empirical evidence base that informs this tension is currently limited but growing; several authors have recently examined issues of gentrification in cycling through qualitative case studies (Stehlin 2015, Hoffman and Lugo 2014, Lubitow and Miller 2013, Lubitow et al. 2016, Hoffman 2016), while only two studies to date have quantitatively assessed associations between sociodemographic change and bike lane investments over time (Flanagan et al. 2016, Hirsch et al. 2017).

In the present study, we contribute to the emerging evidence base on cycling and gentrification by examining longitudinal associations between bike lane investment and area-level sociodemographic change from 1990 to 2015 in Chicago, IL; Minneapolis, MN; and Oakland, CA, three cities that are often at the forefront of bicycle planning and culture in the U.S. We hypothesize that greater investments in the bike lane network over a given decade, as characterized through increases in the density and connectivity of the bike lane network, will disproportionately occur in areas that either were more advantaged (e.g., higher socioeconomic status, lower presence of racial and ethnic minorities) at the start of the decade or became more advantaged over the course of the decade. We build upon previous work in this area by incorporating more recent data (through 2015 rather than 2010), considering a smaller unit of analysis (block groups rather than census tracts or administrative neighborhoods), and using a variety of alternative methods—including a gentrification indicator that has been well established in the literature (Freeman 2005)—to measure sociodemographic change. Additionally, although our primary focus is on changes that occur within the same decade, we also take steps to examine the temporality between sociodemographic change and changes in the bike lane network. Through this approach, we aim to achieve a more thorough understanding of the relationship between sociodemographic advantage and access to bike lanes, providing quantitative, longitudinal evidence that begins to disentangle the tension between addressing disparities in bike lane access and confronting concerns about gentrification.

## 4.3 Existing literature and conceptual framework

### *4.3.1 Key tensions in social equity and cycling*

Cycling can have diverse benefits for communities and individuals. Over the past two decades, a growing body of evidence has suggested that cycling is favorably associated with physical activity and related health outcomes (Pucher et al. 2010, Bassett et al. 2008, Wanner et al. 2012, Hamer and Chida 2008, Andersen et al. 2000, Matthews et al. 2007), with congestion levels and air quality (de Nazelle et al.

2011, Woodcock et al. 2009), and with local economic development outcomes (Clifton et al. 2012). Responding to this evidence and to the rising social status of cycling in recent years (Golub 2016), cities have increasingly invested in programs, policies, and infrastructure designed to encourage a modal shift to cycling from less sustainable modes of transportation (Pucher et al. 2010).

There is emerging evidence, however, that these investments have been disproportionately made in areas with greater sociodemographic advantage. Researchers have recently found that, compared to relatively advantaged communities, those with a high proportion of low-income and minority residents are less likely to implement plans, policies, and projects that support cycling (Aytur et al. 2008, Cradock et al. 2009) and are characterized by lower access to cycling infrastructure such as bike lanes and bike share stations (Flanagan et al. 2016, Hirsch et al. 2017, Smith et al. 2015, Ursaki and Aultman-Hall 2015). The upshot of these disparities is that the health, environmental, and economic benefits of cycling infrastructure may also be inequitably distributed across communities of varying sociodemographic composition, raising concerns for social equity.

At the same time, the status of bike lanes as an increasingly valued urban amenity may be capitalized into land values (Bartholomew and Ewing 2011, Li and Joh 2017), potentially leading to declines in housing affordability over time. This possibility, combined with institutional issues in bicycle planning and advocacy and the frequent framing of bike lane investment as an economic development strategy (Stehlin 2015, Hoffman and Lugo 2014), has led to perceptions that cycling is associated with sociodemographic advantage and processes of gentrification. These perceptions have contributed in turn to resistance against bike lane projects in some low-income and minority communities, where bike lanes have been viewed as symbols of gentrification (and potential displacement) and as public investments that are primarily intended for advantaged residents.

Confronting these issues requires a nuanced understanding of the relationship between bike lane investment and sociodemographic change. In the sections that follow, we seek to inform this understanding by reviewing the literature on gentrification and transportation investment, then considering the characteristics of bicycle planning and advocacy that uniquely tie cycling to this larger conversation. Although our analysis is framed around a broader conceptualization of sociodemographic advantage, we focus primarily on gentrification in this portion of the review given its prominence in recent conversations about cycling and social equity. We conclude this section by presenting the conceptual framework for our analysis, which describes potential pathways linking bike lane investment to sociodemographic change and outlines key institutional factors that could influence these connections.

### *4.3.2 Gentrification: Definitions and measures*

Gentrification has been the subject of recent theoretical and empirical work in a variety of disciplines, including economic development and labor markets (Lester and Hartley 2014), housing policy (Rayle 2015, Tighe and Ganning 2016), urban green space (Wolch et al. 2014, Dai 2011), and public transportation (Dong 2017, Barton and Gibbons 2017, Dawkins and Moeckel 2016, Revington 2015, Grube-Cavers and Patterson 2015). Initially used by Glass (1964) in the context of neighborhood-level socioeconomic change in London, the term "gentrification" was further conceptualized by Smith (1996) in terms of capital flows and cycles of investment and disinvestment associated with rent-seeking behavior in real estate and development markets. Building from these foundations, scholars have characterized gentrification in a variety of ways. Although no clear consensus has emerged regarding how to define the process or identify gentrifying neighborhoods (Barton 2016), Rayle (2015) notes that definitions of gentrification tend to share the following common elements: racial and socioeconomic transitions (and associated territorial conflicts), new investment in areas that have experienced disinvestment in the past, physical upgrades to the built environment, and residential displacement.

The sociodemographic and physical changes associated with gentrification have proven difficult to measure, particularly with traditional data sources that are available at the national level. Landis (2016) classifies gentrification measures into four broad categories based on the types of data they incorporate: (1) changes in the aggregate sociodemographic and economic composition of neighborhoods, (2) changes to the built environment (e.g., physical condition and occupancy of the building stock, quality of public infrastructure), (3) characteristics of new residents and businesses that arrive in a neighborhood, and (4) physical and capital investment flows across neighborhoods (e.g., building permits, real estate prices). The majority of gentrification measures to date have fallen within the first category, given its reliance on readily available Census data (Landis 2016, Dong 2017). The measures emerging from these categories have been diverse, although Dong (2017) notes that most measures identify gentrification as occurring when the following types of changes are observed: increases in white, young, educated, middle- to high-income, and professionally employed residents, increases in rents and home values, and shifts in housing tenure from rental to ownership.

#### *4.3.3 Connections between transportation and gentrification: Theory and evidence*

To understand how these types of trends may be associated with transportation infrastructure investments, scholars tend to reference the connections between transportation and land use, which in turn are based on neoclassical economic theory. These explanations emphasize the economic value of accessibility: locations that have greater access to the transportation network tend to have greater development potential and can support more intensive land uses, which could in turn lead to higher property values, lower affordability, and corresponding shifts in the sociodemographic composition of surrounding areas over time (Revington 2015, Bartholomew and Ewing 2011, Dawkins and Moeckel 2016, Grube-Cavers and Patterson 2015). While this theoretical relationship may account for associations between gentrification and transportation in general, its applicability to cycling as a specific form of transportation investment may be limited; indeed, given the long-standing role of cycling as a fringe travel mode (Golub 2016), bike lanes are unlikely to add to underlying levels of accessibility in a way that creates a significant price differential.

Other theoretical arguments, then, are likely to be more relevant to the case of cycling investment and gentrification. Bartholomew and Ewing (2011) note that the property value impacts of transportation investments such as transit-oriented development (TOD) may lie not only in the accessibility benefits they can provide, but also in the key design features—such as pedestrian orientation and mixed land uses—that often accompany this type of development. This perspective suggests that transportation infrastructure may serve as an amenity, creating price effects that are not fully captured in measures of accessibility. Given the rising status of cycling in many U.S. cities (Golub 2016), bike lanes may increasingly become an amenity for which individuals and households are willing to pay a price premium. This observation relates to issues of residential selection: to the extent that relatively advantaged individuals have (a) greater preferences for cycling and (b) greater capacity to relocate to bicycle-friendly neighborhoods, the sociodemographic transitions associated with gentrification may occur not only through property value impacts (and subsequent concerns about affordability and displacement), but also through the selection of relatively advantaged populations into neighborhoods with cycling infrastructure.

Others have looked beyond market-based conceptualizations of the relationship between transportation and gentrification, recognizing the role of power dynamics in struggles over urban space. For instance, Revington (2015) advocates for a Marxist approach that focuses more fully on the class struggles that are inherent in processes of gentrification. He notes that while neoclassical economic explanations rooted in accessibility remain prevalent, gentrification may be more adequately described in terms of attempts by advantaged political actors to accumulate capital; this perspective is similar to what Harvey (1976) described as efforts to leverage the "hidden mechanisms" of wealth redistribution through the planning process (p. 73). Investments in bike lanes should also be viewed with reference to social norms, as cycling is often perceived as an elite activity (Golub 2016). Within this context, efforts by relatively advantaged sociodemographic groups—including planners and cycling advocates—to build bike lanes in traditionally disadvantaged neighborhoods may be viewed by residents of these neighborhoods as an imposition of social norms and cultural values that they do not share. Cycling advocates may not fully recognize this potential for cultural imposition, as they often view themselves as the subjects of past distributional inequalities by mode (i.e. automobile-oriented planning) and may not be aware of the political power from which they benefit as cycling has become increasingly mainstream (Henderson 2013, Furness 2010).

These theoretical distinctions aside, empirical research on the potential association between transportation investments and gentrification has focused primarily on transit and TOD, using methods such as hedonic pricing models to assess how property values are associated with access to transit stations and related design features (Revington 2015, Bartholomew and Ewing 2011). The evidence base in this area has been mixed; while some studies have found transit station access to be associated with higher residential property values (Bowes and Ihlanfeldt 2001, Cervero and Duncan 2002, Duncan 2008, Duncan 2011, Hess and Almeida 2007, McMillen and McDonald 2004) and with indicators of gentrification (Grube-Cavers and Patterson 2015) in a number of large North American cities, others have recently found limited evidence of such associations (Dong 2017, Barton and Gibbons 2017). This work offers an interesting parallel to the case of cycling, as investments in public transportation are also frequently viewed as a way to support socioeconomically disadvantaged communities but could paradoxically lead to declines in affordability through the mechanism of increased property values (Dawkins and Moeckel 2016). As previously noted, however, the relevance of these studies may be limited by the long-standing status of cycling as a fringe travel mode, leading to smaller potential gains in accessibility compared to transit investments.

Fewer studies have examined associations between property values and cycling infrastructure. Using data from the Twin-Cities region, Krizek (2006) found that while closer proximity to off-road paths was associated with higher housing values, the reverse was true for side paths along roads and no significant associations were observed for on-street bike lanes; moreover, in the suburban context, all three types of cycling infrastructure were inversely associated with housing values. Welch et al. (2016) also recorded mixed results, finding that property values were higher in proximity to multi-use bike paths but lower in proximity to on-street bike lanes. More recently, Pelechrinis et al. (2017) used a quasi-experimental research design to examine the potential housing price impacts of Pittsburgh's bicycle sharing program, finding that the implementation of program stations was associated with increases in both sale prices and rents measured at the ZIP code level. These impacts may differ for bike lanes, however, given that bicycle sharing programs represent a different type of investment and a different scale of intervention than individual bike lanes.

Others have considered associations between cycling and gentrification using measures of sociodemographic change rather than property values. Flanagan et al. (2016) examined census tracts in Chicago, IL, and Portland, OR between 1990 and 2010, creating an index of cycling infrastructure investment (e.g., bike lanes, bike share stations) and relating this index to area-level sociodemographic attributes typically used to characterize gentrification (e.g., race, homeownership, educational attainment, income, employment, population age structure, home values). Although the results varied by city and were at times unexpected, the authors found evidence that cycling infrastructure investment was higher in areas that experienced increases in educational attainment, median household income, median home value, and the proportion of white residents. Hirsch et al. (2017) examined neighborhood-level changes in transportation infrastructure and sociodemographic composition in Birmingham, AL, Chicago, IL, Minneapolis, MN, and Oakland, CA between 1985 and 2010, finding that additions to the bike lane network tended to be higher in areas that experienced declines in unemployment and increases in median household income. While some findings were unexpected (e.g., the rate of bike lane expansion was lower in neighborhoods that experienced an increase in housing occupancy), the results provide some empirical support for an association between bike lane investment and sociodemographic advantage. Thus, while the quantitative evidence base is currently limited, early studies point to a potential relationship between cycling infrastructure and gentrification that warrants further empirical investigation.

#### *4.3.4 Cycling and gentrification: Social and institutional issues*

While quantitative evidence about the potential relationship between cycling and gentrification is only beginning to emerge, this relationship has been the focus of a rich body of qualitative research during the past several years. Drawing upon diverse case studies in San Francisco, CA, Portland, OR, Los Angeles, CA, Minneapolis, MN, and Chicago, IL, this work has emphasized the role of institutional factors—including social norms surrounding cycling, the framing of bike lane projects, and issues with the planning process—in creating both literal and symbolic concerns about gentrification within the context of bicycle planning and advocacy (Lubitow et al. 2016, Herrington and Dann 2016).

First, conversations about bike lane investment and gentrification are influenced by social norms toward cycling, which may vary considerably across different subpopulations. Golub (2016) notes that while cycling is often framed as a positive choice that conveys a sense of freedom, it may also be seen as a "second class" travel mode or an oppressive activity borne out of economic necessity (p. 25). Hoffman (2016) similarly argues that cycling tends to hold different social meanings for different sociodemographic groups; indeed, cycling is often perceived as an activity for either the elite or the very poor (People for Bikes and Alliance for Biking & Walking 2015, Hoffman and Lugo 2014, Golub 2016, Lubitow and Miller 2013, Flanagan et al. 2016). These varying perspectives may create tensions between bicycle planners and advocates—who tend to be white and middle- to upper-class in socioeconomic position (Golub 2016)—and residents of traditionally disadvantaged neighborhoods, contributing in turn to concerns that bike lane projects are intended for incoming gentrifiers rather than existing residents.

Second, as previously noted, bike lane projects are often framed and justified based on their economic development potential. Indeed, bike lanes are frequently viewed as a mechanism to attract and retain an elite "creative class" of talented workers and firms, a perspective that both reflects and gains a sense of urgency from the idea that cities are in competition with one another for scarce economic resources (Lubitow et al. 2016, Stehlin 2015, Hoffman and Lugo 2014). These arguments, while often appealing to broad and ostensibly inclusive notions of livability (Stehlin 2015), may subtly suggest that bike lanes are intended to serve advantaged users and to spur economic benefits that could ultimately increase property values and decrease housing affordability over time. Thus, the narratives used to frame bike lane projects can have notable implications for how community members perceive the goals and intended beneficiaries of these investments.

Similarly, bike lane projects fall within the realm of planning interventions that are often framed as *apolitical* or *post-political*, representing broad goals—such as livability and sustainability—that appear to transcend political discussion (Lubitow et al. 2016, Lubitow and Miller 2014, Herrington and Dann 2016). This framing discourages opposition by appealing to universal public goods, striking "an air of neutrality…that obscures the very real power differentials" that characterize the allocation of public resources (Lubitow et al. 2016, p. 2639). Through a qualitative case study of contested bike lane plans in a gentrifying neighborhood of Portland, OR, Lubitow and Miller (2014) describe how this type of framing can mask underlying histories of socio-spatial injustice and contribute to a perceived association between environmentally sustainable infrastructure investment and larger forces of gentrification.

Finally, qualitative studies of cycling and gentrification have also examined procedural issues within bicycle planning and advocacy. Lubitow et al. (2016) describe a case of opposition to proposed bike lanes in a traditionally underserved but gentrifying neighborhood in Chicago, IL, noting that community concerns stemmed in part from inadequate attempts to engage diverse community members, from the pursuit of rapid implementation in a resource-constrained environment, and, more broadly, from a top-down planning process that was viewed as imposed upon rather than led by community members. Herrington and Dann (2016) describe a bike lane project facing similar forms of opposition in Portland, OR, where black residents in a gentrifying neighborhood expressed frustration that they had not been adequately engaged in the planning process. Concerns about community engagement may stem from more fundamental issues in bicycle planning and advocacy, including the predominantly white and middle- to upper-class composition of the planning profession and advocacy organizations and the obstacles that marginalized communities face in participating in public input opportunities (Golub 2016). Within this context, the perspectives of relatively disadvantaged community members may not be meaningfully incorporated into the planning process and concerns about the potential associations between bike lane investment and gentrification may therefore be amplified.

#### *4.3.5 Conceptual framework: Sociodemographic advantage and bike lane investment*

The results of the quantitative and qualitative bodies of work on cycling and gentrification informed the conceptual framework for our analysis (**Figure 4-1**). This framework illustrates potential pathways linking sociodemographic advantage to bike lane investment and builds upon the cross-sectional diagram presented in Chapter 3 (Figure 3-1), adding a longitudinal dimension to the relationship between sociodemographic characteristics and cycling infrastructure. Our primary objective is to determine whether a longitudinal association exists between sociodemographic advantage and bike lane investment (i.e. increases in the bike lane network), regardless of the temporal ordering of this association—that is, whether bike lane investment precedes sociodemographic change, sociodemographic change precedes bike lane investment, or these changes occur simultaneously—and regardless of whether this relationship is causal. This association is represented in Figure 4-1 by the bold, dashed line. We hypothesize that greater bike lane investment (i.e. higher increases in the bike lane network) will tend to occur in block groups that are either already advantaged (e.g., higher socioeconomic status, lower presence of racial and ethnic minorities) or becoming more advantaged over time (e.g., through processes of gentrification or more general shifts in sociodemographic composition).

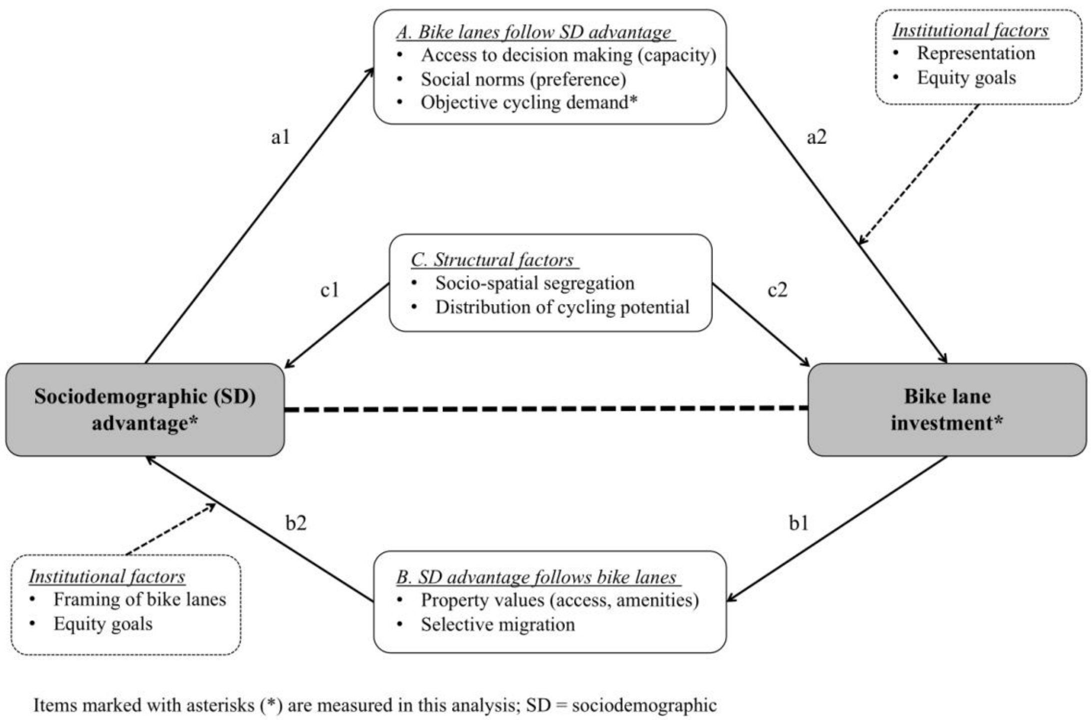



**Figure 4-1.** Conceptual framework

If such an association is found, it could result from one or more of three basic relationships. First, the association could reflect a process in which bike lane investment follows, and potentially responds to, changes in sociodemographic advantage (relationship "A"). Neighborhoods that are relatively advantaged or becoming more advantaged over time (e.g., through an influx of wealthier households) may consist of residents who are more likely to advocate for bike lanes, for reasons of both capacity and preference (arrow “a1”). Socioeconomically advantaged groups tend to have greater access to decision making processes, such as formal public involvement opportunities (Golub 2016), and may have better overall capacity to organize in support of infrastructure investment. Furthermore, advantaged groups may have a stronger preference for bike lane investments in their neighborhoods, given that prevailing social norms tend to cast cycling as a predominantly white, middle- to upper-class travel mode (People for Bikes and Alliance for Biking & Walking 2015, Hoffman and Lugo 2014, Golub 2016, Lubitow and Miller 2013, Flanagan et al. 2016). Thus, advantaged or gentrifying neighborhoods may have both the capacity and the desire to influence the planning process in support of bike lane investment (arrow “a2”). This process, in turn, is influenced and potentially facilitated by key institutional factors, including the disproportionate representation of white, middle- to upper-class decision makers in bicycle planning and advocacy (Golub 2016) and the frequent absence of social equity goals from transportation plans (Manaugh et al. 2015, Karner and Niemeier 2013, Martens et al. 2012, Golub and Martens 2014, Evenson et al. 2012, Lee et al. 2017). Additionally, sociodemographic shifts may be correlated with other factors that are typically used to conceptualize and estimate cycling demand—including urban form (e.g., population and employment density), the age structure of the population (e.g., influx of younger residents), and the presence of bicycle commuters—which in turn inform the process of determining where bike lanes will be located.

Second, an association between sociodemographic advantage and bike lane investment could reflect the opposite direction of effect: a relationship in which the sociodemographic composition of neighborhoods changes after, and potentially in response to, investments in the bike lane network (relationship “B”). As previously noted, bike lanes may influence property values through their status as a desired urban amenity (Bartholomew and Ewing 2011, Li and Joh 2017); furthermore, individuals who prefer to travel by bicycle may select residential locations in close proximity to bike lanes in order to act upon this preference (arrow “b1”). If any associated increases in property values are sufficient to decrease housing affordability, and if individuals who selectively migrate to neighborhoods with bike lanes are relatively advantaged, the sociodemographic composition of neighborhoods that receive bike lane interventions may shift toward greater levels of advantage over time (arrow “b2”). This relationship is also influenced by institutional factors in bicycle planning and advocacy, including the aforementioned dearth of social equity goals in transportation plans and the frequent framing of bike lane investment as an economic development strategy (Stehlin 2015, Hoffman 2013).

Third, an association between sociodemographic advantage and bike lane investment may not reflect a causal or otherwise sequential relationship, but rather the influence of structural factors that determine both where various sociodemographic groups are located in space and where bike lane investments tend to occur. For instance, Stehlin (2015) uses the San Francisco Bay Area as a case study to describe how distinct patterns of socio-spatial segregation have resulted from the suburbanization of poverty—fueled in part by federal transportation investments and housing policy—as well as from more recent structural trends embodied in the “return to the city” movement. These forces have influenced the distribution of various sociodemographic groups in U.S. cities (arrow “c1”), leading to a spatial pattern in which disadvantaged populations increasingly live in outlying areas that are not conducive to cycling investments. Indeed, the feasibility of cycling, and thus of bike lane investments, tends to be concentrated in dense, central areas (arrow “c2”). Thus, various structural forces may lead to a situation in which bike lane investments are more likely to be made in places where relatively advantaged populations are more likely to live.

Our primary objective in this analysis is not to determine which of these relationships offers the most accurate representation of reality, but rather to determine whether an association between sociodemographic advantage and bike lane investment (i.e. increases in the bike lane network) is evident in our data after adjusting for other objective determinants of cycling demand, regardless of how such an association may arise (association represented by the bold, dashed line in Figure 4-1). This approach is particularly appropriate given the emerging nature of the quantitative research base on cycling and gentrification, in which evidence of associations (regardless of the direction of causality) is currently limited. However, we take steps to examine the temporality between sociodemographic change and bike lane investment in an attempt to inform the interpretation of our results with respect to this conceptual framework.

## 4.4 Data and Variables

### *4.4.1 Study sample*

We measured longitudinal associations between bike lane investment (i.e. increases in the bike lane network) and area-level sociodemographic change over a 25-year period in Chicago, IL; Minneapolis, MN; and Oakland, CA. Data were collected for four time points within this period: 1990, 2000, 2010, and 2015. We used 2010 census block groups as the primary unit of analysis, selecting all block groups whose centroids fell within the municipal boundaries of these three cities (combined n=2,893). Among these, 2,743 block groups had complete information on all variables of interest for all four time points; we retained these block groups for our analyses, resulting in a final study sample of n=2,062 block groups in Chicago, n=366 block groups in Minneapolis, and n=315 block groups in Oakland.

### *4.4.2 Data sources*

We used several data sources to create a time-varying Geographic Information System (GIS) database of bike lane features in the three cities at each time point. Bike lane data for 1990, 2000, and 2010 were collected as part of a larger research effort that documented changes in recreational facilities and transportation infrastructure over time in these three and other cities. Research assistants visited these four cities in 2012 to collect current and historic GIS data and maps (e.g., bike lane shapefiles, bike route maps), Transportation Improvement Plans (TIPs), and Capital Improvement Plans (CIPs), and to consult with local planners and stakeholders in each city. These sources were used to create a GIS database showing the location, extent, and attributes of facilities and infrastructure each year between 1985 and 2010. Additions to the bike lane network across years were documented if they were at least 300 feet in length or significantly contributed to network connectivity.

We narrowed this GIS database in two ways. First, given our specific focus on on-street, dedicated bike lanes, we used the attributes of the GIS files (e.g., fields indicating infrastructure type), combined with current and historic Google Earth imagery as needed, to identify traditional, buffered, and protected bike lanes and to remove all other infrastructure types (e.g., off-street trails, shared lanes, signed and/or recommended routes without dedicated facilities) from the database. Second, although data were available for every year between 1985 and 2010, we extracted a snapshot of the data at each time point relevant to our analysis (i.e. 1990, 2000, 2010) in order to remain consistent with the timing of census data.

To account for more recent changes in the bike lane network, we combined these data with GIS shapefiles collected in 2016 from open data repositories, municipal planning websites, and bicycle coordinators in each city. (For consistency with the timing of census data, we hereafter refer to these bike lane data as 2015 data.) We thoroughly reviewed these shapefiles to determine how various infrastructure types were coded in each city, using Google Earth imagery as needed for confirmation; we used this information to consistently classify infrastructure types across the three cities and to extract on-street, dedicated bike lanes (i.e. traditional, buffered, protected) for our analysis. To address potential differences from the database used for earlier bike lane data (i.e. 1990, 2000, 2010), we overlaid the 2015 and 2010 shapefiles and identified areas that did not overlap. We used the attributes of the GIS files (e.g., fields indicating year of bike lane construction), combined with current and historic Google Earth imagery, to verify whether (a) lanes appearing in the 2015 but not in the 2010 shapefile reflected true additions to the bike lane network and (b) lanes appearing in the 2010 but not in the 2015 shapefile reflected true removals from the bike lane network. We edited the shapefiles as needed to reconcile any differences that did not reflect true additions or removals. In documenting additions, we used the same criteria as in the longitudinal database to determine significant changes (i.e. segments that were at least 300 feet in length or contributed significantly to network connectivity).

We collected data from the 1990 Census, 2000 Census, 2007–2011 American Community Survey (ACS) (for 2010), and 2011–2015 ACS (for 2015) to describe block group-level sociodemographic characteristics. We also used these data sources, as well as the 1990, 2000, and 2010 Census Transportation Planning Package (CTPP), to measure covariates related to urban form, population age structure, and bike commuting. To reconcile changes in census block group geographies over time, we normalized all data to 2010 block group boundaries; this process involved assigning data from 1990 and 2000 block groups to 2010 block groups based on the proportion of their overlapping land area (2015 data were already reported in terms of 2010 block group boundaries).

### *4.4.3 Dependent variables: Density and reach of bike lanes*

We created two dependent variables to describe key characteristics of the bike lane network at each time point. In calculating these variables, we drew 10-meter buffers around all block groups to allow bike lanes along boundaries to be attributed to all block groups they touched. First, we created a measure of bike lane *density*, or meters of lanes per square mile of land area. Second, we calculated a measure of bike lane *reach* (in meters) indicating the total distance that could be traveled from each block group without deviating from bike lanes. This measure, which serves as a proxy for network connectivity, was calculated by adding the total length (i.e. not truncated by block group boundaries) of bike lane segments that passed through any portion of the block group, as well as the total length of all bike lane segments to which they connected without breaks in infrastructure presence.

It is important to recognize that these infrastructure variables are not measures of investment per se, since we do not have data describing dollar expenditures on bike lanes over this time period. However, since there were virtually no removals of bike lanes across decades in these three cities, and since increases in the bike lane network involve a commitment of public funds, we consider changes (i.e. increases) in the density and reach of the bike lane network to represent investments in cycling infrastructure.

### *4.4.4 Primary independent variables: Sociodemographic characteristics*

The primary independent variables in this analysis were two categorical indicators describing sociodemographic change between each set of consecutive time points (i.e. 1990 to 2000, 2000 to 2010, and 2010 to 2015, hereafter referred to as “decades”). As described in the sections that follow, these two indicators accounted both for the sociodemographic composition of block groups at the start of a decade and for changes in sociodemographic characteristics over the course of the decade. We used these indicators as alternative ways to characterize shifts in socioeconomic advantage over time.

#### 4.4.4.1 Gentrification indicator

The first categorical variable was a gentrification indicator based on the methodology of Freeman (2005). To remain consistent with the geographical scale of this methodology, we measured gentrification at the census tract level and attributed to block groups the value of the tract within which they were located. The Freeman (2005) approach involves two major steps. First, tracts are classified as either eligible or ineligible to gentrify based on geographic location and sociodemographic characteristics at the beginning of a decade. This step recognizes that gentrification is an inherently urban phenomenon that occurs from an initial position of relative socioeconomic disadvantage. Specifically, a tract is deemed eligible to gentrify in a given decade if it meets all of the following three criteria:

- Geographic location: tract is located within the central city of its respective metropolitan statistical area (MSA) (all tracts in our study sample meet this criterion).
- Presence of low-income residents: median household income of the tract is lower than that of its respective MSA at the beginning of the decade.
- Recent disinvestment: proportion of housing stock built in the tract during the 20 years immediately preceding the decade is lower than that of its respective MSA.

Second, eligible tracts are further classified as either gentrifying or not gentrifying based on changes in sociodemographic characteristics over the decade. This step emphasizes the role of educational attainment and home values as markers of increasing socioeconomic advantage and gentrification. Specifically, tracts are classified as gentrifying if they meet both of the following additional criteria:

- Increase in educational attainment: percentage increase in educational attainment in the tract (i.e. proportion of adults with at least a bachelor's degree) over the decade is greater than the median percentage increase for its respective MSA.
- Increase in housing value: median housing value in the tract increases in real terms (i.e. adjusted for inflation) over the decade.

As shown in **Figure 4-2**, this approach allowed us to classify tracts, and subsequently block groups, into three categories: already advantaged (i.e. not eligible to gentrify), disadvantaged but not gentrifying (i.e. not experiencing increases in advantage over time), or gentrifying (i.e. disadvantaged at the beginning of the decade but experiencing increases in advantage over time).

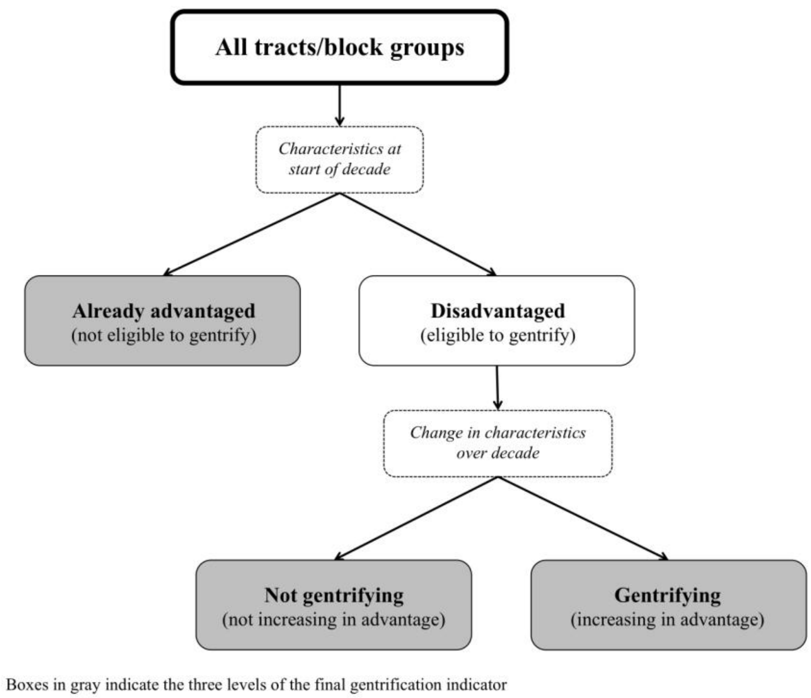



**Figure 4-2.** Construction of three-level gentrification indicator

Although the Freeman (2005) methodology is relatively well established in the literature, gentrification is a challenging construct to measure, particularly with nationally available census data (Landis 2016). Recognizing this challenge, we also calculated two alternative gentrification indicators following the methodologies proposed by Bostic and Martin (2003) and Landis (2016). The three indicators led to different spatial representations of gentrification, even within the same city and decade. To address these differences, we consulted with experts familiar with the dynamics of gentrification in the three cities; the results of these consultations—combined with the prominence of educational attainment, a key force in the process of gentrification, in the Freeman (2005) indicator (Lester and Hartley 2014)—led us to retain the Freeman (2005) variable as the primary gentrification indicator for our analysis. Additionally, to account for the inherent challenges of measuring gentrification, we calculated an alternative indicator describing more general shifts in socioeconomic status over time, as described in the section that follows.

#### 4.4.4.2 Socioeconomic status indicator

The second categorical variable was a socioeconomic status (SES) indicator that accounted for how block groups changed in SES over a given decade relative to their initial SES. This indicator was based on a continuous SES index that we calculated using an adaptation of the methodology of Christine et al. (2015). To calculate this index, we performed principal factor analysis (PFA) on 17 sociodemographic variables related to race and ethnicity, educational attainment, income and wealth, poverty, occupation, employment, and housing. Because the output of this approach is a relative and sample-specific measure, we performed PFA separately by city and by year, thus producing a city-specific SES index for each of the four time points. We reviewed the PFA results to ensure that the direction and general magnitude of factor loadings suggested a similar characterization of SES within each city over time. We used the first factor in each PFA to create the composite SES index, multiplying standardized values of each variable by their respective factor loadings and coding all inputs to ensure that higher values of the index represented higher SES.

To create the categorical SES indicator for a given decade, we first classified block groups into three categories based on how their continuous SES index value changed over the course of the decade: decrease (< 25$^{th}$ percentile of change in SES), limited change (between 25$^{th}$ and 75$^{th}$ percentile of change), or increase (> 75$^{th}$ percentile of change). For the subset of the sample that experienced a decrease or increase in SES, we further classified block groups by their initial SES level at the beginning of the decade: low (< 50th percentile of initial SES) or high (> 50th percentile of initial SES). As shown in **Figure 4-3**, this process resulted in a five-level categorical indicator that accounted for both baseline characteristics and change in SES over time.

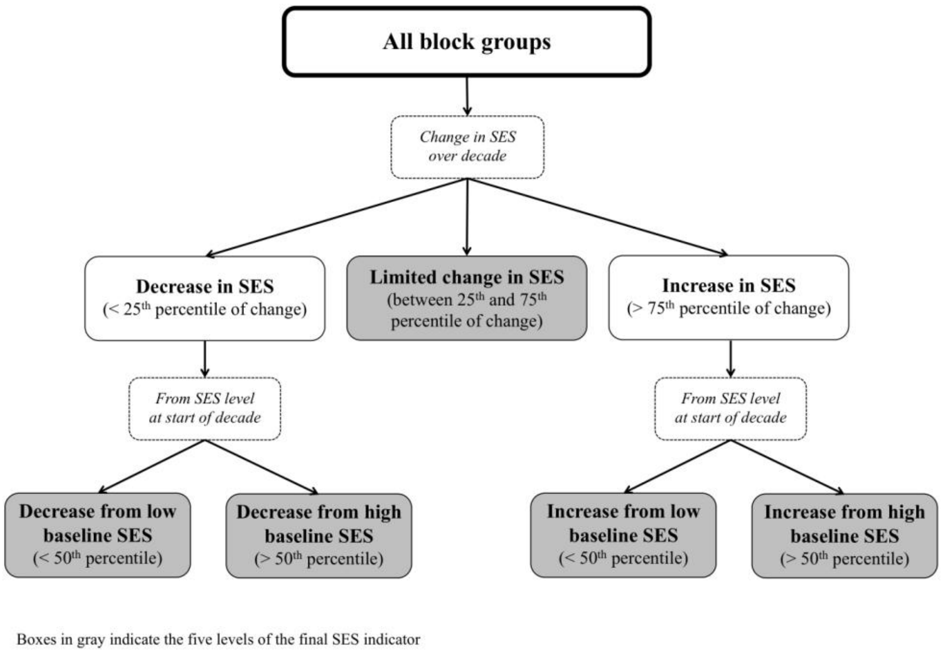



**Figure 4-3.** Construction of five-level socioeconomic status (SES) indicator

4.4.4.3 Other sociodemographic characteristics

In addition to the two categorical indicators, we also measured the following continuous variables at each time point: race (percentage non-Hispanic black), ethnicity (percentage Hispanic or Latino), educational attainment (percentage with at least a bachelor's degree), median household income, poverty (percentage below the federal poverty line), and the raw SES index described in the previous section. These variables were used in descriptive and sensitivity analyses.

*4.4.5 Covariates: Urban form, age structure, and bike commuting patterns*

To account for other factors that could influence the placement of bike lanes over time, we measured several covariates related to urban form, population age structure, and bike commuting to work at each of the four time points in our analysis. First, we accounted for urban form using measures of population density (in thousands of persons per square mile of land area) and distance to the nearest employment center (in hundreds of meters). The latter measure, which builds upon the methodology of Cho et al. (2008), uses CTPP data to delineate employment centers throughout a metropolitan area based on both the total number of workers and the density of workers per square mile of land area. We incorporated this measure into our analysis by calculating the straight-line distance between each block group centroid and the boundary of the nearest employment center; due to data limitations, this variable was not available for 2015 and was thus treated as constant during the final decade in our analysis (i.e. from 2010 to 2015). Next, to characterize the age structure of the population, we measured the percentage of residents between the ages of 18 and 34, reflecting age groups that tend to cycle at relatively high rates (Winters et al. 2010, Dill and Voros 2007, Heinen et al. 2013). Finally, we measured bike commuting levels as the percentage of workers who commuted by bicycle at each time point.

## 4.5 Methods

### *4.5.1 Descriptive analyses*

For each city, descriptive statistics were used to assess the characteristics of block groups at baseline (i.e. 1990) and changes in these characteristics over each decade (i.e. 1990–2000, 2000–2010, 2010–2015). Additionally, changes in bike lane density and reach were examined by levels of the categorical gentrification and SES indicators, offering a preliminary understanding of unadjusted associations between sociodemographic change and changes in the bike lane network over time.

### *4.5.2 Regression analyses*

In adjusted regression analyses, we estimated longitudinal associations between changes in each dependent bike lane variable (density, reach) and changes in sociodemographic characteristics (gentrification indicator, SES indicator), adjusting for covariates. Decades served as the unit of time in these regression models, resulting in three observations for each block group (1990–2000, 2000–2010, 2010–2015). We used linear multilevel mixed-effects regression models to account for the hierarchical structure of the data, which contained three levels of clustering: decades were clustered within block groups, which in turn were clustered within census tracts.

All regressions in the main analysis were fully stratified by city, given the potential for varying contextual dynamics and associations across locations and the likelihood that block groups from Chicago, which constituted 75 percent of the combined three-city sample, would strongly influence the pooled regression results. For each city, we estimated four separate regression models that varied by dependent variable (density, reach) and the sociodemographic indicator used as the primary independent variable (gentrification indicator, SES indicator).

The general specification for these regression models is presented in **Equation 4-1**. We modeled changes in each bike lane variable over a given decade (i.e. from time *t–1* to time *t*) as a function of independent variables measured at the beginning of the decade (i.e. time *t–1*) and changes in these variables over the course of the decade. This strategy allowed us to test our hypothesis that increases in the bike lane network disproportionately occur in areas that are either already advantaged or experiencing increases in advantage over time. While considering both baseline and change variables is a useful approach given the aims of this analysis, it is also important to consider the interaction between these variables. Indeed, increases in SES may entail different dynamics and implications for bike lane investment when occurring in places that begin from a position of low versus high SES; for instance, increases in socioeconomic advantage are typically only viewed as indicative of gentrification when they take place in areas that had previously been disadvantaged. As previously described in **Section 4.4.4**, the gentrification and SES indicators used in this analysis account, by definition, for the interaction between baseline and change in sociodemographic characteristics, incorporating both constructs into a single variable. To address these potential interactions for the continuous covariates in our analysis, we included in our model specification an interaction term between the baseline and change variables for each covariate.

**Equation 4-1:**

$$\Delta Y_{ki(t-1,t)} = \beta_0 + \beta_1 X_{ki(t-1,t)} + \beta_2 C_{ki(t-1)} + \beta_3 \Delta C_{ki(t-1,t)} + \beta_4 (C_{ki(t-1)} * \Delta C_{ki(t-1,t)}) + \eta_k + \alpha_{ki} + \varepsilon_{kit}$$

where:

- $\Delta Y_{ki(t-1,t)}$ = change in bike lanes over decade (i.e. from *t–1* to *t* )
- $X_{ki(t-1,t)}$ = indicator that accounts for both sociodemographic characteristics at beginning of decade (i.e. *t–1*) and change in sociodemographic characteristics over decade (i.e. from *t–1* to *t* ) (gentrification indicator, SES indicator)
- $C_{ki(t-1)}$ = level of covariates at beginning of decade (i.e. *t–1*)
- $\Delta C_{ki(t-1,t)}$ = change in covariates over decade (i.e. from *t–1* to *t* )
- $\eta_k$ = random effect for tract
- $\alpha_{ki}$ = random effect for block group *i*
- $\varepsilon_{kit}$ = measurement error associated with dependent variable

### *4.5.3 Additional analyses*

We conducted two sensitivity analyses to assess the robustness of our findings to changes in the study sample and model specification. First, as a complement to the city-stratified models in the main analysis, we re-estimated our regression models for the pooled, three-city sample (n=2,743). While, as previously noted, the pooled results could be largely influenced by block groups from Chicago (n=2,062), this analysis allowed us to assess this possibility and to consider whether different associations may be observed for a more generalizable sample. Second, we estimated two sets of regression models that substituted continuous sociodemographic characteristics (race, ethnicity, educational attainment, income, and poverty in one alternative model; the continuous SES index in a second alternative model) in place of the categorical sociodemographic indicators used in the main analysis. These models allowed us to assess the sensitivity of our main findings to the constructs used to measure sociodemographic change and to consider the role of separate SES variables as an alternative to the composite indicators.

Additionally, we conducted two analyses designed to examine the potential temporality between bike lane investment and sociodemographic change. We conducted these analyses to further examine any regression models (by city and dependent variable) that showed an expected association between bike lane investment and gentrification in the main analysis (i.e. higher increases in the bike lane network in gentrifying block groups); we did not conduct these analyses for cities (Minneapolis) or dependent variables (reach) for which expected associations between bike lane investment and gentrification were *not* observed, given our focus on addressing concerns that higher bike lane investment is positively associated with—and could precede or even cause—gentrification. In the first of these additional analyses, we estimated a series of simple regression models that incorporated lags in order to test three temporal relationships between increases in the bike lane network and the gentrification indicator: (a) bike lane increases during a given decade modeled as a function of gentrification during the previous decade (i.e. gentrification precedes bike lane investment), (b) gentrification during a given decade modeled as a function of bike lane increases during the previous decade (i.e. bike lane investment precedes gentrification), and (c) bike lane increases during a given decade modeled as a function of gentrification during the same decade (i.e. bike lane investment and gentrification are concurrent). In the second additional analysis, we estimated Granger causality tests to examine the temporality between changes in the bike lane network and changes in the continuous version of the composite SES index. This method involves regressing one variable (Y) on its own lagged values and on lagged values of another variable (X), and testing the null hypothesis that the coefficients of the lagged values of X are jointly equal to zero. If the null hypothesis is rejected, the variable X is said to "Granger-cause" the variable Y because it provides useful predictive information above and beyond past values of Y. We alternated the designation of X and Y variables, allowing us to test whether past values of the SES index influenced future values of bike lane density (i.e. whether SES "Granger-caused" bike lane investment) and vice versa (i.e. whether bike lane investment "Granger-caused" SES).

## 4.6 Results

### *4.6.1 Descriptive analyses*

The extent of the bike lane network in 1990 was relatively limited in all three cities. No block groups in Oakland contained bike lanes meeting our inclusion criteria in 1990; only three percent of block groups in Chicago and two percent of block groups in Minneapolis contained bike lanes in 1990, leading to an average density of 154 and 46 meters per square mile across all block groups in these two cities, respectively (**Table 4-1**). Both the density and the reach of the bike lane network increased over each decade in all three cities, generally at an increasing rate over time. Additions to the bike lane network were consistently highest during the five-year period between 2010 and 2015, when approximately 30 percent of block groups in Chicago, 60 percent of block groups in Minneapolis, and 50 percent of block groups in Oakland received new lanes. Increases in bike lanes over time were particularly dramatic for the reach (i.e. connectivity) variable, as additions to the bike lane network in a given location also increased connectivity for the entire network and for all block groups to which these lanes connected downstream. The exponential growth in this variable therefore reflects both the expansion of bike lanes into new areas and the progressive filling in of gaps in the existing bike lane network over time.

Among sociodemographic characteristics, the proportions of black and Hispanic residents in the three cities tended either to decrease over time or to increase in progressively smaller increments each decade. Educational attainment increased in all three cities across all three decades. Changes in median household income and poverty generally mirrored national trends, suggesting consistent increases in average socioeconomic status (SES) (i.e. increases in income, decreases in poverty) during the 1990s, followed by decreases in SES during the 2000s and some rebounding after 2010.

Among covariates, changes in population density over time were fairly limited in all three cities, while trends in distance to the nearest employment center were less consistent and suggested different dynamics in each city. The percentage of residents between ages 18 and 34 decreased in all three cities during the 1990s, with relatively minor changes (both positive and negative) in subsequent decades. Finally, the percentage of bike commuters was consistently highest in Minneapolis and lowest in Chicago, and increased in all cities across all three decades.

**Table 4-1.** Descriptive statistics for selected characteristics at baseline (1990) and change over each decade, 1990–2015

| | **Baseline (1990)** | | **Change 1990–2000** | | **Change 2000–2010** | | **Change 2010–2015** | |
|---|---|---|---|---|---|---|---|---|
| | *Mean or #* | *(SD or %)* | *Mean or #* | *(SD or %)* | *Mean or #* | *(SD or %)* | *Mean or #* | *(SD or %)* |
| **Chicago (n=2,062 block groups)** | | | | | | | | |
| *Bike lanes* | | | | | | | | |
| BGs with any (new) lanes (#, %) [a] | 64 | (3%) | 179 | (9%) | 459 | (22%) | 638 | (31%) |
| Average density of bike lanes (m/mi$^2$) | 154.21 | (1139.99) | 536.34 | (2271.56) | 1179.63 | (3168.85) | 1227.39 | (3313.75) |
| Average reach of bike lanes (m) | 143.72 | (965.48) | 744.54 | (2691.81) | 5456.99 | (12,604.73) | 26,719.42 | (54,413.78) |
| *Selected sociodemographic characteristics* | | | | | | | | |
| Race (% black) | 35.13 | (42.68) | 1.31 | (8.20) | –1.11 | (6.29) | –0.80 | (5.91) |
| Ethnicity (% Hispanic) | 18.31 | (24.43) | 5.37 | (13.69) | 2.77 | (9.90) | 0.26 | (7.80) |
| Education (% with bachelor's or more) | 18.74 | (18.48) | 5.45 | (9.74) | 6.45 | (11.35) | 1.88 | (9.67) |
| Med. HHD income (1000s of 2015$) | 51.53 | (21.13) | 6.71 | (16.02) | –4.59 | (19.77) | –1.33 | (16.44) |
| Poverty (% < federal poverty line) | 19.09 | (16.27) | –0.72 | (10.22) | 2.75 | (12.87) | 1.04 | (12.80) |
| *Covariates* | | | | | | | | |
| Population density (1,000 persons/mi$^2$) | 20.55 | (14.07) | 1.17 | (4.50) | –0.31 | (16.90) | 0.16 | (5.57) |
| Distance to employment center (100m) | 29.08 | (33.59) | 8.11 | (15.77) | –2.39 | (16.23) | — | — |
| Age (% 18 to 34) | 30.70 | (8.57) | –1.54 | (5.45) | 0.15 | (5.52) | –0.49 | (6.94) |
| Bike commuters (%) | 0.27 | (0.88) | 0.16 | (1.26) | 0.60 | (2.42) | 0.27 | (2.76) |
| **Minneapolis (n=366 block groups)** | | | | | | | | |
| *Bike lanes* | | | | | | | | |
| BGs with any (new) lanes (#, %) [a] | 7 | (2%) | 91 | (25%) | 72 | (20%) | 216 | (59%) |
| Average density of bike lanes (m/mi$^2$) | 46.07 | (381.60) | 1302.75 | (3175.94) | 759.27 | (1960.98) | 2777.27 | (3901.69) |
| Average reach of bike lanes (m) | 24.34 | (182.87) | 1483.55 | (3854.44) | 2922.48 | (6280.87) | 43,769.30 | (47,844.23) |
| *Selected sociodemographic characteristics* | | | | | | | | |
| Race (% black) | 11.87 | (15.61) | 4.26 | (9.44) | 0.93 | (7.80) | –0.75 | (7.99) |
| Ethnicity (% Hispanic) | 2.07 | (1.26) | 4.83 | (7.24) | 2.99 | (5.64) | –0.84 | (7.08) |
| Education (% with bachelor's or more) | 30.12 | (18.18) | 7.20 | (9.39) | 6.76 | (11.37) | 3.00 | (10.31) |
| Med. HHD income (1000s of 2015$) | 53.12 | (24.00) | 8.88 | (18.81) | –3.28 | (18.69) | 2.85 | (16.07) |
| Poverty (% < federal poverty line) | 17.45 | (15.94) | –1.93 | (9.02) | 4.68 | (11.40) | –0.68 | (12.15) |
| *Covariates* | | | | | | | | |
| Population density (1,000 persons/mi$^2$) | 8.98 | (4.89) | 0.66 | (3.06) | 0.26 | (5.51) | 0.44 | (1.97) |
| Distance to employment center (100m) | 20.30 | (17.12) | –1.23 | (6.61) | –4.58 | (7.15) | — | — |
| Age (% 18 to 34) | 35.89 | (13.01) | –2.49 | (6.01) | 0.03 | (5.84) | –0.69 | (6.76) |
| Bike commuters (%) | 1.48 | (2.02) | 0.22 | (2.29) | 1.96 | (4.40) | 0.39 | (4.87) |

*(continued on next page)*

| | Baseline (1990) | | Change 1990–2000 | | Change 2000–2010 | | Change 2010–2015 | |
|---|---|---|---|---|---|---|---|---|
| | *Mean or #* | *(SD or %)* | *Mean or #* | *(SD or %)* | *Mean or #* | *(SD or %)* | *Mean or #* | *(SD or %)* |
| **Oakland (n=315 block groups)** | | | | | | | | |
| *Bike lanes* | | | | | | | | |
| BGs with any (new) lanes (#, %) [a] | 0 | (0%) | 15 | (5%) | 101 | (32%) | 163 | (52%) |
| Average density of bike lanes (m/mi$^2$) | 0.00 | (0.00) | 183.60 | (966.47) | 1693.31 | (3536.75) | 2115.97 | (3773.03) |
| Average reach of bike lanes (m) | 0.00 | (0.00) | 45.15 | (211.54) | 989.47 | (2170.50) | 6106.86 | (9733.14) |
| *Selected sociodemographic characteristics* | | | | | | | | |
| Race (% black) | 43.61 | (26.82) | –7.82 | (9.32) | –7.78 | (7.46) | –2.52 | (8.93) |
| Ethnicity (% Hispanic) | 13.08 | (13.06) | 7.00 | (8.52) | 3.98 | (6.38) | 0.48 | (9.00) |
| Education (% with bachelor’s or more) | 25.17 | (20.53) | 4.19 | (7.24) | 5.90 | (11.15) | 3.04 | (10.08) |
| Med. HHD income (1000s of 2015$) | 56.62 | (30.66) | 8.51 | (16.12) | –1.35 | (18.93) | 1.55 | (18.01) |
| Poverty (% < federal poverty line) | 18.66 | (12.64) | –0.01 | (8.85) | 0.09 | (11.34) | 0.76 | (10.65) |
| *Covariates* | | | | | | | | |
| Population density (1,000 persons/mi$^2$) | 13.78 | (8.33) | 1.64 | (3.54) | –0.60 | (3.12) | 0.66 | (3.61) |
| Distance to employment center (100m) | 38.50 | (35.04) | –11.64 | (14.00) | 6.52 | (8.54) | — | — |
| Age (% 18 to 34) | 29.01 | (6.48) | –1.80 | (3.27) | –0.95 | (4.47) | 0.15 | (6.65) |
| Bike commuters (%) | 1.07 | (2.05) | 0.12 | (2.33) | 0.71 | (3.34) | 1.00 | (4.16) |

SD = standard deviation, BGs = block groups, HHD = household

[a] In 1990, value indicates the percentage of block groups that contained any bike lanes; for change over each decade, value indicates percentage of block groups that received any new lanes (including block groups that had already contained lanes in previous decades, if they received additional lanes)

Changes in bike lane density varied by levels of the gentrification and SES indicators, exhibiting different patterns in each city (**Table 4-2**). In Chicago, increases in bike lane density in all three decades were greatest among block groups that were either already advantaged or gentrifying, and correspondingly low among block groups that remained disadvantaged over time. Similarly, during the 1990s and 2000s, increases in bike lane density tended to be greatest among block groups that were increasing in SES from either a high or a low baseline SES. Between 2010 and 2015, relatively large increases in bike lane density were observed among block groups that began the decade with low SES, regardless of their trajectory of sociodemographic change.

In Minneapolis, the two indicators suggested slightly different relationships between changes in the bike lane network and changes in sociodemographic advantage. For instance, during the 1990s, increases in bike lane density were relatively high among block groups that were disadvantaged but not gentrifying, but also high among block groups that experienced an increase in socioeconomic advantage from a low baseline SES (i.e. that most closely reflected the dynamics of gentrification within the SES indicator). Similarly, during the 2000s, increases in bike lane density were relatively high among block groups that were already advantaged at the start of the decade, but also among those that experienced decreases in SES from a low baseline level. The two indicators pointed to more consistent conclusions for change between 2010 and 2015, when increases in bike lane density were relatively high among block groups that were gentrifying and among those that increased in SES from a low baseline level.

In Oakland, increases in bike lane density were consistently highest in gentrifying block groups across all three decades. Similarly, relatively large increases in bike lane density were observed in all three decades for block groups that experienced increases in SES over time, regardless of SES at the beginning of the decade.

Changes in bike lane reach by indicator level showed an overall pattern of results that was similar to those observed for bike lane density (**Appendix Table C-1**).

**Table 4-2**. Change in bike lane density by gentrification status and SES indicator level, by decade and by city

| | **Change 1990–2000** | | **Change 2000–2010** | | **Change 2010–2015** | |
|---|---|---|---|---|---|---|
| | n (%) | Density ($100m/mi^2$) *Mean (SD)* | n (%) | Density ($100m/mi^2$) *Mean (SD)* | n (%) | Density ($100m/mi^2$) *Mean (SD)* |
| **Chicago (n=2,062 block groups)** | | | | | | |
| *Gentrification indicator* | | | | | | |
| Disadvantaged but not gentrifying | 1,021 (50%) | 2.84 (13.52) | 778 (38%) | 8.22 (26.07) | 1,180 (57%) | 10.79 (32.89) |
| Already advantaged | 517 (25%) | **10.11 (35.34)** | 614 (30%) | **16.09 (37.27)** | 865 (42%) | 13.93 (32.97) |
| Gentrifying | 524 (25%) | 5.59 (20.24) | 670 (32%) | 12.01 (31.62) | 17 (1%) | **30.65 (48.37)** |
| *Socioeconomic status indicator* [a] | | | | | | |
| Limited change in SES | 1,032 (50%) | 4.07 (19.46) | 1,031 (50%) | 10.46 (29.54) | 1,031 (50%) | 12.11 (33.13) |
| Decrease from low baseline SES | 248 (12%) | 2.16 (10.48) | 231 (11%) | 9.41 (25.80) | 224 (11%) | **15.39 (37.02)** |
| Decrease from high baseline SES | 267 (13%) | 3.45 (16.18) | 284 (14%) | 7.69 (22.76) | 292 (14%) | 7.02 (24.91) |
| Increase from low baseline SES | 336 (16%) | 6.84 (26.72) | 318 (15%) | **17.46 (37.93)** | 307 (15%) | **16.70 (39.52)** |
| Increase from high baseline SES | 179 (9%) | **17.43 (41.39)** | 198 (10%) | **18.32 (44.42)** | 208 (10%) | 10.55 (27.08) |
| **Minneapolis (n=366 block groups)** | | | | | | |
| *Gentrification indicator* | | | | | | |
| Disadvantaged but not gentrifying | 139 (38%) | **19.43 (40.05)** | 94 (26%) | 5.50 (15.94) | 197 (54%) | 25.26 (35.88) |
| Already advantaged | 57 (16%) | 8.25 (17.13) | 85 (23%) | **10.09 (25.49)** | 153 (42%) | 29.60 (41.70) |
| Gentrifying | 170 (46%) | 9.39 (26.77) | 187 (51%) | 7.51 (18.14) | 16 (4%) | **41.15 (47.90)** |
| *Socioeconomic status indicator* [a] | | | | | | |
| Limited change in SES | 182 (50%) | 10.32 (27.42) | 183 (50%) | 6.13 (19.65) | 183 (50%) | 30.41 (41.03) |
| Decrease from low baseline SES | 58 (16%) | 18.52 (28.13) | 48 (13%) | **13.86 (24.55)** | 43 (12%) | 26.34 (37.23) |
| Decrease from high baseline SES | 34 (9%) | 4.36 (13.37) | 44 (12%) | 3.71 (13.76) | 48 (13%) | 19.52 (36.85) |
| Increase from low baseline SES | 59 (16%) | **26.46 (52.15)** | 57 (16%) | 10.25 (19.69) | 55 (15%) | **32.24 (37.27)** |
| Increase from high baseline SES | 33 (9%) | 3.22 (10.97) | 34 (9%) | 7.20 (16.11) | 37 (10%) | 20.45 (35.17) |
| **Oakland (n=315 block groups)** | | | | | | |
| *Gentrification indicator* | | | | | | |
| Disadvantaged but not gentrifying | 186 (59%) | 1.23 (7.09) | 117 (37%) | 12.29 (32.08) | 137 (43%) | 23.50 (39.92) |
| Already advantaged | 87 (28%) | 1.25 (7.46) | 94 (30%) | 11.52 (30.58) | 152 (48%) | 16.06 (31.73) |
| Gentrifying | 42 (13%) | **5.72 (18.81)** | 104 (33%) | **27.05 (40.69)** | 26 (8%) | **38.65 (51.20)** |
| *Socioeconomic status indicator* [a] | | | | | | |
| Limited change in SES | 159 (50%) | 1.20 (6.69) | 158 (50%) | 15.16 (36.36) | 159 (50%) | 16.67 (32.02) |
| Decrease from low baseline SES | 38 (12%) | 1.35 (8.33) | 36 (11%) | 5.15 (12.66) | 38 (12%) | 21.89 (36.11) |
| Decrease from high baseline SES | 40 (13%) | 0.00 (0.00) | 42 (13%) | 20.43 (39.88) | 40 (13%) | 22.87 (41.59) |
| Increase from low baseline SES | 45 (14%) | **2.69 (10.23)** | 46 (15%) | **28.85 (39.18)** | 51 (16%) | **26.02 (43.76)** |
| Increase from high baseline SES | 33 (10%) | **6.53 (21.00)** | 33 (10%) | 17.22 (31.98) | 27 (9%) | **34.84 (49.60)** |

SD = standard deviation, SES = socioeconomic status; bold cells indicate the highest observed change(s) in bike lane density in each indicator-year combination

### *4.6.2 Regression analyses*

In regression models that accounted for spatial clustering of block groups within tracts and adjusted for covariates, associations between changes in the bike lane network and changes in area-level sociodemographic characteristics varied by city (**Table 4-3**). In Chicago, results for the gentrification indicator (Model A) suggest that increases in bike lane density and bike lane reach were significantly higher for block groups that were already advantaged at the start of a given decade than for those that remained disadvantaged over time. However, increases in bike lane reach were significantly lower for gentrifying block groups than for those experiencing persistent disadvantage. The results for the SES indicator (Model B) in Chicago suggest that increases in bike lane density were significantly higher for block groups that experienced increases in SES from a position of baseline disadvantage than for block groups that experienced limited change (either positive or negative) in SES over time. Compared to block groups that experienced limited sociodemographic change, however, block groups that experienced increases in SES (regardless of baseline SES) experienced significantly smaller increases in bike lane reach.

In Minneapolis, increases in both bike lane density and bike lane reach were greater for already-advantaged block groups than for block groups that remained disadvantaged over time. However, the opposite relationship was observed for gentrifying block groups, which experienced smaller increases in both bike lane variables compared to persistently disadvantaged block groups (Model A). No significant differences in either dependent variable were observed by levels of the SES indicator (Model B).

In Oakland, gentrifying block groups experienced larger increases in bike lane density but smaller increases in bike lane reach relative to block groups that remained disadvantaged over time (Model A). Additionally, increases in bike lane density were higher for block groups that experienced an increase in SES from a low baseline SES than for block groups that experienced limited change in SES over time (Model B).

**Table 4-3**. Longitudinal associations of gentrification indicator and SES indicator with change in bike lanes using linear multilevel mixed-effects regression models, by city, across all decades 1990–2015

| | Bike lane density ($m/mi^2$) [a] | | | Bike lane reach (m) [b] | | |
|---|---|---|---|---|---|---|
| | *Coeff.* | *SE* | *p* | *Coeff.* | *SE* | *p* |
| **Chicago (n=2,062 block groups)** | | | | | | |
| *Model A: Gentrification indicator* | | | | | | |
| Disadvantaged but not gentrifying | (ref) | | | (ref) | | |
| Already advantaged | 276.06 | 99.37 | 0.01*** | 13,615.62 | 1131.43 | 0.00*** |
| Gentrifying | –33.48 | 105.16 | 0.75 | –5052.70 | 1132.11 | 0.00*** |
| *Model B: Socioeconomic status indicator* | | | | | | |
| Limited change in SES | (ref) | | | | | |
| Decrease from low baseline SES | 162.36 | 122.30 | 0.18 | 815.66 | 1307.05 | 0.53 |
| Decrease from high baseline SES | –149.86 | 112.50 | 0.18 | 145.74 | 1192.44 | 0.90 |
| Increase from low baseline SES | 242.38 | 109.69 | 0.03** | –4918.04 | 1176.94 | 0.00*** |
| Increase from high baseline SES | 55.93 | 135.72 | 0.68 | –3265.68 | 1443.53 | 0.02** |
| **Minneapolis (n=366 block groups)** | | | | | | |
| *Model A: Gentrification indicator* | | | | | | |
| Disadvantaged but not gentrifying | (ref) | | | | | |
| Already advantaged | 679.81 | 291.48 | 0.02*** | 10,408.56 | 2988.55 | 0.00*** |
| Gentrifying | –579.13 | 228.56 | 0.01*** | –15,512.64 | 2400.80 | 0.00*** |
| *Model B: Socioeconomic status indicator* | | | | | | |
| Limited change in SES | (ref) | | | | | |
| Decrease from low baseline SES | –422.10 | 294.58 | 0.15 | 216.64 | 3182.86 | 0.95 |
| Decrease from high baseline SES | –266.63 | 289.06 | 0.36 | –1893.40 | 3178.20 | 0.55 |
| Increase from low baseline SES | –53.96 | 275.97 | 0.85 | –2956.09 | 2999.59 | 0.32 |
| Increase from high baseline SES | –277.92 | 314.81 | 0.38 | –1396.25 | 3452.61 | 0.69 |
| **Oakland (n=315 block groups)** | | | | | | |
| *Model A: Gentrification indicator* | | | | | | |
| Disadvantaged but not gentrifying | (ref) | | | | | |
| Already advantaged | 80.81 | 261.20 | 0.76 | 786.93 | 521.88 | 0.13 |
| Gentrifying | 694.85 | 300.32 | 0.02** | –1971.64 | 583.79 | 0.00*** |
| *Model B: Socioeconomic status indicator* | | | | | | |
| Limited change in SES | (ref) | | | | | |
| Decrease from low baseline SES | –0.09 | 323.25 | 0.99 | 222.84 | 628.93 | 0.72 |
| Decrease from high baseline SES | 456.61 | 306.20 | 0.14 | 835.38 | 592.43 | 0.16 |
| Increase from low baseline SES | 667.55 | 297.04 | 0.03** | 125.54 | 579.15 | 0.83 |
| Increase from high baseline SES | 437.47 | 354.45 | 0.22 | –206.10 | 687.34 | 0.76 |

SE = standard error, SES = socioeconomic status; ** = significance at 95%, *** = significance at 99%
All models estimated using two-level clustering (block groups nested within tracts)
All models adjusted for covariates (start of decade, change over decade, and interaction between start/change); coefficients for covariates presented in Appendix Table C-2
All coefficients represent associations averaged over three decades (1990–2000, 2000–2010, 2010–2015)
[a] Mean per-decade change in bike lane density = 981m in Chicago, 1613m in Minneapolis, 1331m in Oakland
[b] Mean per-decade change in bike lane reach = 10,974m in Chicago, 16,058m in Minneapolis, 2380m in Oakland

Coefficients for covariates are presented in **Appendix Table C-2** and summarized below. In Chicago, increases in bike lanes tended to be higher among block groups with higher baseline proportions of young residents and bike commuters, lower baseline population density, and lower (i.e. closer) baseline distance to the nearest employment center. Increases in bike lanes also tended to be higher among block groups that experienced greater increases in young residents and bike commuters and decreases in distance to the nearest employment center over time. Coefficients on the interaction terms for these variables suggested that associations between young residents, bike commuters, and distance to the nearest employment center tended to be weaker among block groups that began with more favorable baseline values for these characteristics (i.e. higher proportions of young residents and bike commuters, lower distance to the nearest employment center).

In Minneapolis, increases in bike lanes tended to be higher among block groups with higher baseline population density, lower baseline distance to the nearest employment center, lower proportions of young residents, and higher baseline proportions of bike commuters. Increases in bike lane reach tended to be higher among block groups that experienced decreases in population density and increases in distance to the nearest employment center over time; associations with changes in covariates were not statistically significant for bike lane density. None of the coefficients on the interaction terms for covariates were statistically significant in Minneapolis.

In Oakland, increases in bike lanes tended to be higher among block groups with higher baseline population density, lower baseline distance to the nearest employment center, and higher baseline proportions of young residents and bike commuters. Increases in bike lanes also tended to be higher among block groups that experienced greater increases in the proportion of bike commuters over time. None of the coefficients on the interaction terms for covariates were statistically significant in Oakland.

### *4.6.3 Additional analyses*

The results for the pooled, three-city sample (n=2,743) were very similar to those observed in Chicago (data not shown), reflecting the prominence of Chicago block groups in our study sample and confirming the importance of stratifying our analyses by city to capture varying local contexts. In alternative regression models that substituted continuous sociodemographic variables in place of the gentrification and SES indicators, the pattern of results varied by city (**Appendix Table C-3**). In Chicago, higher increases in bike lane density tended to occur in areas with higher baseline educational attainment, higher baseline poverty, and lower baseline SES, and in areas that experienced decreases in income and increases in poverty over time. In Minneapolis, higher increases in bike lane density tended to occur in areas with higher baseline proportions of black residents, higher baseline educational attainment, higher baseline poverty, and lower baseline SES; increases in bike lane density were not significantly associated with changes in any of the measured sociodemographic characteristics. In Oakland, higher increases in bike lane density tended to occur in areas with higher baseline proportions of black and Hispanic residents, higher baseline educational attainment, and lower baseline income, and in areas that had increases in educational attainment and decreases in the proportion of Hispanic residents over time.

We used lagged regression models and Granger causality tests to examine the potential temporality of sociodemographic and infrastructure changes in Chicago and Oakland, as we observed expected associations between gentrification and bike lane density in these two cities. In the lagged regression models, we found some evidence that gentrification preceded increases in bike lane density in Chicago, while these changes appeared to occur within the same decade in Oakland (**Table 4-4**). In both cities, changes in the bike lane network in a given decade were significantly associated with gentrification status in the following decade, although this association was in the unexpected direction (i.e. higher increases in bike lane density were associated with a *lower* likelihood of subsequent gentrification). In Chicago, the results of the Granger causality tests suggested that past values of the SES index were useful in predicting future values of bike lane density; while the reverse was also true (i.e. past values of bike lane density were useful in predicting future values of the SES index), this association was only marginally significant ($p < 0.10$) (**Table 4-5**). The results of the Granger causality tests were not statistically significant in Oakland.

**Table 4-4**. Lagged models examining temporality between gentrification status and changes in bike lane density in Chicago and Oakland, 1990–2015

| | Change in bike lane density (m/mi$^2$) [a,b] | | | Gentrification status (yes/no) [c,d] | | |
|---|---|---|---|---|---|---|
| | *Coeff.* | *SE* | *p* | *OR* | *SE* | *p* |
| **Chicago (n=2,062 block groups)** | | | | | | |
| *Temporal Model A: Gentrification in decade t predicts bike lane changes in decade t+1* | | | | | | |
| Not gentrifying [c] | (ref) | | | | | |
| Gentrifying | 290.06 | 122.20 | 0.02** | — | — | — |
| *Temporal Model B: Bike lane changes in decade t predict gentrification in decade t+1* | | | | | | |
| Change in bike lane density (m/mi$^2$) | — | — | — | 0.99 | 0.00 | 0.00*** |
| *Temporal Model C: Gentrification in decade t predicts bike lane changes in decade t* | | | | | | |
| Not gentrifying [c] | (ref) | | | | | |
| Gentrifying | –82.80 | 98.94 | 0.40 | — | — | — |
| **Oakland (n=315 block groups)** | | | | | | |
| *Temporal Model A: Gentrification in decade t predicts bike lane changes in decade t+1* | | | | | | |
| Not gentrifying [c] | (ref) | | | | | |
| Gentrifying | –293.56 | 379.84 | 0.44 | — | — | — |
| *Temporal Model B: Bike lane changes in decade t predict gentrification in decade t+1* | | | | | | |
| Change in bike lane density (m/mi$^2$) | — | — | — | 0.99 | 0.00 | 0.00*** |
| *Temporal Model C: Gentrification in decade t predicts bike lane changes in decade t* | | | | | | |
| Not gentrifying [c] | (ref) | | | | | |
| Gentrifying | 994.66 | 278.67 | 0.00*** | — | — | — |

OR = odds ratio, SE = standard error, SES = socioeconomic status
** = significance at 95%, *** = significance at 99%
All models estimated using two-level clustering (block groups nested within tracts)
Dependent variables by model: change in bike lane density for Models A and C, gentrification for Model B
[a] Estimated using linear multilevel mixed-effects regression models
[b] Mean per-decade change in bike lane density = 981m in Chicago, 1613m in Minneapolis, 1331m in Oakland
[c] Estimated using logistic multilevel mixed-effects regression models
[d] "Already advantaged" and "disadvantaged but not gentrifying" levels of the gentrification indicator collapsed into a single category to create a binary (yes/no) indicator of gentrification for the purposes of this additional analysis

**Table 4-5**. Granger causality tests between composite SES index and bike lane density in Chicago and Oakland, 1990–2015

| | **Chicago (n=2,062)** | | **Oakland (n=315)** | |
|---|---|---|---|---|
| | *Chi*$^2$ | *p* | *Chi*$^2$ | *p* |
| SES "Granger-causes" bike lane density | 48.93 | 0.00*** | 0.13 | 0.72 |
| Bike lane density "Granger-causes" SES | 2.93 | 0.09* | 0.01 | 0.94 |

SES = socioeconomic status
* = significance at 90%, *** = significance at 99%
If Chi$^2$ test statistic is significant, variable X "Granger-causes" variable Y (i.e. provides useful predictive information about X above and beyond past values of Y)

## 4.7 Discussion

We found some evidence of longitudinal associations between bike lane investment (i.e. increases in the bike lane network) and area-level sociodemographic change over 25 years in Chicago, Minneapolis, and Oakland, although these associations were not consistently in the expected direction (i.e. sociodemographic advantage positively associated with higher increases in the bike lane network) and considerable variation was observed across the three cities. Broadly, the results of the descriptive, adjusted, and supplemental analyses suggest a nuanced and highly contextualized association between bike lane investment and sociodemographic change. We begin this section by discussing the major findings by city, grouping Chicago and Oakland due to basic similarities in the regression results for these two cities. We then briefly discuss variations in the results for continuous sociodemographic variables and outline key policy implications emerging from this research.

### *4.7.1 Chicago and Oakland: Higher bike lane density associated with greater sociodemographic advantage*

Associations between bike lane density and sociodemographic change in Chicago and Oakland generally aligned with our main hypothesis, suggesting that higher increases in bike lane density occurred disproportionately in areas that either were already advantaged or experienced increases in advantage over time. In descriptive (i.e. unadjusted) analyses, increases in bike lane density in both cities tended to be greatest among block groups that experienced an increase in composite SES over time, regardless of their starting SES. Gentrifying block groups experienced relatively large increases in bike lane density across all three decades in Oakland, and between 2010 and 2015 in Chicago; in earlier decades, increases in bike lane density in Chicago were relatively large in block groups that were already advantaged.

These associations generally persisted in the adjusted regression analyses. In both Chicago and Oakland, block groups that experienced increases in SES from a low baseline position—the SES indicator level that most closely reflects the dynamics of gentrification (i.e. increase in advantage from an initial position of disadvantage)—had greater increases in bike lane density compared to block groups that experienced limited change, either positive or negative, in sociodemographic composition over time. When sociodemographic change was instead characterized using the Freeman (2005) gentrification indicator, increases in bike lane density were higher among already-advantaged block groups in Chicago and among gentrifying block groups in Oakland, relative to block groups in these cities that remained disadvantaged over time.

Thus, we found evidence in both of these cities that higher increases in the bike lane network over the study period disproportionately occurred in areas experiencing sociodemographic changes consistent with gentrification; in Chicago, the results further suggested higher increases in the bike lane network in areas that were already advantaged at the start of a given decade. These findings align with previous work on cycling and gentrification in these two cities. As previously noted, Lubitow et al. (2016) documented a case of community resistance to a proposed bike lane project in a gentrifying neighborhood of Chicago, describing several institutional issues—including top-down planning approaches, limited community engagement, rapid implementation attempts, and the framing of bike lane investment as an economic development strategy—that led to a perceived association between bike lanes and gentrification. Indeed, the authors note that the city’s plan to substantially increase its bike lane network by 2020 was described by Chicago Mayor Rahm Emanuel as, in part, a method to attract high-tech companies and workers to the city (Davies 2012). Similarly, Stehlin (2015) describes how cycling advocates in the San Francisco Bay Area have played a pivotal role in promoting the economic benefits of cycling as a rationale for public investment. Placed against the backdrop of economic restructuring, the technology boom, and housing affordability crises in the Bay Area, Stehlin (2015) notes that these arguments have contributed to an uneasy relationship between cycling and gentrification in the region and associated concerns related to social justice. Thus, the results of the present analysis likely reflect and offer a quantitative illustration of the arguments derived from rich qualitative research in Chicago and Oakland (Lubitow et al. 2016, Stehlin 2015). Furthermore, our findings generally correspond with those of Flanagan et al. (2016) and Hirsch et al. (2017), who used quantitative data to examine longitudinal associations between sociodemographic change and bike lane investment in these two cities over similar periods of time.

As outlined in the conceptual framework for this analysis (Figure 4-1), a longitudinal association between higher bike lane investment (i.e. higher increases in the bike lane network) and increasing sociodemographic advantage could reflect a number of potential relationships: bike lane investment may follow and potentially respond to increases in neighborhood sociodemographic advantage, increases in sociodemographic advantage may follow and potentially respond to bike lane investment, and sociodemographic and infrastructure changes may take place concurrently as the result of confounding structural factors. To examine these possibilities, we assessed the temporality of changes in bike lane density and changes in sociodemographic advantage using lagged regression models and Granger causality tests. Taken together, the results of these supplemental analyses generally lend support to the hypothesis that gentrification occurs either before or during the same decade as bike lane investment; less support is evident for a relationship in which gentrification comes after, and potentially as a result of, investment in the bike lane network. While these supplemental analyses do not address questions of causality, and while changes that occur during the same decade may still have a sequential ordering, they do add a temporal lens to our main findings and begin to disentangle the complex relationships illustrated in our conceptual framework.

While expected associations with sociodemographic advantage were observed when bike lanes were measured in terms of network density, the findings for Chicago and Oakland were frequently in the unexpected direction when changes to the bike lane network were instead measured in terms of reach (i.e. connectivity). Indeed, the results suggested that increases in bike lane connectivity tended to be higher in relatively disadvantaged block groups. One set of potential explanations for this finding lies in the distribution of early cycling infrastructure in these two cities. If disadvantaged block groups were *more* likely to contain bike lanes at the start of the study period, and if those bike lanes were not removed over time, then disadvantaged block groups would benefit from downstream (i.e. external to the block group) additions to the bike lane network to which they were connected by early infrastructure, regardless of whether they received new additions within their boundaries over time. Alternatively, if disadvantaged block groups were *less* likely to contain bike lanes at the start of the study period, they could benefit substantially (i.e. experience relatively large gains in connectivity) if later efforts were made to connect gaps in the bike lane network through relatively disadvantaged neighborhoods. To assess these possibilities, we measured the sociodemographic characteristics of block groups by presence or absence of bike lanes at the first time point for which bike lanes were observed in each city (1990 in Chicago, 2000 in Oakland) (**Appendix Table C-4**). The findings suggest that block groups that had bike lanes in the earlier decades of our analysis tended to be relatively disadvantaged, although these associations were only statistically significant in Chicago. Thus, we found some support for the explanation that early bike lanes tended to be located in disadvantaged block groups, and that these block groups may therefore have experienced large gains in connectivity from later bike lane investments that occurred outside of their boundaries but nevertheless connected downstream to their existing infrastructure.

#### *4.7.2 Minneapolis: Mixed associations between bike lane investment and sociodemographic advantage*

Associations between increases in the bike lane network and changes in sociodemographic advantage in Minneapolis were mixed, pointing to relationships that were at times consistent and at times inconsistent with our main hypothesis. Before adjusting for spatial clustering and covariates, block groups that were already advantaged (in the 2000s) or gentrifying (between 2010 and 2015) received higher increases in bike lane density relative to persistently disadvantaged block groups; during the 1990s, however, persistently disadvantaged block groups received relatively high increases in bike lane density. Similarly complex descriptive results were found for the SES indicator, which suggested that bike lane investment was highest in block groups that experienced increases in SES from a low baseline SES in the first and last decades of our analysis, but that increases in bike lane density during the early 2000s were greatest among block groups that experienced a decrease in SES from a low baseline SES.

In regression analyses that accounted for spatial clustering and adjusted for covariates, increases in both bike lane density and bike lane reach were significantly higher for already-advantaged block groups but significantly *lower* for gentrifying block groups, relative to block groups that remained disadvantaged over time. Thus, the results partially align with but partially contradict our main hypothesis: bike lane investment was higher in areas that were already advantaged but lower in areas that experienced gentrification over time.

While the association between bike lane investment and baseline sociodemographic advantage was expected, the inverse association between gentrification and changes to the bike lane network (i.e. lower bike lane investment in gentrifying areas) was unanticipated, particularly given the results of qualitative work on cycling and gentrification in Minneapolis. Hoffman (2016) and Hoffman and Lugo (2014) describe how the city's bicycle culture in general—and an urban greenway project in particular—have been framed in terms of their economic benefits. Indeed, Hoffman and Lugo (2014) describe an interview in which former Mayor R.T. Rybak cites cycling as a tool for recruiting talent, promoting economic growth, and competing with other cities for scarce economic resources. A quantitative association between bike lane investment and gentrification might be expected in this context, given the predominance of economic benefits in the framing of bicycle culture and infrastructure investments in Minneapolis.

There are several potential explanations for this apparent inconsistency. First, the unexpected regression results for the gentrification indicator could reflect the pervasive challenges of measuring gentrification, particularly using nationally available census data. It is possible that the dynamics of gentrification in Minneapolis are unique and not as well represented using the Freeman (2005) indicator as they are in Chicago and Oakland. Second, if the inverse association between gentrification and bike lane investment is accepted as valid, the inconsistency of our findings with qualitative work in

Minneapolis could reflect a difference in the types of cycling infrastructure considered. While Hoffman (2016) and Hoffman and Lugo (2014) focus in part on broad notions of bicycle culture, they also focus on a specific greenway project that provides off-road infrastructure for cyclists. In the present analysis, we instead focus on on-street bike lanes, which may be subject to different associations with sociodemographic advantage in the Minneapolis context. Past research has revealed differences between the property value impacts of bike lanes and off-road trails; for example, both Krizek (2006) and Welch et al. (2016) found evidence that property values were higher in proximity to off-road cycling infrastructure but lower or not significantly different in proximity to on-street bike lanes. A third explanation lies in the potential for bike lane projects to serve as a symbolic platform for voicing larger community concerns about gentrification (Lubitow et al. 2016, Herrington and Dann 2016). A lack of quantitative evidence associating bike lane investment with gentrification does not make concerns about this relationship invalid and does not preclude the potential for bike lane projects to catalyze public resistance, particularly given that processes of gentrification are relatively decentralized and have few points of government intervention for which formal public input opportunities are offered.

Although associations between increases in the bike lane network and gentrification were unexpected in Minneapolis, we did find evidence that higher increases in the bike lane network disproportionately occurred in areas that were already advantaged and thus ineligible to be classified as gentrifying. This finding, which suggests an expected association between baseline sociodemographic advantage and bike lane investment, has implications for social equity and could reflect a greater capacity and preference among relatively advantaged populations to advocate for and attract public investment.

#### *4.7.3 Variations in the results for continuous sociodemographic variables*

When changes in sociodemographic advantage were measured using separate, continuous variables (i.e. race, ethnicity, educational attainment, income, poverty, composite SES index) rather than the categorical gentrification and SES indicators, we observed a mix of expected and unexpected results. In all three cities, higher increases in bike lane density were associated with higher baseline educational attainment; in Oakland, higher increases in bike lane density were associated with increases in educational attainment and decreases in the proportion of Hispanic residents over time. These results could reflect the importance of educational attainment—a more consistent and potentially more meaningful indicator of SES than fluctuating measures such as income—in processes of gentrification (Lester and Hartley 2014), and offer further support to the relatively consistent association between gentrification and changes in bike lane density observed for Oakland in the main analysis.

With the exception of educational attainment, the remainder of significant associations between bike lane investment and baseline sociodemographic characteristics were in the unexpected direction (i.e. higher increases in bike lane density were associated with lower baseline SES). These findings are not necessarily unexpected; for instance, if bike lanes are more likely to be placed in gentrifying areas, these investments must occur in places that were, by definition, disadvantaged to begin with. More illustrative from the perspective of this analysis are the associations between bike lane investment and *changes* in sociodemographic characteristics. As noted above, changes in both educational attainment and the proportion of Hispanic residents were associated in the expected direction with increases in the bike lane network in Oakland. In Chicago, however, higher increases in the bike lane network tended to occur in areas where median income was decreasing and poverty rates were increasing over time; interestingly, these results offer a parallel to those observed in Chapter 3 of this dissertation, where unexpected cross-sectional associations were observed between bike lane presence and measures of income and poverty. These unexpected findings could result from correlations between the individual sociodemographic characteristics considered in our analysis, which were accounted for through the creation of composite, categorical indicators in the main analysis. Moreover, these findings could reflect the nature of gentrification as a gradual rather than an immediate transition, which could produce a situation in which pockets of persistent disadvantage (by one set of measures) are spatially co-located with areas of increasing advantage (by another set of measures).

### 4.7.4 *Policy implications*

We found some evidence that higher increases in the bike lane network disproportionately occurred in block groups that were already advantaged or increasing in advantage over time, illustrating the longitudinal process by which disparities in access to bike lanes may emerge. While investing in bike lanes in disadvantaged neighborhoods may be perceived—and is often recommended—as an appropriate policy response, the positive associations we observed between higher bike lane investment and gentrification complicate this approach. These associations do not necessarily imply a causal relationship and were not universally observed across all cities and time points in our analysis. Nevertheless, our findings lend empirical support to the perception that conversations about cycling and about gentrification are uniquely intertwined, thus suggesting the potential for continued resistance to bike lane investment in neighborhoods that are susceptible to gentrification.

Wolch et al. (2014) outline a similar paradox in planning for urban green space, noting that reducing socioeconomic disparities in access to parks, community gardens, and other forms of green space could lead to increased property values and thereby counteract potential gains in environmental justice. The authors argue that confronting this tension requires an adequate balance between ecological and social sustainability, involving what they describe as "the challenge of making cities 'just green enough'" (Wolch et al. 2014, p. 234). Viewed within this framework, planning for social equity in access to cycling infrastructure may require a parallel challenge of making neighborhoods "just bikeable enough" to both support and protect socioeconomically disadvantaged communities.

How might this challenge be achieved in the context of bicycle planning in U.S. cities? The creation of just and socially sustainable bike lane networks may involve a two-fold approach of grassroots, community-led planning efforts and proactive partnership with housing and anti-displacement advocacy groups. First, as bicycle planners and advocates seek to expand the bike lane network and to address sociodemographic disparities in access to cycling infrastructure, efforts should be made to actively engage affected communities in the planning process. Lubitow et al. (2016) describe how top-down, city-imposed planning approaches in Chicago led to community resistance against a bike lane project in a gentrifying neighborhood, but how subsequent grassroots efforts to engage community members—parallel to but outside of formal public involvement structures—led to improved public perceptions of the project. The authors highlight the potential for community-led approaches to leverage local knowledge and institutions, including grassroots advocates who "are in touch with the 'strategies that work' in their neighbourhood and are more sustainable in the long term" and who know how to frame the benefits of bike lanes in a way that resonate with the residents of their particular community (Lubitow et al. 2016, p. 2647). Importantly, planners and advocates should recognize through this process that cycling is not universally aspired to as a travel mode (Hoffman 2016, Golub 2016, Lubitow and Miller 2013, People for Bikes and Alliance for Biking & Walking 2015), that neighborhoods may have more fundamental needs for intervention—both within and beyond transportation—than bike lanes (Lubitow et al. 2016), and that bike lane interventions interact with a complex socio-cultural landscape (Golub 2016) characterized by histories of injustice and subsequent mistrust (Lubitow and Miller 2013). Through recognizing these complexities and engaging communities in a grassroots, community-led planning process, planners and advocates may be able to craft solutions that effectively respond to gentrification concerns and are contextually appropriate for the unique neighborhoods they intend to serve.

Second, bicycle planners and advocates could proactively seek partnerships with advocacy groups working on issues of gentrification and displacement. Herrington and Dann (2016) note that gentrification is a complex structural issue that "operate[s] at scales far larger than that of a single neighborhood" (p. 35) or any given project, and that issues of "gentrification and displacement will not be solved in the realm of bicycle infrastructure and policy" (p. 50). Despite these limitations, cycling interventions often serve as a symbolic platform upon which larger concerns about gentrification can be expressed (Lubitow et al. 2016, Herrington and Dann 2016). This situation lends bicycle planning and advocacy to strategic partnerships with other groups working on issues of affordable housing, displacement prevention, and economic justice (Herrington and Dann 2016, Stehlin 2015). Such intersections are warranted by the perceived or, in our analysis, observed associations between cycling and gentrification, and might allow bike lane investment to be seen as an opportunity rather than a threat in traditionally underserved and disadvantaged communities.

### 4.7.5 *Study strengths and limitations*

This study is among the first to use quantitative, longitudinal data to examine associations between cycling infrastructure investment and sociodemographic change over time. In comparison to previous work, our analysis benefits from the availability of more recent data (through 2015 rather than 2010), thus capturing important developments—such as considerable growth in U.S. bike lane investment and the increasing prominence of conversations about cycling and gentrification—that have occurred since 2010. Additionally, our study considers a relatively small unit of analysis in order to reflect the importance of close proximity in influencing the use of bike lanes (Krizek and Johnson 2006), and uses a variety of composite indicators—including a gentrification measure that has been relatively well established in the existing literature—to characterize changes in sociodemographic advantage.

Despite these strengths, a key limitation of this work is the difficulty of measuring gentrification, particularly with data that are available at the national level. While our focus on three cities in diverse geographic locations constrained us to the use of nationally available census data, this approach limited our ability to capture any ways in which the dynamics of gentrification may have differed across the three cities. More broadly, census data have key limitations in measuring gentrification because they do not track individuals or households over time, thus losing information about displacement and about how changes in sociodemographic composition occur; and because they do not capture how change is perceived and experienced by community members (Landis 2016). As previously noted, we attempted to address these concerns by creating multiple gentrification indicators and consulting with local experts to consider which indicator most closely reflected the nature of gentrification in our three cities.

The dependent and independent variables in this analysis may also have been subject to measurement error due to the data sources used. In measuring bike lanes over time, we used one data source for 1990, 2000, and 2010 data and another set of sources—combined from the three individual cities—to measure bike lanes in 2015. Combining bike lane data from different sources in this way may have introduced measurement error. However, the addition of 2015 as a time point was deemed valuable due to significant investment in bike lanes after 2010, and we engaged in a thorough process of data cleaning to maximize consistency between the two sources over time, as well as between the three individual cities in 2015. Similarly, due to changes in the content of the decennial census over time, the sociodemographic characteristics of interest for this analysis were contained in the decennial census for 1990 and 2000 and in the American Community Survey (ACS) for 2010 and 2015. This required us to combine data from these two sources, which may have introduced error due to the different format and sampling approaches for the decennial census and the ACS. This approach was deemed appropriate, however, in order to examine sociodemographic changes over a considerable (i.e. 25-year) period of time.

Finally, our analysis is based on the experiences of three large cities and the findings may not be generalizable to other locations. However, these three cities are characterized by diverse socio-political environments and bicycle cultures, potentially making our sample relevant to a diverse set of large U.S. cities. Additionally, our focus on only three cities allowed us to stratify all analyses by city and thus to delve into the unique dynamics and associations that were present in each setting.

### 4.8 Conclusion

Bike lanes are simultaneously viewed as a way to advance health equity and to enhance economic prosperity (Carpenter and Zaccaro 2017). While these claims do not inherently conflict, the framing of bike lanes as an economic development strategy, including for attracting the creative class, has led to the emergence of a perceived and problematic association between cycling and gentrification in U.S. cities. In this analysis, we have provided quantitative evidence that bike lane investment is associated with sociodemographic advantage in three large U.S. cities, with varying dynamics by location. Although our findings do not suggest a causal relationship, they add preliminary empirical support to the notion that cycling and gentrification may be uniquely connected in practice. The findings suggest that efforts to address sociodemographic disparities in access to bike lanes—an approach that is often recommended to promote health equity—should be pursued with a nuanced and context-sensitive understanding of how infrastructure interventions may impact the communities they are designed to serve. Through approaches that recognize the role of gentrification in conversations about cycling, bicycle planners and advocates may more closely approach a just and socially sustainable distribution of bicycle infrastructure.

# CHAPTER 5. CONCLUSION: IMPLICATIONS FOR RESEARCH AND PRACTICE

## 5.1 Overview

In the three papers of this dissertation, I have examined the distribution of environments and infrastructure that support active transportation (i.e. walking and cycling) in U.S. cities. Using a combination of cross-sectional and longitudinal data, I have found some quantitative evidence of sociodemographic differences in access to “walkable” built environments and to on-street, dedicated bike lanes, although the nature and implications of these differences vary across analyses. The findings suggest a number of ways in which planners might work toward greater social equity in the distribution of opportunities for active transportation. In the sections that follow, I briefly summarize the results of each analysis and outline the major implications for planning research and practice emerging from this work.

## 5.2 Summary of findings

### *5.2.1 Sociodemographic characteristics and walkable built environments*

In the first paper of this dissertation (Chapter 2), I find that different sociodemographic groups have different levels of access to built environments that are traditionally viewed as “walkable” (e.g., high population density, street connectivity, and development intensity). Specifically, non-white individuals and those with low socioeconomic status (SES) tend to live in more walkable neighborhoods, reflecting a socio-spatial arrangement that King and Clarke (2015) have called a “disadvantaged advantage” in walkability. This finding, however, could relate to how walkability was measured in this analysis, as the walkability index considered larger characteristics of urban form rather than fine-grained characteristics of the pedestrian environment (e.g., infrastructure quality and safety, aesthetics). At the same time, non-white and low-SES individuals are less likely to be distributed across the full range of neighborhood built environment types, and are particularly absent from neighborhoods of low walkability. These results suggest that while disadvantaged populations tend to reside in built environments that are objectively more "walkable," they also face constraints on residential choice that warrant consideration from an equity perspective.

The distribution of different sociodemographic groups across different types of built environments also has methodological implications for research on the built environment and travel behavior. I find that estimates of the association between walkability and walking behavior may be biased by up to 15 percent when sociodemographic characteristics are adjusted for using traditional regression analysis methods. I find that a non-parametric matching method called coarsened exact matching (CEM) offers a promising alternative to traditional regression analysis when individuals living in different neighborhood types are systematically and fundamentally different from one another.

*5.2.2 Cross-sectional associations between bike lanes and area-level sociodemographic characteristics*

While the first paper focuses on the distribution of walkable built environments, the second paper of the dissertation (Chapter 3) analyzes the distribution of cycling infrastructure. In this analysis, I find that access to on-street, dedicated bike lanes varies by area-level sociodemographic characteristics in a cross-sectional sample of 22 large U.S. cities (n=21,846 block groups). As hypothesized, these patterns reflect a disadvantaged *dis*advantage" in which disadvantaged block groups (i.e. those with lower SES and/or higher proportions of minority residents) have significantly lower access to bike lanes. Many of these associations persist even after adjusting for traditional indicators of cycling demand; specifically, access to bike lanes remains lower among block groups with lower educational attainment, higher proportions of Hispanic residents, and lower composite SES. These findings suggest the presence of systematic disparities in bike lane access across a broad sample of U.S. cities, providing quantitative support for advocates' claims of distributional inequalities in access to cycling infrastructure.

### *5.2.3 Longitudinal associations between bike lanes and area-level sociodemographic characteristics*

In the third paper of the dissertation (Chapter 4), I build upon the second analysis using longitudinal data in a smaller number of cities, allowing for a more place-based assessment of associations between bike lane investment and area-level sociodemographic change (e.g., gentrification). I find that between 1990 and 2015, investments in the bike lane networks of Chicago, Minneapolis, and Oakland tended to be made disproportionately in block groups that were either already advantaged or increasing in advantage (e.g., gentrifying) over time. The nature of these associations varies by city; for instance, gentrifying block groups in Chicago and Oakland tended to experience greater increases in bike lane density over time relative to persistently disadvantaged block groups, while the opposite was true in Minneapolis (i.e. gentrifying block groups received *lower* bike lane investment) and block groups that were already advantaged received higher bike lane investment in Minneapolis and Chicago. The results also provide insight into the temporality between sociodemographic change and bike lane investment, suggesting that gentrification tends to either precede or occur within the same decade as investments in the bike lane network. These findings complement the cross-sectional, multi-city analysis in Chapter 3, providing longitudinal evidence that processes of cycling investment and gentrification are uniquely (even if not causally) connected and suggesting that efforts to expand access to bike lanes in traditionally disadvantaged neighborhoods must appropriately contend with these associations.

## 5.3 Implications for research and practice

### *5.3.1 Implications for planning research*

The results of this dissertation highlight three primary directions for future planning research. First, research on the built environment and travel behavior should more closely consider the distribution of different sociodemographic groups across space with respect to built environment characteristics (e.g., walkability). The results of the first paper suggest that sociodemographic characteristics are not simply control variables to be statistically adjusted for, but rather important variables that could have both methodological and substantive implications for planning research. From the methodological perspective, future research should continue to seek appropriate methods to account for socio-spatial segregation with respect to built environment characteristics. Traditional regression control methods may not be sufficient if individuals living in different neighborhood types are systematically different from one another, and alternative methods (e.g., matching, experimental research designs) may allow researchers to more fully account for sociodemographic characteristics in estimating associations between the built environment and travel behavior. Future research may also focus on improved measures of walkability that capture not just structural aspects of urban form, but also finer-grained characteristics of the pedestrian realm that influence the experience of walkability.

From the substantive perspective, understanding the ways in which different groups are distributed across different types of built environments, and the potential reasons for this distribution, could reveal structural issues related to segregation and social equity. For instance, while the observed scarcity of low-income and minority individuals in neighborhoods of low walkability could reflect an active choice by these groups to live in more walkable neighborhoods, this socio-spatial arrangement could also reflect systematic exclusion from certain neighborhood types (e.g., in newer suburban developments). Examining how larger patterns of socio-spatial segregation are related to built environment characteristics such as walkability is important to both research and practice, as accounting for these patterns can reduce bias in research on the built environment and travel behavior and understanding these patterns may provide information for targeting planning interventions designed to support active transportation and health equity.

Second, while research on cycling typically considers infrastructure such as bike lanes as predictors of travel behavior, additional research should extend the contributions of this dissertation by continuing to consider cycling infrastructure as a dependent variable. As in the case of walkability, sociodemographic characteristics in this area of research are of substantive interest to questions of social equity, with implications beyond their traditional role as statistical control variables. This dissertation has contributed a broad understanding of trends in access to bike lanes across a larger number of U.S. cities. Future research should complement these findings with more place-based approaches, leveraging local data sources and knowledge to more fully understand and account for the planning context of individual cities. These place-based approaches could incorporate finer-grained measures of cycling supports—such as infrastructure quality and safety, access to destinations, and availability of trip-end facilities (e.g., bicycle parking and storage)—to provide a more comprehensive view of access to opportunities for cycling; these measures may provide a more accurate assessment of bikeability than the infrastructure measures considered in this dissertation. While there is room for further cross-sectional research in this area of the literature, longitudinal analyses focusing on individual cities could leverage local data sources to develop more contextualized indicators of sociodemographic change. Additionally, extending this type of analysis to other countries would provide an opportunity to understand whether planning for social equity in access to bike lanes has similar dynamics in a broader geographic context.

Third, there is a need for additional qualitative research designed to complement, contextualize, and add depth to the findings of quantitative analyses. Several authors have examined issues of social equity and gentrification in cycling using bicycle planning projects in large cities—including San Francisco, Portland, Minneapolis, and Los Angeles—as in-depth case studies (Stehlin 2015, Lubitow et al. 2016, Lubitow and Miller 2014, Herrington and Dann 2016, Hoffman 2016, Hoffman and Lugo 2014). Future research could add to this growing qualitative evidence base by engaging planners, cycling advocates, other community leaders, and community members in dialogue about the challenges faced in planning for a more equitable distribution of cycling infrastructure. This research could reveal the mechanisms potentially linking bike lane investment and gentrification, offer insight into cases in which perceptions of gentrification are not supported by quantitative data, and provide a more thorough understanding of social and institutional issues in bicycle planning and advocacy. Moreover, qualitative research could help to describe how walkability and bikeability are viewed and experienced at a fine level of detail, providing valuable information for improving empirical measures of these constructs.

One promising opportunity for this type of qualitative research would be an analysis of resistance to bike lanes in a traditionally disadvantaged and gentrifying neighborhood. Lubitow et al. (2016) discuss cases of resistance within the context of post-political narratives that frame “sustainable” urban development projects as universal public goods. Employing the work of Fraser (1990), the authors suggest that instances of resistance often materialize outside of formal public engagement structures, forming "counterpublics" or "parallel discursive arenas" in which "marginalized groups collectively withdraw from the injustices of the broader public sphere while developing alternative political strategies or forms of resistance" (p. 2640). For instance, in the authors' case study of a contested bike lane project in Chicago, such a "counterpublic" was formed through the mechanism of a bicycle shop that pursued inclusive, grassroots public engagement strategies outside of (but alongside) the formal planning process (Lubitow et al. 2016). Examining such cases of resistance and parallel engagement is an important exercise for advancing conversations about active transportation and social justice, as these cases represent "critical moments" in which processes of state-sponsored urban redevelopment that assume universal values "can be challenged, critiqued, and potentially altered in pursuit of a more inclusive vision" (Lubitow and Miller 2013, p. 126).

### *5.3.2 Implications for planning practice*

Taken together, the results of the three papers of this dissertation suggest that access to "walkable" built environments and to on-street, dedicated bike lanes varies by sociodemographic characteristics in U.S. cities. While disadvantaged groups may have greater access to built environments traditionally viewed as walkable, past research suggests that the reverse could be true if walkability were measured using finer-grained indicators of infrastructure quality, safety, and aesthetics (Neckerman et al. 2009, Kelly et al. 2007, Sallis et al. 2011, Cerin and Leslie 2008, Wilson et al. 2004, Boslaugh et al. 2004). The findings of the dissertation are more consistent with expectations in the case of cycling infrastructure, suggesting that disadvantaged groups have disproportionately low access to bike lanes both cross-sectionally and over time.

It is likely that these disparities have arisen not from overtly discriminatory planning practices, but rather from institutional and structural factors that tend to lead to public investment in areas of relative advantage. Key institutional factors might include the sociodemographic composition of the planning profession, a general lack of equity goals in active transportation planning, and the challenges associated with engaging disadvantaged populations in formal public involvement opportunities (Golub 2016, Lee et al. 2017). Stehlin (2015) further notes that larger structural forces such as the suburbanization of poverty and the "return to the city" have contributed to a spatial arrangement "in which the *possibility* of replacing car trips by bicycle or mass transit is supremely uneven in distribution" (p. 124, emphasis in original). Due to these forces, advantaged populations may tend to live disproportionately in areas where active transportation investments are often viewed as more technically feasible (e.g., in dense, central locations).

How should planners respond to disparities in access to active transportation within this context? While directly discriminatory practices are likely rare and while structural forces may be difficult to change, the institutional explanations for existing disparities provide a starting point for action. One approach would be to adopt explicit goals, objectives, and strategies related to social equity in active transportation planning, influencing the decision making process in ways that encourage investment in disadvantaged and traditionally underserved neighborhoods. Through this approach, planners could work to address disparities in access to neighborhoods of choice and to environments and infrastructure that support active transportation.

It is important to recognize, however, that expanding active transportation infrastructure in disadvantaged communities is neither universally appropriate nor value-neutral. For instance, prevailing social norms suggest that cycling may not be a mode of aspiration for all sociodemographic groups, as it is often viewed as reserved for the very rich or the very poor (People for Bikes and Alliance for Biking & Walking 2015, Hoffman and Lugo 2014, Golub 2016, Lubitow and Miller 2013, Flanagan et al. 2016). Furthermore, these investments do not take place on a neutral landscape, but rather have the potential to create and reinforce spatial patterns of advantage and disadvantage in cities (Soja 2010, Harvey 1973). Within this socio-spatial context, the frequent framing of bike lane projects as universal public goods (Lubitow et al. 2016) has the potential to isolate groups with real concerns about the impacts of infrastructure investment on their communities—concerns that, in the case of gentrification, are empirically supported by the findings of this dissertation.

Thus, the answer to questions of social equity in active transportation may not be as simple or straightforward as building infrastructure in disadvantaged communities. Instead, planners should engage members of these communities in meaningful dialogue about their needs, preferences, and concerns related to active transportation investment, remaining open to the possibility that other types of interventions—both within and beyond the realm of transportation—may be more contextually appropriate in a given situation. Lubitow et al. (2016) note that whereas top-down planning approaches can lead to resistance, grassroots efforts to actively engage community members in the planning process may result in projects that are more widely accepted. Moreover, because grassroots efforts have the potential to leverage local knowledge, institutions, and resources, they may offer a greater understanding of strategies that will work within a particular community (Lubitow et al. 2016). Thus, while community-led planning processes may point to other types of interventions beyond active transportation, they may also result in walking and cycling investments that are more contextually appropriate and ultimately more successful in achieving their stated goals.

The transportation planning profession has a long legacy of exerting significant impacts, both positive and negative, on the communities it serves. Through approaches designed to address disparities in infrastructure access while also remaining sensitive to the unique social context of active transportation projects, planners can work to ensure that the legacy of walking and cycling interventions in the U.S. remains positive, just, and socially sustainable.

## APPENDIX A: SUPPLEMENTAL MATERIALS FOR CHAPTER 2

**Table A-1.** Descriptive statistics by density level, n=16,785 adults (ages 37–54) in the 2009 National Household Travel Survey

| **Characteristics** | **All participants (n=16,785)** | **Groups by density level** | | | | |
|---|---|---|---|---|---|---|
| | | Low n=1,999 | Medium n=6,830 | Med.-High n=6,059 | High n=1,897 | p-value for differences |
| *Density (persons/mi$^2$)* | | | | | | |
| 0–99 (%) | 0.52 | 4.40 | — | — | — | |
| 100–499 (%) | 4.46 | 37.42 | — | — | — | |
| 500–999 (%) | 6.93 | 58.18 | — | — | — | |
| 1,000–1,999 (%) | 13.91 | — | 34.17 | — | — | |
| 2,000–3,999 (%) | 26.79 | — | 65.83 | — | — | |
| 4,000–9,999 (%) | 36.10 | — | — | 100.00 | — | |
| 10,000–24,999 (%) | 8.36 | — | — | — | 74.01 | |
| 25,000–999,999 (%) | 2.94 | — | — | — | 25.99 | |
| *Covariates* | | | | | | |
| Race (white) (%) | 78.47 | 86.09 | 83.53 | 76.89 | 57.25 | 0.00*** |
| Education (>HS) (%) | 80.34 | 78.09 | 83.09 | 80.64 | 71.85 | 0.00*** |
| Income, in 1000s of US$ | 82.31 (40.17) | 85.65 (38.82) | 88.12 (38.11) | 80.41 (40.22) | 63.93 (42.57) | 0.00*** |
| Household size | 3.03 (1.37) | 3.15 (1.37) | 3.08 (1.31) | 2.99 (1.39) | 2.82 (1.52) | 0.00*** |
| Currently working (%) | 75.47 | 75.79 | 76.24 | 75.64 | 71.80 | 0.00*** |
| Census division | | | | | | 0.00*** |
| New England (%) | 1.07 | 2.30 | 1.04 | 0.64 | 1.21 | |
| Middle Atlantic (%) | 10.01 | 14.66 | 8.81 | 5.36 | 24.30 | |
| East North Central (%) | 4.33 | 7.05 | 5.72 | 2.57 | 2.00 | |
| West North Central (%) | 0.66 | 0.85 | 0.98 | 0.40 | 0.16 | |
| South Atlantic (%) | 25.91 | 33.22 | 32.77 | 20.60 | 10.49 | |
| East South Central (%) | 1.39 | 3.10 | 2.17 | 0.38 | 0.00 | |
| West South Central (%) | 20.27 | 18.36 | 24.55 | 21.16 | 4.06 | |
| Mountain (%) | 6.88 | 3.25 | 5.74 | 10.76 | 2.37 | |
| Pacific (%) | 29.48 | 17.21 | 18.21 | 38.13 | 55.40 | |

HS = high school, USD = U.S. dollars; values in parentheses indicate standard deviation (not presented for categorical variables/percentages)

# APPENDIX B: SUPPLEMENTAL MATERIALS FOR CHAPTER 3

**Table B-1**. Cities and corresponding number of block groups included in final study sample, by 2015 MSA population

| City | MSA population in 2015 | Number of block groups |
|---|---|---|
| New York, NY | 20,182,305 | 5,866 |
| Los Angeles, CA | 13,340,068 | 2,438 |
| Chicago, IL | 9,551,031 | 2,083 |
| Dallas, TX | 7,102,796 | 892 |
| Houston, TX | 6,656,947 | 1,290 |
| Washington, DC | 6,097,684 | 433 |
| Philadelphia, PA | 6,069,875 | 1,228 |
| Miami, FL | 6,012,331 | 285 |
| Atlanta, GA | 5,710,795 | 296 |
| Boston, MA | 4,774,321 | 496 |
| San Francisco, CA | 4,656,132 | 559 |
| Phoenix, AZ | 4,574,531 | 932 |
| Detroit, MI | 4,302,043 | 785 |
| Seattle, WA | 3,733,580 | 462 |
| Minneapolis, MN | 3,524,583 | 366 |
| San Diego, CA | 3,299,521 | 810 |
| Tampa, FL | 2,975,225 | 315 |
| Denver, CO | 2,814,330 | 473 |
| Charlotte, NC | 2,426,363 | 438 |
| Portland, OR | 2,389,228 | 425 |
| Orlando, FL | 2,387,138 | 115 |
| San Antonio, TX | 2,384,075 | 859 |
| **Total** | | **21,846** |

**Table B-2**. Correlations between independent variables, n=21,846 block groups in 22 large U.S. cities

| | Black | Hispanic | Education | Income | Poverty | SES index | Pop. dens. | Job dens. | Dist. DT | Age | Bike |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Black | 1.0000 | | | | | | | | | | |
| Hispanic | –0.3186 | 1.0000 | | | | | | | | | |
| Education | –0.3839 | –0.4998 | 1.0000 | | | | | | | | |
| Income | –0.3583 | –0.3489 | 0.7306 | 1.0000 | | | | | | | |
| Poverty | 0.3445 | 0.2889 | –0.5611 | –0.6590 | 1.0000 | | | | | | |
| SES index | –0.3780 | –0.5314 | 0.9083 | 0.8650 | –0.7620 | 1.0000 | | | | | |
| Pop. density | –0.0569 | 0.0746 | 0.0627 | –0.0160 | 0.0687 | –0.0432 | 1.0000 | | | | |
| Job density | –0.0769 | –0.0698 | 0.1770 | 0.1284 | –0.0402 | 0.1327 | 0.1178 | 1.0000 | | | |
| Dist. to DT | –0.0267 | 0.0721 | –0.1570 | 0.0529 | –0.1465 | –0.0150 | –0.0852 | –0.1257 | 1.0000 | | |
| Age | –0.0980 | 0.0056 | 0.2029 | –0.1100 | 0.0873 | 0.0201 | 0.1238 | 0.1211 | –0.2595 | 1.0000 | |
| Bike commute | –0.1293 | –0.0472 | 0.1938 | 0.0503 | 0.0007 | 0.1141 | 0.0181 | 0.0267 | –0.2116 | 0.2086 | 1.0000 |

**Table B-3.** Partially adjusted associations of each block group-level sociodemographic characteristic (separate model for each characteristic, adjusted for covariates) with block group-level bike lane characteristics using multilevel mixed-effects regression, n=21,846 block groups in 22 large U.S. cities

| | **1A. Presence (y/n)** [a] | | | **2A. Density ($m/mi^2$)** [b] | | | **3A. Reach (m)** [b] | | | **4A. Distance to nearest (m)** [c] | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *OR* | *SE* | *p* [d] | *Coeff.* | *SE* | *p* [d] | *Coeff.* | *SE* | *p* [d] | *Coeff.* | *SE* | *p* [d] |
| Race (% black) | 1.00 | 0.00 | 0.55 | –0.32 | 9.15 | 0.97 | –12.45 | 56.61 | 0.83 | –0.38 | 0.32 | 0.24 |
| Ethnicity (% Hispanic) | 1.00 | 0.00 | 0.19 | –20.18 | 5.44 | **0.00** | –150.26 | 67.31 | **0.03** | 0.31 | 0.28 | 0.26 |
| Education (% with bachelor’s or more) | 1.01 | 0.00 | **0.00** | 27.76 | 10.26 | **0.01** | 139.26 | 40.20 | **0.00** | –0.14 | 0.31 | 0.64 |
| Median household income ($1000s) | 1.00 | 0.00 | 0.15 | 7.28 | 3.69 | **0.05** | 56.80 | 18.08 | **0.00** | 0.23 | 0.23 | 0.31 |
| Poverty (% < federal poverty line) | 1.00 | 0.00 | 0.47 | –12.15 | 8.69 | 0.16 | –28.75 | 31.74 | 0.37 | –0.31 | 0.23 | 0.18 |
| Composite SES index | 1.04 | 0.02 | **0.03** | 105.13 | 43.78 | **0.02** | 656.45 | 236.13 | **0.01** | 0.67 | 1.96 | 0.73 |

OR = odds ratio, SE = standard error, SES = socioeconomic status

Each coefficient is from a separate model associating each separate sociodemographic characteristic with bike lanes, adjusting only for covariates; coefficients for covariates not presented

For all models: two-level clustering (block groups nested within tracts), city specified as a factor variable (coefficients not presented), standard errors clustered at the city level

[a] Modeled using multilevel mixed effects (MLME) logistic regression on full sample (n=21,846)

[b] Modeled using two-part models: first part modeled likelihood of having any lanes among full sample (n=21,846) using MLME logistic regression (identical to Models 1A/1B), second part modeled density/reach of bike lanes among block groups with any (n=9,359) using MLME linear regression (presented in Models 2A/2B and 3A/3B)

[c] Modeled using MLME linear regression on full sample (n=21,846)

[d] p-values in bold indicate statistical significance at 90% confidence or greater

# APPENDIX C: SUPPLEMENTAL MATERIALS FOR CHAPTER 4

**Table C-1**. Change in bike lane reach by gentrification status and socioeconomic status (SES) indicator level, by decade and by city

| | Change 1990–2000 | | Change 2000–2010 | | Change 2010–2015 | |
|---|---|---|---|---|---|---|
| | n (%) | Reach (100m) *Mean (SD)* | n (%) | Reach (100m) *Mean (SD)* | n (%) | Reach (100m) *Mean (SD)* |
| **Chicago (n=2,062 block groups)** | | | | | | |
| *Gentrification indicator* | | | | | | |
| Disadvantaged but not gentrifying | 1,021 (50%) | 5.29 (22.24) | 778 (38%) | 24.48 (76.47) | 1,180 (57%) | 116.80 (365.38) |
| Already advantaged | 517 (25%) | 10.00 (30.34) | 614 (30%) | 97.31 (162.09) | 865 (42%) | 471.99 (666.40) |
| Gentrifying | 524 (25%) | 9.12 (31.04) | 670 (32%) | 50.34 (123.83) | 17 (1%) | 285.38 (621.14) |
| *Socioeconomic status indicator* [a] | | | | | | |
| Limited change in SES | 1,032 (50%) | 5.85 (23.21) | 1,031 (50%) | 44.92 (114.51) | 1,031 (50%) | 275.16 (548.32) |
| Decrease from low baseline SES | 248 (12%) | 5.71 (22.66) | 231 (11%) | 26.29 (72.80) | 224 (11%) | 219.28 (497.71) |
| Decrease from high baseline SES | 267 (13%) | 5.61 (22.52) | 284 (14%) | 30.61 (96.74) | 292 (14%) | 187.92 (472.45) |
| Increase from low baseline SES | 336 (16%) | 8.89 (31.54) | 318 (15%) | 108.45 (172.45) | 307 (15%) | 252.23 (538.54) |
| Increase from high baseline SES | 179 (9%) | 19.08 (41.97) | 198 (10%) | 85.67 (149.21) | 208 (10%) | 408.25 (640.87) |
| **Minneapolis (n=366 block groups)** | | | | | | |
| *Gentrification indicator* | | | | | | |
| Disadvantaged but not gentrifying | 139 (38%) | 21.29 (45.86) | 94 (26%) | 26.37 (53.86) | 197 (54%) | 449.61 (474.45) |
| Already advantaged | 57 (16%) | 10.90 (34.79) | 85 (23%) | 44.17 (94.90) | 153 (42%) | 422.59 (488.12) |
| Gentrifying | 170 (46%) | 10.88 (32.17) | 187 (51%) | 23.86 (45.70) | 16 (4%) | 435.42 (458.33) |
| *Socioeconomic status indicator* [a] | | | | | | |
| Limited change in SES | 182 (50%) | 11.87 (34.09) | 183 (50%) | 20.36 (55.47) | 183 (50%) | 428.51 (479.78) |
| Decrease from low baseline SES | 58 (16%) | 20.27 (39.96) | 48 (13%) | 39.32 (56.79) | 43 (12%) | 624.70 (437.27) |
| Decrease from high baseline SES | 34 (9%) | 11.05 (36.46) | 44 (12%) | 12.68 (33.18) | 48 (13%) | 265.60 (434.78) |
| Increase from low baseline SES | 59 (16%) | 27.23 (54.59) | 57 (16%) | 57.52 (81.56) | 55 (15%) | 535.67 (475.34) |
| Increase from high baseline SES | 33 (9%) | 3.38 (14.82) | 34 (9%) | 36.63 (83.44) | 37 (10%) | 343.40 (492.78) |
| **Oakland (n=315 block groups)** | | | | | | |
| *Gentrification indicator* | | | | | | |
| Disadvantaged but not gentrifying | 186 (59%) | 0.37 (1.93) | 117 (37%) | 6.01 (14.68) | 137 (43%) | 62.21 (100.37) |
| Already advantaged | 87 (28%) | 0.30 (1.64) | 94 (30%) | 9.66 (22.12) | 152 (48%) | 53.25 (89.20) |
| Gentrifying | 42 (13%) | 1.11 (3.36) | 104 (33%) | 14.48 (26.71) | 26 (8%) | 100.78 (118.73) |
| *Socioeconomic status indicator* [a] | | | | | | |
| Limited change in SES | 159 (50%) | 0.32 (1.66) | 158 (50%) | 6.51 (15.96) | 159 (50%) | 53.23 (90.60) |
| Decrease from low baseline SES | 38 (12%) | 0.26 (1.63) | 36 (11%) | 7.60 (21.24) | 38 (12%) | 42.64 (73.20) |
| Decrease from high baseline SES | 40 (13%) | 0.00 (0.00) | 42 (13%) | 5.20 (9.44) | 40 (13%) | 82.09 (115.67) |
| Increase from low baseline SES | 45 (14%) | 0.69 (2.42) | 46 (15%) | 27.42 (35.94) | 51 (16%) | 73.37 (108.33) |
| Increase from high baseline SES | 33 (10%) | 1.53 (4.18) | 33 (10%) | 10.14 (20.40) | 27 (9%) | 78.83 (109.92) |

**Table C-2**. Longitudinal associations of gentrification indicator and covariates with change in bike lanes using linear multilevel mixed-effects regression models, by city, across all decades 1990–2015

| | Bike lane density (m/mi$^2$) | | | Bike lane reach (m) | | |
|---|---|---|---|---|---|---|
| | *Coeff.* | *SE* | *p* | *Coeff.* | *SE* | *p* |
| **Chicago (n=2,062 block groups)** | | | | | | |
| *Gentrification indicator* | | | | | | |
| Disadvantaged but not gentrifying | (ref) | | | (ref) | | |
| Already advantaged | 276.06 | 99.37 | 0.01*** | 13,615.62 | 1131.43 | 0.00*** |
| Gentrifying | –33.48 | 105.16 | 0.75 | –5052.70 | 1132.11 | 0.00*** |
| *Baseline covariates* | | | | | | |
| Population density (1,000 persons/mi$^2$) | –5.57 | 2.76 | 0.04** | –150.16 | 31.35 | 0.00*** |
| Distance to employment center (100m) | –8.08 | 1.62 | 0.00*** | –127.34 | 20.07 | 0.00*** |
| Age (% 18 to 34) | 33.48 | 4.91 | 0.00*** | 504.27 | 56.97 | 0.00*** |
| Bike commuters (%) | 21.05 | 32.87 | 0.52 | 4464.51 | 348.57 | 0.00*** |
| *Change in covariates* | | | | | | |
| Population density (1,000 persons/mi$^2$) | –0.75 | 6.20 | 0.90 | –34.43 | 66.28 | 0.60 |
| Distance to employment center (100m) | –20.81 | 4.53 | 0.00*** | –147.64 | 48.70 | 0.00*** |
| Age (% 18 to 34) | 73.41 | 15.34 | 0.00*** | 700.61 | 159.89 | 0.00*** |
| Bike commuters (%) | 54.51 | 20.24 | 0.01*** | 1269.43 | 211.89 | 0.00*** |
| *Baseline * change interaction terms* | | | | | | |
| Population density (1,000 persons/mi$^2$) | –0.04 | 0.07 | 0.57 | –0.51 | 0.78 | 0.52 |
| Distance to employment center (100m) | 0.27 | 0.13 | 0.04** | 1.29 | 1.44 | 0.37 |
| Age (% 18 to 34) | –1.26 | 0.42 | 0.00*** | –24.56 | 4.33 | 0.00*** |
| Bike commuters (%) | –7.24 | 4.09 | 0.08* | 39.05 | 42.78 | 0.36 |
| **Minneapolis (n=366 block groups)** | | | | | | |
| *Gentrification indicator* | | | | | | |
| Disadvantaged but not gentrifying | (ref) | | | | | |
| Already advantaged | 679.81 | 291.48 | 0.02*** | 10,408.56 | 2988.55 | 0.00*** |
| Gentrifying | –579.13 | 228.56 | 0.01*** | –15,512.64 | 2400.80 | 0.00*** |
| *Baseline covariates* | | | | | | |
| Population density (1,000 persons/mi$^2$) | 95.24 | 17.62 | 0.00*** | 382.56 | 183.79 | 0.04** |
| Distance to employment center (100m) | –35.61 | 11.52 | 0.00*** | –459.76 | 116.04 | 0.00*** |
| Age (% 18 to 34) | 0.11 | 9.48 | 0.99 | –343.93 | 97.17 | 0.00*** |
| Bike commuters (%) | 48.37 | 37.59 | 0.20 | 1310.33 | 395.18 | 0.00*** |
| *Change in covariates* | | | | | | |
| Population density (1,000 persons/mi$^2$) | 21.01 | 54.34 | 0.70 | –1095.92 | 576.26 | 0.06* |
| Distance to employment center (100m) | –13.50 | 37.74 | 0.72 | 869.64 | 399.79 | 0.03** |
| Age (% 18 to 34) | –45.92 | 37.59 | 0.22 | 423.05 | 398.75 | 0.29 |
| Bike commuters (%) | –6.79 | 28.82 | 0.81 | 492.32 | 305.45 | 0.11 |
| *Baseline * change interaction terms* | | | | | | |
| Population density (1,000 persons/mi$^2$) | –0.85 | 1.95 | 0.66 | 32.39 | 20.65 | 0.12 |
| Distance to employment center (100m) | 0.24 | 1.05 | 0.82 | –16.48 | 11.17 | 0.14 |
| Age (% 18 to 34) | 1.12 | 0.89 | 0.21 | –7.29 | 9.43 | 0.44 |
| Bike commuters (%) | –4.35 | 3.87 | 0.26 | –12.77 | 41.02 | 0.76 |

*(continued on next page)*

| **Oakland (n=315 block groups)** | | | | | | |
|---|---|---|---|---|---|---|
| *Gentrification indicator* | | | | | | |
| Disadvantaged but not gentrifying | (ref) | | | | | |
| Already advantaged | 80.81 | 261.20 | 0.76 | 786.93 | 521.88 | 0.13 |
| Gentrifying | 694.85 | 300.32 | 0.02** | –1971.64 | 583.79 | 0.00*** |
| *Baseline covariates* | | | | | | |
| Population density (1,000 persons/mi$^2$) | 36.43 | 14.69 | 0.01** | –45.43 | 29.96 | 0.13 |
| Distance to employment center (100m) | –1.15 | 5.16 | 0.82 | –27.61 | 11.16 | 0.01** |
| Age (% 18 to 34) | 6.60 | 19.10 | 0.73 | 78.60 | 38.51 | 0.04** |
| Bike commuters (%) | 193.74 | 50.63 | 0.00*** | 655.00 | 99.89 | 0.00*** |
| *Change in covariates* | | | | | | |
| Population density (1,000 persons/mi$^2$) | –70.06 | 53.23 | 0.19 | –156.56 | 101.66 | 0.12 |
| Distance to employment center (100m) | –8.43 | 21.54 | 0.70 | –31.72 | 41.13 | 0.44 |
| Age (% 18 to 34) | –0.12 | 69.53 | 0.99 | –62.60 | 133.01 | 0.64 |
| Bike commuters (%) | 94.92 | 37.65 | 0.01** | 271.26 | 72.06 | 0.00*** |
| *Baseline * change interaction terms* | | | | | | |
| Population density (1,000 persons/mi$^2$) | 1.04 | 1.64 | 0.53 | 3.46 | 3.14 | 0.27 |
| Distance to employment center (100m) | 0.33 | 0.30 | 0.27 | 0.46 | 0.57 | 0.42 |
| Age (% 18 to 34) | 0.48 | 2.37 | 0.84 | 5.74 | 4.54 | 0.21 |
| Bike commuters (%) | –6.75 | 6.83 | 0.32 | 2.29 | 13.15 | 0.86 |

SE = standard error, SES = socioeconomic status
* = significance at 90%, ** = significance at 95%, *** = significance at 99%
All models estimated using two-level clustering (block groups nested within tracts)
All coefficients represent associations averaged over three decades (1990–2000, 2000–2010, 2010–2015)

**Table C-3**. Longitudinal associations of continuous sociodemographic variables with change in bike lane density using linear multilevel mixed-effects regression models, by city, across all decades 1990–2015

| | Model with separate sociodemographic variables | | | Model with composite SES index | | |
|---|---|---|---|---|---|---|
| | *Coeff.* | *SE* | *p* | *Coeff.* | *SE* | *p* |
| **Chicago (n=2,062 block groups)** | | | | | | |
| *Baseline characteristics* | | | | | | |
| Race (% black) | 2.19 | 2.08 | 0.29 | — | — | — |
| Ethnicity (% Hispanic) | –2.03 | 2.65 | 0.45 | — | — | — |
| Education (% with bachelor's or more) | 10.52 | 3.98 | 0.01*** | — | — | — |
| Med. HHD income (1000s of 2015$) | 3.22 | 2.95 | 0.28 | — | — | — |
| Poverty (% < federal poverty line) | 22.47 | 4.64 | 0.00*** | — | — | — |
| Composite SES index | — | — | — | –133.47 | 50.25 | 0.01*** |
| *Change in characteristics* | | | | | | |
| Race (% black) | –4.30 | 8.78 | 0.62 | — | — | — |
| Ethnicity (% Hispanic) | –2.49 | 7.64 | 0.74 | — | — | — |
| Education (% with bachelor's or more) | –9.35 | 6.73 | 0.17 | — | — | — |
| Med. HHD income (1000s of 2015$) | –9.35 | 4.53 | 0.04** | — | — | — |
| Poverty (% < federal poverty line) | 15.17 | 5.90 | 0.01** | — | — | — |
| Composite SES index | — | — | — | –31.42 | 95.97 | 0.74 |
| *Baseline * change interaction terms* | | | | | | |
| Race (% black) | –0.08 | 0.17 | 0.63 | — | — | — |
| Ethnicity (% Hispanic) | –0.09 | 0.18 | 0.62 | — | — | — |
| Education (% with bachelor's or more) | 0.28 | 0.17 | 0.11 | — | — | — |
| Med. HHD income (1000s of 2015$) | 0.09 | 0.05 | 0.08* | — | — | — |
| Poverty (% < federal poverty line) | –0.26 | 0.16 | 0.11 | — | — | — |
| Composite SES index | — | — | — | –25.19 | 78.37 | 0.75 |
| **Minneapolis (n=366 block groups)** | | | | | | |
| *Baseline characteristics* | | | | | | |
| Race (% black) | 23.37 | 10.49 | 0.03** | — | — | — |
| Ethnicity (% Hispanic) | 11.89 | 14.63 | 0.42 | — | — | — |
| Education (% with bachelor's or more) | 21.60 | 9.85 | 0.03** | — | — | — |
| Med. HHD income (1000s of 2015$) | –8.02 | 7.07 | 0.26 | — | — | — |
| Poverty (% < federal poverty line) | 40.67 | 12.28 | 0.00*** | — | — | — |
| Composite SES index | — | — | — | –460.95 | 149.58 | 0.00*** |
| *Change in characteristics* | | | | | | |
| Race (% black) | –34.52 | 21.25 | 0.10 | — | — | — |
| Ethnicity (% Hispanic) | –30.05 | 20.56 | 0.14 | — | — | — |
| Education (% with bachelor's or more) | –15.35 | 19.40 | 0.43 | — | — | — |
| Med. HHD income (1000s of 2015$) | 9.65 | 10.06 | 0.34 | — | — | — |
| Poverty (% < federal poverty line) | –23.83 | 15.58 | 0.13 | — | — | — |
| Composite SES index | — | — | — | 69.17 | 270.74 | 0.80 |
| *Baseline * change interaction terms* | | | | | | |
| Race (% black) | 0.86 | 0.63 | 0.17 | — | — | — |
| Ethnicity (% Hispanic) | –0.33 | 1.08 | 0.76 | — | — | — |
| Education (% with bachelor's or more) | 0.42 | 0.40 | 0.30 | — | — | — |
| Med. HHD income (1000s of 2015$) | –0.14 | 0.10 | 0.15 | — | — | — |
| Poverty (% < federal poverty line) | 0.99 | 0.43 | 0.02** | — | — | — |
| Composite SES index | — | — | — | 449.82 | 191.27 | 0.02** |

*(continued on next page)*

| | | | | | | |
|---|---|---|---|---|---|---|
| **Oakland (n=315 block groups)** | | | | | | |
| *Baseline characteristics* | | | | | | |
| Race (% black) | 36.45 | 10.13 | 0.00*** | — | — | — |
| Ethnicity (% Hispanic) | 37.05 | 11.74 | 0.00*** | — | — | — |
| Education (% with bachelor's or more) | 77.98 | 12.18 | 0.00*** | — | — | — |
| Med. HHD income (1000s of 2015$) | –33.26 | 6.87 | 0.00*** | — | — | — |
| Poverty (% < federal poverty line) | 15.93 | 13.94 | 0.25 | — | — | — |
| Composite SES index | — | — | — | –220.30 | 149.48 | 0.14 |
| *Change in characteristics* | | | | | | |
| Race (% black) | –33.50 | 29.95 | 0.26 | — | — | — |
| Ethnicity (% Hispanic) | –55.20 | 29.54 | 0.06* | — | — | — |
| Education (% with bachelor's or more) | 73.31 | 19.65 | 0.00*** | — | — | — |
| Med. HHD income (1000s of 2015$) | –6.41 | 11.74 | 0.59 | — | — | — |
| Poverty (% < federal poverty line) | 34.13 | 22.22 | 0.12 | — | — | — |
| Composite SES index | — | — | — | 347.31 | 333.90 | 0.30 |
| *Baseline * change interaction terms* | | | | | | |
| Race (% black) | 0.66 | 0.61 | 0.28 | — | — | — |
| Ethnicity (% Hispanic) | 1.33 | 0.73 | 0.07* | — | — | — |
| Education (% with bachelor's or more) | –0.87 | 0.46 | 0.06* | — | — | — |
| Med. HHD income (1000s of 2015$) | 0.01 | 0.11 | 0.90 | — | — | — |
| Poverty (% < federal poverty line) | –0.58 | 0.69 | 0.41 | — | — | — |
| Composite SES index | — | — | — | –486.28 | 360.75 | 0.18 |

SE = standard error, SES = socioeconomic status, HHD = household
* = significance at 90%, ** = significance at 95%, *** = significance at 99%
All models estimated using two-level clustering (block groups nested within tracts)
All models adjusted for covariates (start of decade, change over decade, and interaction between start/change); coefficients for covariates not presented
All coefficients represent associations averaged over three decades (1990–2000, 2000–2010, 2010–2015)

**Table C-4**. Sociodemographic characteristics of block groups in Chicago and Oakland by presence/absence of bike lanes at first time point for which bike lanes were observed in each city

| | **Chicago (1990)** | | | **Oakland (2000)** | | |
|---|---|---|---|---|---|---|
| | BGs with no lanes (n=1,998) | BGs with any lanes (n=64) | *p* | BGs with no lanes (n=300) | BGs with any lanes (n=15) | *p* |
| *Selected sociodemographic characteristics* | | | | | | |
| Race (% black) | 34.93 (42.69) | 41.20 (42.17) | 0.25 | 36.13 (22.16) | 28.95 (17.70) | 0.22 |
| Ethnicity (% Hispanic) | 17.71 (23.94) | 36.77 (31.56) | **0.00** | 20.04 (17.38) | 20.93 (23.19) | 0.85 |
| Education (% with bachelor's or more) | 18.95 (18.64) | 12.20 (10.77) | **0.00** | 29.32 (24.03) | 30.03 (19.41) | 0.91 |
| Med. HHD income (1000s of 2015$) | 52.12 (21.08) | 33.18 (13.37) | **0.00** | 65.45 (37.11) | 58.59 (30.39) | 0.48 |
| Poverty (% < federal poverty line) | 18.54 (15.93) | 36.33 (17.54) | **0.00** | 18.55 (12.60) | 20.57 (12.18) | 0.54 |
| Composite SES index | 0.03 (0.99) | -0.96 (0.81) | **0.00** | 0.00 (1.00) | -0.04 (0.83) | 0.87 |

SES = socioeconomic status, HHD = household

[a] Significance of group differences based on ANOVA; boldface indicates statistical significance at 90% confidence or greater

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