(Mis)Perceiving the Metropolis:
The Correlates and Consequences of Imperfect Neighborhood Knowledge

by

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Dedication

To the members of my family—past and present—who taught me the words to and spirit of the fight song.

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In my first week in Ann Arbor, I found myself walking through the players tunnel of The Big House. Passing under the iconic banner THE TEAM, THE TEAM, THE TEAM, I was overwhelmed by a sense of accomplishment for getting to Michigan and by the work that lay ahead. Now, as I wrap up my studies and move into the next phase of life, my thoughts frequently rest on THE TEAM that got me here, THE TEAM that sustained me, and THE TEAM that will keep me going. Each of them deserves more thanks than I can fit into this space.

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Abstract

Despite calls for greater attention to the symbolic qualities attached to neighborhoods, quantitative urban scholars' standard research methods rarely examine how people make sense of their social environments. Existing scholarship typically emphasizes the effects of objective neighborhood characteristics on individual behavior and outcomes without asking what individuals are responding to or considering the ways in which distorted understandings of place shape the behaviors and preferences underlying neighborhood dynamics. Though emerging research highlights the relevance of cognition and subjectivity in neighborhood assessments and endeavors to develop realistic models of residential decision making, more work explicitly examining the role of perceptions and reputations in shaping residents' understanding of place is needed.

In my dissertation, I contribute to a growing corpus of scholarship on the subjective nature of neighborhood knowledge. Taking seriously the idea that people lack complete information about their social environments, my research explores the ways in which individual and collective understandings of neighborhoods may be at odds with objective neighborhood measures. Using survey data and multi-level models, I explore how three distinct dimensions of respondents' local knowledge reflect, refract, and combine objective measures of neighborhood conditions. Chapter 2 examines perceptions of levels, considering how residents' understandings of the ethnoracial composition of their neighborhood compares to objective measures and varies among neighbors. Chapter 3 examines perceptions to change, considering how residents' perceptions of change in neighborhood safety reflect local crime trends. Chapter 4 considers the nature of neighborhood

reputation and how underlying attributes of individuals and neighborhoods give shape to and are reflected by collective understandings of neighborhood identity.

My results make clear the importance of centering greater sociological inquiry on residents' distorted views of place by demonstrating the incongruence between subjective and objective measures of local environments. Chapter 2 finds that residents' perceptions of neighborhood racial composition are generally at odds with objective measures and that residents who share a neighborhood context perceive the same space very differently. Additionally, I find a consistent, biased pattern of perceptions across ethnoracial identity groups, where respondents in each group inflate the size of their own group compared to other groups in their neighborhood. Chapter 3 similarly illustrates that perceptions of change in neighborhood safety vary considerably among neighbors. Moreover, results suggest that while perceived change in safety is not wholly divorced from crime conditions, residents' perceptions are especially sensitive to one's recent experience as a crime victim and to current neighborhood demographics. Finally, Chapter 4 illustrates the collective nature of neighborhood reputations and the ways in which differently positioned stakeholders and diverse neighborhood attributes combine to give structure to the urban status hierarchy. Specifically, my findings suggest that collective assessments of neighborhood reputation are strongly tied to neighborhood economic markers, suggesting the role of reputation in reproducing and ingraining neighborhood advantage and disadvantage.

Collectively, these studies suggest that important information about how people understand and make decisions in relation to neighborhoods is missed by traditional, objectivist approaches to neighborhood research. By focusing on how people make sense of place through greater attention to and integration of subjective understandings of neighborhoods, there is great potential to improve upon existing models of neighborhood dynamics and residential experience. This dissertation provides a starting point for scholarship that develops a more realistic understanding of the perceptual mechanisms that shape neighborhoods and perpetuate place-based inequalities.

Chapter 1

Introduction

Seventy-five years ago, Firey (1945) broke from the deterministic way many demographers and ecologists typically studied neighborhoods and asserted that prevailing theories of urban dynamics would benefit from greater attention to and understanding of the symbolic and sentimental qualities attached to place. Despite this call, quantitative urban researchers have tended to ignore or defer to ethnographic studies residents' subjective understandings of neighborhoods and the "softer" criteria that structure our lived environments (Molotch, Freudenburg, and Paulsen 2000; Suttles 1984). To date, much research on neighborhood processes continues to view places as reducible to "a cluster of variables"—the commonly measured, objective dimensions of neighborhoods captured in administrative and census data (Gieryn 2000; Sampson 2013). Little attention has been afforded to how people assimilate those variables into mental schemas used to navigate everyday life (Suttles 1972). As a result, within both our theories and our models of neighborhood dynamics, quantitative urban scholars continue to elevate the role of objective understandings of neighborhoods while placing insufficient emphasis on subjective assessments or how people actually make sense of their environments.

Many studies in urban sociology linking social environments and individuals suggest a direct relationship between objective neighborhood characteristics and individual behaviors or outcomes. For example, studies of neighborhood effects seek to measure the influence of neighborhood socio-demographic conditions—typically the degree of poverty or segregation—on a variety of individual outcomes, including educational attainment, criminal involvement, teen sexual activity, and employment (Ellen and Turner 1997; Sampson, Morenoff, and Gannon-Rowley 2002; Sharkey and Faber 2014). Similarly, studies of residential preferences and mobility typically model the probability that an individual chooses a neighborhood based on objective measures of a place's demographic composition, linking the proportion of a racial group in a neighborhood to the likelihood of residential selection (Bruch and Mare 2006; Clark 1992; Krysan 2002a; Schelling 1971). Missing from these studies is consideration of the fact that people lack precise knowledge of their surroundings and that distorted understandings of place—or what we *think* a place is like—play a role in urban life by mediating or moderating the effect of objective conditions.

The notion that individuals lack perfect knowledge of their environments is not novel. Simmel (1903) long ago suggested that dampening our sensitivity to our surroundings might be a feature, not a bug, of human adaptation to the ever-increasing complexity of life in cities. Writing at the turn of the 20th century, he argued that without adapting a detached understanding of urban environments, individuals risk being "swallowed up" by the sheer amount of information and stimuli in our surroundings (Simmel 2014). Similarly, research from psychology has suggested the utility of sensory adaptation—the reduction of awareness to constant stimuli to free up attention and cognitive resources—and the importance of heuristics—strategies that ignore part of the information to draw good-enough conclusions—as critical and efficient cognitive processes in response to dynamic and uncertain environments (Gigerenzer 2008; Gigerenzer and Gaissmaier 2011; Webster 2012). More recently, sociological studies emphasizing the relevance of cognition and subjectivity in neighborhood assessments have endeavored to capture more realistic models of how individuals understand and make decisions about neighborhoods. For example, some research has documented residents' use of heuristics and knowledge biases in the process of residential selection (Bruch and Swait 2019; Krysan and Crowder 2017). Meanwhile, a growing literature on neighborhood reputations—the sentiments and identities collectively ascribed to places—has brought to the foreground the relevance and consequences of neighborhood identity in structuring the urban hierarchy (Brown-Saracino and Parker 2017; Evans and Lee 2020; Permentier, van Ham, and Bolt 2007; Zelner 2015). Taken together, these studies emphasize the need for scholarship on neighborhood dynamics shaped less in response to simple objective measures than by reaction to residents' complex, socially embedded, and ever-adapting understandings of place.

To that end, my dissertation endeavors to build on this movement towards the articulation of more realistic measures and models of neighborhoods. Taking seriously the idea that people lack complete information about their social environments, the three empirical chapters explore the ways in which individual and collective understandings of neighborhoods may be at odds with typical measures of social environments. Each chapter focuses on a distinct dimension of neighborhood knowledge and how residents' subjective assessments reflect, refract, and combine objective measures of neighborhood conditions. Chapter 2 examines perceptions of current neighborhood demographics, considering how residents' understandings of who their neighbors are compares to objective measures of neighborhood composition and to the perceptions of other residents in the same neighborhood. Chapter 3 considers how residents make sense of change in neighborhood conditions, documenting the relationship between residents' perceptions of change in neighborhood safety and local crime trends. Chapter 4 considers the nature of neighborhood reputation and how underlying attributes of individuals and neighborhoods give shape to and are reflected by collective understandings of neighborhood identity. By scrutinizing the links between objective neighborhood conditions and subjective neighborhood knowledge, a goal of my dissertation is to advance the argument that the pictures individuals hold in their heads—and the distortions inherent to those pictures—function as a key but underappreciated mechanism shaping neighborhood dynamics.

Why Emphasize Subjectivity?

What is gained by focusing on subjective assessments of neighborhoods? I argue that bringing greater scholarly attention to the stylized ways people understand the world around them is relevant to social science researchers and policymakers for a few reasons. First, better accounting for how people make sense of their environments is important because how one interprets the world around them shapes their behavior. As the Thomas Theorem states, "the subject's view of the situation, how he regards it, may be the most important element for interpretation…*if men define situations as real, they are real in their consequences*" (Thomas and Thomas 1928:572). That is, people react to the world as they understand it, even if that understanding bears only passing resemblance to "reality." Thus, failure to acknowledge the subjective nature of individual experience of neighborhoods limits our ability to really understand the motivations and actions of individuals.

This leads directly to a second reason why greater focus on imperfect neighborhood knowledge is important: it holds the potential to correct errors in existing models of neighborhood dynamics. Urban scholarship often assumes a direct relationship between objective measures of neighborhood conditions and residential processes. As I describe in greater detail in Chapters 2 and 3, models of residential mobility and White flight generally imply that individuals choose neighborhoods by drawing, in part, on their knowledge of neighborhood conditions and how those conditions have changed (Crowder 2000; Schelling 1971). However, few studies attempt to measure individual awareness of these aspects of neighborhoods—what I call the first link in the causal chain of residential decision making. Thus, it is unknown the extent to which resulting patterns of residential segregation are the product of deliberate response to real conditions or reflect responses to embellished understandings of local environments. Teasing out the role of subjective assessments of place may thus enable the refinement of models of residential processes and help explain, for example, why people often live in neighborhoods more segregated than their stated preferences (Havekes, Bader, and Krysan 2016).

Finally, greater attentiveness to subjective assessments of neighborhoods—and the gap between subjective and objective measures—might reveal bias in objective data. Administrative data are often treated by scholars and policymakers as though they capture valid, unbiased measurement of real conditions. However, research has documented the ways in which official metrics of neighborhood conditions might be less impartial than is often implied. For example, in tracing the evolution of official racial categories in the United States, Snipp (2003) observed that government measures of racial composition are constructs of the state and are highly politicized and inconsistent across time. Moreover, assessments of survey data have shown that individual identity itself is malleable (Penner and Saperstein 2008). Similarly, crime scholars have acknowledged that official statistics may underreport the nature of crime in some places because not all crime is reported, not all violations of law are viewed equally in all contexts, and there are incentives at different points in the criminal justice process that incentivize shifting the nature, number and severity of crime reports (Buil-Gil, Moretti, and Langton 2021; Skogan 1974). Thus, a strength of subjective data might be that it contains real conditions of place that are missing from official data sources. While I do not explore this possibility in depth, a benefit of studies that integrate subjective and objective data might be reining in bias from each data source.

A Semantic Note on Perceptions and Reputation

In exploring the nature of individuals' imperfect knowledge, the chapters of this dissertation focus on *perceptions* of neighborhood characteristics on the one hand and assessments of *reputation* on the other. Because these chapters are freestanding empirical inquiries, it is useful here to briefly review how I distinguish between perceptions and reputation and why I consider them distinct dimensions of neighborhood knowledge.

As described above, a central goal of these empirical studies is to examine whether and how individuals' subjective assessments relate to objective measures of neighborhoods conditions. Thus, these studies are first and foremost exercises in measurement. Measuring the subjective ways people think about their surroundings is an admittedly difficult task, another reason perhaps why researchers have shied away from such endeavors. In my effort to triangulate the subjective nature of neighborhood knowledge I take two approaches. My first approach is to measure residential perceptions, by which I mean individuals' discrete evaluations of a specific dimension of neighborhood conditions. This way of thinking about perception borrows heavily from psychology, where perception is a subfield concerned with individuals' sensory experience of the world. The psychological study of perception explores how individuals recognize and interpret sensory stimuli—sights, sounds, smells, etc.—as they take in and make sense of their surroundings. For example, classic studies of perception have examined individuals' ability to detect changes in volume and to separate signals from visual noise. Much as these sensory studies test for acuity and recognition of a stimuli in response to levels and change in inputs, my chapters on residential perceptions examine respondents' assessments of level and change in a particular dimension of their environment with objective measures. Specifically, in Chapter 2, I focus on how residents perceive levels of neighborhood racial composition. Chapter 3 examines how residents perceive change, with a focus on change in neighborhood safety.

By contrast, my study of reputation considers the subjective nature of neighborhood knowledge from a very different perspective. Rather than focus on how respondents make sense of a single dimension of their surroundings, my study of reputation instead can be thought of as a dissection of residents' collective mental schemas—a cognitive mechanism or knowledge structure used to organize and interpret an array of information (Boutyline and Soter 2021). As I expand upon in Chapter 4, neighborhood reputations are generally understood by scholars as the collective, symbolic representation of a place encapsulating a wide array of local attributes that may bear only passing resemblance to any given objective measure (Kaliner 2014; Parker 2019). Thus, rather than testing for acuity, this chapter takes a more relational and interpretive approach to understanding how reputation reflects objective measures of place.

The distinction between these concepts may be further elucidated through a few simple comparisons. First, perceptions are best measured at the individual level whereas reputations are produced collectively and thus are better measured at the group level. This means that while a person can hold a perception of a place, they cannot alone give rise to a place's reputation. Second, perceptions examine a single dimension of a neighborhood—like racial composition—whereas reputations focus on amalgamations of neighborhood characteristics. And finally, perceptions as I conceive of them relate to the understanding of facts whereas reputations reflect collective judgements. In measuring perceptions, one can capture the distance between a perceived and an observed dimension of a neighborhood, while reputations by their nature cannot be so discretely measured. Thus, while both perceptions and reputations may be detached from the objective ways we assess neighborhoods, I think of perceptions as reflecting the gap between individual assessments of a dimension of a neighborhood and its objective measurement whereas reputations offer more symbolic and holistic portrayals of place.

Conclusion and Chapter Summaries

To summarize, though some researchers have acknowledged that "place narratives are never filled with complete, unadulterated facts" (Borer 2006:186), urban scholars—especially quantitative scholars—have generally focused on the role of objective neighborhood measures in shaping urban life. Little attention has been afforded to the subjective or distorted ways individuals understand the world around them, meaning our models of neighborhood processes and policies that seek to drive neighborhood change draw on data that at best reveal partial truths about urban dynamics. In this dissertation, I extend a growing body of research that demonstrates the biased nature of neighborhood knowledge. In three empirical chapters, I endeavor to measure distinct dimensions of neighborhood knowledge. Below I briefly summarize those studies and their findings.

Chapter 2 offers a first exploration of the nature of residents' subjective assessments of place and neighborhood knowledge biases. Building on findings that demographic misperceptions are widespread at larger geographic scales (Alba, Rumbaut, and Marotz 2005; Kunovich 2017; Nadeau, Niemi, and Levine 1993; Wong 2007), the study uses multilevel models to examine the prevalence and pattern of residents' distorted perceptions of their neighborhood's ethnoracial composition. Leveraging unique data from an online survey developed to capture differences in neighborhood knowledge among residents of Los Angeles, Chicago, and Washington, D.C., I examine how residents' perceptions of their own neighborhood composition compare to both objective measures of neighborhood composition and to perceptions of other residents in the same neighborhood. I also examine if there are systematic variations in residents' perceptions of neighborhood composition, particularly among residents of different ethnoracial identities. My findings show that residents' perceptions are generally at odds with objective measures and that a significant degree of variation in neighborhood perception lies within neighborhoods, meaning residents who share a neighborhood context perceive the same objective space very differently. Moreover, I find a consistent, biased pattern to local perceptions across ethnoracial identity groups where respondents in each ethnoracial group inflate the size of their own group compared to other groups in their neighborhood, even when controlling for respondents' individual attributes and for census measures of neighborhood composition. These findings not only illustrate the imperfect nature of neighborhood knowledge, but they also suggest that distorted perspectives may serve a purpose by emphasizing one's compatibility with their surroundings and the idea that individuals live in neighborhoods inhabited primarily by others like themselves.

Chapter 3 extends my exploration of perceptions to change in neighborhood conditions. Motivated by the puzzle that despite historic drops in crime in recent decades public opinion polls show perceptions of local and national crime are increasing, I explore how residents' perceptions of change in neighborhood safety relate to objective crime trends. Using the city of Detroit as a case study, I interrogate residents' sensitivity to changing environments and the extent to which objective levels and changes in neighborhood crime conditions, respondent characteristics, and broader neighborhood conditions predict residents' perceptions of change in safety over the previous five-years. My findings highlight the highly subjective nature of perceptions of change. Echoing scholarship on present-time perceptions of safety, I show that while perceived change in safety is not wholly divorced from levels and change in crime it is especially sensitive to one's recent experience as a victim of crime and to the current demographic makeup of one's neighborhood. After accounting for these individual and neighborhood characteristics, crime and change in crime do not significantly affect how residents perceive safety to have changed. These findings point to the influence of recency bias when assessing neighborhood change. Moreover, they suggest that perceptions of safety, and change in safety, are driven by more than crime conditions. Ultimately, my findings advance the argument that while theories and public policy priorities emphasize the salience of change for neighborhood dynamics, individuals themselves may be poor judges of change in social environments.

Chapter 4 shifts its focus to neighborhood reputation. While a growing body of literature focused on place reputation has emerged in recent years (Brown-Saracino and Parker 2017; Evans and Lee 2020; Parker 2018b; Permentier et al. 2007), most of this scholarship has focused on the utility and consequences of place reputations. By comparison, few studies consider the ways in which reputations combine, reflect, and refract neighborhood characteristics. Drawing on data from the same survey used in Chapter 2, I take an ecometric approach to examine how the underlying attributes of individuals and neighborhoods in Los Angeles, Chicago, and Washington, D.C. give shape to and are reflected by collective understandings of neighborhood reputation among city residents. My results offer strong evidence of internal consistency around reputational assessments, suggesting that reputations are indeed the product of collective judgements. Additionally, my results show that while both demographic composition and the built environment influence judgements of reputation, neighborhood demographic composition—especially socio-economic status—is most strongly associated with how the public assesses neighborhoods and their place on the urban status hierarchy. This emphasis on economic markers is true whether one is judging their own neighborhood or other neighborhoods across the city. My findings point to the role place reputations likely play in the reproduction of neighborhood status, suggesting that reputations function more as a mechanism to ingrain differences between neighborhoods than as a tool for urban regeneration and evolution.

These studies mark the beginning of a broader research agenda that endeavors to better integrate individuals' subjective understandings of neighborhoods with traditional objectivist approaches to measuring and modeling neighborhood dynamics. Ultimately, my goal is to study how residents' incomplete information and measurable conditions mutually produce, reinforce, reshape, and perpetuate urban environments. To that end, this dissertation offers a first step towards that goal by documenting the nature of imperfect knowledge. It is my hope that by taking seriously the ways in which people make sense of their environments this work will lay the foundation for future research that can better answer fundamental questions about the mechanisms shaping processes of neighborhood choice and neighborhood change.

Chapter 2

(Mis)Perceiving the Metropolis:
Residents' Distorted Assessments of Neighborhood Racial Composition

Within neighborhood research, theories of neighborhood change and residential choice processes have generally implied that, when it comes to evaluating and choosing neighborhoods, individuals are reasonable judges of their social environments and possess sufficient knowledge to make informed decisions. In recent years, however, social scientists interested in neighborhood dynamics have emphasized the importance of developing more realistic models of how individuals understand and make decisions about their surroundings (Bruch and Swait 2019; Krysan and Crowder 2017). One dimension these models seek to address is the prevalence of neighborhood knowledge bias: the limited or distorted ways we understand the environments in which we live. In contrast to classic theories of residential behavior—which invoke a rational actor framework to imply individuals have complete and accurate information about their residential options—a growing body of research illustrates the limited or imperfect nature of neighborhood knowledge (DeLuca and Jang-Trettien 2020; Krysan, Crowder, and Bader 2014).

While most research critiquing assumptions of perfect neighborhood knowledge explores the prevalence of community blind spots and *if* a place is known (Krysan and Bader 2009), less focus has been given to *what* individuals know about that place. Though a core tenet of the literature on residential segregation contends that people evaluate and select neighborhoods in part based on demographic composition (Charles 2003; Clark 1992), few studies explicitly ask residents to enumerate their perceptions of neighborhood composition and examine how those perceptions reflect reality. Fewer still seek to quantify how residents' perceptions vary by ethnoracial[1] identity or within and between neighborhoods. As a result, we lack evidence of the extent to which individuals hold distorted views about their neighborhood environments and how these distortions might influence individual behavior in ways that shape neighborhood processes.

This article addresses this gap in our understanding of neighborhood knowledge biases by examining residents' perceptions of their neighborhood's ethnoracial composition. Building on findings that demographic misperceptions are widespread at larger geographic scales (Alba et al. 2005; Kunovich 2017; Nadeau et al. 1993; Wong 2007), I explore individuals' neighborhood perceptions using unique data I collected from an online survey of residents of Los Angeles, Chicago, and Washington, D.C. First, I examine how residents' perceptions of their own neighborhood composition compare to both objective measures of neighborhood composition and to perceptions of other residents in the same neighborhood. Second, I examine if there are systematic variations in residents' perceptions of neighborhood composition, particularly among residents of different ethnoracial identities. My findings show that residents' perceptions are generally at odds with objective measures and that a significant degree of variation in neighborhood perception lies within neighborhoods, meaning residents who share a neighborhood context perceive the same objective space very differently. Moreover, I find a consistent, biased pattern to local perceptions across ethnoracial identity groups. Results from descriptive analyses and multilevel models show respondents in each ethnoracial group inflate the size of their own group compared to other groups in their neighborhood, even when controlling for respondents'

[1] Throughout this article, I use the term *ethnoracial* to reflect that my study examines perceptions of both racial and ethnic demographic categories. This follows prior literature including Telles (2018) and Schachter et al (2021).

individual attributes and for census measures of neighborhood composition. These findings not only document that individuals possess imperfect knowledge of their neighborhood environments, but they also suggest that these distorted perspectives may function to emphasize one's compatibility with their surroundings and the idea that individuals live in neighborhoods inhabited primarily by others like themselves.

This study of neighborhood perceptions makes a number of contributions to the sociological literature. First, it explicitly extends the study of demographic perception to the neighborhood level, considering perceptual variation within and between neighborhoods as well as perceptions of and among white, Black, Latino, and Asian residents. Second, it demonstrates the utility of online survey instruments to collect and quantify data on neighborhood perceptions from a large sample of respondents. Finally, this article builds on efforts to develop more realistic—or cognitively plausible—models of residential processes by documenting the prevalence and pattern of biased neighborhood knowledge. Many existing quantitative studies of neighborhood dynamics (e.g., locational attainment models and discrete choice models) imply through their use of census measures that residential choices are driven by accurate assessments of neighborhood conditions and that residents in a neighborhood will have a shared understanding of their surroundings (Logan et al. 1996; Quillian 2015). The empirical evidence of biased neighborhood knowledge presented here challenges the utility of those assumptions. By highlighting the distorted and varied nature of neighborhood perceptions, this study encourages future research to incorporate perceptual bias into models of residential selection and mobility, prompting the development of more realistic theories and models of urban processes.

Background

Challenging the Assumption of Perfect Neighborhood Knowledge

Sociologists generally recognize that the rational actor framework—which assumes individuals possess perfect information, consider all available options, and make voluntary decisions—presents an unrealistic depiction of individual behavior (Bruch and Feinberg 2017). Despite acknowledging its limits, core ideas of this framework have often been incorporated into the study of neighborhood processes, especially quantitative models of neighborhood selection. To develop more realistic understandings of selection and resulting patterns of inequality, recent work has taken aim at exposing or dismantling some of the assumptions included in these models. For example, Krysan and Bader (2009) show that rather than know about every neighborhood in a metro area, individuals' neighborhood knowledge is fragmented along ethnoracial lines such that individuals report significantly more awareness of neighborhoods in which their own group has a larger demographic presence and little awareness of areas inhabited predominantly by other groups. Bruch and Swait (2019) further critique the assumption that individuals give neighborhoods equal consideration by showing their model of sequential decision making and selective consideration fits data on observed residential mobility better than conventional models. Additionally, in contrast to assumptions about the voluntary nature of residential decisions, DeLuca and colleagues (2020; 2019; 2012) demonstrate that, particularly for low-income households, choosing where to live is often reactive rather than deliberative. While these critiques target assumptions about whether and how people know of, consider, and make choices about neighborhoods, to date less research has taken to task the notion that individuals possess accurate and complete information about neighborhood characteristics (for exceptions see Krysan and Crowder 2017; Quillian and Pager 2001; Sampson and Raudenbush 2004).

On its face, it is farfetched to assume that humans are omniscient observers of their social environments. However, the notion that people know the characteristics of neighborhoods well enough to evaluate and select where to live based on demographic composition is essential to sociological theories of residential segregation (Crowder and Krysan 2016). Specifically, the theory of racial residential preference contends that observed patterns of neighborhood stratification result, in part, from ethnoracial preferences to live among own group neighbors (Charles 2006; Clark 2002; Krysan 2002b; Krysan et al. 2009; Lewis, Emerson, and Klineberg 2011). Research in this area suggests that residents' knowledge of and preference for specific neighborhood racial compositions interact, leading whites, Blacks, Latinos, and Asians to choose homes in areas populated by their own group and to avoid areas populated by other groups. This presupposes that individuals possess sufficient, correct information on neighborhood demographics and can choose their preferred neighborhoods based on that information.

Although this presumption of neighborhood knowledge is central to the theory of racial residential preference, it generally goes untested. In fact, most studies of residential preference don't ask respondents about the composition of a neighborhood but instead dictate the composition and ask if it aligns with individual preference. For example, the traditional Farley-Schuman showcard method uses simple cards to illustrate the demographic composition of hypothetical neighborhoods and then asks respondents how they would feel living in such a place (Bobo and Zubrinsky 1996; Charles 2000; Farley et al. 1978; Krysan 2002b). Similarly, factorial experiments using vignettes to tease apart residential preferences by class and race generally specify the racial composition of a neighborhood (e.g. "the neighborhood is 20% Latino") before asking a respondent if they would choose to live there (Emerson, Chai, and Yancey 2001; Shlay and DiGregorio 1985; St. John and Bates 1990). Even simulation models designed to demonstrate how residential preferences translate into sustained patterns of segregation take as a core assumption that complete and accurate knowledge of neighborhood demographics motivates decision making (Bruch and Mare 2006; Schelling 1971). Thus, because by design these methods assume or ensure residents possess full knowledge of local racial composition, existing research generally leaves little room to consider the prevalence and effect of distorted perceptions or imperfect neighborhood knowledge.

Previous Research on Perceptions of Social Environments

There is good reason to think residents would have distorted understandings of the content and characteristics of their neighborhoods. Research suggests individuals are poor judges of their broader environments. When asked to estimate the size of demographic groups nationally, respondents tend to greatly *over*estimate the size of racial, ethnic, and religious minority populations and *under*estimate the size of majority groups (Alba et al. 2005; Nadeau et al. 1993; Sigelman and Niemi 2001; Wong 2007). For example, a 1990 Gallup poll found the average American thought the nation was 32 percent Black, 21 percent Latino, and 18 percent Jewish, perceptions that inflated the demographic composition of each group by between 2.5 and 7 times their true size (Nadeau et al. 1993). More recent research on perceptions of national composition finds similarly outsized assessments of majority and minority populations, leading scholars to comment that a sizable percentage of Americans believed in 2000 whites were already the numeric minority in the U.S., a demographic event not projected to occur until the mid-2040s or later (Alba et al. 2005; Gallagher 2003).

These demographic misperceptions are not unique to Americans or to perceptions of race and ethnicity.[2] People around the world overstate the size and composition of immigrant populations (Blinder 2015; Gorodzeisky and Semyonov 2020; Herda 2010, 2015). Misperceptions are also common in estimations of other dimensions of social status: we tend to overestimate the share of the population that is gay, the share of the population that is unemployed, and the share of the population living in poverty or receiving welfare (Kuklinski et al. 2000; Kunovich 2012; Lawrence and Sides 2014; Martinez, Wald, and Craig 2008).

While past research reveals the pervasive nature of people's distorted views of *national* composition, considerably less attention has been paid to demographic perceptions of local environments. The few studies that examine demographic estimates at smaller scales generally focus on meso-level geographies—capturing perceptions of county or town composition—rather than neighborhoods (Alba et al. 2005; Hidalgo et al. 2015; Kunovich 2017; Wong 2007).[3] Irrespective of their scale, these studies suggest that though individuals' perceptions are less distorted when estimating the composition of local versus national populations, people still have biased understandings of their own environment. These biases follow the same general pattern as perceptions of national composition: overstating the size of minority groups and understating the size of the majority. These studies also suggest as the meaning of majority and minority group position varies by geographic scale, so too do perceptions. For example, in contexts where the population is predominantly white, studies have found both white and Black residents tend to

[2] Some scholars have referred to inaccurate estimates of demographic group size as innumeracy. However, Alba et al (2005) contend "innumeracy" confounds two distinct mechanisms: one involving the perception of group size; the other, the ability to translate a perception into numerical terms. Though innumeracy is widely used in the literature on perception of composition, I follow Alba and avoid the term.

[3] There are two notable exceptions where papers examine perceptions at a more local scale. In one, Wong et al (2012) consider perceptions of composition as a secondary focus of their examination of differences between respondent-drawn neighborhood boundaries and administrative units. The other, (Laméris, Kraaykamp, et al. 2018) focuses on Dutch natives estimations of the size of the ethnic minority population in their neighborhoods in the Netherlands.

overestimate the percentage of Black residents and underestimate that of whites (Hidalgo et al. 2015; Wong et al. 2012). But when examining perceptions of group size in a majority-Latino county, Kunovich (2017) finds residents underestimate the size of the largest group (Latinos) but overestimate the size of the Black and Asian minority populations. These findings raise the question of whether neighborhood perceptions follow a similar pattern of perceptual bias or whether residents' views of their communities—where legacies of segregation mean local populations may differ substantially from those of the nation or even of the broader city—reveal a unique pattern of perceived demographic composition.

The lack of existing research on residents' perceptions of neighborhood composition does not mean scholars of neighborhood dynamics are naïve to the idea that residents hold distorted views of their local environments. Despite the limited direct evidence of skewed demographic perceptions at the neighborhood level, a wealth of indirect evidence exists of neighborhood knowledge biases including many instances in which people conflate two or more neighborhood attributes. This pattern is clearest in research examining how racial composition is used to make broad inferences about neighborhood conditions and quality (Krysan 2002b; Krysan and Crowder 2017). For example, asked to rate attributes of a fictive neighborhood based on video vignettes that vary residents' race, Krysan, Farley, and Couper (2008) find respondents use visual cues of racial composition to form strong perspectives about other aspects of the community. In their experiment, white respondents whose video showed only white residents judged that neighborhood to have significantly higher and appreciating home prices, less crime, and better schools than did whites who saw the identical neighborhood with Black residents. Related research has shown that perceptions of neighborhood price and desirability are often similarly judged through the lens of race (Bader and Krysan 2015; Charles 2002; Krysan and Bader 2007). Scholarship on perceptions of crime and disorder further provides evidence of the biased ways in which individuals view neighborhoods. These studies consistently find that, regardless of objective measures of crime and blight, neighborhoods with larger minority populations are perceived to be more dangerous and disorderly than white neighborhoods (Quillian and Pager 2001; Sampson and Raudenbush 2004). Taken together, this research suggests demographics are commonly substituted for other neighborhood characteristics. However, studies focused on these types of neighborhood perceptions generally do not consider the ways in which neighborhood demographics themselves might be distorted in the minds of residents and how these distortions contribute to and reinforce the stigmatization of communities.

Consequences of Distorted Perceptions

Understanding the prevalence and pattern of imperfect neighborhood knowledge is important for several reasons. First, documenting distorted perceptions of neighborhood racial composition can correct the dubious assumption that individuals possess perfect information of neighborhood characteristics. Just as neighborhood blind spots have been theorized to influence segregation by limiting where people can choose to live—because you can't choose a neighborhood you don't know (Krysan and Bader 2009)—holding distorted views of neighborhood composition may shape residential processes by incorrectly influencing whether and where individuals choose to move. If people make residential decisions based on neighborhood composition (Charles 2006; Clark 1992, 2002; Krysan 2002b), then distorted perceptions of composition might lead housing searchers to overlook neighborhoods that fit their tastes and pursue neighborhoods at odds with their preferred degree of diversity (see also Wong 2014). Moreover, if distorted neighborhood perceptions vary by ethnoracial identity—that is, if different groups perceive composition differently—this might further explain how underlying differences in neighborhood information can ingrain patterns of segregation (Krysan and Crowder 2017).

Beyond shaping residential processes, distorted views of neighborhood composition may influence other important dimensions of communal life. At the national level, inaccurate views of group size have been associated with racist or xenophobic attitudes and policy preferences. Research shows people with inflated perceptions of the size of non-white populations are more likely to oppose policy programs like affirmative action and the provision of welfare benefits (Alba et al. 2005; Gilens 1999). Similarly, those who inflate the scale of foreign-born populations are more likely to hold negative attitudes toward immigration and favor rescinding immigrants' rights (Herda 2010; Semyonov, Raijman, and Gorodzeisky 2008).[4] In fact, evidence suggests distorted perceptions of group size are more influential than actual group size. Pottie-Sherman and Wilkes' (2017) meta-analysis of 55 studies concluded that perceived size of an outgroup, rather than its actual size, exerts the biggest and most consistent effect on attitudes and policy perspectives. Perceptions are not only influential in shaping attitudes and preferences, but they are also enduring. Studies that seek to address biased views by providing respondents with correct information find possessing objective data does little to reshape attitudes (Hopkins, Sides, and Citrin 2018; Lawrence and Sides 2014). Together, this suggests that what we think about our social environments, regardless of their actual characteristics, has an impactful and lasting effect on attitudes and policies.

Some evidence already suggests that distorted perceptions are similarly influential in shaping dynamics of neighborhoods, based on a small number of studies that use perception of

[4] Studies on the connection between perception and attitudes have been careful to observe that the relationship between these variables go both ways. Researchers acknowledge the causal relationship between these factors are thus difficult to tease out and likely are mutually reinforcing.

local demographics as an explanatory variable for social processes. For example, studies find outsized perceptions of local ethnic diversity are associated with lower or declining neighborhood social cohesion, a relationship that holds even when controlling for objective demographics (Koopmans and Schaeffer 2016; Laméris, Hipp, and Tolsma 2018). Others have found perceptions of local disorder, crime, and fear of victimization are driven more by residents' overestimates of the presence of minorities in their neighborhood than by the actual ethnoracial composition (Chiricos, Hogan, and Gertz 1997; Wickes et al. 2013). This research suggests embellished understandings of the racial composition of one's local environment may amplify explicit and implicit bias in ways that could reinforce neighborhood disadvantage and disinvestment.

Explaining Misperception

What might drive individuals to misjudge their environment? While some point to simple, individual level prejudice (Allport 1954), most studies that observe demographic misperceptions draw on competition-based arguments grounded in group position theory. Group position theory argues that thoughts and actions that appear prejudicial are not necessarily a product of individual bias but instead arise from relational processes whereby groups struggle to define and defend their relative position in the hierarchical, racialized order and claim areas of privilege associated with that order (Blumer 1958; Bobo 1999). This competition manifests in inequalities and ideology based on subjective understandings of a group's status vis-à-vis other groups (Bobo and Hutchings 1996). Existing research on demographic perceptions has generally used this line of reasoning to explain inflated perceptions of minority populations, suggesting overestimates of the size of these groups are embellishments reflective of the perceived threat minorities pose to the majority (Alba et al. 2005; Deener 2010; Gallagher 2003; Herda 2010; Kunovich 2017). However, an alternative application of group position theory might instead suggest the opposite: group members will exaggerate the perceived size of their own group in an effort to assert or justify their status position and claim associated privileges (see for example Abascal 2020). These contradicting applications of group position theory raise questions about how distorted perceptions might function at different geographic scales. Because the meaning of majority and minority status depends on context—a group might be in the local majority but in the national minority—dynamics of intergroup-competition may play out differently for perceptions of neighborhoods compared to broader areas. At present, it is unknown how varying, circumstantial understandings of positionality, dominance, and threat might shape perceptions of neighborhood group size.

Another theory that might explain demographic misperception draws on psychological studies of social cognition, which suggest perceptions express one's underlying goals, motives, and needs (Fiske 1993). Focusing primarily on the nature of dyadic relationships and interpersonal interactions (e.g., individuals' perceptions of someone's personality or motives), social cognition researchers argue that, rather than aiming for accuracy, perceptions serve an instrumental purpose and depict the world just accurately enough to serve one's needs. For example, a person who is highly motivated to find a long-term partner may perceive their first date more positively than a casual dater. To borrow from Swann (1984:461), "The accuracy of social beliefs is therefore determined by how well they serve the goals of perceivers rather than by the extent to which they are accurate in an ultimate sense." Extending this idea of instrumental perceptions to broader social environments, one could imagine distorted neighborhood perceptions similarly function in service of an individual's underlying motives. For example, perceptions that amplify the size of one's own group might enhance one's sense of connectedness to their neighborhood. Conversely, perceptions that overstate the size of other groups might be employed subconsciously to eliminate a neighborhood as a potential residential option.

Residents' Assessments of Neighborhood Racial Composition

In sum, though limited research to date has explicitly interrogated the assumption that individuals possess complete information about neighborhood demographics, existing research finds biased demographic perceptions at the macro- and meso-levels are widespread, consequential, and persistent. Evidence of neighborhood blind spots and individuals' tendency to conflate neighborhood attributes, as well as the emphasis of past research on the role of racial residential preference in shaping residential patterns, suggests distorted perceptions of neighborhood composition might similarly be prevalent and consequential. Thus, a first goal of this study is to examine individuals' perceptions of neighborhood composition. Specifically, I interrogate both how individuals' neighborhood knowledge compares to objective conditions and the extent to which residents in the same neighborhood hold similar or diverging views of their shared environments. Given that related research suggests imperfect neighborhood knowledge may vary by ethnoracial identity (Krysan and Bader 2009; Krysan and Crowder 2017), a second goal is to examine if there are systematic variations in residents' perceptions of neighborhood composition. My analyses explore if the nature of neighborhood perception is consistent across groups being perceived as well as across respondents, with particular focus on if perceptions differ depending on whether a respondent is assessing the size of their own group or other ethnoracial groups.

Data and Methods

To examine residents' perceptions of their neighborhood's ethnoracial composition, I designed and fielded an online survey that captures differences in neighborhood knowledge among residents of Los Angeles, Washington, D.C., and Chicago.[5, 6] The data were collected between January and April 2018 via Qualtrics, an online survey platform. In addition to hosting the survey, Qualtrics was contracted to recruit survey participants from an existing online research pool using quotas for gender parity and city-specific, proportionally representative quotas for respondent racial/ethnic identity based on 2016 American Community Survey (ACS) estimates.[7] Survey responses were captured only if a respondent lived in the relevant city, reported being 18 years or older, and was either a native English speaker or self-reported proficient fluency in English. In total, the survey collected 1,766 responses (Los Angeles N = 734; Chicago N = 552; D.C. N = 480).

Collecting data on neighborhood perceptions benefits from first defining the respondents' neighborhood. Rather than rely on census tracts, which research suggests are generally not meaningful to residents (Wong et al. 2012), the survey instrument asked respondents to select their neighborhood of residence using a city-specific map tool that included a discrete number of large, identifiable neighborhoods with clearly delineated names, boundaries, and spatial configurations.

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[5] Funding for this survey was provided by the Population Studies Center and the Center for Local State and Urban Policy at the University of Michigan. Prior to fielding the survey, I received approval from the Health Sciences and Behavioral Sciences Institutional Review Board at the University of Michigan (HUM00139059).

[6] For this survey, Los Angeles was defined as the City of Los Angeles and not Los Angeles County. The three cities were selected for their geographic diversity, relevance to urban research, and for the pervasiveness of named neighborhoods. For more on survey development, see Appendix A and Wileden (2019).

[7] Though efforts were made to ensure respondent demographics were representative of the population of each city, the data are drawn from a nonprobability sample and thus should be viewed cautiously in terms of their representativeness. For more on the utility and data quality of online surveying, see Goel, Obeng, and Rothschild (n.d).; Heen, Lieberman, and Miethe (2014).

The map tool was developed to include neighborhood areas widely identifiable and meaningful to the general public, drawing on municipal maps of neighborhood boundaries, other reputable place-mapping projects (such as the Mapping LA project by the Los Angeles Times), and neighborhood names and boundaries used on place-based amenity websites like Zillow, OpenTable, and Airbnb.[8] In total, survey participants could select their neighborhood of residence from 83 neighborhoods in Los Angeles, 83 neighborhoods in Chicago, and 72 neighborhoods in Washington, D.C. The resulting data is multilevel, with 1,766 respondents clustered in 230 neighborhoods.[9]

After identifying their neighborhood of residence, respondents answered a series of in-depth questions about their neighborhood, including perceptions of racial composition. This approach of combining pre-defined neighborhood maps with detailed questions on neighborhood perceptions offers a number of potential improvements upon related surveys of demographic perceptions.[10] First, using maps with identifiable neighborhoods to ask about perceptions creates more targeted, digestible data than similar surveys that interrogate local perceptions by asking only about larger geographies (e.g. counties or towns) or about perceptions of an undefined "local community" (Alba et al. 2005; Hidalgo et al. 2015; Kunovich 2017; Wong 2007). Second, presenting maps that feature explicitly defined, recognizable neighborhoods and neighborhood names provides respondents with heuristics that encourage them to tap into their lived experience, mental schemas, and associations with specific places. Third, priming responses using maps that specify community boundaries encourages respondents to limit their perceptions, to the best of

[8] See Appendix A for greater detail on survey design.

[9] Though respondents were not recruited to explicitly produce geographic distribution, the resulting sample included residents of 230 of the 238 possible neighborhoods. The average number of respondents per neighborhood in the data is 7.68 with a min of 1 and a max of 45.

[10] For a similar approach, see Bader and Krysan 2015; Krysan and Bader 2007, 2009.

their ability, to a defined space and increases the face-validity of comparisons between respondents within a given neighborhood who should be holding the same general geography in mind. Finally, defining the geography of each neighborhood makes it possible to more clearly compare perceptions to secondary data measuring local conditions.

In addition to area of residence and neighborhood perceptions, I also draw on survey respondents' self-reported socio-demographic characteristics and 2014-2018 American Community Survey 5-year estimates of neighborhood conditions. To enable comparisons between respondent perceptions and objective neighborhood conditions, tract level ACS data were conformed with neighborhood boundaries using proportional weights.[11] Table 2.1 summarizes descriptive statistics for dependent and independent variables used in my analyses.

[TABLE 2.1 ABOUT HERE]

Dependent Variables

In keeping with related literature on demographic perception, I focus on respondents' perceived group size as my outcome variable.[12] Respondents' perceptions of group size in their neighborhood was captured by a survey item that asked, "Using the below slider scales, which range from 0 to 100 percent, please offer your best estimate of the percent of each racial or ethnic

[11] I use ArcGIS to allocate counts of people and households from census tracts to neighborhoods, using weights based on the proportional overlap in area between the two geographies. In proportionally allocating census data to neighborhoods, it is assumed that the population is equally distributed across a census tract.

[12] Appendix B presents sensitivity analyses testing alternate measures of the dependent variable. Within the literature on demographic perception, demographic perceptions are often assessed in three ways: (1) through a measure of the actual size of the population (the approach I take here), (2) as the difference between estimated size and real size of a population, and (3) categorically through the assignment of respondents to groups of under-, over-, and accurate estimators. (See Gorodzeisky and Semyonov 2020 for thorough discussion of the tradeoffs of these approaches.)

group living in your neighborhood."[13] Respondents used separate sliders to estimate the percent of white, Black or African American, Hispanic or Latino, Asian, and other race residents.[14] The total across all groups was constrained in the instrument to sum to 100 percent to avoid unrealistic estimates. Following recent research on racial appraisals that supports the use of single-category measures of ethnoracial identity (Croll and Gerteis 2019; Telles 2018), I interpret these demographic categories to be mutually exclusive such that the response for white means the percent non-Hispanic white within a neighborhood, the response for Black means the percent non-Hispanic Black within a neighborhood, etc.

Independent Variables

My focal independent variables are respondent ethnoracial identity and objective measures of neighborhood racial composition from the ACS. Respondent identity is based on survey data asking, "Which one or more of the following describe your race or ethnicity?" Response options included white, Black or African American, Hispanic or Latino, Asian, and other. Respondents were invited to select all that apply. Similar to Croll and Gerteis (2019), I find that despite the option to self-identify with one or multiple identity groups, 97 percent of respondents categorized themselves using a single identifier. This single-identity classification is true even among Latinos, who may be more likely to specify both a racial and ethnic identity thanks to standards set by the Census. Given this tendency towards single-identity classification, I code respondents into binary

[13] This question was developed based on the 2000 General Social Survey Multiethnic United States module that asked "Just your best guess—what percentage of the United States population is each group?" and "Just your best guess—what percentage of the people who live in your local community is each group?" (Smith et al. 2000). GSS respondents gave estimates for the proportion of whites, Blacks/African Americans, Jews, Hispanics, Asian Americans, and American Indians.

[14] For parsimony, I omit perceptions of the proportion other race residents in a neighborhood from my analysis.

categories indicating whether they identified as white, Black, Latino, Asian, or other race. For those 56 respondents who selected two or more identities, I followed the approach of the Census and coded respondents who selected any race and Latino as Latino. Respondents who selected multiple races (e.g., white and Black) but not Latino were coded as other.

To examine the relationship between perceived and "objective" measures of neighborhood racial composition, I use data from the ACS.[15] In an effort to most closely proxy the categories used for respondent self-identification and perceived neighborhood composition, I include contextual neighborhood variables that can be interpreted as single-category—percent non-Hispanic white alone, percent non-Hispanic Black alone, percent Hispanic/Latino, percent non-Hispanic Asian alone, and percent non-Hispanic multi-race/other. Within the models, I include linear, grand mean-centered measures of objective neighborhood composition for ease of interpretation.[16]

Control Variables

In keeping with past studies, I include a number of control variables shown in related work to be associated with demographic perceptions (Alba et al. 2005; Kunovich 2017; Wong 2007). These variables include measures meant to capture individual characteristics that could influence perceptions, including length of exposure to a neighborhood, degree of real estate investment in or attachment to a neighborhood, and interaction with other local-level systems like schools.

[15] Though the Census is often used as an official metric of demographics in the United States, the true objectivity of ACS data should be viewed with some skepticism. Many scholars have observed that government measures of racial composition are constructs of the state and are highly politicized and inconsistent across time (Snipp 2003).

[16] Additional analyses tested if perceptions were better modeled with non-linear specifications of objective neighborhood composition. Results showed non-significant effects of polynomial forms for all outcomes except perceptions of percent Asian in one's neighborhood. For parsimony and consistency across models, I limit my results to the linear effect.

Specifically, I control for respondent gender, age, educational attainment, household income, if the household has kids, the number of years living in one's neighborhood, and residential tenure type. Gender is measured with a dummy variable indicating if a respondent self-identifies as male (reference) or female.[17] Age is measured categorically and captures if a respondent falls into the age group 18 to 29 (reference); 30 to 44; 45 to 59; or 60 and older. Educational attainment is measured to indicate if the respondent's highest completed level of education is high school or less (reference); some college or an associate degree; college; or a postgraduate degree. Household income is measured categorically: $19,999 or less (reference); $20,000 to $44,999; $45,000 to $74,999; $75,000 to $124,999; and more than $125,000. Household composition is a dummy variable indicating if the household includes children or not (reference). Years living in one's neighborhood is also captured categorically: 1 or fewer years (reference); 2 to 3 years; 4 to 9 years; or 10 or more years. Finally, tenure type is a dummy variable indicating if the respondent is a homeowner or renter (reference). To address a small number of respondents lacking complete data on these variables, missing values were corrected using multiple imputation.[18]

In addition to these individual-level control variables, I also include a neighborhood-level variable to capture neighborhood disadvantage. Past studies have shown neighborhood racial composition is frequently conflated with attributes indicative of disadvantage (Quillian and Pager 2001; Sampson and Raudenbush 2004). To control for the association between racial composition and other dimensions of neighborhood status, I include a scale variable capturing socio-economic disadvantage from census data. I follow the approach of the National Neighborhood Data Archive

[17] Within the survey, only two gender categories (male and female) were included.

[18] Across the full sample (N = 1,766) 1 respondent was missing data on their education level and 4 respondents were missing data on homeownership. Sensitivity analyses limiting models to only respondents with complete data yielded equivalent results to models that included imputed values.

and calculate neighborhood disadvantage as the average of four census indicators (percent of female headed families with children; percent of households with public assistance income or food stamps; percent of families with income below the federal poverty level; percent of population age 16+ unemployed) (Melendez et al. 2019). The scale variable ranges from 0 to 100 and has been grand mean-centered for interpretability.

Analytic Method

To examine the effects of both individual and neighborhood characteristics on perceptions of demographic composition I first illustrate the nature of respondents' perceptions using simple, descriptive findings before estimating a series of multilevel models. Multilevel models allow for the simultaneous estimation of the effects of variables at different levels of observation and address the violation of assumed independence that arises from having respondents clustered within neighborhoods. These models also control for unmodeled differences between neighborhoods and allow intercepts and individual level coefficients to vary across neighborhoods (Rabe-Hesketh and Skrondal 2012; Raudenbush and Bryk 2002). I use a two-level model, with individuals nested within neighborhoods.

Throughout these analyses, I estimate separate models to predict respondents' perceived percentage of their white, Black, Latino, and Asian neighbors, respectively. For each focal perceived group, I present a series of models. First, to examine the extent to which perceptions of neighborhood composition vary within and between neighborhoods, I estimate a random intercept model with no predictors (Model 1), which allows me to decompose the proportion of variance in perceptions that exists between neighborhoods—reflecting real differences in neighborhood context—and the proportion of variance that exists within neighborhoods. This measure of variance within neighborhoods provides initial evidence of the degree to which residents who share the same local context hold diverging neighborhood views.

Next, I examine if perceptions of neighborhood composition vary systematically by respondent identity and neighborhood condition. In particular, I focus on if perceptions differ depending on whether a respondent is assessing the size of their own racial group or other ethnoracial groups in their neighborhood. Model 2 offers a simple illustration of this relationship, testing if and how perceptions of neighborhood composition vary depending on respondents' ethnoracial identity, controlling for differences in neighborhood composition. Elaborating on this, Model 3 adds in my full set of controls for individual and neighborhood characteristics to examine if other dimensions of respondent and neighborhood identity influence the relationship between ethnoracial identity and neighborhood perceptions. In my final model (Model 4), I add in a cross-level interaction between individual identity and neighborhood composition, controlling for an array of individual and neighborhood characteristics. This cross-level model tests how the effect of objective neighborhood composition on perceptions varies depending on if respondents are estimating the percent of own group or other group neighbors.

The following equation represents the individual-level of the final model (Model 4) with controls, where the perception of the size of a local ethnoracial group for respondent *i* in neighborhood *j* is denoted as Y_{ij}:

(1)

$$\begin{aligned} Y_{ij} = \ & B_{0j} + B_1(race)_{ij} + B_2(gender)_{ij} + B_3(age)_{ij} + B_4(education)_{ij} \\ & + B_5(income)_{ij} + B_6(kids\ in\ household)_{ij} \\ & + B_7(neighborhood\ tenure)_{ij} + B_8(homeowner)_{ij} + r_{ij} \end{aligned}$$

where r_{ij} is the individual-level error term.

The neighborhood-level model (β_{0j}) includes the ACS-reported percentage of the ethnoracial group in the neighborhood and degree of neighborhood disadvantage. The secondary model (β_{1j}) includes a cross-level interaction between respondent ethnoracial identity and the objective size of own group in the neighborhood. These neighborhood-level models can be captured as:

$$\beta_{0j} = \gamma_{00} + \gamma_{01}(\%\ group\ in\ neighborhood)_j + \gamma_{02}(neighborhood\ disadvantage\ index)_j + \mu_{0j} \tag{2}$$

$$\beta_{1j} = \gamma_{10} + \gamma_{11}(\%\ group\ in\ neighborhood)_j + \mu_{1j} \tag{3}$$

where μ_{0j} and μ_{1j} are neighborhood-level error terms.

Results

Before turning to specific models, I begin by examining descriptive findings of the relationship between respondent perceptions and objective measures of neighborhood demographics. Figure 2.1 uses locally weighted scatterplot smoother (LOWESS) plots to illustrate the relationship between perceived and objective measures of neighborhood composition for the full sample of respondents. In the figure, the grey diagonal reference line illustrates a perfect association between objective and perceived neighborhood composition. Figure 2.1 shows respondents' perceptions of racial composition generally deviate from objective conditions, though perceptions and objective measures are positively associated.[19] Respondents' perceptions are typically overstated when a group constitutes a small portion of a neighborhood's population and understated when a group constitutes a large portion. In other words, akin to patterns of skewed perceptions found at broader geographies (e.g. Kunovich 2017), these results suggest that when an ethnoracial group makes up the local majority, respondents typically underestimate group size, whereas they typically overestimate groups in the local minority. This pattern holds for all perceived groups, though the degree to which a group is under or overestimated varies.

[FIGURE 2.1 ABOUT HERE]

To confirm the finding that respondents' perceptions are generally at odds with objective measures, I next examine the average absolute difference between perceived and objective composition. Because, as Figure 2.1 illustrates, gaps in perception of neighborhood composition can be both positive (overestimates) and negative (underestimates), I focus on the absolute value of difference to avoid averaging out these directional differences and erroneously concluding respondents' perceptions are accurate. One can think of this measure of absolute value as capturing the typical size of the gap between a neighborhoods' real and perceived characteristics. Table 2.2 highlights the sizable difference between respondents' perceptions and objective conditions. The first column shows that the average respondent misperceives the size of the white population in their neighborhood by 18 percentage points, the size of the Black population by 16 percentage

[19] Results from regression models (available upon request) support this positive but imperfect relationship between perceived group size and objective group size. Regression coefficients show a percentage point increase in objective group size is associated with roughly a .60 percentage point increase in respondent estimates, statistically significantly different from a 1.00 coefficient representing a perfect relationship.

points, the size of the Latino population by 15 percentage points, and the size of the Asian population by 7 percentage points. Table 2.2 further shows these gaps are common regardless of the ethnoracial identity of the respondent, though misperceptions appear to be largest for own group estimates. For example, the average Latino respondent misperceives the proportion of Latino residents in their neighborhood by 19 percentage points, whereas the average white, Black, or Asian respondent misperceives the proportion of Latino residents by 13, 11, and 17 percentage points, respectively. This same pattern of amplified perceptions for own group is found for white, Black, and Asian respondents.

[TABLE 2.2 ABOUT HERE]

While these descriptive findings illustrate the general nature of misperception, another way of thinking about the prevalence of imperfect neighborhood knowledge is to examine the degree to which residents of the same neighborhood differ in their perceptions. Perceptions that are universally held by residents of a neighborhood—for example perceiving a large population of Asian neighbors in a city's Chinatown neighborhood—might suggest a different mechanism of neighborhood knowledge is at work than misperceptions that vary within a neighborhood. Turning to my multilevel models, Table 2.3 shows results from the random intercept model (Model 1), which gauges the relative degree of variance in perceptions of neighborhood composition within and between neighborhoods for each focal ethnoracial group. Results captured by the intraclass correlation (ICC) reveal that variation between neighborhoods—for example, their underlying differences in objective demographic composition—account for between 25 and 56 percent of the variation in perceptions of group size. The remaining variation in perceptions of neighborhood composition—between 44 and 75 percent—lies within neighborhoods or at the level of the respondent. This means that though underlying differences between neighborhoods are associated with different perceptions of neighborhood composition, the bulk of variation in perceptions of neighborhood composition is found between residents of the same neighborhood. These results offer empirical evidence of the, perhaps unsurprising, reality that residents who share neighborhood contexts perceive the same spaces very differently.

[TABLE 2.3 ABOUT HERE]

Thus far, these findings help answer the question “to what extent do residents hold distorted perceptions of neighborhood conditions?” by documenting the general pattern of misperception and the location of variance. The remaining models dig into the suggestive finding from Table 2.2 that perceptions vary along ethnoracial lines, teasing apart the role of respondent identity and neighborhood composition in explaining differences in perceptions of one’s local community.

To that end, Model 2 examines how perceptions of neighborhood composition vary by identity of the respondent, introducing a set of dummy variables to capture an individual’s ethnoracial group. In this set of models, the reference category is specified to capture respondents of the same self-reported ethnoracial group as the focal group in the outcome variable (e.g., Black respondents are the reference category for models of perceived percent Black in a neighborhood). Thus, this set of models examines how neighborhood perceptions vary depending on if a respondent is assessing the size of their own group or the size of other groups. In Table 2.4, the intercepts measure the size of own group perceptions while the coefficients for the ethnoracial dummy variables capture differences between own group perceptions and the perceptions held by members of other ethnoracial groups. The model also includes the objective measure of neighborhood racial/ethnic composition from the ACS to control for underlying differences in neighborhood context.

The key takeaway from Model 2 is that, across all focal ethnoracial groups, respondents perceive their own group to make up a significantly larger portion of their neighbors than do respondents of other groups. This is illustrated most simply by the fact that in each column the ethnoracial dummy variables are associated with negative coefficients.[20] Breaking this down by group, results from this model show white respondents (Model 2W) living in a neighborhood with the sample average percent of white residents (35%) on average estimate their neighborhood to be 47 percent white. By comparison, Black respondents living in the same neighborhood estimate the size of the neighborhood's white population to be, on average, 19 percentage points lower than whites' estimates. Latino, Asian, and other-raced respondents' estimates are 17, 9, and 9 percentage points lower than that of whites, respectively. The other columns in Table 2.4 repeat this trend of outsized own group perceptions compared to other group perceptions. Black respondents (Model 2B) living in a neighborhood with the sample average neighborhood percent of Black residents (29%) on average estimate 45 percent of their neighbors to be Black. This is significantly inflated from the estimates of other respondents: white respondents in the same neighborhood would estimate 25 percent of that neighborhood's residents to be Black, Latino respondents would estimate that neighborhood as 27 percent Black, and Asian respondents would estimate that neighborhood as 29 percent Black.

[TABLE 2.4 ABOUT HERE]

[20] This pattern is also illustrated in descriptive LOWESS plots included in Appendix B.

Turning to the effect of the objective measure of neighborhood composition on perceptions, Model 2 captures the positive but imperfect relationship between perceived and objective measures of group size observed in Figure 2.1. In general, coefficients suggest a percentage point increase in the objective size of the focal group in a neighborhood is associated with half a percentage point increase in respondent estimates. For instance, each additional percent Asian in a neighborhood is associated with a .48 percentage point increase in perceived percent of the neighborhood population that is Asian. Measures of model fit (R^2 Between) show the inclusion of the objective measure of neighborhood composition explains nearly all (approximately 90 percent) of the variance in perceptions of neighborhood composition that exists between neighborhoods. However, considerable variation in residents' perceptions of neighborhood composition within a neighborhood remains unexplained. Modeling individual perceptions based only on respondents' ethnoracial identity explains around 11 percent of the within-group variance, highlighting that unmeasured individual-level attributes beyond race are needed to explain differences in perceptions of neighborhood composition between residents of the same neighborhood.

Table 2.5 captures results of my final two models. First, to examine the effects of individual and neighborhood dimensions beyond race/ethnicity on perceptions of neighborhood ethnoracial composition, Model 3 incorporates a battery of individual level controls as well as adding a control for neighborhood disadvantage. Though the effects of the control variables are heterogenous depending on the focal ethnoracial group being perceived, four main conclusions can be drawn. First, and most importantly, the addition of these variables controlling for greater variation in respondent and neighborhood characteristics does not shift the main finding: across ethnoracial identity groups, respondents consistently and systematically perceive that they live among more own group neighbors, even when controlling for objective neighborhood composition. For example, adjusting for other characteristics, Model 3 shows Latino respondents (Model 3L) on average estimate 34 percent of their neighbors to be Latino, perceptions that are roughly 13 percentage points higher than their non-Latino neighbors. A second takeaway from this expanded model is that there appears to be no significant effect of respondent age or length of tenure in a neighborhood on perceptions of neighborhood composition, controlling for other individual and neighborhood characteristics. Though one might expect neighborhood exposure and life experience to influence perceptions of neighborhood composition—through greater knowledge of compositional change or through increased familiarity with a neighborhood and its surroundings—neither appear to systematically impact respondents' views of their neighborhood compared to younger residents or those who have lived in the neighborhood for a year or less. Third, Model 3 shows perceptions of composition appear to vary by level of education of the respondent. Compared to those with only a high school education, respondents with higher levels of education are significantly more likely to report their neighborhood has a higher percent of white residents and are significantly less likely to report their neighborhood has a higher percent of Black or Latino residents. For example, Model 3W finds a respondent with a graduate degree perceives their neighborhood to be 12 percentage points whiter than a respondent with a high school degree or less, holding all else equal. Thus, even when judging objectively comparable contexts, those with higher education levels perceive their neighbors to be whiter than respondents with lower levels of education. I observe a similar effect among respondents with children and respondents in the highest income echelon. Holding neighborhood context constant, these respondents are significantly more likely than those without children or their lower income peers to view their neighborhoods as whiter. Finally, despite the inclusion of a wide array of individual characteristics, goodness of fit measures for Model 3 suggest only slight increases to the proportion of within-neighborhood variance explained by the model, meaning that considerable variation in neighborhood perceptions among neighbors remains unexplained.

[TABLE 2.5 ABOUT HERE]

Model 4 adds a cross-level interaction between respondent ethnoracial identity and neighborhood racial composition to examine if as the actual percent of own group in a neighborhood increases respondents typically outsized own group perceptions grow more or less exaggerated. Coefficients in Table 2.5 suggest that for white, Black, and Latino respondents, the effect of objective neighborhood composition on neighborhood perceptions is contingent on respondent ethnoracial identity.[21] For Latino and Black respondents, a percentage point increase in the objective size of the respondents' own group in their neighborhood is associated with a greater increase in the perceived percent of own group neighbors compared to other respondents, holding all else constant. For white respondents, this cross-level interaction has the opposite effect. A percentage point increase in the objective size of the white population in a neighborhood is associated with a smaller increase in the perceived percent of own group neighbors compared to the increase for other respondents. The cross-level interaction is non-significant for Asian respondents, suggesting they do not respond differently compared to non-Asian respondents to the objective size of the Asian population in their neighborhood. Thus, the results of the cross-level

[21] A series of sensitivity tests for estimating cross-level interaction models found that models estimating the interaction between all respondent ethnoracial categories and neighborhood composition did not substantively change the central finding that the effect of objective neighborhood composition on perceptions matters differently depending on if respondents are estimating the proportion of own group neighbors or other group neighbors. Additionally, measures of model fit suggested models estimated with only own group*composition interactions provided the best model fit.

models show Black and Latino respondents' outsized perceptions of same-race neighbors diverge from the perceptions of other groups as the size of the true population increases, while the opposite relationship is true for white respondents.

[FIGURE 2.2 ABOUT HERE]

Figure 2.2 illustrates two key takeaways of this analysis. First and most notably, each panel highlights the gap between respondents' perceptions of the size of own group in a neighborhood and the perceptions of other groups. For example, in the top right panel, Black respondents' perceptions of the percent of Black residents in their neighborhood is significantly higher than the perceptions of other respondents, regardless of the true composition of the neighborhood. The second key takeaway is the effect of the cross-level interaction of ethnoracial identity and neighborhood composition on own group perceptions. As described above, the graphs show that for Black and Latino respondents an increase in the objective size of own group in one's neighborhood is associated with a widening gap in perceptions between own group and other group respondents.[22] For example, the gap in perceptions between Latino and non-Latino respondents when judging a neighborhood that is 30 percent Latino is approximately 14 percentage points. That gap increases to approximately 19 percentage points when judging a neighborhood that is 70 percent Latino. By contrast, the graph of perceived percent white in a neighborhood shows the gap in perception between white respondents and non-white respondents converges as the true percent of white residents increases.

[22] For parsimony and to highlight the effect of own group compared to other group effects, this model constrains the slopes of other ethnoracial groups.

Discussion & Conclusions

A more complete understanding of the nature of individuals' imperfect neighborhood knowledge is necessary to understand how people make sense of and make decisions about their social environments. In this article, I focus on residents' perceptions of their neighborhood's demographic composition to highlight the ways in which perceptions offer distorted reflections of objective conditions. I find that not only do residents hold biased perceptions of their neighborhoods but that these biases vary by ethnoracial identity of the perceiver.

My results demonstrate empirically that residents' perceptions of their neighborhood are often at odds with census measures of demographic composition. A simple illustration of the relationship between perceptions and objective conditions shows residents generally overstate the size of groups that constitute a small portion of their neighborhood's population and understate the size of a group making up the local majority. These findings echo research on perceived composition at other geographic scales that similarly find respondents tend to overestimate minority populations and underestimate majority groups (e.g. Alba et al. 2005; Kunovich 2017; Wong 2007; Wong et al. 2012). Moreover, my findings suggest that the degree of individual misperception can be considerable. Among my respondents, the typical gap between perceived and objective group size was around 15 percentage points. Thus, a neighborhood that is, for example, a third Black might be perceived as ranging from 15 to 45 percent Black. This has substantial implications for theories of residential preference and selection, which suggest residential decisions are based on neighborhood composition (Charles 2006; Clark 1992). If residents' perceptions of their environments range as widely as my results suggest, then assumptions about individuals' ability to sort into neighborhoods based on their alignment with one's preferences requires re-examination. While patterns of residential segregation clearly demonstrate the outcome of residential sorting, more research is required to understand the underlying processes driving these patterns and how distorted perceptions factor in (see Krysan and Crowder 2017).

Not only are perceptions of neighborhood composition at odds with objective conditions, but my results also suggest distorted perceptions arise primarily out of differences in perspective among residents in the same neighborhood. A decomposition of variation in perceptions finds that the bulk of variation lies between neighbors. While this finding may not be surprising given qualitative work illustrating the diverging neighborhood views of distinct residential groups (e.g. Brown-Saracino 2010; Pattillo 2007; Wherry 2011), the subjective nature of neighborhood experience is rarely highlighted in quantitative urban research. Whereas most models of residential processes (e.g. Schelling 1971) imply that residents evaluate neighborhood conditions with some consistency—i.e. a neighborhood that is half white and half Latino would be viewed as such by every housing searcher—this dubious assumption is greatly undermined by my findings.

Ethnoracial identity clearly shapes residents' neighborhood perceptions. My results show that when estimating their neighborhood's demographic composition, respondents in each ethnoracial group perceive their own group to make up a significantly larger percent of neighborhood residents compared to the estimates of other respondents, even controlling for underlying differences in neighborhood composition. For example, a white resident would estimate their percent of white neighbors to be 20 percentage points higher than a Black resident living in the same neighborhood, and vice versa. This pattern suggests respondents generally believe they live in neighborhoods filled with others like themselves. This finding offers an interesting extension to related research on ethnoracial variation in neighborhood familiarity

(Krysan and Bader 2009), suggesting that biased familiarity with neighborhoods and biased perceptions of those neighborhoods may be complimentary processes through which imperfect information shapes how we judge and select where to live.

What might explain these patterns of skewed perceptions? Adherents to group position theory might claim that these findings of inflated perceptions of the size of own group are further evidence of the inter-group struggle to define and defend one's relative position in the hierarchical, racialized order (Blumer 1958; Bobo and Hutchings 1996). By inflating the size of own group in their neighborhood, individuals may be, consciously or unconsciously, seeking to assert or justify their status locally, demarcate the neighborhood as a place for them, and otherwise lay claim to space. Similarly, social cognition researchers might point to my findings as affirmation of the theory that perceptions reflect the motives, goals, or needs of an individual (Fiske 1993; Swann 1984). From this perspective, the consistent amplification of the size of own group neighbors compared to others may function to emphasize respondents' sense of compatibility with their surroundings, reflecting individuals' desires to believe they live in a neighborhood best suited to people like them. These underlying motives might also explain why respondents with certain status attributes—higher income, higher education, and those with children—perceive their neighborhoods to be whiter. If white neighborhoods are often associated with certain desirable conditions—high socio-economic status, lower crime, lower blight—residents' of higher status may seek to identify with whiter neighborhoods to enforce their belief that they live in a neighborhood suited to and inhabited by others like them.

In considering the implications of my research findings, it is important to acknowledge that this article focuses on residents' perceptions of their current neighborhood of residence. I do not examine perceptions of other communities in the metropolitan area. One can only speculate as to whether the patterned nature of perceptions documented here would hold when assessing the composition of other neighborhoods. On the one hand, residents possess greater familiarity with their immediate environment. This ability to draw on first-hand knowledge may mean perceptions of one's own neighborhood are less prone to bias than perceptions of unfamiliar places. Thus, we might expect perceptions of other neighborhoods to be more distorted than my findings suggest. On the other hand, residents' first-hand experience with their neighborhood may increase rather than reduce variability in perceptions. Because individual identity and attachment may be shaped in reference to where you live (Wacquant 2007), the stakes for and meaning of own neighborhood perceptions may be greater. An individual's personal, familial, or financial attachment to a neighborhood may lead to more biased perceptions compared to an impartial outsider. Moreover, this attachment to a neighborhood may encourage residents to inflate their sense of compatibility with their surroundings. Related research on internal vs. external assessments of neighborhood reputation supports this idea, finding that residents generally hold positively biased views of their neighborhoods compared to outsiders (Permentier, Van Ham, and Bolt 2008; Wileden 2019). Thus, it is possible that individuals' perceptions of other neighborhoods would be less distorted than my findings. Determining the pattern and prevalence of neighborhood perceptions of other neighborhoods, and how those perceptions relate to processes of residential selection, is an area ripe for further research.

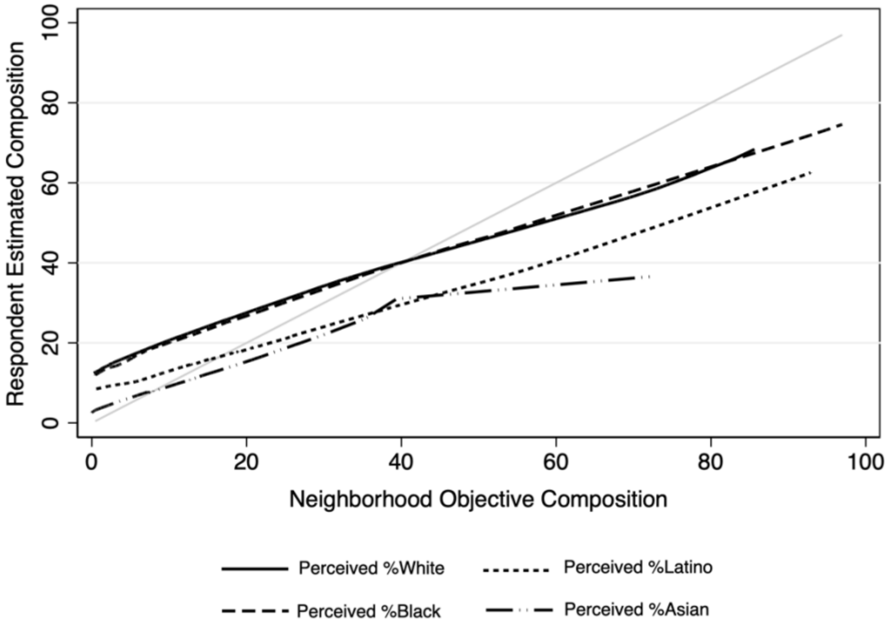
In addition to the need to examine perceptions of other neighborhoods, central limitations of the present study suggest a number of prospects for future research. While this study is among the first to ask residents to explicitly enumerate their perceptions of bounded, recognizable neighborhoods, a limitation of my approach is that respondents only reported their neighborhood of residence and not a more specific location within that neighborhood. Similarly, my survey did not collect any information on respondents' social networks or activity areas. As a result, it is difficult to tease out what if any effect micro-patterns of segregation within neighborhoods or divergent direct and indirect neighborhood experiences have on my results. While the design of this analysis sought to minimize these issues to the extent possible by asking residents to estimate the composition of the same, pre-defined neighborhood area, the segregated nature of communities, institutions, and social groups within these areas might have an unmeasured influence on perceptions. Moreover, the current study only inquired about residents' perceptions of neighborhood racial composition and not about the many other neighborhood dimensions that constitute the broader image of a neighborhood individuals hold in their heads. Data on such perceptions remain thin, and thus there is ample opportunity for future research to advance our understanding of how individuals perceive and discern a variety of neighborhood attributes. Additionally, because this analysis focuses on the relationship between perceptions and current objective conditions it does not factor in the ways in which change in neighborhood composition over time might be reflected in residents' perceptions. It is undoubtedly true that different environments—with distinct histories, compositional profiles, etc.—will carry with them unique legacies that likely influence perceptions. A next phase of analysis might examine the relationship between contemporary perceptions of neighborhood composition and demographic trajectories over time.

By relying on census measures of neighborhood conditions and failing to account for residents' distorted views of their neighborhoods, existing theories of residential processes and neighborhood dynamics miss a critical dimension of how people experience and make sense of the world around them. As my findings show, the images of our communities we hold in our heads are often at odds with objective measures. Moreover, they are strongly influenced by individual identity. These distorted perceptions likely have micro-level consequences—shaping where we look for housing, where we choose to live, and how we live in those places—that aggregate up to reproduce or structure macro-level patterns of spatial inequity. Documenting the knowledge biases and distorted perceptions residents use to navigate and make sense of their environments is a necessary step toward develop more realistic theories of urban processes. By appreciating the complex, socially embedded, and ever-adapting perceptions of place that shape residential processes, we can develop more accurate theories and policies to develop and incentivize more equitable communities.

Table 2.1 Descriptive Statistics for Individual- and Neighborhood-Level Variables

	Mean / %	SD	Min	Max
Dependent Variables				
Perceived % White	37.47	27.66	0	100
Perceived % Black	29.19	27.72	0	100
Perceived % Latino	22.58	22.56	0	100
Perceived % Asian	7.90	10.86	0	90
Perceived % Other	2.87	6.44	0	84
Individual-level Variables (N = 1766)				
Respondent Race				
White	0.36	0.48	0	1
Black	0.28	0.45	0	1
Latino	0.25	0.43	0	1
Asian	0.08	0.27	0	1
Multi-Race or Other	0.03	0.17	0	1
Female	0.52	0.50	0	1
Age				
18-29	0.27	0.45	0	1
30-44	0.37	0.48	0	1
45-59	0.22	0.41	0	1
60+	0.14	0.35	0	1
Education				
High School or less	0.15	0.35	0	1
Some Col/Assoc	0.32	0.47	0	1
BA	0.32	0.47	0	1
Grad	0.22	0.41	0	1
Income				
$0 - $19,999	0.12	0.33	0	1
$20,000-$44,999	0.20	0.40	0	1
$45,000-$74,999	0.24	0.43	0	1
$75,000-$124,999	0.27	0.44	0	1
$125,000+	0.17	0.37	0	1
Household with kids	0.28	0.45	0	1
Length of Tenure in Neighborhood				
0-1 year	0.05	0.22	0	1
2-3 years	0.09	0.29	0	1
4-9 years	0.16	0.36	0	1
10+ years	0.70	0.46	0	1
Homeowner	0.50	0.50	0	1
Neighborhood-level Variables (N = 230)				
Neighborhood Composition				
% White	34.78	26.92	0.25	85.63
% Black	28.51	33.36	0.44	96.96
% Latino	25.97	25.28	0.57	92.86
% Asian	7.99	8.86	0.00	72.42
% Multi-Race or Other	2.74	1.42	0.03	6.33
Disadvantage Index	9.62	6.24	0.85	35.66

Figure 2.1 Comparison of Perceived and Objective Neighborhood Racial Composition



Notes: Locally weighted scatterplot smoother (LOWESS) plot of perceived racial composition for full sample. Grey diagonal reference line illustrates a hypothetical, perfect relationship between variables. The range for each focal ethnoracial group is limited to the maximum proportion of each group observed within neighborhoods in data.

Table 2.2 Means and Standard Deviations of Absolute Difference Between Perceived and Objective Neighborhood Composition by Respondent Race

	Full Sample		White Respondents		Black Respondents		Latino Respondents		Asian Respondents	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Difference % White	18.03	16.72	20.05	16.99	15.78	16.60	17.50	16.48	16.68	14.86
Difference % Black	15.51	16.68	12.96	14.71	20.88	19.93	13.79	14.45	11.23	12.55
Difference % Latino	14.55	14.99	13.45	14.07	11.49	12.83	18.52	16.39	16.68	17.92
Difference % Asian	6.77	7.87	6.69	6.84	4.48	6.12	7.24	7.08	13.41	14.03

Table 2.3 Location of Variance in Perceptions of Neighborhood Racial Composition

	Perceived % White	Perceived % Black	Perceived % Latino	Perceived % Asian
	Model 1W	Model 1B	Model 1L	Model 1A
Intercept	37.00***	31.03***	21.45***	7.68***
	(1.29)	(1.51)	(1.07)	(.45)
Variance Components				
Between-group variance	285.63	446.32	202.19	29.42
Within-group variance	461.54	347.73	275.62	89.45
ICC	.38	.56	.42	.25
BIC	16222.5	15856.3	15341.6	13225.0

Notes: Level 1 N=1,766; Level 2 N=230. Coefficients reported from linear mixed-effects models. Standard errors in parentheses. ICC = Intraclass correlation. BIC = Bayesian information criterion. * p<0.05, ** p<0.01, *** p<0.001 (two-tailed tests)

Table 2.4 Effects of Respondent Race and Objective Neighborhood Composition on Perceptions of Neighborhood Racial Composition

	Perceived % White	Perceived % Black	Perceived % Latino	Perceived % Asian
	Model 2W	Model 2B	Model 2L	Model 2A
Intercept	46.78***	44.93**	32.48***	18.57***
	(.92)	(.94)	(.89)	(.81)
Individual-level Variables				
White	*ref*	-20.10***	-14.39***	-11.19***
		(1.25)	(1.06)	(.86)
Black	-18.88***	*ref*	-13.64***	-12.60***
	(1.34)		(1.20)	(.93)
Latino	-16.71***	-17.70***	*ref*	-11.74***
	(1.33)	(1.38)		(.89)
Asian	-9.11***	-22.09***	-15.07***	*ref*
	(1.92)	(1.85)	(1.55)	
Multi-Race or Other	-9.31**	-15.75***	-12.38***	-10.26***
	(2.94)	(2.63)	(2.34)	(1.48)
Neighborhood-level Variables (Grand Mean Centered)				
% White	0.50***			
	(.02)			
% Black		.48***		
		(.02)		
% Latino			.47***	
			(.02)	
% Asian				.48***
				(.04)
Variance Components				
Between-group variance	16.66	12.32	17.48	6.36
Within-group variance	410.17	308.52	245.85	80.76
R^2 Between	0.94	0.97	0.91	0.78
R^2 Within	0.11	0.11	0.11	0.10
R^2 Total	0.43	0.60	0.45	0.27
BIC	15755.0	15251.3	14884.3	12925.8

Notes: Level 1 N=1,766; Level 2 N=230. Coefficients reported from linear mixed-effects models. Standard errors in parentheses. BIC = Bayesian information criterion. Significance for the effect of objective measure of neighborhood composition (e.g., neighborhood level % white) was tested separately against the hypothesis that the coefficient was significantly difference from 1.00.

* p<0.05, ** p<0.01, *** p<0.001 (two-tailed tests)

Table 2.5 Effects of Respondent and Neighborhood Attributes on Perceptions of Neighborhood Racial Composition

	Perceived % White		Perceived % Black		Perceived % Latino		Perceived % Asian	
	Model 3W	Model 4W	Model 3B	Model 4B	Model 3L	Model 4L	Model 3A	Model 4A
Intercept	37.47***	38.71***	49.45***	47.86***	34.28***	32.78***	18.11***	17.54***
	(2.87)	(2.89)	(2.49)	(2.50)	(2.23)	(2.26)	(1.48)	(1.53)
Individual-level Variables								
Respondent Race								
White	*ref*	*ref*	-18.24***	-17.60***	-13.35***	-12.03***	-11.17***	-10.61***
			(1.28)	(1.28)	(1.12)	(1.17)	(.87)	(.95)
Black	-15.63***	-16.49***	*ref*	*ref*	-14.58***	-13.51***	-12.56***	-12.03***
	(1.36)	(1.39)			(1.25)	(1.28)	(.95)	(1.01)
Latino	-13.44***	-14.41***	-17.88***	-17.37***	*ref*	*ref*	-11.47***	-10.90***
	(1.30)	(1.42)	(1.42)	(1.41)			(.92)	(.99)
Asian	-9.16***	-10.49***	-20.33***	-20.09***	-13.94***	-12.14***	*ref*	*ref*
	(1.87)	(1.92)	(1.87)	(1.86)	(1.58)	(1.64)		
Multi-Race or Other	-7.68**	-8.94**	-15.02***	-13.71***	-11.87***	-10.36***	-10.08***	-9.49***
	(2.86)	(2.88)	(2.61)	(2.61)	(2.32)	(2.35)	(1.49)	(1.54)
Female	-3.80***	-3.92***	1.91*	1.95*	1.27	1.30	.20	.23
	(.97)	(.97)	(.86)	(.86)	(.77)	(.77)	(.45)	(.45)
Age								
18-29	*ref*	*ref*	*ref*	*ref*	*ref*	*ref*	*ref*	*ref*
30-44	1.12	.97	-0.71	-.84	.24	.35	-.67	-.65
	(1.29)	(1.28)	(1.14)	(1.13)	(1.03)	(1.02)	(.59)	(.59)
45-59	2.10	2.05	-1.43	-1.51	-.42	-.36	-.07	-.08
	(1.46)	(1.46)	(1.30)	(1.29)	(1.17)	(1.16)	(.68)	(.68)
60+	3.22	3.32	-2.53	-2.88	-.05	.08	-.24	-.24
	(1.70)	(1.70)	(1.51)	(1.50)	(1.36)	(1.35)	(.79)	(.79)
Education								
High School or less	*ref*	*ref*	*ref*	*ref*	*ref*	*ref*	*ref*	*ref*
Some Col/Assoc	5.59***	5.48***	-1.87	-1.58	-2.06	-2.00	-.26	-.26
	(1.54)	(1.54)	(1.37)	(1.36)	(1.23)	(1.22)	(.71)	(.71)
BA	7.96***	7.93***	-4.25**	-3.91**	-2.45	-2.37	.48	.46
	(1.66)	(1.66)	(1.48)	(1.47)	(1.33)	(1.32)	(.77)	(.77)
Grad	11.64***	11.77***	-6.24***	-6.04***	-3.32*	-3.46*	-.23	-.28
	(1.88)	(1.87)	(1.67)	(1.66)	(1.50)	(1.49)	(.87)	(.87)
Income								
$0 - $19,999	*ref*	*ref*	*ref*	*ref*	*ref*	*ref*	*ref*	*ref*
$20,000-$44,999	-1.41	-1.53	-1.20	-1.11	2.43	2.54	-.10	-.08
	(1.74)	(1.74)	(1.55)	(1.54)	(1.39)	(1.38)	(.80)	(.80)
$45,000-$74,999	.70	.63	-1.17	-1.15	.10	.07	-.61	-.57
	(1.76)	(1.76)	(1.57)	(1.56)	(1.41)	(1.40)	(.82)	(.82)
$75,000-$124,999	3.12	3.07	-2.72	-2.76	-1.51	-1.56	.50	.54
	(1.84)	(1.83)	(1.63)	(1.62)	(1.46)	(1.46)	(.85)	(.85)
$125,000+	6.15**	6.28**	-2.54	-2.83	-3.61*	-3.77*	.11	.16
	(2.14)	(2.14)	(1.90)	(1.89)	(1.71)	(1.70)	(.99)	(.99)
Household with kids	2.74*	2.86**	.68	.69	-2.25*	-2.37**	-.33	-.32
	(1.11)	(1.11)	(.99)	(.98)	(.87)	(.88)	(.51)	(.51)
Years in Neighborhood								
0-1 year	*ref*	*ref*	*ref*	*ref*	*ref*	*ref*	*ref*	*ref*
2-3 years	.93	.96	-.61	-.89	.04	.13	-.08	-.09
	(2.60)	(2.59)	(2.31)	(2.29)	(2.07)	(2.06)	(1.20)	(1.20)
4-9 years	.56	.40	.34	.02	-1.65	-1.70	.14	.09
	(2.41)	(2.41)	(2.14)	(2.13)	(1.92)	(1.91)	(1.11)	(1.11)
10+ years	-1.35	-1.28	-.23	-.77	.85	.70	.13	.09
	(2.22)	(2.22)	(1.97)	(1.97)	(1.77)	(1.77)	(1.03)	(1.03)
Homeowner	-.57	-.62	-.88	-.80	.66	.84	1.14*	1.13*
	(1.10)	(-.62)	(.97)	(.97)	(.88)	(.87)	(.52)	(.52)
Neighborhood-level Variables (Grand Mean Centered)								

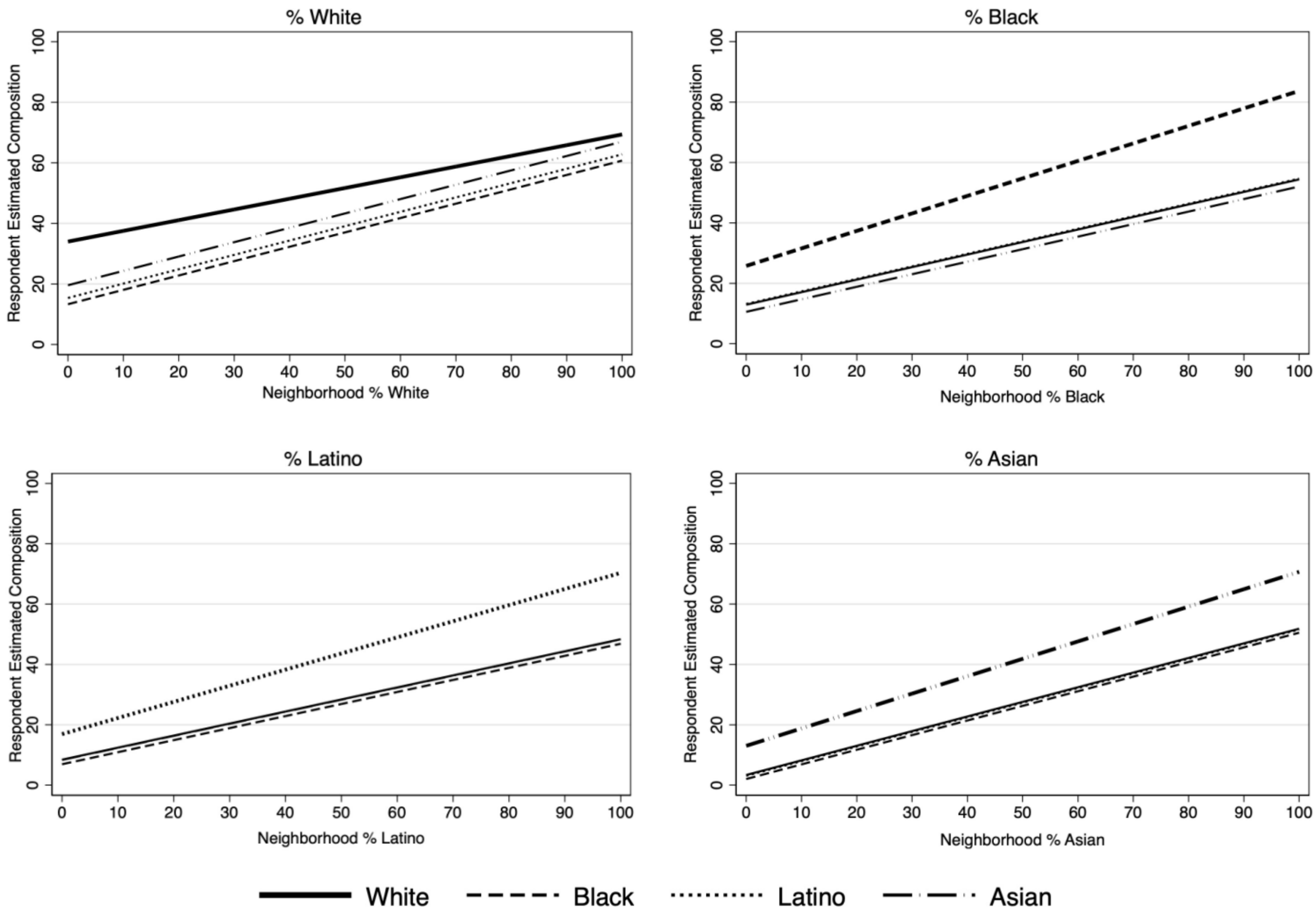
Neighborhood Composition								
% White	.42***	.48***						
	(.04)	(.04)						
% Black			.49***	.41***				
			(.03)	(.03)				
% Latino					.45***	.40***		
					(.02)	(.03)		
% Asian							.50***	.48***
							(.04)	(.04)
Disadvantage Index	-.22	-.16	-.18	-.26*	.10	.07	.10	.09
	(.18)	(.19)	(.12)	(.12)	(.09)	(.09)	(.05)	(.05)
Cross-level Interactions								
White Respondent x % White		-.12**						
		(.04)						
Black Respondent x % Black				.17***				
				(.04)				
Latino Respondent x % Latino						.13***		
						(.04)		
Asian Respondent x % Asian								
								.15
Variance Components								(.10)
Between-group variance	15.05	15.08	10.54	12.97	15.56	15.69	5.86	5.67
Within-group variance	380.22	378.24	300.64	295.17	239.06	236.99	80.2	80.20
R^2 Between[a]	0.95	.95	0.97	.97	0.92	.92	0.78	.79
R^2 Within[a]	0.18	.18	0.13	.15	0.13	.14	0.10	.10
R^2 Total[a]	0.47	.47	0.61	.61	0.47	.47	0.27	.27
BIC[a]	15710.37	15708.9	15292.82	15279.0	14924.1	14917.2	12955.21	12961.7

Notes: Level 1 N=1,766; Level 2 N=203. Coefficients reported from linear mixed-effects models. Standard errors in parentheses. BIC = Bayesian information criterion. Significance for the effect of objective measure of neighborhood composition (e.g., neighborhood level % white) was tested separately against the hypothesis that the coefficient was significantly difference from 1.00.

* p<0.05, ** p<0.01, *** p<0.001 (two-tailed tests)

[a] Goodness of fit measures reflect values from non-imputed models (N = 1762) due to modeling limitations within STATA's multiple imputation package. Results from non-imputed models show no meaningful differences in coefficients, standard errors, or measures of fit

Figure 2.2 Perceptions of Neighborhood Racial Composition by Race of Respondent, Objective Neighborhood Racial Composition, and Cross-Level Interactions



Notes: Marginal effects of objective neighborhood composition on perceptions of neighborhood composition with cross-level interactions (Model 4). Grey diagonal reference line illustrates a hypothetical, perfect relationship between variables. To highlight the effect of own group compared to other group effects, this cross-level model constrains the slopes of other ethnoracial groups.

Chapter 3

Measuring and Modeling Perceptions of Change in Neighborhood Safety: Evidence from Detroit

Like many cities in the United States, Detroit has experienced a considerable drop in crime since the 1990s (Baumer, Vélez, and Rosenfeld 2018; Blumstein and Wallman 2006; Federal Bureau of Investigation n.d.). Official statistics show that reported crime occurrences in the city have fallen by 70 percent over the past thirty years, including a 78 percent decline in property crime and a 48 percent decline in violent crime (Federal Bureau of Investigation n.d.; Hunter and Harding 2021).[1] Even after adjusting for the city's shrinking population over that period, falling crime rates suggest Detroit was demonstrably safer by the end of the 2010s than at any time in recent history. But residents' perceptions generally do not reflect how crime has changed. Despite these improving crime conditions, the majority of Detroiters in 2019 believed that local safety had remained the same or gotten worse over time (Detroit Metro Area Communities Study 2020).

Incongruity between public perceptions and change in crime is not unique to Detroit.[2] Statistics from the Federal Bureau of Investigations and the National Crime Victimization survey show that rates of property and violent crime nationally have fallen precipitously in the last three

[1] It has been widely acknowledged that official crime reports may not reflect the total amount of crime in a community. Not all crime incidents are reported to the police and policing data has been shown to sometimes reflect errors or bias. Despite this, the use of official statistics to assess crime conditions is common in academic research (Hipp 2007b).

[2] Within the large literature on crime and perceptions, researchers have employed a range of measures including questions about perceived crime levels, perceived fear of crime, perceived risk of victimization, and perception of safety. While some have drawn distinctions between these measures, they are frequently used interchangeably. See for discussion (Hipp 2013; Michalos and Zumbo 2000).

decades (Bureau of Justice Statistics 2021; Federal Bureau of Investigation 2020, n.d.). However, public opinion polls routinely find that Americans believe crime is on the rise (Gramlich 2020). Two decades of data from Gallup show that a majority of respondents believe national crime rates remained the same or went up annually (Gallup Inc. n.d.; McCarthy 2020). This pessimism about change in crime extends to local environments, where respondents are more likely to believe crime in their community is increasing than decreasing despite evidence that local crime trends generally conform to national patterns (McDowall and Loftin 2009). In the average year between 2000 and 2019, 40 percent of Gallup respondents believed there was more crime in their local area than the year before while just a third believed crime had declined (Gallup Inc. n.d.).

Public perceptions of crime conditions are a topic of considerable interest to social scientists. Scholarship interrogating the causes and correlates of residents' fear of crime and perceptions of safety have identified a wide array of variables that explain who has a greater fear of crime and what places are perceived to be less safe, including measures of (1) objective crime conditions (Ambrey, Fleming, and Manning 2014; Hipp 2013; Manning et al. 2022); (2) individual characteristics and biases (Elo et al. 2009; Gaub, Wallace, and Hoyle 2020; Hinkle and Yang 2014; Hipp 2010b; Rountree and Land 1996; Sampson, Raudenbush, and Earls 1997); and (3) stereotypes or associations with other neighborhood attributes (Hipp 2010a; Quillian and Pager 2001). However, these explanations are often limited to residents' assessments of present-time crime conditions. Little research to date has focused on how residents perceive neighborhood safety to have changed over time.

From a practical perspective, examining residents' perceptions of *change* in safety is important because whether and how safety has changed is often held up as an indicator of community quality. Reducing crime and improving safety are policy priorities that enjoy broad, bipartisan support (Noble, Reeves, and Webster 2022; Pew Research Center 2022). In fact, in Detroit reducing crime was the most commonly mentioned change residents wanted to see in their neighborhood in 2019 (Detroit Metro Area Communities Study 2020). Thus, the gap between residents' perceptions and falling crime rates creates a public policy paradox where the public's desire for safety is not satisfied by improvements in objective crime conditions. Understanding what influences residents' perceptions of change in neighborhood safety may offer relevant insights for policymakers and stakeholders seeking to improve local sentiment.

Additionally, the fact that public perceptions and crime trends diverge so dramatically raises questions about how individuals make sense of change in their social environments more broadly. Classic models of neighborhood dynamics are premised on the idea that individuals are aware of and responsive to evolving neighborhood conditions (Schelling 1971; Schwirian 1983). However, these models generally do not measure the extent to which individuals are knowledgeable about changes in their neighborhood such that their awareness of change shapes behavior and residential choice. Evidence that residents fail to detect or hold counter-valent perceptions of change in neighborhood safety raises important questions about how individuals understand and respond to other changes in their surroundings.

In this study, I examine how residents' perceptions reflect, or fail to reflect, change in objective neighborhood conditions, with a focus on change in local safety. Drawing on data from a representative survey of Detroit residents, crime data from the Detroit Police Department, and census data, I interrogate residents' sensitivity to changing environments and the extent to which objective levels and changes in neighborhood crime conditions, respondent characteristics, and broader neighborhood conditions predict residents' perceptions of change in safety over the previous five-years. My findings highlight the highly subjective nature of perceptions of change.

Echoing scholarship on present-time perceptions of safety, I show that while perceived change in safety is not wholly divorced from levels and change in crime it is especially sensitive to one's recent experience as a victim of crime and to the current demographic makeup of one's neighborhood. After accounting for these individual and neighborhood characteristics, crime and change in crime do not significantly affect how residents perceive safety to have changed. These findings point to the influence of recency bias when assessing neighborhood change. Moreover, they suggest that perceptions of safety, and change in safety, are driven by more than crime conditions. Ultimately, my findings advance the argument that while theories and public policy priorities emphasize the salience of change for neighborhood dynamics, individuals themselves may be poor judges of change in social environments.

Background

Resident Perceptions of Neighborhood Safety

Crime is broadly understood to be an undesirable characteristic of neighborhoods, fostering fear and creating uncertainty about local environments (Rountree and Land 1996). Considerable research has documented that crime and disorder reduce residents' satisfaction and increase one's desire to move (Austin and Baba 1990; Harris 2001; Hipp 2009; Lu 1999; Skogan 1990; Woldoff 2002). Moreover, crime is strongly linked to metrics of neighborhood instability, including greater population loss and more turnover in homesales (Hipp, Tita, and Greenbaum 2009; Morenoff and Sampson 1997).

Though crime is a meaningful indicator of neighborhood quality, past research has found that people are relatively poor judges of neighborhood crime conditions. Evidence shows that perceptions of crime tend to be significantly higher than actual crime rates and risk of victimization

(Drakulich 2013; Hipp 2013). One study found residents' perceptions of local crime rates were as much as double the crime rate captured by police data and that these outsized perceptions had increased over time (Ambrey et al. 2014). This discrepancy between perceived and objective crime measures may be all the more important as perceptions—or what one believes about neighborhood conditions—have been shown to have equal if not greater effects on satisfaction than objective measures (Manning et al. 2022).

This is not to imply that residents' perceptions of crime and safety in their neighborhood are random. Scholars have found a degree of fidelity between local crime rates and perceptions, though the association may be weak. For example, a classic study of residents' perceptions of safety in Baltimore (Furstenberg 1971) found that after splitting neighborhoods into categories by degree of crime, residents of "high" crime neighborhoods reported greater fear than those in "average" or "low" crime neighborhoods. A similar study in Seattle found a positive association between tract-level burglary rates and residents' perceived risk (Rountree and Land 1996). More recently, Hipp's (2013) study of 22 cities over a 25-year period revealed a positive but weak correlation between tract-level crime and residents' perceptions of safety.

Given the tenuous relationship between objective crime conditions and perceptions, many scholars have questioned the extent to which perceptions of neighborhood safety reflect individual bias. Studies investigating which residents perceive higher rates of neighborhood crime have drawn mixed conclusions. While an exhaustive review of the literature is outside the scope of this paper (see Elo et al. 2009; Hinkle and Yang 2014; Hipp 2010b), I highlight some general findings. The most consistent individual characteristics associated with perceptions of safety are gender, length of residence, and past victimization. Women consistently report heightened perceptions of fear and disorder than men (Gaub et al. 2020; Hale 1996; Liska, Sanchirico, and Reed 1988), which scholars attribute to gendered dimensions of crime and women’s perceived risk of sexual assault (Ferraro 1996). A similarly consistent finding is that perceptions of safety decline the longer one lives in a neighborhood (Hipp 2010b; Salm and Vollaard 2021; Sampson et al. 1997; Taylor, Gottfredson, and Brower 1984). Additionally, it is perhaps unsurprising that past victimization has been shown to contribute significantly to how residents perceive safety. In a study of eight US cities, Garofalo (1979) found that crime victims expressed greater general fear than non-victims, a finding widely replicated in related research (Austin, Furr, and Spine 2002; Rountree and Land 1996; Skogan and Maxfield 1981; Taub, Taylor, and Dunham 1987). Evidence of differences in perceptions by other individual characteristics is considerably less clear. While some have hypothesized that non-White residents have a higher threshold for and thus are less attuned to crime and disorder based on exposure (Sampson and Raudenbush 2004), actual evidence to that effect is mixed (Hipp 2010b; Quillian and Pager 2001; Sampson et al. 1997). Similarly mixed results find that age (Quillian and Pager 2001; Rountree and Land 1996; Skogan and Maxfield 1981), socioeconomic status (Quillian and Pager 2001; Rountree and Land 1996; Sampson and Raudenbush 2004; Sampson et al. 1997), household composition (Ross and Jang 2000; Ross and Mirowsky 2001), and whether one rents or owns their home (Sampson and Raudenbush 2004; Sampson et al. 1997) inconsistently predict perceptions of safety and disorder.

Beyond the role of individual biases in shaping perceptions, related literature has consistently observed associations between perceptions of safety and other neighborhood characteristics. Most notably, perceived safety appears to be strongly influenced by neighborhood racial composition. In their study of Chicago, Baltimore, and Seattle, Quillian and Pager (2001) found that neighborhoods with greater concentrations of racial/ethnic minorities were perceived as less safe even after controlling for objective crime levels. Related research has found that minority composition of a neighborhood is similarly associated with heightened perceptions of disorder and perceived concentrations of more serious crime, and that these perceptions are not reducible to objective levels of crime and disorder in a neighborhood (Hipp 2007a; Sampson and Raudenbush 2004; Sampson et al. 1997). Taken together, the existing literature finds that biased perceptions of neighborhood safety are widespread and are influenced not only by objective conditions of crime but also by individual characteristics and other neighborhood attributes.

Missing from the lengthy literature on perceptions of safety is research on how residents perceive safety in their neighborhoods to have changed over time. In a review of past scholarship, Baumer, Velez, and Rosenfeld (2018) acknowledge that criminology has devoted little attention to understanding the effects of change in aggregate crime rates. As a result, most studies about fear of crime and perceptions rely on static observations of present-time perceptions while little is known about how perceptions of safety emerge or change (Prieto Curiel and Bishop 2017). This present-time focus is surprising in part because many of the ways we think about safety—as something to be enhanced, as a feature of neighborhoods that compel residents to move, and as an indicator or catalyst of a place's downward trajectory—point to its dynamic rather than static nature.

Some recent research has begun to explore residents' dynamic response to crime. Drawing on theories of opinion diffusion, Prieto Curiel and Bishop (2017) developed a simulation model to explore how perceptions of security might change in relation to changing crime conditions. Focusing on manipulating attributes of crime that may influence perceptions, they find that small changes in crime rates have negligible impact and that to shift perceptions instead requires a considerable degree of change over time. The authors acknowledge that these simulated findings would benefit from corroboration from survey data. A related study examined what drives change over time in the broader salience of crime—the extent to which the collective public views crime as a pressing social problem. Shi, Lu, and Pickett (2020) find that collective public attention to crime is driven largely by changes in media coverage and political rhetoric and generally does not reflect change in crime conditions. While these studies offer some suggestive evidence about changing perceptions, much remains to be understood about how individual perceptions of change reflect shifts in crime conditions.

Theorizing Response to Neighborhood Change

Extending the literature on perceptions of safety to perceptions of change is important in part because response to change is core to classic models of neighborhood dynamics. Starting with the Chicago School, theories of invasion-succession hypothesized that patterns of demographic turnover in local population composition are produced in response to the “invasion” of socially or racially different individuals into a neighborhood (Hoover and Vernon 1959; Park 1952). Similarly, the long literature on White flight suggests that patterns of residential segregation result from Whites’ decisions to relocate away from neighborhoods with growing minority populations (Crowder 2000; Crowder and South 2008; Krysan 2002b). Implicit in these theories is the idea that people recognize and react to change in social environments.

Quantitative research endeavoring to illustrate residents’ responsiveness to neighborhood change typically takes one of two approaches. Most commonly, studies have examined residential mobility—either intentions to move or actual mobility behavior—in relation to change in neighborhood conditions captured in administative data. For example, Crowder (2000) examined White families out-migration from neighborhoods in relation to change in the size of the Black population, finding that the likelihood of White mobility is positively associated with recent increases in the proportion of Black neighbors. A related study on response to change in neighborhood conditions in the Netherlands found that though change in neighborhood socioeconomic status had no effect on mobility intentions, change in the proportion of non-Western ethnic minorities increased residents' desire to move (Feijten and van Ham 2009). A second approach to studying responsiveness to neighborhood change relies on the use of hypothetical neighborhoods and asks respondents to rate their likelihood of choosing a neighborhood based on a stated level or direction of change in some attribute. Two studies using factorial experiments asked respondents if they would move into an imagined neighborhood where property values were increasing, decreasing, or staying the same (Emerson et al. 2001; Lewis et al. 2011), finding a positive association between changing home values and desire to move in. A related four city study using diagrams to illustrate hypothetical racial change in a neighborhood found that thirty-eight percent of White survey respondents said they would leave an integrating neighborhood (Krysan 2002b).

While results from these studies support the idea that individuals are responsive to changing environments a shortcoming is that they presume rather than explicitly test residents' perceptions of change. Studies comparing residential mobility with change in neighborhood conditions assume that residential choice was made in response to neighborhood change without actually measuring awareness. Alternatively, factorial experiments and similar research designs dictate respondents' awareness of change rather than test for it organically. Missing from existing research is clear evidence of the first link in the causal chain of residential decision making in response to change: that to respond to neighborhood change one must first recognize that change is occurring. Researchers generally lack data on or fail to incorporate measures of perceptions of change into their models.

Some evidence that residents are attuned to change in neighborhood conditions can be found in ethnographic research. A variety of neighborhood studies have captured prospective and current residents' articulations of local change processes (Anderson 1992; Brown-Saracino 2010; Jones and Jackson 2018). For example, in her study of Chicago's North Kenwood-Oakland neighborhood, Pattillo (2007) documents the deliberations of Black, middle-class families considering their residential options, including discussions of the neighborhood's evolution and their potential role in its continued socioeconomic turnover. Similarly, studies of gentrifying neighborhoods find that long-time residents and in-movers are both aware of the ways in which neighborhoods are changing (Besbris 2020; Brown-Saracino 2010; Deener 2012; Hyra 2017), with some seeking to capitalize on a place's upward trajectory and others worrying about their potential displacement. But these studies do not capture how widespread perceptions of change are and how perceptions reflect objective conditions, underlining the need for more systematic measurement. To date, only one study (to my knowledge) captures a sizable sample's subjective perceptions of neighborhood change. In a study of mobility behavior in Nashville, Lee, Oropesa, and Kanan (1994) asked residents if they perceived change in local residential turnover, the built environment, and the social environment. They found that residents' perceptions, especially perceptions of residential turnover, influenced their desire to move. However, the authors crucially did not capture objective measures of these variables, meaning the study could not examine the relationship between perceptions, objective conditions, and mobility.

To summarize, though response to change is a core tennet of models of neighborhood dynamics, few studies to date explicitly capture residents' perceptions of change. Instead, common approaches either assume residents' awareness of changing conditions or dictate those conditions explicitly. While ethnographic research offers illustrative examples of residents' and newcomers' perceptions of changing neighborhood conditions, there is need for more systematic exploration of the first link in the causal chain of many models of neighborhood dynamics: that residents recognize change when it is happening.

Present Sudy

Given past research on perceptions of safety and the dynamics of neighborhood change, how should we understand the discrepancy between improving crime conditions and public perceptions of a growing crime crisis? In the present study, I interrogate residents' perceptions of change in neighborhood safety using change in crime in the city of Detroit as a case study. Specifically, I examine if systematic differences in objective crime conditions, respondent identity, and neighborhood characteristics predict Detroiters' perceptions of how safety in their neighborhood has changed over the previous five years. The aim of this study is to contribute to existing research on perceptions of safety and models of neighborhood change by answering the following research questions:

1. To what extent do residents' perceptions of change in neighborhood safety reflect objective crime conditions and how those conditions have changed over time?
2. Do similar dimensions of individual and neighborhood bias found to influence present-time perceptions of safety influence perceptions of change in neighborhood safety?

Data

To gain insight into residents' perceptions of change in neighborhood safety over time, I use survey data from the Detroit Metro Area Communities Study (DMACS), crime data from the Detroit Police Department (DPD), and neighborhood composition data from the American Communities Survey (ACS). DMACS is a panel study of Detroit residents launched in 2016 that captures the perceptions and priorities of a representative sample of Detroiters. The original panel of DMACS respondents was drawn in 2016 from an address-based probability sample of all occupied Detroit households and has been refreshed in subsequent years through additional address-based sampling to correct for panel attrition and sample bias. In this study, I draw on data from DMACS' fall 2019 survey—fielded between August 2 and December 17, 2019—which captured information on residents' perceptions of neighborhood conditions and how those conditions have changed over time, including perceived change in neighborhood safety. Respondents could self-administer the survey online or complete the survey in-person or by telephone with an interviewer. In total, the fall 2019 DMACS survey collected responses from 1,842 of 7,249 invited Detroit residents, a response rate of 25.4 percent.

Data on levels and change in crime over time are drawn from two sources of administrative data made publicly available by the Detroit Police Department through Detroit's open data portal. Baseline data on neighborhood crime conditions in 2014—five years prior to the DMACS survey—come from a DPD data set of reported major crime offenses from 2011 through 2014 (City of Detroit 2019). Available data are limited to six index crime types[3] commonly reported to the Federal Bureau of Investigation's Uniform Crime Reporting Program: homicide, robbery,

[3] Index crimes used in the FBI's Uniform Crime Reports commonly include data on forcible rape. Data on this crime type was not included in the public Detroit Police Department, potentially due to privacy concerns for victims in incident-level data with identifiable locations. For this reason, my measures of crime rates do not include data on rape.

aggravated assault, burglary, larceny, and motor vehicle theft. The first three crime types (homicide, robbery, aggravated assault) are aggregated to capture violent crimes due to their use or threat of force while burglary, larceny, and motor vehicle theft are aggregated to capture property crimes. From this multi-year data set, I extract all reported major crime offenses—totaling 50,165 crime events—that occurred within the 2014 calendar year and geocode these crimes to the census block group in which they occurred using incident latitude and longitude provided by the DPD. In the process of data cleaning for geographic coordinates and geocoding to block groups, a small proportion of crimes (313 crime events or 0.62 percent) were omitted due to a lack of location data or geographic referencing that placed the crimes outside of city boundaries. In total, the resulting 2014 data include 49,852 crime occurrences, from which I create violent and property crime rates per 1,000 residents at the block group level.

Crime conditions at the time of the fall 2019 DMACS survey are drawn from the Detroit Police Department's Records Management System, which captures the date, location, and type of reported criminal offenses at the incident level starting in 2017 (City of Detroit 2022). From this continuously updated database, I extract temporally relevant reported crimes—those that occurred between 12 months prior to the opening of the DMACS survey (August 2, 2018) and the survey's close (December 17, 2019)—to construct a data set of respondent-specific violent and property crime rates that captures crime occurrences in a respondents' residential block group in the 12-months prior to their survey participation.[4] These respondent-specific crime windows allow me to focus analysis on perceptions of safety in relation to spatially and temporally proximate crime occurrences and improves upon studies that use annual data by omitting crime events occurring after a respondent was surveyed. While data in the Record Management System includes a wider

[4] In addition to creating a respondent specific data set, I create a data set violent and property counts and rates for the 2019 calendar year for descriptive comparison with general 2014 crime conditions.

set of crime types (e.g., disorderly conduct), for comparability with 2014 baseline data and to minimize the influence of incidents involving the commission of multiple offenses that may inflate crime levels I limit 2019 crime data to the six index crime types highlighted above: homicide, robbery, aggravated assault, burglary, larceny, and motor vehicle theft. As with the 2014 data, I geocode these crimes to the census block group in which they occurred using incident latitude and longitude provided by the DPD, omitting the small number of crimes that fall outside of city boundaries. For example, of the 36,994 crime occurrences in the 2019 calendar year, I omit 259 or 0.70 percent to create a 2019 data set of 36,735 crime occurrences.

To capture the relationship between residents' perceptions of crime and the levels and change in neighborhood characteristics over time, I incorporate data on neighborhood sociodemographic conditions from the 2010-2014 and 2015-2019 American Communities Survey 5-year estimates. Combining this data with DMACS data on respondent perceptions and demographics and DPD crime data, I construct a multi-level data set reflecting the views of perceived change in neighborhood safety from 1,821 residents living in 356 block groups in the city of Detroit.[5] [6]

Perceived Change in Neighborhood Safety

My outcome variable captures DMACS respondents' perceptions of change in neighborhood safety based on responses to the question, "In the last five years I have noticed my neighborhood is… [safer/less safe/safety hasn't changed/don't know]." Because this question is

[5] I restrict my sample to 1,821 respondents due to missing data for 21 respondents on the outcome variable, perceived change in neighborhood safety.

[6] On average there are 5.12 respondents per block group in the data, with a minimum of 1 respondent and a maximum of 27.

focused on perceptions over a discrete period it allows for an explicit examination of how residents make sense of changing environments, in contrast to related research focused on residents' present-time perceptions. From this question, I construct a three-point ordered scale capturing if respondents believe their neighborhood has grown less safe, remained the same, or gotten safer over time, recoding "don't know" responses to the neutral middle category of the scale.[7]

Levels and Change in Crime Over Time

I draw on 2014 and 2019 crime data from the DPD detailed above to create variables capturing levels and change in crime over time within a respondent's block group of residence. Though the outcome variable refers to perceptions of change in a respondent's neighborhood, the survey does not define the size and meaning of neighborhood. I focus on block groups to emphasize the relationship between crime occurrences within a short distance of a respondent's residence (the average area of a block group in Detroit is .16 square miles) and safety, as it follows that one's awareness of criminal activity and associated sense of danger likely increase with proximity. This focus on smaller geographic units is in keeping with past research that finds that aggregating crime into larger geographic units adds bias to estimates of residents' perceptions (Hipp 2010b). Use of block groups also facilitates the incorporation of neighborhood demographic data using the smallest geography for which census data is publicly available.

To capture underlying variation in crime levels, I calculate the crime rate as the number of crime events reported to police in 2014 per 1000 residents in a block group and use a natural log transformation to reduce data skew and minimize the influence of outliers. To capture change in

[7] I tested the effect of this coding choice by running supplemental models that drop respondents who said "don't know" (n=201) rather than including them in the neutral middle category. Results from these models were substantively the same as those run on the full sample.

crime over time, I similarly transform the respondent-specific 12-month crime data to logged rates of crime incidents per 1000 residents in a block group and create a difference measure by subtracting 2014 rates from 2019 rates. Throughout my analysis, I evaluate violent and property crime separately, as perceptions of safety has been shown to differ by crime type (Boggess 2017; Hipp 2013; Zimring 1997).

Neighborhood Composition

As past research has shown that neighborhood socio-demographic conditions may more strongly influence perceptions of safety than actual crime levels, I construct measures of neighborhood racial and socio-economic composition levels and change from ACS data. Much like the approach used to measure local crime conditions, I use data from 2010-2014 ACS estimates to capture baseline levels of percent non-Hispanic Black, percent Latino, and degree of neighborhood disadvantage in a block group.[8] Following the approach of the National Neighborhood Data Archive (Melendez et al. 2019), I measure neighborhood disadvantage as the average proportion of four neighborhood characteristics: percent of households living in poverty, percent of residents 16 and older who are unemployed, percent of female headed households, and percent of households receiving public assistance. Data from 2015-2019 ACS estimates are used to approximate neighborhood conditions at the time of the survey while change in neighborhood conditions is captured by difference scores between 2010-2014 and 2015-2019 ACS data.

Individual Characteristics

[8] Additional models including neighborhood median income levels and change were tested and ultimately omitted due to high collinearity with the measure of neighborhood disadvantage.

In keeping with research on present-time perceptions of safety that illustrates the relationship between individual identity and perceptions, I include measures of respondent demographics captured in the DMACS survey. Specifically, following related research, I include measures of respondent race/ethnicity, level of education, income, gender, age, length of residential tenure, homeownership, if a household contains children, and recent experience as a victim of a crime. I code race/ethnicity as four mutually exclusive categories capturing if a respondent identifies as either non-Hispanic White (reference category), non-Hispanic Black, Latino, or non-Hispanic Other/Multiracial. Education level is coded as a binary variable capturing if the respondent holds at least a bachelor's degree or not. Income is included as a five-category variable that summarizes household earnings as: (1) incomes below $10,000 (reference category); (2) incomes between $10,000 and $29,999; (3) incomes between $30,000 and $59,999; (4) incomes between $60,000 and $99,999; and (5) incomes greater than $100,000. Gender is measured with a dummy variable indicating if a respondent self-identifies as female or not while age is measured as a continuous variable in years and is centered at 50 (the approximate sample mean) for interpretability. Because perceived change in safety has been shown to reflect exposure based on how long a respondent has lived in a neighborhood, I include length of residential tenure as a three-category variable capturing if the respondent has lived in their neighborhood for (1) 5 or fewer years (reference category); (2) 6-10 years; (3) or 11 years or more. Tenure type is a dummy variable indicating if the respondent is a homeowner or renter while household composition is a dummy variable indicating if the respondent lives in a household with any children under the age of 18.

Finally, to understand the role of crime victimization in shaping perceptions of safety, I draw on a series of questions about respondents' recent experience with crime in and around their neighborhood. The fall 2019 DMACS survey asked respondents to indicate if in the past 12 months they had had (1) a motor vehicle stolen; (2) a motor vehicle broken into or deliberately damaged; (3) anyone get into their residence without permission and steal or attempt to steal something; (4) their home vandalized or intentionally damaged; (5) items kept outside their home taken; and/or (6) had been personally attacked or threatened.[9] Respondents were coded as recent victims of crime if they reported they had experienced one or more of these incidents in the prior 12 months.

To address respondents lacking complete data on these variables, missing values were corrected using hot deck imputation in STATA 17.[10] See Table C.1 in the appendix for a summary of imputed variables. Table 3.1 summarizes descriptive statistics for dependent and independent variables used in my analyses.

[TABLE 3.1 ABOUT HERE]

Methods

To examine the effects of crime levels and change, individual characteristics, and neighborhood characteristics on respondents' perceptions of change in neighborhood safety I

[9] Some of these measures of experience with crime ask about "you or a member of your household" while others are specific to the respondent. As a result, this measure may overestimate the frequency of individual crime victims. However, as perceptions of safety are likely also influence by family members' experience with crime, I elect to not limit this variable to only questions where it is clear the respondent was directly victimized.

[10] Hot deck imputation was used in place of multiple imputation to overcome limitations in applying the multiple imputation framework for multi-level ordinal models. Specifically, the `meologit` command is not compatible with mi estimate, making it difficult to determine appropriate confidence intervals for ordinal coefficients. Sensitivity tests run on results from that used multiple imputation and listwise deletion to respond to missing data yielded substantively consistent results to hot deck imputed models. 129 respondents were missing data on one or more demographic variable.

estimate a series of multilevel models.[11] Multilevel models allow for the simultaneous estimation of the effects of variables at different levels of observation and address the violation of assumed independence that arises from having respondents clustered geographically in shared block group environments. These models also control for unmodeled differences between neighborhoods and allow intercepts and individual level coefficients to vary across neighborhoods (Rabe-Hesketh and Skrondal 2012; Raudenbush and Bryk 2002). Throughout, I use a two-level model, with individuals nested in block groups.

As a first step in making sense of residents' perceptions of changing neighborhood safety, I estimate a random intercept model that captures the general location of variance in the data. Next, I specify a series of models to test the effects of measures found to explain present-time perceptions of safety in past research to examine if these explanations hold when considering perceived change in safety over time. Model 1 examines the degree to which residents' perceived changes in neighborhood safety are associated with underlying rates of local violent and property crime at baseline (in 2014) and with change in property and violent crime over the following five years. Building on this, Model 2 examines the role of individual bias in shaping perceptions of change by adding in measures of respondent demographics. Model 3 considers the additional effects of local context in shaping perceived changes in neighborhood safety. I conclude by detailing findings from sensitivity analyses that explore results from the three core models and point to avenues for future research.

[11] Sensitivity tests comparing results from multilevel ordinal logit models and multilevel linear models found consistent patterns across modeling approaches. Because my outcome variable is a three-level, categorical measure of perception of change, I focus my interpretation of effect sizes on results from the ordinal model. I also draw on results from the linear model to discuss degree of variance in perceptions left unexplained with each model. See Table C.2 in Appendix for results from linear models.

Results

Before examining model results, I begin by describing crime conditions in Detroit generally and variation in crime levels and change among my respondents. As noted above, Detroit experienced a precipitous drop in crime starting in the 1990s. Between 2014 and 2019—the period of interest for this study—crime across the city continued to decline. Table 3.2 offers summary statistics of crime data for the city of Detroit overall as well as a comparison of crime levels and change across all Detroit block groups and in block groups inhabited by DMACS respondents. The data show that in the city total, violent, and property crime rates per 1000 residents each fell by roughly 24 percent. Of course, crime conditions across a city are not constant, with some neighborhoods serving as loci for greater concentrations of criminal activity than others. Thus, one might expect that the decline in crime for the city might not be reflected in change in a given neighborhood. While some neighborhoods in Detroit saw an uptick in crime between 2014 and 2019, violent crime in the average Detroit block group fell by 22 percent while property crime fell by 20 percent. Crime conditions in neighborhoods inhabited by DMACS respondents are generally comparable to conditions in the average block group: the average respondent block group saw a 25 percent decline in the violent crime rate and a 26 percent decline in the property crime rate.

[TABLE 3.2 ABOUT HERE]

How are residents' perceptions of change in neighborhood safety associated with levels and change in crime? Figure 3.1 offers a simple illustration of perceptions in relation to crime conditions. The upper panel includes a scatter plot of respondents based on the 2014 level and 2014-2019 change in violent crime rates in a block group, with different symbols indicating if a respondent thought their neighborhood had grown less safe (square), safer (plus), or not changed over time (circle). The lower panel captures the same information but for property crime. The plots also include best fit lines. The primary takeaway of each graph is that residents exposed to the same neighborhood conditions often hold opposing views on how neighborhood safety has changed. While one might expect that respondents who perceive their neighborhood has grown safer would be clustered in neighborhoods where crime had dropped—captured to the left of the dashed grey line in each graph—this is not the case. Moreover, there are many examples where two respondents experience the same level and change in block group crime rates, but one believes the neighborhood has grown less safe while the other believes the neighborhood has grown safer. These plots offer initial evidence of the highly subjective nature of perceived change in safety.

[FIGURE 3.1 ABOUT HERE]

Another way of illustrating residents' diverging perceptions of change in local crime conditions is with random intercept models, which capture the extent to which variation in perceived change in safety is explained by differences among respondents living in the same block group—who share general neighborhood and crime conditions—compared to differences among respondents across block groups—who are exposed to different neighborhood conditions. A higher proportion of within-neighborhood variation implies a greater role of individual bias and subjectivity in shaping perceptions whereas a greater proportion of between-neighborhood variation points to the role of objective differences in conditions across neighborhoods. The intra-class correlation (ICC)—calculated by dividing between-neighborhood variance by the total (between-neighborhood plus within-neighborhood) variance—produced by this model finds that variation in crime and neighborhood conditions between neighborhoods accounts for just 8 percent of the overall variance in perceived change in safety, meaning that the bulk of variation in perceptions lies between respondents living in the same block group. This is in keeping with my above findings and research on present-time perceptions in that it suggests residents' perceptions are highly subjective such that people living in shared environments hold very different understandings of how their environments have changed over time.

The limited role of between-neighborhood differences in shaping perceptions does not necessarily mean that perceptions are wholly detached from objective crime conditions. Turning to the extent to which crime conditions are reflected in residents' perceptions of change in neighborhood safety, Model 1 (Table 3.3) estimates the relationship between neighborhood violent and property crime rates in 2014, change in crime rates between 2014 and 2019, and perceptions. By including levels and change as well as violent and property crime measures this model allows the simultaneous examination of the temporal effects of crime as well as the relative effects of crime types on perceptions. Results point to a few key findings. Starting with crime levels, I find that underlying differences in the rate of crime occurrences within a neighborhood—captured by baseline crime rates from 2014—significantly influence how respondents perceive safety in their neighborhood to have changed over time. Specifically, a standard deviation increase in violent crime rates at baseline is associated with a 24 percent decrease (standardized OR = .765) in the odds of perceiving one's neighborhood to have grown safer over time. Property crime rates at baseline appear to have the opposite effect on perceived change in safety: a standard deviation increase in the local 2014 property crime rate is associated with 27 percent increase (standardized OR = 1.272) in the odds of perceiving one's neighborhood has grown safer. These countervailing effects of violent and property crime rates, which have been noted in past scholarship (Hipp 2013;

Zimring 1997), likely point to unmodeled, underlying differences between neighborhoods. For example, neighborhoods with more property crime may also be wealthier areas with fewer physical signs of disorder. In general, these findings suggest that residents' perceptions of change in neighborhood safety reflect in part underlying levels of crime, such that neighborhoods with higher rates of violent crime are less likely to be viewed as growing safer whereas those with higher rates of property crime are somewhat more likely to be viewed as increasing in safety.

[TABLE 3.3 ABOUT HERE]

In addition to the effect of crime levels, Model 1 shows that change in violent crime rates between 2014 and 2019 significantly impacts residents' perceptions of change in neighborhood safety. As the degree of change in violent crime in a block group increases the likelihood of residents reporting they feel safer decreases. Specifically, residents in block groups where the violent crime rate changed by a standard deviation more than the mean—i.e., where the logged violent crime rate over the past five years increased by .509 compared to the average change of -.324—had 20 percent (standardized OR = .800) lower odds of thinking their neighborhood had grown safer over time. Though one might hypothesize that the effect of change would vary depending on the baseline level of crime in a neighborhood—for example residents in the least violent neighborhoods may be more sensitive to increases in crime than residents in more dangerous neighborhoods—supplemental models testing interactions between crime levels and change in crime do not yield significant results. I similarly find no significant effect of change in property crime rates. Taken together, results from this first model suggest that perceptions of change in neighborhood safety are influenced by both underlying levels and degree of change in crime, especially violent crime, such that residents in neighborhoods with higher or increasing violent crime rates are less likely to state that their neighborhoods have grown safer over time.

Though these results indicate that residents' perceptions of change in safety track generally with objective data on violent crime levels and rates in one's neighborhood, contradicting the idea that individuals' perceptions are incongruent with measures of crime conditions, fit statistics from linear models reveal that crime conditions only tell a small part of the story of residents' perceptions. Table 3.4 captures R^2 statistics—computed as the difference in the amount of explained variance between the current model and the unconditional, random intercept model (Raudenbush and Bryk 2002)—for the overall model as well as level 1 (individual) and level 2 (neighborhood) variables, drawing on the linear model specification. R^2 statistics for Model 1 show that the inclusion of crime level and change explains 18 percent of the variation in perceived change in safety between neighborhoods and just 1 percent of the variation in the overall model, emphasizing that crime conditions alone are insufficient to understand variation in perceptions of changing neighborhood safety.

[TABLE 3.4 ABOUT HERE]

Turning to the role of individual identity in shaping perceptions, Model 2 adds in respondents' sociodemographic and household characteristics to examine if dimensions of individual bias and subjectivity identified in research on present-time perceptions, as well as the effects of crime conditions, hold when assessing perceived change in neighborhood safety. In general, my findings affirm past research on the role of individual characteristics and patterns of systematic bias in shaping perceptions. Specifically, respondent gender, length of neighborhood tenure, and experience as a recent crime victim are each significantly and negatively associated with the perception that one's neighborhood has gotten safer while respondent race, education level, income, age, household composition, and household type show no significant effect. The strongest effect of individual identity on perceptions of change in safety reflects respondents' experience as a victim of crime. Those who report they have been a victim of crime in the past 12 months have half the odds (OR = .483) of perceiving their neighborhood has grown safer over time compared to those who have not been recently victimized, controlling for objective neighborhood crime conditions and other dimensions of individual identity. Similarly, females have 30 percent (OR = .700) lower odds of perceiving their neighborhood have grown safer over time, in keeping with past research on the gendered nature of perceived risk. Respondents who have resided in their neighborhood for more than a decade have 35 percent lower odds (OR = .653) of perceiving their neighborhood has grown safer over time compared to residents who moved in within the past five years.

A second, notable finding is that the effects of neighborhood crime levels and change detailed above are generally robust to the inclusion of measures of respondent identity, though effect sizes are somewhat dampened. After accounting for variation in respondent demographics, a standard deviation increase in the level of violent crime in a block group is associated with a 20 percent decrease (standardized OR = .803) in the odds of perceiving that one's neighborhood had grown safer over time while a similar increase in property crime level is associated with a 24 percent increase (standardized OR = 1.236) in the odds of perceiving your neighborhood has grown safer. Additionally, the negative effect of change in violent crime on perceptions of shifting neighborhood safety persists such that a standard deviation increase in change in the violent crime rate is associated with an 18 percent (standardized OR = .822) decrease in the odds of perceiving one's neighborhood has grown safer over time. Change in property crime rates continues to have no significant effect. Thus, though individual bias is implicated in perceptions of change in neighborhood safety, the nature of this bias does not eliminate the relationship between actual crime conditions and perceptions.

Given the earlier finding that most variation in perceptions of change come from within block groups rather than across neighborhood contexts, it is interesting to note that the inclusion of these individual demographic variables captures only a small amount of the variation in perceived change in safety among clustered respondents and makes only modest improvements to overall model fit. Fit statistics (Table 3.4) for individual level variables suggest respondents' sociodemographic characteristics explain just 5 percent of variation in perceptions of changing neighborhood safety, hinting at the considerable unmodeled subjectivity in perceptions. At the same time, the inclusion of these individual characteristics increases the percent of explained variation between neighborhoods to 31 percent. That the inclusion of individual socio-demographic variables nearly doubles the percent of neighborhood variation explained reflects the high degree of segregation along racial and economic lines within Detroit, such that controlling for variation across people also captures a degree of variation across neighborhoods. Overall, levels and change in crime and individual characteristics explain just 7 percent of the variation in perceptions in the overall model.

A third aspect of social environments established in prior research as influencing perceptions of safety is neighborhood composition. To test the influence of neighborhood composition on perceptions of change in safety over time, Model 3 adds in measures of level and change in the percent Black residents, Latino residents, and degree of neighborhood disadvantage. Results in Table 3.3 show that the inclusion of these neighborhood characteristics minimizes to the point of statistical insignificance the effect of violent crime levels and change on perceptions of safety, though the effect of property crime levels continues to be positively and significantly associated with perceptions of improving neighborhood safety. Because these variables only vary at the neighborhood level, modeling additional neighborhood measures has no effect on individual sources of perceptual bias observed in Model 2. Females, those who have lived in a neighborhood for more than a decade, and respondents who report being recent victims of crime remain less likely to perceive their neighborhood safety has improved over time, controlling for levels and change in crime and other neighborhood conditions.

Results from Model 3 show that neighborhood racial composition has a strong effect on perceived change in safety. Specifically, after controlling for crime levels and individual characteristics, the percent of Black residents in one's neighborhood is significantly and negatively associated with perceptions that one's neighborhood has grown safer. A standard deviation increase in the proportion of Black residents in one's neighborhood is associated with a 22 percent decrease (standardized OR = .775) in the odds of perceiving that one's neighborhood has grown safer over time. Other measures of neighborhood conditions—percent of Latino residents and level of neighborhood disadvantage—do not appear to significantly shape perceived change in neighborhood safety. Moreover, though one might expect that perceptions of change in safety would be influenced by composition change, measures capturing change in neighborhood socio-demographics over the past five years show no significant association with perceived change in neighborhood safety. This likely reflects the slow nature of demographic change in most Detroit neighborhoods and the limited ability of averaged 5-year estimates from the ACS to capture large shifts in neighborhood composition.

A final observation from Model 3 is that the inclusion of levels and change in neighborhood composition improves model fit such that the combination of crime conditions and neighborhood composition explains roughly half (44 percent) of the underlying variation in perceived change in safety between neighborhoods. Overall, results from this model suggest that residents' perceptions are strongly influenced by neighborhood racial composition. In Detroit, where the average neighborhood is roughly 80 percent Black, these findings implicate the long and enduring impacts of racial segregation on perceptions of safety and the ways in which enduring segregation counteracts how residents experience and make sense of crime conditions.

Sensitivity Analyses

As a final step, I conduct a number of sensitivity analyses to examine the effect of model specifications on perceived change in neighborhood safety. First, I tested if the effect of crime conditions and sociodemographic composition show evidence of a multiplicative (interaction) effect on perceptions—for example, if low levels or degrees of change in neighborhood conditions have less effect on perceptions than higher levels or degrees of change. After controlling for individual characteristics and neighborhood characteristics, I find suggestive evidence that change in violent crime on perceptions follows a quadratic pattern such that greater increases in violent crime over time are associated with increasingly lower probabilities of perceiving one's neighborhood to have grown safer. No other measures of crime or neighborhood composition indicate any significant multiplicative effects with residents' perceived change in neighborhood safety.

In response to past research that argues some residents are more responsive to crime conditions and experiences with crime victimization than others (Sampson and Raudenbush 2004), I also test a number of interactions. Examining if the effect of crime levels or change in crime conditions varies by race of respondent, I find no significant differences in response to violent or property crime levels or change. However, I do find some evidence that the effect of direct experience as a victim of crime on perceptions varies by race. Predicted probabilities suggest that Latino residents who have not been the recent victim of a crime are roughly half as likely (Predicted probability = 0.07) to think their neighborhood has grown less safe over time compared to Black residents who have not been victimized (predicted probability = 0.15).

Finally, to gain insight into for whom racial composition shapes perceived change in neighborhood safety, I examine cross-level interactions between individual characteristics and neighborhood racial composition. Specifically, I test whether the effect of levels or change in the percent of Black residents in a neighborhood varies depending on respondent race, length of tenure in a neighborhood, and recent experience as a victim of crime. While one might hypothesize that living in predominantly Black neighborhoods will influence Black residents' perceptions of safety differently than the perceptions of other-race residents, results from cross-level interactions do not support this hypothesis. I find no significant difference in perceived change in neighborhood safety by race of respondent in response to levels or change in neighborhood racial composition. Similarly, the effect of racial composition on perceptions does not appear to vary by length of tenure in a neighborhood. However, the effect of neighborhood racial composition does appear to significantly influence perceptions of safety among crime victims. Recent crime victims are less responsive to the effect of racial concentration in a neighborhood compared to those who have not been victimized. This suggests that residents without recent, first-hand experience with crime may rely more strongly on context clues of racial composition to determine how safety in their neighborhood has changed. Figure 3.2 illustrates this finding, showing that among recent crime victims, the concentration of Black residents in a neighborhood has minimal effect on the probability of feeling safer, while those who have not been a recent victim of crime are significantly more responsive to neighborhood composition.

[FIGURE 3.2 ABOUT HERE]

Discussion & Conclusions

This study set out to examine how residents' perceptions reflect, or fail to reflect, change in objective neighborhood conditions. Building on the insight that despite historic drops in crime in recent decades public opinion polls show perceptions of local and national crime are increasing, I explore how residents' perceptions of change in neighborhood safety in Detroit relate to objective levels and change in crime conditions, individual identity, and other neighborhood characteristics.

My results point to four key takeaways that collectively suggest that residents' perceptions of change offer at best a distorted view of change in local crime conditions. First, I find that residents' perceptions are highly subjective and that neighbors exposed to the same general crime conditions within a block group diverge considerably in how they think local safety has changed. Scholarship on present-time perceptions of safety has found similar variation in perceptions among residents when assessing crime and disorder (Hipp 2010b, 2013; Sampson and Raudenbush 2004). Given this, it is perhaps unsurprising that in extending this inquiry to change I find little agreement among residents. While the idea that individuals are responsive to changing neighborhood conditions implies some level of agreement about local environments, the fact that the bulk of variation in perceptions of change (92 percent) comes from differences in perspective among neighbors points to the nuanced nature of residents' neighborhood evaluations.

While descriptive findings and model results both illustrate that residents exposed to the same neighborhood crime conditions draw very different conclusions about change in local safety over time, a second key takeaway from my analysis is that residents' perceptions of change are not entirely divorced from objective crime conditions. Simple models testing the relationship between levels and change in crime and perceptions show that living in neighborhoods with higher or growing levels of violent crime decreases the likelihood that a resident believes their neighborhood is growing safer. Moreover, sensitivity tests offer marginal evidence that this effect of change in violent crime may grow at an accelerating rate, echoing findings from Prieto Curiel and Bishop (2017) that a considerable degree of change over time is required to shift perceptions. However, the relationship between crime and perceived change in safety is relatively weak—explaining only a small amount of the overall variation in residents' perceptions—and are not robust—disappearing after controlling for other measures of neighborhood context. Thus, these findings collectively illustrate that while crime conditions likely do influence how residents believe local safety has changed over time, as in past research crime only tells a small part of the story of perceived safety (Furstenberg 1971; Hipp 2013; Pickett et al. 2012; Rountree and Land 1996).

The third key takeaway from my findings is that despite my explicit focus on change, results from my models show that perceptions of change are generally influenced by the same individual and neighborhood characteristics identified in past research as shaping present-time perceptions of safety. Gender, length of tenure, and experience as a victim of a crime are all associated with lower likelihoods of perceiving one's neighborhood has gotten safer. Additionally, I find that perceptions of change are strongly influenced by current neighborhood composition. Like Quillian and Pager (2001), I find that the proportion of Black residents in one's neighborhood significantly decreases the likelihood of perceiving one's neighborhood has grown safer over time, regardless of actual change in crime. This effect of neighborhood composition on perceptions is fairly stable. Sensitivity analyses show that the negative effect of neighborhood composition does not depend on respondent race, meaning Black respondents are as likely to associate the proportion of Black residents in their neighborhood with lower levels of safety as White or Latino respondents. Stratified models examining if the effect of racial composition on perceptions varies by degree of racial segregation—among neighborhoods where more than 75 percent of residents are Black compared to more racially integrated neighborhoods—similarly do not find that the effect of the proportion of Black residents in a neighborhood disappears even in highly segregated areas. However, I do find evidence that the effect of neighborhood racial composition disappears among recent crime victims, suggesting that racial composition might be especially relevant to respondents who lack firsthand experience with crime.

The finding that perceptions of change are predicted by the same variables that predict present-time perceptions of safety is notable in part because it suggests residents' understandings of change might be strongly influenced by recency bias—a phenomenon where recently presented facts or impressions are weighted more heavily in one's views or memories than information presented earlier. While the cognitive task suggested by the outcome variable is one of comparison between past and present conditions, the strong effect of recent crime victimization and levels of neighborhood composition, but not change in composition, imply that residents' perceptions of change may be clouded by views of what the neighborhood is like now. Recency bias may help explain the incongruity between perceptions captured in public opinion polls and crime trends. If individuals feel that their neighborhood is unsafe at present, this sense of fear may overshadow recollections of how their current sense of safety relates to how safe they felt previously. Additionally, the role of recency bias might also help explain the discrepancy between those who have and have not recently been victimized in terms of the effects of local racial composition, where current neighborhood composition serves as a heuristic for beliefs about safety only among those who lack other recent signals about neighborhood safety.

A final takeaway from my analyses is that even after considering these individual and contextual variables, substantial variation in residents' perceptions of change remain. Overall, my models explain just 8 percent of the variation in residents' perceptions of change in neighborhood safety, indicating that a comprehensive understanding of how residents perceive change in their social environments requires further research. This is especially true when it comes to understanding individual-level perceptions, given that respondent characteristics in my models explain just 5 percent of the variation in perceptions of change among neighbors.

How should we understand the limited explanatory power of individual and neighborhood conditions on residents' perceptions of neighborhood change? One clear finding is that sense of safety is not reducible to crime conditions. While crime and victimization contribute to how safe one feels, there are many other omitted dimensions to consider. On the individual level, consumption of media—which past research has shown influences beliefs about the salience and nature of crime (Shi et al. 2020; Callanan 2012)—might strongly shape sense of change in safety by highlighting egregious crimes and exacerbating views of criminal activity. Additionally, experience with police might help explain one's sense of safety, as increased policing linked with declining crime might actually make one feel less safe than more safe. At the neighborhood level, neighborhood conditions like physical disorder—the amount of graffiti, garbage, and other visual cues of dilapidation—have been shown to be associated with fear of crime and perceptions of safety (Perkins and Taylor 1996; Ross and Jang 2000) as have other aspects of the built environment including neighborhood housing conditions (Austin et al. 2002) and the presence or absence of other neighborhood amenities (Wilcox, Quisenberry, and Jones 2003). In Detroit, where many neighborhoods contain abandoned houses and empty lots, these broader neighborhood dimensions may greatly influence how residents perceive local safety to have changed over time. Future research incorporating these individual and neighborhood measures would aid in detangling the extent to which unmeasured variables shape perceived changes in neighborhood safety.

The limited effect of crime conditions on perceptions of neighborhood change may also be a consequence of geographic and temporal scale. In this study, my outcome variable asks residents to assess how safety in their neighborhood has changed over the last five years. Past research has demonstrated that perceptions are sensitive to geographic scale and that residents' perceptions of safety grow less attuned to objective measures of crime over larger geographies (Hipp 2010b). Thus, though my use of block groups improves upon studies that ask about perceptions at the tract or city level, it is likely that the weak association between perceptions of change and neighborhood conditions in part reflect the fact that residents' awareness of local crime conditions do not conform to block group boundaries and are likely influenced by nearby crimes that occur in neighboring block groups. Similarly, it is possible that perceptions of change are hampered by my use of a five-year time horizon. Because this study is among the first to explicitly interrogate residents' perceptions of how local safety has evolved over time, there is little literature to draw on regarding the appropriate time window over which to examine change. Studies considering residential mobility in response to neighborhood change often rely on ten-year periods of change as captured by the census (see for example Crowder 2000) or assume change without specifying a length of time (see for example Lee et al. 1994). Given the suggested role of recency bias in my findings, it is possible that five years is too long a period for residents to recall past conditions. Alternatively, it is possible that five years is too short a period for sufficient change to have occurred to rise to residents' awareness. Future research that varies the geographic scale and time horizon over which residents are asked about change would be useful in clarifying the impacts of these factors on my findings.

A final limitation to consider is the extent to which my findings on residents' perceptions of change are specific to Detroit. While Detroit has seen a considerable drop in crime over time it remains one of the nation's most dangerous cities (MacDonald and Hunter 2020). Moreover, Detroit is a majority Black city with a high degree of racial segregation in which the average block group if 77 percent Black. These factors as well as the city's history of depopulation and disinvestment likely influence perceptions of change in neighborhood safety and findings about the role of racial composition on those perceptions. Future research replicating this study in other communities or drawing on a nationally representative sample would help disentangle the extent to which these results are particular to Detroit.

While prior scholarship has examined the drivers of present-time perceptions of safety, this study is among the first to focus on change and explicitly interrogate residents' perceptions of how local safety has evolved over time. My findings suggest that though change in neighborhood conditions—or desire for change—is often seen as a catalyst for theories of neighborhood dynamics and public policies, residents' ability to detect change or agree about when change has occurred is limited. This raises important questions for researchers and policymakers. For researchers, my findings suggest that models of residential processes that assume choice in response to change would be improved with more explicit modeling of resident knowledge. This requires a new approach to data collection and analysis that combines perceptions, objective conditions, and behavior to better test the first link in the causal chain of many models of neighborhood dynamics: that residents recognize change when it is happening. For policymakers, residents' distorted understandings of change in neighborhood conditions suggest that simply shifting local conditions is insufficient to shape public perceptions. Recognizing this discrepancy is an important first step towards improving public sentiment and has the potential to shape investments in and communications about local policy priorities in the future.

Table 3.1 Descriptive Statistics for Crime, Respondent, and Neighborhood Characteristics

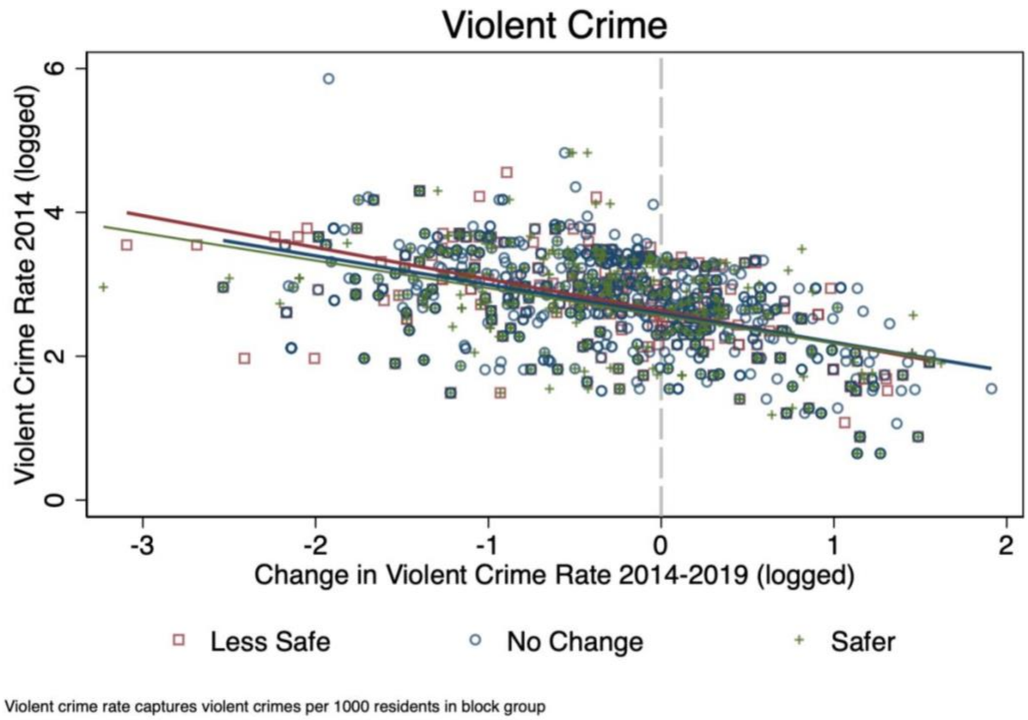
	Mean / %	SD	Min	Max
Perceived Change in Safety	2.080	0.663	1	3
Crime				
2014 Violent Crime Rate (logged)	2.723	0.681	0.648	5.859
2014 Property Crime Rate (logged)	3.836	0.532	2.233	6.682
Change in Violent Crime Rate, 2014-2019 (logged)	-0.324	0.833	-3.228	1.912
Change in Property Crime Rate, 2014-2019 (logged)	-0.330	0.653	-2.752	1.490
Respondent Characteristics				
Race				
White	0.130	0.337	0	1
Black	0.717	0.450	0	1
Latino	0.059	0.235	0	1
Other/Multi Race	0.094	0.292	0	1
College+	0.269	0.444	0	1
Income				
Under $10,000	0.252	0.434	0	1
$10,000-$29,999	0.276	0.447	0	1
$30,000-$59,999	0.269	0.443	0	1
$60,000-$99,999	0.132	0.338	0	1
$100,000+	0.072	0.259	0	1
Age (Centered)	51	16.877	18	94
Female	0.675	0.468	0	1
Residential Length				
Less than 5 years	0.411	0.492	0	1
6-10 years	0.197	0.398	0	1
11+ years	0.392	0.488	0	1
Households with children	0.366	0.482	0	1
Homeowners	0.489	0.500	0	1
Recent Crime Victim	0.419	0.493	0	1
Neighborhood Characteristics				
2014 % Black	0.801	0.275	0	1
2014 % Latino	0.057	0.173	0	0.920
2014 % Disadvantaged	0.220	0.074	0.051	0.527
△ % Black (2014-2019)	-0.027	0.099	-0.372	0.446
△ % Latino (2014-2019)	0.007	0.060	-0.386	0.399
△ % Disadvantaged (2014-2019)	-0.042	0.075	-0.313	0.235

Notes: N=1,821 respondents clustered in 356 block groups. Values reflect imputed data. See Table C.1 in Appendix for table detailing imputed cases.

Table 3.2 Summary Statistics of Official Crime Rates in Detroit

	Detroit Overall	All Detroit Block Groups		Respondent Block Groups	
		Mean	Std. Dev	Mean	Std. Dev
2014					
Violent Crime Rate	19.83	24.70	29.50	18.96	15.07
Property Crime Rate	51.86	57.88	56.22	54.60	48.46
Total Major Crime Rate	71.68	82.58	81.31	73.56	59.14
2019					
Violent Crime Rate	15.14	19.27	15.69	14.21	9.99
Property Crime Rate	39.30	46.28	40.84	40.58	31.38
Total Major Crime Rate	54.44	65.54	51.56	54.79	37.87
2014 - 2019 Change					
Violent Crime Rate	-4.69	-4.77	21.98	-4.76	14.72
Property Crime Rate	-12.56	-10.79	45.73	-14.30	36.64
Total Major Crime Rate	-17.25	-15.56	61.75	-19.05	46.49

Figure 3.1 Levels and Change in Neighborhood Crime Conditions by Perceptions of Change in Neighborhood Safety



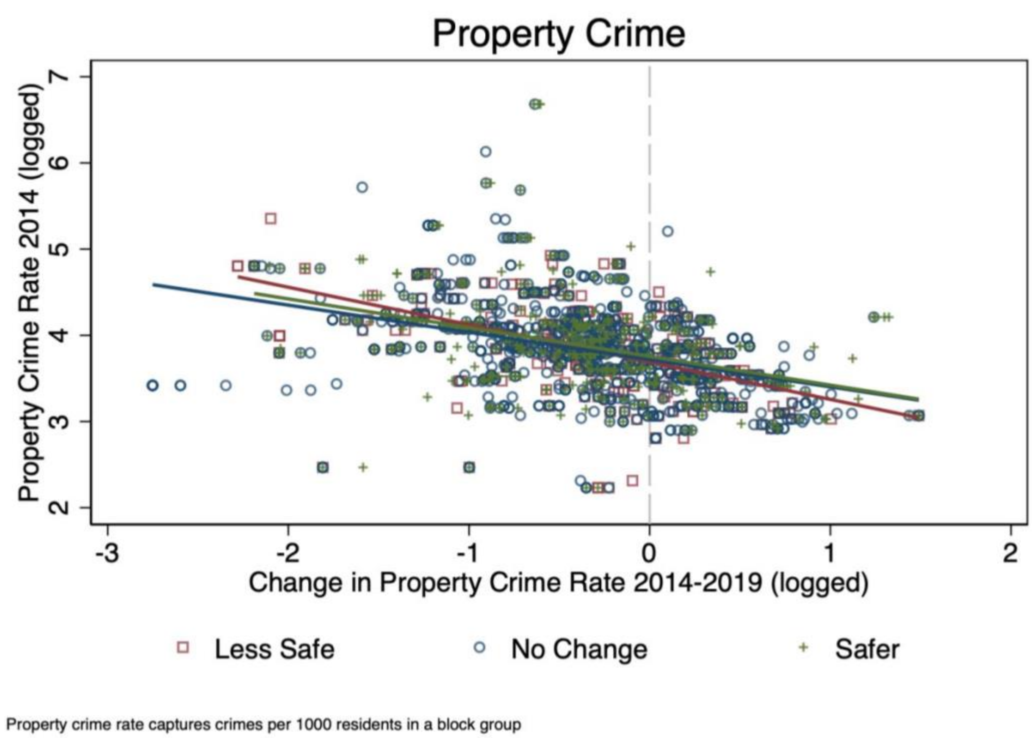


Table 3.3 Effects of Crime Levels and Change, Respondent Characteristics, and Neighborhood Composition and Change on Perceived Change in Neighborhood Safety

	Model 1		Model 2		Model 3	
Crime						
2014 Violent Crime Rate	-.394**	(.127)	-0.322*	(.132)	-0.152	(.140)
2014 Property Crime Rate	.452**	(.452)	0.399*	(.160)	0.348*	(.163)
△ Violent Crime Rate (2014-2019)	-.268**	(.137)	-0.235*	(.097)	-0.136	(.101)
△ Property Crime Rate (2014-2019)	0.137	(.119)	0.146	(.121)	0.18	(.120)
Personal Characteristics						
Race/Ethnicity						
Non-Hispanic White						
Non-Hispanic Black			-0.245	(.156)	-0.087	(.162)
Latino			0.32	(.251)	0.237	(.267)
Non-Hispanic Other/Multi Race			-0.267	(.209)	-0.246	(.210)
College+			-0.035	(.125)	-0.026	(.125)
Income						
Under $10,000						
$10,000-$29,999			0.123	(.133)	0.131	(.133)
$30,000-$59,999			0.015	(.139)	0.013	(.139)
$60,000-$99,999			-0.243	(.177)	-0.245	(.177)
$100,000+			0.23	(.230)	0.258	(.231)
Age (Centered)			-0.004	(.003)	-0.003	(.003)
Female			-0.357**	(.103)	-0.349**	(.103)
Residential Length						
Less than 5 years						
6-10 years			-0.017	(.134)	-0.036	(.134)
11+ years			-0.425**	(.129)	-0.438**	(.129)
Households with children			-0.025	(.113)	-0.03	(.113)
Homeowners			0.017	(.115)	-0.001	(.115)
Recent Crime Victim			-0.727***	(.101)	-0.738***	(.101)
Neighborhood Characteristics						
2014 % Black					-0.925**	(.338)
2014 % Latino					-0.205	(.519)
2014 % Disadvantaged					-0.805	(1.014)
△ % Black (2014-2019)					-0.906	(.640)
△ % Latino (2014-2019)					0.38	(.982)
△ % Disadvantaged (2014-2019)					-0.839	(.932)
Variance Component	0.232		0.211		0.168	
ICC	0.066		0.060		0.049	
AIC	3582.87		3509.2		3506.9	
BIC	3621.42		3630.4		3661.1	

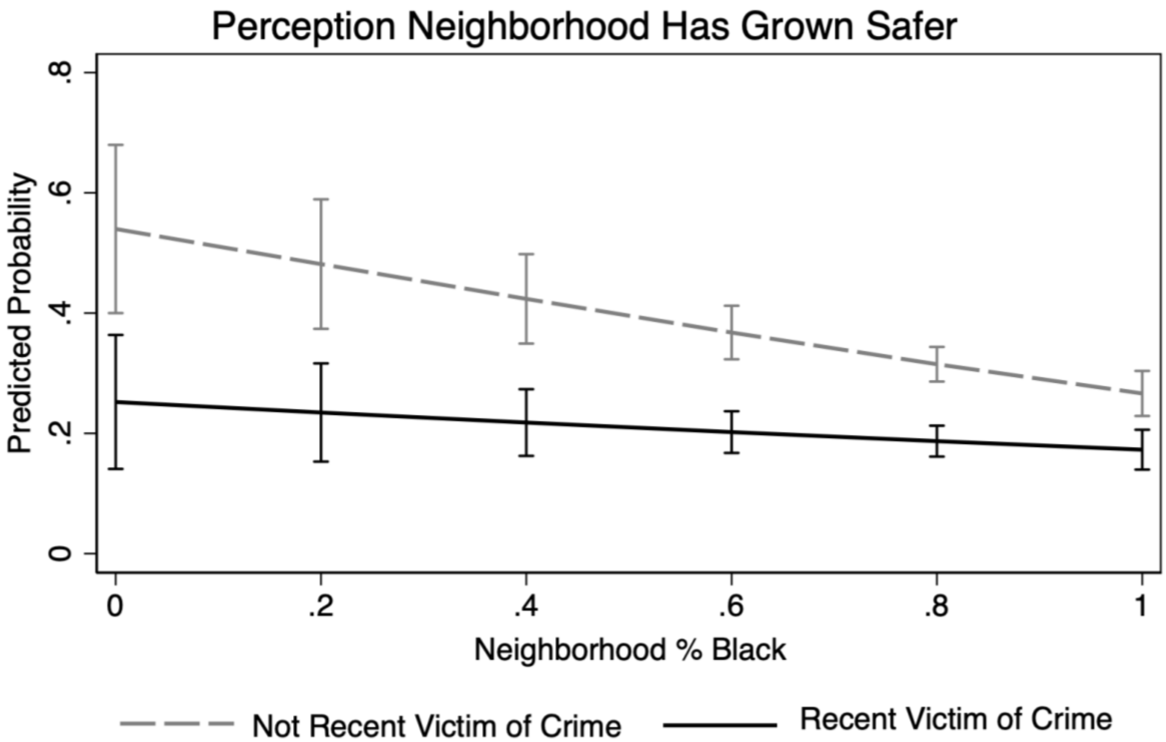
Notes: N=1,821 respondents clustered in 356 block groups. Coefficients reported from multi-level ordinal logit models. Standard errors in parentheses. ICC = Intraclass correlation. AIC = Akaike information criterion. BIC = Bayesian information criterion.
* p<0.05, ** p<0.01, *** p<0.001 (two-tailed tests)

Table 3.4 Measures of Model Fit

	Null Model	Model 1	Model 2	Model 3
Variance Components				
Between-neighborhood variance	0.031	0.025	0.021	0.017
Within-neighborhood variance	0.411	0.411	0.39	0.389
ICC	0.069	0.058	0.052	0.042
R^2 Total		0.0124	0.07	0.080
R^2 Between (Level 1)		0.00	0.053	0.053
R^2Within (Level 2)		0.178	0.309	0.444
AIC	3659.250	3652.094	3575.420	3572.682
BIC	3675.771	3690.644	3696.577	3726.882
N	1821	1821	1821	1821
Groups	356	356	356	356

Fit statistics reported from multi-level linear regression models. ICC = Intraclass correlation. AIC = Akaike information criterion. BIC = Bayesian information criterion.

Figure 3.2 Effect of Neighborhood Percent Black on Perceived Change in Neighborhood Safety by Recent Victimhood



Chapter 4

Making Sense of 'A Sense of Place':
Evaluating the Underlying Dimensions of Neighborhood Reputation

Following decades of sprawl, suburban growth, and urban decline, many U.S. cities have experienced rebounding populations and increased competition over space since the turn of the millennium (Frey 2014, 2020). In response to this rising appetite for urban life, governments and local entities have invested in efforts like placemaking and neighborhood branding to safeguard and develop appealing neighborhood environments aimed at attracting people and capital (Greenberg 2009; Markusen and Gadwa 2010). At the same time, technological advancements and the proliferation of place-based amenity websites like Zillow, OpenTable, and Airbnb have made it easier than ever for the public to filter and select communities based on little more than a neighborhood name and vague sense of neighborhood identity. These trends of neighborhood promotion and sorting point to the salience of neighborhood reputation as an essential dimension and mechanism shaping urban life.

Though Firey (1945) long ago argued for a greater understanding of the symbolic and sentimental qualities of place and Suttles (1972) observed the utility of reputation in structuring individuals' cognitive maps of the city, the concepts of neighborhood identity and reputation have generally been afforded little attention by urban scholars. While some qualitative work on neighborhood change and residential choice imply the use of neighborhood reputation as a heuristic through which people navigate and select among their residential options (e.g., Hyra

2017; Krysan and Crowder 2017), only recently has a substantial body of research emerged that makes explicit mention of place reputations (Brown-Saracino and Parker 2017; Evans and Lee 2020; Hohle 2022; Lee 2018; Pais, Batson, and Monnat 2014; Parker 2018b; Permentier et al. 2007; Zelner 2015). These newer studies have defined neighborhood reputation, how and by whom place reputations are deployed, and the consequences of reputational prestige and stigma for neighborhoods and their residents. By comparison, few studies have focused on how collective understandings of reputation combine, reflect, and refract neighborhood characteristics commonly used by social scientists to measure community quality.

To some extent, research on neighborhood reputation has intentionally avoided drawing direct associations between "objective" neighborhood characteristics and place identity. Scholars following in the cultural ecology tradition have critiqued contemporary urban scholarship for its outsized emphasis on understanding communities as "a cluster of variables" and its insufficient attention to how people assimilate those variables into mental schemas (Gieryn 2000; Sampson 2013; Suttles 1972). Additionally, scholars of reputation are quick to observe that reputation is distinct from fact and by its very nature may bear only passing resemblance to typically measured neighborhood attributes (Kaliner 2014). As Parker writes (2019:12), "a key component of place reputation is its non-congruency (or at least its non-mandated congruency) with the way things 'actually are' on the ground…In other words, reputations have consequences regardless of whether or not they are what we would call 'true.'"

While these potential objections to a reductive or overly objectivist view of reputation are well taken, I argue it remains relevant to consider how neighborhood attributes are reflected in reputational assessments of place for a few reasons. First, because many theories of neighborhood differentiation and residential selection assume there is a correspondence between objective conditions and individuals' attitudes and preferences (Clark 1992; Krysan 2002a; Schelling 1971), understanding the link between reputation and place characteristics can reveal how and on what basis people evaluate place (Logan and Collver 1983). Accepting, as Borer (2006:186) says, that "place narratives are never filled with complete, unadulterated facts," there is useful information to be gleaned from the relationship between objective and subjective dimensions of neighborhoods. Second, by examining associations between reputation and neighborhood characteristics one can develop clearer systematic evidence for the ways in which local conditions give structure to the urban status hierarchy. And finally, given that much urban scholarship remains focused on the cluster of variables that constitute urban spaces, drawing links between these objective dimensions of neighborhoods and reputation may help bridge the gap between the traditional structuralist approach to studying place and the emerging urban culturalist perspective that views neighborhood reputations as abstracted but essential dimensions of urban life. Thus, by explicitly intermingling these perspectives in this study, I hope to inspire future research that takes seriously both subjective and objective understandings of place.

To that end, this study endeavors to develop new insights into the ways in which people use reputation to make sense of urban environments. Drawing on data from a survey of respondents in Los Angeles, Chicago, and Washington, D.C., it considers the underlying attributes of individuals and neighborhoods that give shape to and are reflected by collective understandings of neighborhood reputation. Taking an ecometric approach (Raudenbush and Sampson 1999) that emphasizes the aggregate nature of reputation as a trait of places, rather than of individuals, this study seeks to answer the following research questions:

(1) To what extent is there agreement among city residents regarding the reputation of neighborhoods?

(2) What is the relative importance of different dimensions of neighborhood demographic composition and the built environment in shaping reputational assessments?

(3) Do the same neighborhood characteristics influence the reputation assessments of residents and non-residents?

(4) How do the characteristics of respondents' own neighborhood influence their reputational assessments of other places?

My findings show that neighborhood reputation enjoys a high degree of reliability, meaning there is strong evidence of internal consistency around reputational assessments. However, in keeping with past research (Permentier et al. 2008), I find that residents tend to hold their own neighborhood in higher esteem than outsiders. Additionally, my results show that while both demographic composition and the built environment influence judgements of reputation, neighborhood demographic composition—especially socio-economic status—is most strongly associated with how the public assesses neighborhoods and their place on the urban status hierarchy. This emphasis on economic markers is true whether one is judging their own neighborhood or other neighborhoods across the city. My findings suggest that even as a great deal of scholarship and public investment has focused on processes through which places evolve—for example, through gentrification, rebranding, and other modes of urban regeneration—place reputations are likely durable and self-perpetuating, functioning more as a mechanism of status reproduction and differentiation than as a tool for change (Sampson 2013).

Background

In their foundational text on the study of urban spaces, Park and Burgess (1925:1) remarked that cities are best conceived of as "a state of mind, a body of customs and traditions, and of organized attitudes and *sentiments*" (emphasis added). Despite this early recognition of the collective cultural ecology of communities, scholarship in urban sociology—particularly quantitative analyses—has trended towards an individualistic and variables-oriented paradigm (Gieryn 2000; Sampson 2013). Compared to the large literature on neighborhood effects and residential stratification, which typically link objective measures of neighborhood attributes to individual outcomes, the collective, symbolic, and sentimental nature of neighborhoods has received only occasional scholarly attention. However, in recent years a body of literature has emerged that explicitly counteracts this trend (see Evans and Lee 2020). Building on the work of Firey (1945) and Suttles (1972), researchers have begun to pinpoint the symbolic character of neighborhoods, recognizing that much as reputations are impactful for the lives of individuals (Fine 2001, 2011; Goffman 1986) reputations similarly play an important role in shaping the present and future conditions of place. Below, I detail how existing scholarship has conceived of place reputation and why reputations matter before considering what research to date says about how reputations reflect objective neighborhood conditions.

Defining Neighborhood Reputation

Perhaps the clearest definition of neighborhood reputation comes from Brown-Saracino and Parker (2017:841), who characterize reputation as "*a collective understanding about a place based on stories people out in the world tell about it*." Hortulanus (1995) similarly defined reputation as "the meaning and esteem residents and other involved parties attribute to a neighborhood…[and] the relatively stable image a neighborhood has among city residents [with regards] to its place in the urban neighborhood hierarchy" (translated from Dutch by Permentier et al. 2008:835). In a similar vein, sociocultural theorists have described place reputations as collective memories constructed through meaning making and reified through interactions and information sharing (Zelner 2015). These characterizations highlight three important and interrelated aspects of neighborhood reputation: (1) reputations are constructed; (2) reputations are the product of first-hand and second-hand knowledge; and (3) reputations are relational, constituted in part through comparison and contrast.

Though identifying social constructs—phenomena that exist not in objective reality but as the product of human interaction—is something of a sociological cliché (Buono 2015), recognizing the constructed nature of neighborhood reputation reveals a few essential attributes. As noted above, scholars argue that place reputations are understood to be divorced, in whole or in part, from objective aspects of a place, lying on the continuum between information and rumor (Kaliner 2014; Parker 2019). Reputations can be neither confirmed nor denied, but instead are best understood as judgements. Thus, one can say that reputations are constructed in that they are not facsimile of measurable neighborhood conditions. Moreover, reputations can be understood as constructed in that they are multidimensional, agglomerating many aspects of neighborhood conditions into a general assessment of place. While some literature discusses neighborhood reputation along a specific dimension—as hip (attractive to young people), dangerous, gay-friendly, etc. (Brown-Saracino and Parker 2017; Parker 2018b, 2019)—more often place reputations are used to locate neighborhoods within a less-descript, positive-negative hierarchy. For example, places often are described as being nice, good, desirable, etc. Finally, reputations are socially constructed in that they are produced collectively. Much as Cooley's (1902) "lookingglass self" suggests that individual identity is produced from interpersonal interaction and the assessments of others, neighborhood reputations grow out of shared and competing understandings than cohere into a cumulative texture of place (Sampson 2013; Suttles 1984).

Expanding on the idea of reputations as collective social-ecological phenomena, scholars have argued that place reputations are produced out of assent and friction between differently positioned groups whose diverse knowledge and incentives shape how they conceive of communities (Brown-Saracino and Parker 2017). One group integral to the production of place reputation are neighborhood residents, who draw upon their personal knowledge of and subjective feelings towards their neighborhood to craft and share place narratives (Small 2004). Residents also act as ambassadors of place, transmitting information about their neighborhood as they move about the city, through interpersonal interactions, and via social networks. A second group essential to the production of place reputations are other city residents. As Kaliner (2014) notes, outsiders by their nature constitute a numerical majority of city residents and thus their assessments carry significant power in assigning and perpetuating place reputations. Compared to residents, outsiders often have less or no direct information about neighborhoods and instead draw on and integrate simplified images, media reports, rumors, and other bits of second-hand information to form opinions about communities. Finally, a third group engaged in reputation construction are institutions, who take an instrumental approach to forming and shaping impressions of place through branding campaigns, tours, and the establishment of special zoning or business improvement districts (Greenberg 2009; Wherry 2011; Zelner 2015). Reputations thus are born out of, rearticulated, reshaped, and ingrained through the combined efforts of these differently situated actors.

A final defining aspect of reputation highlighted by scholars is its relational nature. Here there are two essential points to convey: that reputations are defined through comparison and that the relational sorting of neighborhoods has been shown to give structure to the broader neighborhood hierarchy. In his seminal work on neighborhood identity, Suttles (1972:51) argued that neighborhood reputations are "embedded in a contrastive structure in which each neighborhood is known primarily as a counterpart to some others." Thus, much like the construction of individual identity (Cooley 1902), neighborhoods gain their identity largely through difference such that when people assess the reputation of a place they do so with other places in mind (Parker 2019). Building on the understanding that reputations are at best distorted reflections of objective conditions, this suggests that place reputation might be shaped as much by a neighborhood's own attributes as by the ways in which it is like or unlike other places. Scholars argue that this contrastive nature of reputation, in which neighborhoods are situated vis-à-vis other places, lends structure and consistency to neighborhood status hierarchies. For example, Logan and Collver (1983) found that when asked to sort suburban communities on Long Island, working-class and affluent respondents produced generally consistent views of neighborhoods, drawing heavily on assessments of community status in their formation of like and unlike groups. This idea of consistency produced through contrast has similarly been found in a study of community status rankings in Israel (Semyonov and Kraus 1982) and, more recently, in work by Parker (2018b) who shows that merchants with competing interests deploy surprisingly homogenous conceptions of Wicker Park's reputation in their effort to demarcate that neighborhood from other places.

Consequences of Reputation

Gaining greater insight into the underlying dimensions of reputation matters because reputations have consequences. Past research documents a variety of ways in which place reputations affect residents and neighborhoods. Starting with the impact of reputation on residents, studies show that living in stigmatized neighborhoods impacts residents' well-being, health, and economic opportunities. The neighborhood stigma hypothesis suggests that individuals who reside in disreputable neighborhoods have the negative stigma of their neighborhoods read onto their bodies (Wacquant 2007). By virtue of their address, residents take on "spoiled identities" and are treated with suspicion and mistrust by others (Anderson 1992; Goffman 1986). Residents also internalize this stigma, resulting in diminished self-image and a powerful sense of shame and indignity (Hastings and Dean 2003; Wacquant 1993). Beyond these psychological effects, living in stigmatized neighborhoods has been shown to impact physical health (Keene and Padilla 2014). Scholars have connected negative assessments of place with lower self-reported health, poorer sleep quality and duration, higher blood pressure, and increased risk of obesity and hypertension (Duncan et al. 2016; Kelaher et al. 2010; Ruff et al. 2018; Wutich et al. 2014). Additionally, research shows that neighborhood stigma affects residents' economic opportunities by constraining employment options and shaping prospects for economic exchange (Bertrand and Mullainathan 2003; Musterd and Andersson 2005; Wilson 1997). In an audit study, Besbris et al. (2015) found that online classified ads from stigmatized neighborhoods received many fewer inquiries than the same ads from non-stigmatized areas, limiting residents' economic potential.

Beyond reputations' impacts on individuals, scholars suggest that reputations are consequential for neighborhood dynamics. Permentier et al. (2007) found that living in disreputable neighborhoods is linked with greater desire to move (see also Andersen 2008). This effect on neighborhood mobility and neighborhood attachment may lead to the depopulation of neighborhoods with poor reputations, perpetuating their negative stigmas. This avoidance and disinvestment of stigmatized neighborhoods is reinforced by real estate agents and lenders, whose explicit or implicit use of neighborhood stereotypes to steer people and capital away from certain communities compounds and reproduces the idea that some neighborhoods should be avoided (Besbris 2020; Faber 2020; Korver-Glenn 2018). In addition to shaping residential mobility, reputations have been shown to shape the long-term economic potential of neighborhoods. For example, Sampson (2013:146) found that neighborhood stigma was a stronger predictor of future neighborhood poverty than original poverty levels, an effect he describes as a “self-fulfilling prophecy and mechanism of durable inequality that fortifies spatially patterned disadvantage.” Similarly, studies of public housing rehabilitation projects in Europe suggest that the stickiness of negative place reputations limits the impact of redevelopment efforts (Andersen 2002; Hastings and Dean 2003; Kearns, Kearns, and Lawson 2013; Norris, Byrne, and Carnegie 2019).

Of course, reputations can also have positive effects. Scholarship illustrates the ways in which residents and visitors alike use reputation to screen and select locations in a city they want to inhabit, briefly or permanently (Brown-Saracino and Parker 2017; Florida 2003). For example, Hyra (2017) shows that Washington D.C.’s Shaw neighborhood draws young, white professionals thanks in part to its reputation as a gentrifying area that retains a sense of grit as well as its strong links to its African American history. Others have noted similar comingling of intrigue and stigma attracting outsiders to historically Black and brown neighborhoods (Boyd 2008; Freeman 2006; Pattillo 2007; Wherry 2011). And increasingly trends of gentrification are being viewed through the lens of reputation, drawing in new residents and economic opportunity to urban spaces (Besbris 2020; Brown-Saracino 2010; Parker 2018b). Thus, while research has often focused on the negative effects of reputation—particularly in stigmatized areas—reputation can also draw new residents and curious visitors, and the investment that accompanies them, to a place.

What Do Place Reputations Reflect?

The literature cited thus far emphasizes the nature and consequences of reputation. Less research to date has explicitly focused on the relationship between local conditions and place reputation. As noted above, this is to some extent by design. Because reputations reflect an agglomeration of factors and perspectives, and because reputations are understood to be consequential regardless of their fealty to objectively measured conditions, there is a degree of reductivity in seeking to determine the core attributes associated with place assessments. Despite this, existing scholarship on reputation and related concepts point to some dimensions commonly associated with assessments of neighborhood quality.

Within the limited existing scholarship linking reputation and neighborhood characteristics, research suggests that a neighborhood's location in the urban status hierarchy is strongly associated with demographic composition, including an area's racial/ethnic makeup. Four studies from the U.S., Israel, Denmark, and the Netherlands find that neighborhoods with higher concentrations of minority residents are more likely to suffer reputational penalties than neighborhoods with larger White or non-immigrant populations (Kearns et al. 2013; Logan and Collver 1983; Permentier, Bolt, and van Ham 2011; Permentier et al. 2008; Semyonov and Kraus 1982). This association between reputation and racial composition is unsurprising, given the wealth of research that finds that racial composition is often used to make broad inferences about neighborhood conditions (Krysan 2002b; Krysan and Crowder 2017). For example, in an experiment using video vignettes to test the relationship between racial composition and assessments of neighborhood quality, Krysan, Farley, and Couper (2008) show that White neighborhoods were judged to have more positive attributes—higher and appreciating home prices, less crime, and better schools—than identical Black neighborhoods. Related research finds that neighborhood desirability is similarly judged through the lens of race (Emerson et al. 2001; Krysan and Bader 2007; Lewis et al. 2011), while scholarship on perceptions of crime and disorder consistently shows that, regardless of objective measures, neighborhoods with larger minority populations are perceived to be more dangerous and disorderly than White neighborhoods (Quillian and Pager 2001; Sampson and Raudenbush 2004). Beyond racial/ethnic composition, studies also find that reputational assessments are associated with neighborhood socio-economic status, such that the higher a neighborhood's socio-economic status the higher its assessed prestige (Permentier et al. 2011; Semyonov and Kraus 1982).[34] In their study of community status on Long Island, Logan and Collver (1983) found that socio-economic status was the most prominent dimension by which respondents evaluated place and that income was the most common sorting criteria respondents named in follow-up interviews. A closely related but unstudied dimension likely linked to reputation is neighborhood home values, which have been shown be associated with both neighborhood desirability and racial composition (Harris 1999; Krysan et al. 2008). Additionally, some research suggests population density and age composition may also be associated with assessments of neighborhood status (Logan and Collver 1983).

Beyond demographic composition, research has also pointed to the role physical attributes and the presence or absence of neighborhood amenities play in shaping reputation. At the micro-level, markers of physical disorder like graffiti, litter, and boarded windows have been shown to

[34] Multiple studies of reputation use index measures that simultaneously measure racial/ethnic composition and socio-economic status (Permentier, Van Ham, and Bolt 2008; Semyonov and Kraus 1982), and thus there is potential that these past studies conflate rather than draw clear distinctions between the role of racial and economic composition.

influence assessments of neighborhood quality (Hwang and Sampson 2014; Murphy 2012; Sampson and Raudenbush 2004) as have subjective assessments of neighborhood attractiveness (Andersen 2008). Other dimensions of the built environment associated with reputation include distance to the city center, housing quality and age, and the presence of vacant lots (Benediktsson 2014; Logan and Collver 1983; Parker 2018a; Permentier et al. 2011; Semyonov and Kraus 1982), while access to green space has been associated with positive neighborhood assessments and an enhanced sense of community (Gómez et al. 2015; Larson, Jennings, and Cloutier 2016). Beyond the built environment, the type and concentration of institutions and businesses in a neighborhood likely shape and are shaped by neighborhood reputation. For example, local institutions like universities, museums, and arts organizations are often understood as indicators of neighborhood prestige (Ehlenz 2016; Meyer 2021; Wherry 2011). Similarly, concentrations of stores, eateries, and coffee shops may provide visual clues to residents and visitors regarding a neighborhoods' positive status (Klinenberg 2018; Kwate et al. 2013; Papachristos et al. 2011; Silver and Clark 2016). Conversely, disadvantaged neighborhoods and places with negative reputations may be marked by greater concentrations of neighborhood disamenities, including liquor stores, dollar stores, and polluting sites (Bush, Moffatt, and Dunn 2001; Jennings et al. 2014; Shannon 2021; Weiss et al. 2011).

Though reputation is viewed as a collective attribute of place and thus ultimately should net out individual biases, there is some evidence to suggest place assessments might vary across different types of people. Past research finds that residents and non-residents diverge in their reputation assessments, with residents judging their neighborhoods' reputation more positively than non-residents. (Permentier et al. 2008; Wileden 2019). These differences are likely driven by differences in positionality, attachment, and level and nature of neighborhood knowledge. Beyond this insider/outsider divide, there are reasons to think that respondents' socio-economic status and racial/ethnic identity might influence individual assessments of place. Given that neighborhood socio-economic status has been found to shape assessments of reputation, one might imagine that high-status individuals would judge neighborhood reputations more critically based on the quality of their own neighborhood while lower-status individuals might be more generous in their assessments. A similar divergence in perspective could play out in relation to race. However, past studies have found that low-income and high-income groups tend to hold similar assessments of neighborhood reputations (Logan and Collver 1983; Permentier et al. 2008) while there is weak evidence to support the idea that reputational assessments vary by individual race/ethnicity. Though a study of neighborhood reputations in Utrecht, Netherlands finds that minority respondents assess the reputation of their own neighborhood to be significantly higher than other respondents (Permentier et al. 2011), these findings have not been extended to assessments of neighborhood reputation more broadly. Similarly, little evidence to date tests if dimensions of individual identity commonly associated with neighborhood satisfaction—like homeownership, length of tenure, household composition, and age—are associated with individual variation in reputational assessments (Hipp 2009; Lu 1999; Parkes, Kearns, and Atkinson 2002; Permentier et al. 2011).

The Present Study & Hypotheses

To summarize, while a growing body of literature explicates the nature and consequences of neighborhood reputation—filling a gap in urban scholarship that long overlooked the sentimental and symbolic aspects of neighborhood—only a few studies have examined how people make sense of place. To that end, this study contributes to the limited literature on the underpinnings of place reputations. Recognizing that reputations reflect incomplete and adulterated, but nonetheless meaningful, assessments of neighborhoods (Borer 2006), I explore how neighborhood composition, the physical environment, and individual identities coalesce to give shape to neighborhood reputation hierarchies. Note that in considering the underlying attributes reflected by neighborhood reputations my goal is distinct from determining where place reputations come from. Such an endeavor would require greater focus on historical neighborhood data and longitudinal measures of reputation, as well as an exploration of how beliefs about reputations are formed and transmitted (Kearns et al. 2013), which are outside the domain of this project.

Returning to my research questions, the scholarship outlined above gives rise to a number of testable hypotheses. First, in exploring the extent of agreement among city residents regarding neighborhood reputations, the collective nature of reputation leads me to hypothesize that (H1) *my measure of neighborhood reputation will attain a high degree of reliability and agreement among respondents.*

Second, in considering the relationship between neighborhood conditions and reputational assessments, the existing literature suggests that both neighborhood demographic composition and the built environment likely play a role in shaping reputation. Few studies have examined these dimensions simultaneously. Those that have generally suggest that neighborhood composition, especially racial composition and socio-economic status, are more consequential for neighborhood reputation than dimensions of the built environment (Logan and Collver 1983; Permentier et al. 2011, 2008; Semyonov and Kraus 1982). Thus, I hypothesize that (H2) *while dimensions of neighborhood composition and the built environment may separately be significant predictors of* *reputation, a stronger association will be found between neighborhood socio-demographic measures and reputation than physical measures and reputation.*

Turning to the question of if the same neighborhood characteristics will influence the reputation assessments of residents and non-residents, past findings on the diverging perspectives of neighborhood insiders and outsiders coupled with theory on the relational nature of reputation that emphasizes the use of different reference points lead me to hypothesize that (H3) *residents and non-residents will differ in the characteristics that predict their reputational assessments*. A sub-hypothesis supported by Permentier et al. (2008) suggests that (H3a) *residents' assessments of neighborhood reputation will be predicted by a wider number of neighborhood measures than non-residents,* though residents more specified, personal, and nuanced knowledge of their neighborhood might alternatively suggest that (H3b) *residents' assessments of neighborhood reputation will be less directly associated with neighborhood variables than non-residents' assessments*.

Finally, my last research question asks, "How do the characteristics of respondents' own neighborhood influence their reputational assessments of other places?" Past literature on the relative nature of neighborhood assessments and the higher regard with which residents view their own neighborhood lead me to hypothesize that (H4) *respondents' own-neighborhood attributes will have a significant and interactive effect on their assessments of other neighborhoods, such that attributes like own-neighborhood socio-economic status will significantly lower the effect of socio-economic status on assessments of other neighborhood reputations.*

Data

Measuring Neighborhood Reputation

To examine the nature of neighborhood reputation, this study draws on data from a survey designed and fielded by the author to capture differences in neighborhood knowledge among residents of Los Angeles, Chicago, and Washington, D.C.[35, 36] The three cities were selected for their geographic diversity, relevance to urban research, and for the pervasiveness and cultural salience of their named neighborhoods. The data were collected between January and April 2018 via Qualtrics, an online survey platform. In addition to hosting the survey, Qualtrics recruited survey participants from an existing online research pool using quotas for gender parity and city-specific, proportionally representative quotas for respondent racial/ethnic identity based on 2016 American Community Survey (ACS) estimates. Though efforts were made to ensure respondent demographics reflect the population of each city, the data are drawn from a nonprobability sample and thus should be viewed cautiously in terms of their representativeness.[37] Survey responses were captured only if a respondent lived in the relevant city, reported being 18 years or older, and was either a native English speaker or self-reported proficient fluency in English.

A central goal of the survey was to tap into city residents' knowledge of and associations with neighborhood identity. Importantly, while related research has often relied solely on respondents' assessments of their own neighborhood (see Evans and Lee 2020), this survey endeavored to capture residents' knowledge of their neighborhood *and* other neighborhoods across the city to better measure the collective nature of neighborhood reputation. To that end, respondents used a city-specific map tool within the survey to identify their neighborhood of

[35] Funding for this survey was provided by the Population Studies Center and the Center for Local State and Urban Policy at the University of Michigan. Prior to fielding the survey, I received approval from the Health Sciences and Behavioral Sciences Institutional Review Board at the University of Michigan (HUM00139059).

[36] For this survey, Los Angeles was defined as the City of Los Angeles and not Los Angeles County. For more on survey development, see Appendix A and Wileden (2019).

[37] For more on the utility and data quality of online surveying, see Heen, Lieberman, and Miethe (2014).

residence and other city neighborhoods with which they were familiar before answering a series of questions on neighborhood attributes, including assessments of neighborhood reputation.[38] [39] Though census tracts are commonly used in quantitative research to approximate neighborhoods, past research suggests that these geographies lack salience to the average resident and rarely reflect people's lived experience of place (Coulton et al. 2001; Hwang 2016; Sastry, Pebley, and Zonta 2002). Instead, the survey's map tool featured a discrete number of large, identifiable neighborhoods with clearly delineated names, boundaries, and spatial configurations. To ensure the maps highlighted collectively identifiable and meaningful neighborhood names and boundaries, I drew on municipal maps of neighborhood boundaries (like Chicago's 77 community areas), other reputable place-mapping projects (such as the Mapping LA project by the Los Angeles Times), and neighborhood names and boundaries used on place-based amenity websites like Zillow, OpenTable, and Airbnb (see Appendix A for greater detail on survey design). This approach of combining pre-defined neighborhood maps with detailed questions on neighborhood assessments is intended to not only cue respondents' mental schemas and associations with specific places but also to specify consistent community boundaries to increase the face-validity of

[38] Design of the map tool was based on development of a similar, interactive data collection tool created by Michael Bader, Maria Krysan, and Kyle Crowder.

[39] In implementing the map tool and recruiting respondents, Qualtrics leveraged IP locations of potential respondents to target research pool members living in each focal city. To verify the residential location of respondents, quality control measures were included in the survey instrument and in the data cleaning process. Within the instrument, there were three quality control checks. Respondents were first required to answer the question, "Are you a resident of X city." Any negative response resulted in the termination of the survey. Respondents were then required to self-report the name of the neighborhood in which they lived. Nonsensical responses and responses indicating residence in a suburb were replaced following the initial data collection. Additionally, respondents were required to complete two attention checks to ensure data quality. In the data cleaning process, two additional vetting methods were implemented to improve the quality of the data. First, in the days following the initial round of data collection the author compared respondents' selected neighborhood and stated neighborhood of residence for proximity. Responses where the named neighborhood was not within a 30-minute drive (per Google Maps) of the centroid of the neighborhood selected on the survey map were replaced in a second round of data collection. Finally, all collected responses were evaluated to compare the neighborhood selected on the map tool and a respondent's stated neighborhood of residence. For this paper, only responses where there was an exact match or a near match due to a typo were retained for analysis.

comparisons across respondents and make it possible to link respondent assessments to secondary data measuring local conditions. In total, the map tool included 83 neighborhoods in Los Angeles, 83 neighborhoods in Chicago, and 72 neighborhoods in Washington, D.C.

After selecting neighborhoods on the map, respondents were asked in-depth questions about their neighborhood of residence and up to five other neighborhoods randomly selected from the set of neighborhoods with which they reported being familiar.[40] Most importantly for this study, respondents used a four-point Likert scale to answer the question, "How would you assess the reputation of [NEIGHBORHOOD X]?" Response categories ranged from 1 (very bad) to 4 (very good). Using responses to this question, I create a multilevel data set capturing respondent assessments nested within rated neighborhoods, limiting the data to only those survey respondents who rated the reputation of their neighborhood of residence and at least one other neighborhood. In total, the resulting data set includes 6,481 neighborhood assessments from 1,303 respondents (Los Angeles n = 470; Chicago n = 461; D.C. n = 372). The respondents resided in 220 neighborhoods and offered reputation ratings of 238 neighborhoods.[41]

Respondent Characteristics

In addition to assessments of neighborhood reputation and neighborhood residence, I also draw on survey respondents' self-reported socio-demographic characteristics to capture whether and how individual identity is associated with reputational judgements of place. Gender is

[40] In a white paper for the Center for Local, State, and Urban Policy (Wileden 2019), I find that respondents on average report familiarity with only a fraction of neighborhoods in a given city. Across all three cities, respondents report being familiar with approximately one-fifth of neighborhoods. For example, I find that in Chicago, the average respondent selected roughly 14 of the 83 neighborhoods identified in the map tool.

[41] Though respondents were not recruited to explicitly produce geographic distribution, the resulting sample included residents of 220 of the 238 possible neighborhoods. The average number of respondents per neighborhood in the data is 5.92 with a min of 1 and a max of 28.

measured with a dummy variable indicating if a respondent self-identifies as male (reference) or female.[42] Age is measured continuously in years. Respondent race/ethnicity is captured categorically based on if the respondent self-identified as non-Hispanic White (reference), non-Hispanic Black, Latino, non-Hispanic Asian, or non-Hispanic Other or Multiracial. Educational attainment is measured as a binary indicating if the respondent holds a bachelor's degree or not (reference) and household composition is a dummy variable indicating if the household includes children or not (reference). Household income is measured categorically: $19,999 or less (reference); $20,000 to $44,999; $45,000 to $74,999; $75,000 to $124,999; and more than $125,000. The respondents' length of tenure in their city of residence is captured as a continuous variable. Finally, tenure type is a dummy variable indicating if the respondent is a homeowner or renter (reference). A small number of respondents (13) who completed the survey but were missing demographic information were dropped from the analysis.[43]

Neighborhood Demographic Compositions and the Built Environment

To capture the relationship between neighborhood characteristics and assessments of place reputation, I draw on contextual data from two sources. To capture neighborhood demographics—including racial composition, socio-economic status, home values, and residential instability—I use data from the 2014-2018 American Community Survey 5-year estimates. Neighborhood racial composition reflects census measures of the proportion of non-Hispanic White, non-Hispanic Black, non-Hispanic Asian, Latino, and non-Hispanic Other or Multiracial residents in a

[42] The survey limited gender categories to male and female.

[43] Across the sample of 1316 respondents who rated the reputation of their neighborhood of residence and at least one additional neighborhood, 13 were missing data on one or more individual demographic characteristic. These 13 respondents provided 62 neighborhood reputation assessments. Null models estimated with and without excluded respondents yielded equivalent results.

neighborhood. I also include a measure of neighborhood median home value, log-transformed to limit extreme values. Following prior research, I use principal component analysis (PCA) to develop scale measures capturing neighborhood socio-economic status and residential instability.[44] My socio-economic status index combines seven variables commonly included in measures of neighborhood advantage and disadvantage (see Hanlon 2009; Hipp 2010a; Melendez et al. 2019; Owens 2012): median household income, proportion of population in poverty, proportion unemployed, proportion of female headed households, proportion of residents receiving public assistance, proportion of residents 25 or older with a college degree, and proportion with high-status (professional or managerial) jobs. Results from the PCA found these variables loaded onto a single component with an eigenvalue of 5.50 and retained 79 percent of the total variance of the original data.[45] As the resulting component scores were negative, I multiplied them by -1 so that higher, positive values indicate more socio-economically advantaged neighborhoods. Similarly, I measure residential instability with an index that combines the proportion of renters and the proportion of residents who have lived in a neighborhood for less than 1 year. These variables loaded onto a single component with an eigenvalue of 1.34 and retained 67 percent of the original variance.

Measures of neighborhood physical environments are drawn from data made available by the National Neighborhood Data Archive (NaNDA). While the literature suggests a wide variety of neighborhood characteristics that might serve as indicators of neighborhood status, the number of neighborhoods included in my study and the impracticalities of collecting granular data through

[44] To account for differences in the scale of variables included in principal component analysis, I first log household median income and standardize all variables to have a mean of 0 and a standard deviation of 1. This avoids skewing the resulting components towards variables with larger values or greater variance.

[45] Eigenvalues measure the explanatory power of each component factor, thus eigenvalues greater than one can be interpreted as possessing more explanatory power than the original variables. See Appendix D for table of eigenvalues and factor loading for variables created using principal component analysis.

systematic social observation (Sampson and Raudenbush 1999) lead me to focus on three general attributes of the physical environment: the presence of park space, cultural amenities, and disamenities. I measure local green space as the total square miles of park space in a neighborhood, drawing on 2018 data compiled by NaNDA from ParkServe (Clarke, Melendez, and Chenoweth 2020). Additionally, I use 2017 data compiled by NaNDA from the National Establishment Time Series database, North American Industry Classification System codes, and 2018 data from the Environmental Protection Agency's Toxics Release Inventory to develop scale measures of neighborhood cultural amenities and disamenities (Esposito et al. 2020; Finlay et al. 2022; Finlay, M. Li, et al. 2020b, 2020a; Finlay, N. Li, et al. 2020; Gomez-Lopez et al. 2020). My scale of cultural amenities is created using principal component analysis to capture the presence of performing arts organizations, museums, and coffee shops within a neighborhood, organizations commonly linked to neighborhood prestige (Klinenberg 2018; Silver and Clark 2016). The variables loaded onto a single component with an eigenvalue of 2.32 and retained 77 percent of the total variance of the original data. My scale of disamenities reflects the presence of liquor stores, dollar stores, and polluting sites, commonly cited markers of neighborhood disadvantage (Bush et al. 2001; Jennings et al. 2014; Shannon 2021; Weiss et al. 2011). Results from the PCA show the variables loaded onto a single component with an eigenvalue of 1.39 and retained 56 percent of the total variance of the original data.

In creating these neighborhood measures, I conformed tract level census data and data on the built environment to the neighborhood boundaries included in my map tool using proportional area weights.[46] Table 4.1 captures descriptive statistics summarizing individual and neighborhood attributes of my sample.

[46] Proportional weights were developed by linking census tracts to the neighborhoods within which they fall. To account for census tracts that fall partially within multiple neighborhoods, I use the union function in ArcGIS to

[TABLE 4.1 ABOUT HERE]

Method

As detailed above, neighborhood reputations are generally understood as collective assessments of a neighborhood's identity and position within the urban hierarchy. As such, reputation is best measured and modeled as a property of place rather than as a characteristic of individuals, suggesting the importance of taking an ecometric approach. Proposed by Raudenbush and Sampson (1999), ecometrics is the study of neighborhood-level or contextual variation intended to capture the social-ecological properties of place (Sampson 2013). By extending the techniques of psychometrics to neighborhoods, ecometrics combines the responses of multiple respondents to compute an estimate of a neighborhood-level construct—in the case of this study, combining assessments of multiple residents and non-residents to compute a collective measure of neighborhood reputation. The benefit of this approach is not only a more relevant measure of local context but also one that offers a more accurate portrayal of ecological conditions (see also Hipp 2013; Mujahid et al. 2007).

Following Raudenbush and Sampson (1999), I estimate a series of multilevel models in which individual assessments of reputation (level 1) are nested within rated neighborhoods (level 2).[47] The following equation represents the basic structure of the level 1 model:

calculate weights based on the percent overlap of 2010 census tract boundaries and neighborhood boundaries. I then multiply demographic counts by this weight to proportionally allocate people and households, collapse data to create approximate aggregate population counts by neighborhood, and recalculated percentage compositions of relevant demographic groups. In allocating people between neighborhoods, I assume that the population is equally distributed across census tracts.

[47] Ecometric studies typically use a three-level model in which multiple items (level 1) are nested in individuals (level 2) which are then nested in neighborhoods (level 3). For examples of three level ecometric studies, see Raudenbush

(1)

$$Y_{ij} = \eta_j + BX_{ij} + \varepsilon_{ij}$$

where Y_{ik}represents the *i*th respondent's assessment of the reputation of neighborhood k, η_k is the intercept reflecting the common (mean) assessment of reputation for neighborhood k, X_{ik} is a matrix of individual-level attributes, B is a vector capturing the effects of individual-level attributes on assessments of reputation, and ε_{ij} is the individual-level error term.

Of potentially greater interest to this study is the effect of neighborhood characteristics—demographic composition and aspects of the physical environment—on collective assessments of place reputation. The following equation represents the basic structure of the level 2 model, which estimates the neighborhood-specific mean of reputation as a function of an overall mean and neighborhood-specific deviations in neighborhood conditions:

(2)

$$\eta_j = \beta Z_j + \varepsilon_j$$

where η_j represents the collective assessment of reputation of neighborhood j, Z represents a matrix of the demographic and built environment attributes of neighborhood j, β is the effect of these neighborhood attributes on overall assessments of neighborhood reputation, and ε_j is the neighborhood-level error term.

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and Sampson (1999) and Mujahid et al (2007). Here, I follow the work of Hipp (2013) and use a two-level model that includes only a single item per person (level 1) nested in neighborhoods (level 2).

My analysis proceeds as follows: First, to examine the collective nature of place reputations I estimate a random intercept model with no predictors. This model allows me to decompose the proportion of variance in reputation assessments that exists within and between neighborhoods to calculate the intraneighborhood correlation coefficient and reliability measure. These measures quantify the strength of agreement among respondents regarding a neighborhood's reputation. Next, I explore if assessments of neighborhood reputation vary systematically by respondent identity and neighborhood conditions. Model 1 explores individual-level predictors of reputation. Models 2-4 add in neighborhood-level predictors of reputation, iteratively testing associations between neighborhood conditions and reputation after adjusting for individual-level factors. Model 2 examines the role of neighborhood socio-demographic composition, Model 3 examines the role of the built environment, and Model 4 combines these models to consider the relative role of each type of neighborhood attribute. Turning to the question of whether and how neighborhood characteristics differently influence the reputation assessments of residents and non-residents, Model 5 presents results from my full model stratified by respondent type. Finally, Model 6 examines the relational nature of neighborhood assessments by adding in respondents' own-neighborhood conditions as predictors of other-neighborhood reputation.

In addition to these models, I explore variation in my results using cross-level interactions to test if the effects of neighborhood attributes vary depending on individual characteristics—for example, if the effect of the proportion of Black residents in a neighborhood has a greater effect on reputation assessments among Black or non-Black respondents. Throughout, I also estimate the percentage of between-neighborhood variability in reputation explained by each model iteration, computed as the difference in the amount of level 2 variance between the model of interest and the original random intercept model with no predictors divided by the random intercept model (Raudenbush & Bryk, 2002).

Results

Assessing the Quality and Reliability of Neighborhood Reputation Measure

A first step in understanding the underpinnings of neighborhood reputation is assessing the quality of the reputation measure. Following the ecometric approach outlined above, which pools assessments of reputation of the same neighborhood across respondents, I begin by estimating two closely related metrics of data quality: the intraneighborhood correlation coefficient (ICC) and the reliability. The ICC quantifies the percentage of variability in reputation that lies between rated neighborhoods and is measured as the ratio of between-neighborhood variance divided by the total variance (the sum of the within-and between- neighborhood variance). The ICC ranges from 0 to 1, with a higher value indicating greater agreement between respondents who rated the same neighborhood. Reliability expands on the ICC by accounting for the number of observations for each neighborhood. It is calculated as the ratio of the ‘‘true’’ reputation variance to the observed reputation variance in the sample mean, with values ranging from 0 to 1. In essence, reliability measures the degree of agreement or internal consistency of ratings within a neighborhood and increases as the number of respondents increase. Intuitively, this measure shows how reliability—or the fealty with which imprecise observations in a data set collectively capture an underlying, “true” attribute of the world—improves with sample size. Whereas the perception of reputation from any single individual may have considerable bias associated with it, pooling measures across respondents should yield considerably more reliable estimate of a places’ collectively held reputation.

Table 4.2 presents the intraneighborhood correlation coefficients, and neighborhood-level reliabilities. Examining the quality of neighborhood reputation ratings from the full sample, the estimated ICC is .247, meaning that around 25 percent of the variation in reputation is estimated to be between neighborhoods. Examining the reliability of assessed neighborhood reputation among respondents, I find an average reliability score of .905. This high reliability score is in part a function of the sufficiently large number of ratings per neighborhood. On average, each neighborhood was rated by 42 respondents, though the number of ratings ranged from 2 to 115. These measures are a useful indication that the reputation measure not only explains a sizable proportion of variation within the data but also that there is strong internal consistency in perceptions among those rating each neighborhood.

[TABLE 4.2 ABOUT HERE]

While this suggests that the overall data on reputation are high quality, we can further affirm the quality of the data by examining the consistency of the ICC measures and reliability between neighborhood residents and non-residents as well as by each city in my three-city sample. Examining reputation assessments of respondents' neighborhood of residence, the estimated ICC is .255, roughly equivalent to the correlation observed in the full sample. The average reliability score for own-neighborhood assessments is .716, somewhat lower than the overall sample. This likely reflects the fact that fewer respondents live in each neighborhood (mean = 5.92, range 1 to 28) making it more difficult to attain the same degree of consistency across observations. Turning to reputation assessments of neighborhoods among non-residents, the estimated ICC is .268 while the average reliability score is of .869. Collectively, these measures suggest that reliability of the reputation measure overall is high, though there is some variation due to sample size depending on if a respondent is rating their own or another neighborhood.

A final point of comparison for affirming data quality is to examine how reliability of the reputation measure varies across the three cities. I find that the measure of neighborhood reputation appears generally consistent. Table 4.2 captures variation in ICC and reliability for LA, Chicago, and DC respectively. It shows that between-neighborhood variation explains slightly more of the overall variation in the data in LA (.276) than in Chicago (.222) or DC (.210) but that all three are within the confidence interval for the full sample. Similarly, when comparing the reliability of neighborhood reputation ratings in each city, there is only slight variation. The average reliability score in LA is .917, in Chicago is .897, and in DC is .882, suggesting general consistency of the measure across these cities and supporting the use of the pooled data.

Predictors of Place Reputation

Though the central focus of this paper is the collective nature of reputations, it is useful to first consider if and to what extent there is individual variation in assessments of place. Model 1 (Table 4.3) explores individual-level predictors of reputation assessments. In general, the results support the idea that reputations are collective phenomena and are not greatly influenced by individual identity, with two exceptions. I find that on the whole Black respondents judge neighborhood reputations slightly more positively than White respondents (.061).[48] More notably, Model 1 captures the difference in reputational assessments between residents and non-residents. In keeping with past research, residents assess the reputation of their own neighborhood significantly more positively than non-residents. Reputational assessments of one's own

[48] Supplemental analyses examined if the effect of respondent racial identity varied in relation to the racial composition of the neighborhood being assessed, using cross-level interactions. However, these interactions were non-significant.

neighborhood are nearly half a standard deviation (.347) higher than judgements of other neighborhoods, a sizeable effect given the limited scale of the outcome variable. Moreover, this difference in perspective between residents and non-residents explains substantially more variation in assessments of reputation than other individual attributes. Whereas respondents' gender, age, household composition, race/ethnicity, education, income, housing type and tenure explain almost no variation in the model, this measure of insider/outsider assessment explains 4 percent of the underlying variation in place reputation. I explore differences among residents and non-residents' place assessments in greater detail below.

Turning to the relative importance of different dimensions of neighborhood characteristics in predicting reputational assessments, Models 2-4 examine how neighborhood composition and the built environment separately and collectively influence judgements of place.[49] Model 2 focuses on the effects of neighborhood socio-demographic characteristics—racial composition, socioeconomic composition, home values, and residential instability—on assessments of place reputation. I find that racial composition, specifically the size of the Black or Latino population in a neighborhood, have significant, negative effects on reputational assessments. Holding all else equal, a 10-percentage point increase in the proportion of Black or Latino residents in a neighborhood is associated with a .031 and a .066-point decline in assessed reputation, respectively. While these effects may seem modest, the limited range of the outcome variable and the variation in racial composition means that minoritized neighborhoods that enjoy a similar socio-economic status as White neighborhoods are at a significant reputational disadvantage. This

[49] Within my models, I focus on the linear relationship between predictors and neighborhood reputation. Sensitivity tests suggested that non-linearities were generally non-significant. The one exception was socio-economic status, which suggested that the effect of neighborhood socio-economic status on reputation might increase at an increasing rate. However, the inclusion of this non-linear term did not improve overall model fit and added complexity to the interpretation of results and thus was omitted.

effect is illustrated in Figure 4.1, Panel A, which shows the marginal effect of racial composition on reputational assessments. Whereas an increase in the White population in a neighborhood is associated with greater reputational prestige, increases in minority populations are associated with a growing degree of stigma. Like the effect of proportion of White residents, Model 2 shows that home values and neighborhood socio-economic composition also have a strong positive effect on reputation. I find that, controlling for other neighborhood attributes and individual characteristics, neighborhoods that enjoy higher SES and higher median home values enjoy significantly greater reputational prestige. A standard deviation increase in socio-economic status is associated with a .224 increase in reputation while a standard deviation increase in median home value is associated with a .105 increase in reputation, holding all else equal. The positive, marginal effects of these measures are illustrated in Figure 4.1, Panel B. Model 2 results also show that, after accounting for these other measures of socio-demographic composition, residential instability has a negative but non-significant effect.

[FIGURE 4.1 ABOUT HERE]

Model 3 examines the effects of neighborhood amenities, disamenities, and green space on neighborhood reputation. It finds that neighborhood amenities—the presence of coffee shops, performing arts organizations, and museums—are significantly and positively associated with more favorable neighborhood reputations while neighborhood disamenities—the location of liquor stores, dollar stores, and pollution sites—have a significant and negative effect on reputation. Holding all else equal, a standard deviation increase in the number of neighborhood amenities is associated with a .146-point increase in assessed reputation while a standard deviation increase in neighborhood disamenities is associated with a .205-point decrease in reputation. Figure 4.1, Panel C illustrates the opposing effects of amenities and disamenities on reputational assessments. Considering green space, I find that each additional square mile of park land in a neighborhood is associated with a .060 increase in reputation, after controlling for other dimensions of the physical environment and respondent characteristics.

[TABLE 4.3 ABOUT HERE]

While these models suggest that both neighborhood demographics and the built environment have meaningful effects on collective assessments of place reputation, Model 4 shows that when combined only the effects of neighborhood demographics endure. In the combined model, the proportion of Black or Latino residents in a neighborhood continue to have significant, negative effects on assessments of reputation while neighborhood economic measures—socioeconomic index and median home values—continue to have significant, positive effects. In fact, the scale of these effects changes very little with the inclusion of measures of the physical environment, underlining their robustness. Conversely, after controlling for the socio-demographic dimensions of neighborhoods, the effects of neighborhood amenities, disamenities, and green space are minimized to the point of insignificance. This likely reflects an overlap between the demographic composition of a neighborhood and the location of amenities and may also suggest that when judging a neighborhood individuals infer considerable information about who comprises the neighborhood from the built environment, though correlations between socio-demographic and physical environment measures included in my models are generally low. Ultimately, this combined model supports my second hypothesis: that a stronger association will be found between neighborhood socio-demographic measures and reputation than physical measures and reputation.

Further proof of the greater relative importance of neighborhood demographic composition compared to the built environment is found when considering the proportion of between-neighborhood variability explained by each set of characteristics. The inclusion of only demographic characteristics in Model 2 explained 82 percent of the neighborhood-level variation in reputation whereas the inclusion of built environment variables in Model 3 explained just 27 percent of the neighborhood-level variation, suggesting the former possessed significantly greater explanatory power. Moreover, the inclusion of both socio-demographic characteristics and built environment measures explained 83 percent of the variation in neighborhood reputation assessments, suggesting that once local demographics are accounted for built environment measures add little by way of explanatory power to the model.

Differences in Predictors of Neighborhood Reputation Between Residents and Non-Residents

Model 1 revealed that residents generally give more glowing assessments of their neighborhood's reputation than outsiders. Given this, it is reasonable to wonder if the same attributes that shape collective assessments of reputation hold when separately considering the assessments of residents and non-residents. Table 4.4 explores this question using a stratified model to examine the relative role of demographic and built environment characteristics on reputational assessments among residents and outsiders, as well as the role of respondent identity.[50] Model 5O shows that outsiders' assessments of neighborhood reputation follow the general pattern

[50] Supplemental analyses tested interactions to see if the effects of neighborhood characteristics varied significantly depending on if the respondent was assessing their own neighborhood or other neighborhoods. While findings were varied, ultimately I chose to use stratified models to more clearly illustrate these differences.

of collective assessments of neighborhood reputation identified by previous models. Neighborhood demographic characteristics—racial composition, socioeconomic composition, and home values—are significant predictors of place reputations. Places with larger Black and Latino populations suffer negative reputation assessments compared to Whiter neighborhoods while those of higher economic status enjoy greater neighborhood prestige. After accounting for socio-demographic characteristics and respondent identity, dimensions of the built environment show no significant relationship. Results from the stratified model reflecting the assessments of outsiders also show that Black respondents generally rate the reputations of neighborhoods they do not live in significantly higher than White respondents, though other dimensions of individual identity do not appear to affect reputational assessments. Moreover, cross-level interactions testing if Black respondents assessed neighborhood reputation differently depending on the racial composition of the neighborhood also yielded non-significant results.

[TABLE 4.4 ABOUT HERE]

The neighborhood reputational assessments of insiders (Model 5I) reveal distinctly different patterns. Among neighborhood residents, only the socio-economic status of one's neighborhood appears to have a significant relationship with reputation. The racial composition, home values, degree of residential instability, and presence or absence of neighborhood amenities and disamenities appear to have no effect on how residents assess the reputation of their own neighborhood. The differences in the effect of neighborhood attributes on residents and non-residents is illustrated in Figure 4.2. Panels A and B of Figure 4.2 show the marginal effect of the proportion of Black and Latino residents in a neighborhood, respectively, on reputation assessments. The graphs highlight the flat or near flat slope among residents in response to own-neighborhood composition compared to the downward slope in reputation assessment for non-residents. Panel C illustrates a similar effect for home values, where the effect of a standard deviation increase in median home value on residents' assessments is nearly flat while a standard-deviation increase in median home value is associated with a .098 increase in reputation. Only Panel C, capturing the effect of socio-economic status on reputation assessments, shows a significant effect on reputational assessments for both residents and non-residents.

[FIGURE 4.2 ABOUT HERE]

In addition to the different effects of neighborhood attributes, results in Model 5I suggest that dimensions of individual identity—especially those markers indicative of economic status—significantly influence how one assesses the reputation of their own neighborhood. Higher income respondents—those in households earning $75,000 or more annually—have significantly higher assessments of their neighborhood's reputation than respondents earning less than $20,000. Similarly, homeowners hold significantly rosier assessments of their neighborhood of residence than renters, likely reflecting their heightened investment in and attachment to a neighborhood and the greater potential to benefit from reputational prestige compared to renters. Results also suggest that parents are less likely to offer heightened assessments of the reputation of their own neighborhood than respondents in households without children. Again, cross-level interactions did not suggest that individual income and neighborhood socio-economic status had a significant effect on assessments of own-neighborhood reputation. Taken together, these models support the hypothesis (H3) that residents and non-residents differ in the characteristics that predict their reputational assessments. Moreover, the results offer support for the sub-hypothesis (H3b) that residents' assessments of neighborhood reputation are less directly associated with neighborhood variables than non-residents' assessments, though the results also suggest that individual attributes play a stronger role in reputational assessment of own-neighborhood than other neighborhoods.

Influence of Own-Neighborhood Attributes on Assessments of Other-Neighborhood Reputations

Given that residents assess the reputation of their own neighborhoods differently than that of other neighborhoods, a final question to interrogate is if assessments of other-neighborhood reputations are biased by the conditions of one's residential environment. The conditions of one's neighborhood of residence might have two distinct types of effects. On the one hand, conditions in a respondent's neighborhood of residence might curtail or amplify the effect of that same condition when assessing other-neighborhood reputations. For example, living in a neighborhood with high socio-economic status might dampen the effect of socio-economic status in the neighborhood one is assessing, suggesting a significant interaction between own-neighborhood and other-neighborhood conditions. On the other hand, conditions in a respondent's neighborhood of residence might have an independent effect on assessments of neighborhood reputation generally. The socio-economic status of one's own neighborhood might generally lower their assessments of other-neighborhood reputations but not impact the role of other-neighborhood socio-economic status in those assessments, suggesting a significant main effect of own-neighborhood socio-economic status in the absence of a significant interaction.

A series of models (not shown) testing interactions between own-neighborhood conditions and the conditions of other neighborhoods found little evidence that attributes of respondents' neighborhood of residence significantly influence the effect of those same attributes in judging other neighborhoods, with one exception. I find that the proportion of Asian neighbors in one's own neighborhood had a significant and positive effect on reputational assessments of other neighborhoods based on the size of their Asian populations, meaning that living among more Asian residents increased the prestige with which one assessed the reputation of other neighborhoods with larger Asian populations. No other interactions between own- and other-neighborhood demographic conditions or elements of the built environment were found.

Turning instead to main effects, Model 6 (Table 4.5) captures how individual identity, neighborhood characteristics, and own-neighborhood characteristics influence reputational assessments of neighborhoods. The results show that much like previous models, the proportion of Black or Latino residents in the focal neighborhood have a significant, negative effect on that neighborhood's assessed reputation while markers of neighborhood economic status have a significant, positive relationship. These same dimensions of one's own neighborhood do not appear to influence general assessments of reputation. Instead, I find that home values and the amount of green space in one's neighborhood of residence have a general, negative effect reputation assessments of other neighborhoods. For example, an additional square mile of park space in one's own neighborhood is associated with a .019 decrease in the how one assesses the reputation of other neighborhoods, holding all else equal. Similarly, higher home values in one's own neighborhood are associated with lower assessments of other-neighborhood reputations. A standard-deviation increase in median home value in a respondents' own neighborhood is associated with a -.068 decrease in their assessments of other-neighborhood reputations.

[TABLE 4.5 ABOUT HERE]

Discussion & Conclusions

This study considers how individuals make sense of their environments by exploring collective understandings of neighborhood reputation in Los Angeles, Chicago, and Washington, D.C. Specifically, I examine how place reputations combine, reflect, and refract individual and neighborhood characteristics, including local socio-demographic composition and the physical attributes of neighborhoods. I argue that such an exploration is an important but largely missing dimension of a growing body of work on the symbolic and sentimental nature of neighborhoods because it offers insights into the links between people's mental schemas and "objective" neighborhood characteristics, provides clearer evidence of the ways in which local conditions give structure to the urban status hierarchy, and helps bridge the conceptual gap between the traditional structuralist approach to studying place and the emerging urban culturalist perspective. Below I review and contextualize my findings in relation to my four research questions before discussing implications of the study and directions for future research.

Within the literature, the concept of neighborhood reputation is often discussed as a collective, ecological phenomenon. Reputation has been defined alternately as "a collective understanding about a place" (Brown-Saracino and Parker 2017:841); "the stable image a neighborhood has among city residents" (Hortulanus (1995) in Permentier et al. 2008:835); and as the product of collective memories (Zelner 2015). Additionally, foundational studies in cultural ecology theorize about the ways in which *shared* symbolism and sentiments give structure to city-dwellers cognitive maps and understandings of the city (Firey 1945; Park and Burgess 1925; Suttles 1972). However, the collective nature of reputation is rarely directly tested and limited existing evidence supports the idea of a consistent structure of reputation hierarchies (Logan and

Collver 1983; Semyonov and Kraus 1982). Thus, the first goal of this study was to empirically test the extent to which city residents agree about place reputations. My findings suggest that neighborhood reputation enjoys a high degree of reliability. Using an ecometric approach to evaluate the nature of reputation from my three-city sample, I find that the reliability from my full sample is .905, meaning there is strong evidence of internal consistency around reputational assessments within my data. These findings are not only in keeping with my theory-driven hypothesis (H1) that *neighborhood reputation will attain a high degree of reliability and agreement among respondents*, but also provide important proof of concept regarding the collective nature of reputation and its relevance as a neighborhood-level construct deserving further study.

In addition to offering evidence of the collective nature of reputation, my results help elucidate the relationship between reputation and neighborhood conditions. While much scholarship has focused on the consequences of neighborhood stigma and prestige for people and places, studies of reputation have largely avoided drawing direct associations between "objective" neighborhood characteristics and place identity. The limited available evidence suggests the ways in which reputation may be associated with socio-demographic composition and dimensions of the built environment but draws primarily on four studies that either are outdated or focus on a non-American context (Logan and Collver 1983; Permentier et al. 2011, 2008; Semyonov and Kraus 1982). Thus, there is a lack of clear evidence about the relative importance of different dimensions of neighborhood demographic composition and the built environment in shaping reputational assessments in contemporary, U.S. cities. My results show that while both the socio-demographic context of a neighborhood and its built environment influence judgements of reputation, neighborhood demographic composition is most strongly associated with how the public assesses neighborhoods and their place on the urban status hierarchy. Specifically, I find the proportion of minority residents in a neighborhood or the presence of disamenities—liquor stores, dollar stores, and pollution sites—are associated with lower assessments of neighborhood reputation whereas socio-economic status, home values, neighborhood amenities—like coffee shops, museums, and performing arts organizations—and green space are associated with greater reputational prestige. When compared, neighborhood socio-demographic conditions have much greater explanatory power in relation to neighborhood reputations than dimensions of the built environment and, when considered simultaneously, the effects of socio-demographic context eliminate the effect of the built environment. On the one hand, this finding—which affirms my hypothesis (H2) that *a stronger association will be found between neighborhood socio-demographic measures and reputation than physical measures and reputation*—is perhaps unsurprising as a great deal of literature points to the effect of racial composition as proxy for a variety of measures of neighborhood quality (e.g. Emerson et al. 2001; Krysan and Bader 2007; Krysan et al. 2008; Quillian and Pager 2001). On the other hand, the diminished role of the built environment in shaping reputation might be surprising in that the built environment is more concrete and easier to observe than race and economic status. This finding points to the importance of further research that asks respondents directly what they form their assessments of neighborhoods in response to in an effort to understand how visual cues and more abstract concepts influence reputational assessments.

While my results show that neighborhood racial composition and economic measures are most strongly associated with assessments of reputation generally, a key finding from my analysis is that these dimensions of neighborhood matter most to how outsiders judge a neighborhood's reputation. By contrast, residents' assessments of their own-neighborhood reputation are predicted by socio-economic status of the neighborhood and individual characteristics, like their income and homeownership status. This supports my hypothesis (H3) that *residents and non-residents will differ in the characteristics that predict their reputational assessments* and is in keeping with past research showing residents and non-residents differ in their assessments of neighborhoods (Permentier et al. 2008). Moreover, this finding emphasizes the ways in which differently positioned groups with diverse knowledge and incentives conceive of communities (Brown-Saracino and Parker 2017). Outsiders are more likely to draw on second-hand knowledge of neighborhoods from the media, word of mouth, rumors, etc. and thus may be more strongly influenced by detached conceptions of what constitutes a place. By contrast, residents are more likely to draw upon personal knowledge and their subjective feelings about their neighborhood, including being attuned to micro-reputations within a neighborhood (Pinkster 2014; Small 2004), leading them to be less swayed by measures of neighborhood context, as suggested by hypothesis H3b. Indeed, the fact that individual characteristics like income and homeownership are significant, positive predictors of residents' assessments of their own neighborhood status speaks to the ways in which individuals internalize the identity of their neighborhoods and intermingle self-image and place of residence (Wacquant 2007).

My findings also addressed the relational nature of neighborhood reputations. While Suttles (1972:51) argued that neighborhood reputations are "embedded in a contrastive structure in which each neighborhood is known primarily as a counterpart to some others," quantitative analyses rarely consider the interdependence of assessments of neighborhood quality (see Parker 2019). Thus, my final research question sought to understand how place reputations might reflect not only the characteristics of the focal neighborhood but also the characteristics of other places, specifically a respondents' neighborhood of residence. While I hypothesized (H4) that *respondents' own-neighborhood attributes will have a significant and interactive effect on their assessments of other neighborhoods*, my findings generally did not support this supposition. Instead, I found that only median home values and access to green space in one's neighborhood of residence are negatively associated with how one assesses the reputation of other neighborhoods. This lack of effect for other dimension of neighborhood composition is surprising and begs further investigation. One possible explanation is that because residents are more likely to know of neighborhoods similar to their own neighborhood (Krysan and Bader 2009), there was minimal statistical difference between characteristics of neighborhoods being judged and where a respondent lived. Another possible explanation is that reputation is produced through comparison but that the typical point of comparison is not one's own neighborhood but some other real or imagined place. Given my findings that respondents' assessments of their own-neighborhood reputation are swayed less by measures of neighborhood context, this seems plausible and an area ripe for future exploration.

An important takeaway of my findings not yet touched on is the way in which reputation appears to be largely a mechanism of reproduction and differentiation. Much has been made of the role of neighborhood identity in influencing neighborhood change. Indeed, change in neighborhood identity is one of the core ways in which scholars have understood the process and effect of gentrification (Brown-Saracino 2010; Hyra 2017; McCabe 2019; Somashekhar 2021; Zukin, Lindeman, and Hurson 2017). But when one considers my findings, it appears instead that reputation may be more appropriately viewed as reinforcing than changing place identity. To illustrate this, consider the finding that socio-economic status and home values are associated with greater reputational prestige. That wealthier places are more prestigious is not surprising but speaks to a sort of Matthew Effect whereby neighborhoods than enjoy better reputations attract high-income residents, driving up home prices, and further adding to local prestige. The opposite process can be imagined in relation to the location of neighborhood disamenities, where stigmatized neighborhoods attract a limited set of retailers, leading to more vacant storefronts or cheaper rents which attract other businesses that commonly locate in disadvantaged neighborhoods. Thus, built and socio-demographic environments likely shape and are shaped by their reputations, further ingraining existing status disparities. Indeed, some existing research points to this durable nature of reputation (Evans and Lee 2020; Kaliner 2014; Parker 2018a; Sampson 2013).

Beyond the ways in which my study contributes empirically to the growing body of research on neighborhood reputation, my data and methodological approach also make several notable contributions. As mentioned above, much of the existing literature exploring the underpinnings of place reputation or status draw on a small number of studies that are either outdated (Logan and Collver 1983; Semyonov and Kraus 1982) or focus on foreign countries whose urban environments may bear little resemblance to the U.S. (Permentier et al. 2011, 2008; Semyonov and Kraus 1982). Thus, most simply, my data offer important contemporary insights to the nature of neighborhood reputation in an American context. Additionally, given the importance of comparison to the study of reputation, the fact that my data include observations from multiple types of respondents, across multiple neighborhoods within a city, and from multiple cities, marks an advancement in the study of reputation. In their review of the literature, Evans and Lee (2020) note that many studies of neighborhood status or desirability focus only on residents' views of their own neighborhood while Parker (2019:29) similarly observes that studies of reputation fail to adequately examine the contrastive nature of neighborhood reputations. It is my hope that my study examining reputational assessments using a multi-city study offers some advancement of the potential for studying reputation more fully moving forward. Finally, by taking an ecometric approach to reputation this study brings focus to the measurement of reputation as a collective ecological phenomenon, in contrast to past studies that have largely modeled neighborhood reputation, status, or desirability at the individual level (see for discussion Evans and Lee 2020; Logan and Collver 1983; Permentier et al. 2011).

In considering the implications of my findings, it is important to acknowledge that this study focused on the attributes of places and people that are associated with neighborhood reputation. This should not be mistaken for a project that considers where reputations come from. As Kearns et al. (2013) note, studies of neighborhood characteristics associated with reputation are not the same as studies of the content or meaning of reputations or as studies of the process by which reputations are created and sustained. A limitation of this study, then, is its focus on the relationship between contemporary neighborhood conditions and reputations, meaning it is limited in its ability to speak to the genesis of reputation. Thus, there is ample opportunity for future research that explores how place identity is formed and shifts over time using longitudinal or qualitative data. Additionally, in this study, I have limited my focus to exploring how reputations are associated with a few discrete features of people and place. Naturally, there are a wealth of neighborhood attributes and aspects of individuals that have been left out. Some of the most glaring omissions include measures of crime, disorder, and media coverage, but there is also reason to imagine that reputations are shaped in relation to an expansive set of neighborhood amenities and disamenities, transit accessibility, housing type, etc. These omissions should not be seen as detracting from the findings presented here but rather as rich avenues for future research as the study of neighborhood reputation—where reputations come from, what constitutes them, how they change, and their consequences—expands.

Table 4.1 Descriptive Statistics for Individual- and Neighborhood-Level Variables

	Mean / %	SD	Min	Max
Dependent Variable				
Neighborhood Reputation	2.960	0.864	1	4
Individual-level Variables (N = 1303)				
Female	0.520	0.500	0	1
Age	41.307	15.421	18	99
Household with kids	0.269	0.443	0	1
Respondent Race				
White	0.381	0.486	0	1
Black	0.283	0.451	0	1
Latino	0.229	0.421	0	1
Asian	0.073	0.260	0	1
Multi-Race or Other	0.033	0.179	0	1
College	0.565	0.496	0	1
Income				
$0 - $19,999	0.110	0.313	0	1
$20,000-$44,999	0.206	0.405	0	1
$45,000-$74,999	0.239	0.426	0	1
$75,000-$124,999	0.264	0.441	0	1
$125,000+	0.181	0.385	0	1
Homeowner	0.499	0.500	0	1
Length of Tenure in City	25.320	18.132	0.1	99
Neighborhood-level Variables (N = 238)				
Percent Non-Hispanic White	0.345	0.271	0.002	0.856
Percent Non-Hispanic Black	0.291	0.338	0.004	0.970
Percent Non-Hispanic Asian	0.078	0.088	0.000	0.724
Percent Latino	0.258	0.253	0.006	0.929
Percent Non-Hispanic Other/Multi	0.027	0.014	0.000	0.063
Socio-Economic Advantage Factor[a]	0.000	2.345	-8.096	3.560
Median Home Value (Logged)	12.986	0.660	11.252	14.503
Residential Instability Factor[a]	0.000	1.159	-2.439	3.684
Neighborhood Amenities Factor[a]	0.000	1.524	-1.011	10.488
Neighborhood Disamenities Factor[a]	0.000	1.180	-1.066	5.204
Square Miles of Park Land	0.409	1.168	0.000	14.123
Own Neighborhood-level Variables (N = 220)				
Percent Non-Hispanic White	0.359	0.269	0.002	0.856
Percent Non-Hispanic Black	0.275	0.329	0.004	0.968
Percent Non-Hispanic Asian	0.078	0.078	0.000	0.394
Percent Latino	0.259	0.251	0.006	0.929
Percent Non-Hispanic Other/Multi	0.028	0.014	0.000	0.063
Socio-Economic Advantage Factor[a]	0.108	2.328	-8.096	3.560
Median Home Value (Logged)	13.011	0.655	11.252	14.503
Residential Instability Factor[a]	0.012	1.161	-2.388	3.684
Neighborhood Amenities Factor[a]	0.063	1.566	-1.011	10.488
Neighborhood Disamenities Factor[a]	0.046	1.211	-1.066	5.204
Square Miles of Park Land	0.426	1.210	0.000	14.123

[a] Factor variables are standardized in models to have a mean of 0 and a standard deviation of 1 for ease of interpretation

Table 4.2 Variance components, intraneighborhood correlation coefficients, and neighborhood-level reliabilities

	Full Sample	Non-Resident Neighborhood	Resident Neighborhood	LA	Chicago	DC
Variance Components						
Between-neighborhood variance (Level 1)	0.180	0.202	0.148	0.212	0.162	0.136
Within-neighborhood variance (Level 2)	0.549	0.550	0.431	0.554	0.570	0.516
Intraclass Correlation	0.247	0.268	0.255	0.276	0.222	0.210
Reliability (average)	0.905	0.895	0.716	0.917	0.896	0.880
Observations	6481	5178	1303	2330	2321	1830
Groups	238	238	220	83	83	72

Figure 4.1 Marginal Effects of Neighborhood Characteristics on Assessments of Neighborhood Reputation

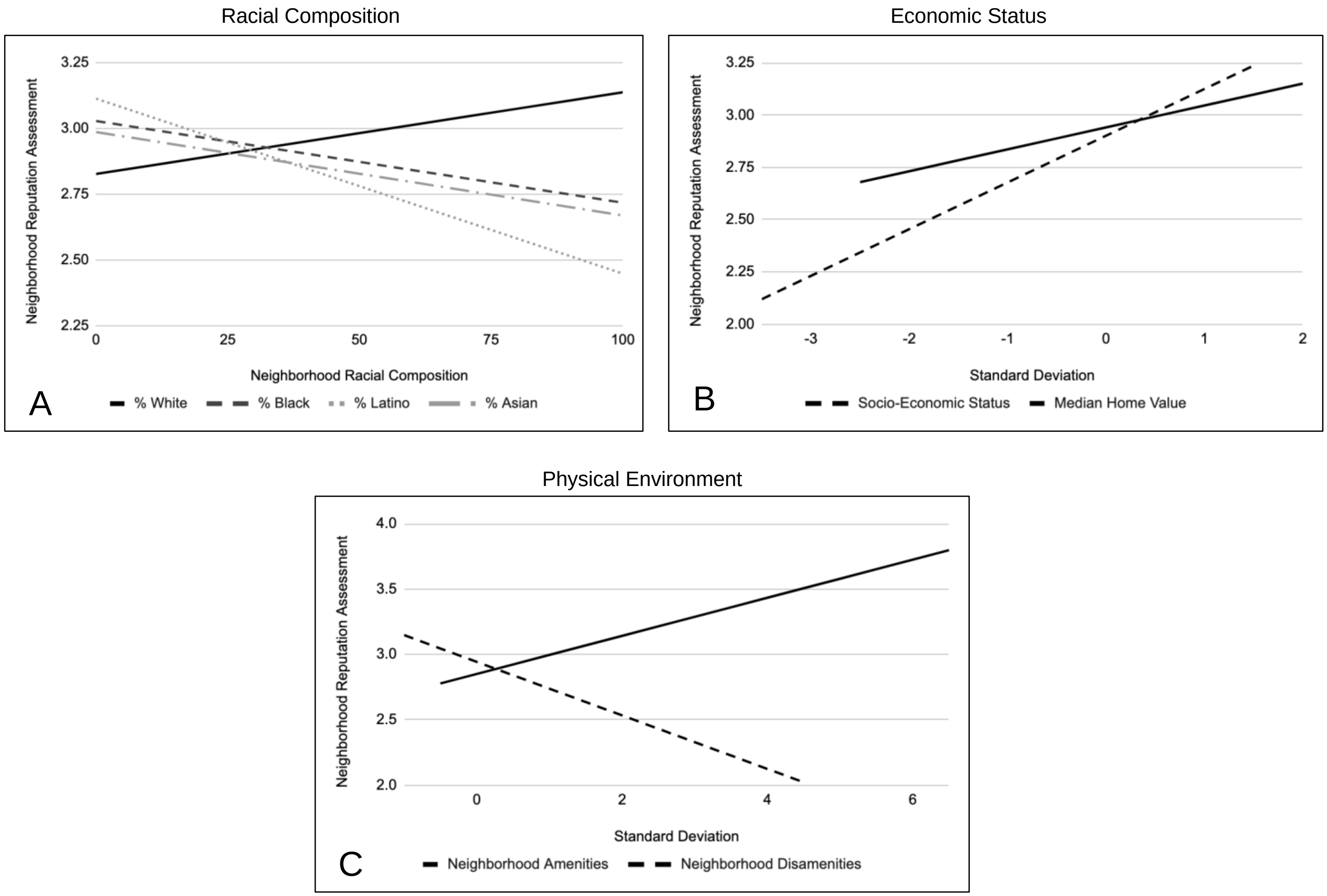


Table 4.3 Effects of Respondent Identity, Neighborhood Socio-Demographic Characteristics, and Physical Environment on Reputation Assessments

	Model 1		Model 2		Model 3		Model 4	
Intercept	2.732***	(.054)	0.953	(.507)	2.709***	(.053)	1.223*	(.545)
Individual-level Variables								
Female	-0.017	(.019)	-0.025	(.019)	-0.018	(.019)	-0.025	(.019)
Age	0.000	(.001)	0.000	(.001)	0.000	(.001)	0.000	(.001)
Household with kids	-0.022	(.021)	-0.018	(.021)	-0.023	(.021)	-0.019	(.021)
Respondent Race								
White	(ref)		(ref)		(ref)		(ref)	
Black	0.061*	(.027)	0.085**	(.027)	0.060*	(.027)	0.084**	(.027)
Latino	0.039	(.028)	0.044	(.027)	0.037	(.027)	0.044	(.027)
Asian	-0.034	(.039)	-0.030	(.039)	-0.040	(.039)	-0.030	(.039)
Multi-Race or Other	-0.082	(.054)	-0.078	(.054)	-0.084	(.054)	-0.078	(.054)
College	-0.015	(.022)	-0.026	(.022)	-0.018	(.022)	-0.026	(.022)
Income								
$0 - $19,999	(ref)		(ref)		(ref)		(ref)	
$20,000-$44,999	0.023	(.035)	0.023	(.035)	0.023	(.035)	0.022	(.035)
$45,000-$74,999	0.049	(.035)	0.048	(.035)	0.048	(.035)	0.047	(.035)
$75,000-$124,999	0.059	(.037)	0.055	(.037)	0.058	(.037)	0.055	(.037
$125,000+	0.029	(.042)	0.022	(.041)	0.027	(.042)	0.021	(.041)
Homeowner	0.032	(.022)	0.034	(.021)	0.033	(.022)	0.034	(.021)
Length of Tenure in City	0.001	(.001)	0.001	(.001)	0.001	(.001)	0.001	(.001)
Own Neighborhood	.347***	(.023)	0.354***	(.023)	0.353***	(.023)	0.356***	(.023)
Neighborhood-level Variables								
Demographic Characteristics								
Percent Non-Hispanic Black			-.310*	(.132)			-0.319*	(.136)
Percent Non-Hispanic Asian			-0.317	(.236)			-0.360	(.244)
Percent Latino			-0.665***	(.137)			-0.622***	(.142)
Percent Non-Hispanic Other/Multi			-0.381	(1.748)			-0.404	(1.769)
Socio-Economic Advantage Factor^			0.224***	(.040)			0.223***	(.041)
Median Home Value (Logged)			0.159***	(.017)			0.138**	(.043)
Residential Instability Factor^			-0.025	(.507)			-0.025	(.018)
Physical Characteristics								
Neighborhood Amenities Factor^					0.146***	(.026)	0.011	(.018)
Neighborhood Disamenities Factor^					-0.205***	(.027)	-0.027	(.021)
Square Miles of Park Land					0.060**	(.022)	0.006	(.013)
Variance Components								
Between-neighborhood variance	0.190		0.031		0.132		0.031	
Within-neighborhood variance	0.528		0.528		0.528		0.528	
X2	244.07***		893.85***		325.85***		897.60***	
ICC	0.265		0.056		0.200		0.056	
BIC	14925.4		14679.1		14879.1		14703.6	

Notes: Level 1 N=6,481; Level 2 N=238. Coefficients reported from linear mixed-effects models. Standard Errors in parentheses. ICC = Intraclass correlation. BIC = Bayesian information criterion. * p<0.05, ** p<0.01, *** p<0.001 (two-tailed tests)
[a] Factor variables are standardized in models to have a mean of 0 and a standard deviation of 1 for ease of interpretation

Table 4.4 Effects of Respondent Identity, Neighborhood Socio-Demographic Characteristics, and Physical Environment on Resident and Non-Resident Reputation Assessments

	Model 5O Non-Residents		Model 5I Residents	
Intercept	1.105	(.617)	2.033**	(.667)
Individual-level Variables				
Female	-0.019	(.021)	-0.043	(.037)
Age	0.000	(.001)	0.001	(.002)
Household with kids	-0.004	(.024)	-0.094*	(.042)
Respondent Race				
White	(ref)		(ref)	
Black	0.115***	(.031)	-0.106	(.057)
Latino	0.050	(.031)	0.004	(.055)
Asian	-0.028	(.045)	-0.048	(.075)
Multi-Race or Other	-0.083	(.062)	-0.129	(.105)
College	-0.036	(.025)	0.013	(.043)
Income				
$0 - $19,999	(ref)		(ref)	
$20,000-$44,999	0.021	(.040)	-0.014	(.068)
$45,000-$74,999	0.029	(.040)	0.109	(.069)
$75,000-$124,999	0.024	(.042)	0.190**	(.072)
$125,000+	-0.013	(.047)	0.197*	(.082)
Homeowner	0.019	(.024)	0.093*	(.043)
Length of Tenure in City	0.001	(.001)	0.002	(.001)
Neighborhood-level Variables				
Demographic Characteristics				
Percent Non-Hispanic Black	-0.338*	(.154)	-0.023	(.187)
Percent Non-Hispanic Asian	-0.346	(.270)	-0.244	(.340)
Percent Latino	-0.641***	(.160)	-0.277	(.187)
Percent Non-Hispanic Other/Multi	-0.427	(1.981)	0.040	(2.349)
Socio-Economic Advantage Factor^	0.226***	(.046)	0.264***	(.055)
Median Home Value (Logged)	0.149**	(.049)	0.080	(.053)
Residential Instability Factor^	-0.030	(.020)	0.021	(.023)
Physical Characteristics				
Neighborhood Amenities Factor^	0.011	(.020)	0.018	(.019)
Neighborhood Disamenities Factor^	-0.034	(.024)	-0.014	(.023)
Square Miles of Park Land	0.008	(.015)	-0.004	(.017)
Variance Components				
Between-neighborhood variance	0.039		8.35E-16	
Within-neighborhood variance	0.547		0.423	
X2	582.59***		520.35***	
ICC	0.067		0.000	
BIC	12001.1		2770.0	
N	5178		1303	
Groups	238		220	

Notes: Coefficients reported from stratified linear mixed-effects models. Standard Errors in parentheses. ICC = Intraclass correlation. BIC = Bayesian information criterion. * p<0.05, ** p<0.01, *** p<0.001 (two-tailed tests)
[a] Factor variables are standardized in models to have a mean of 0 and a standard deviation of 1 for ease of interpretation

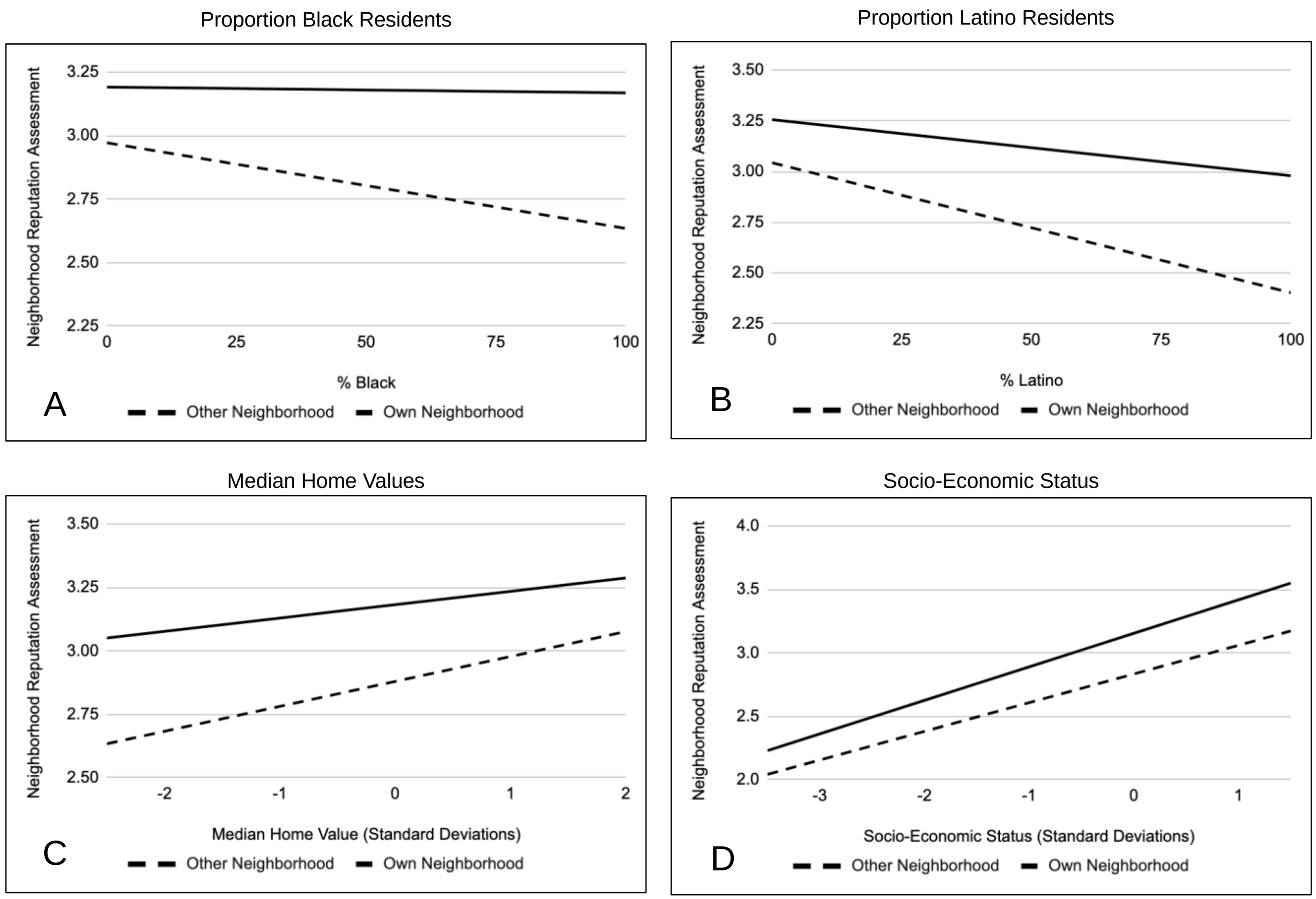
Table 4.5 Effects of Respondent Identity, Other Neighborhood Characteristics, and Own Neighborhood Characteristics on Other Neighborhood Reputation Assessments

	Model 6	
Intercept	0.949	(.645)
Individual-level Variables		
Female	-0.013	(.021)
Age	0.000	(.001)
Household with kids	-0.023	(.024)
Respondent Race		
White	(ref)	
Black	0.035	(.033)
Latino	0.032	(.032)
Asian	-0.017	(.045)
Multi-Race or Other	-0.112	(.062)
College	-0.016	(.025)
Income		
$0 - $19,999	(ref)	
$20,000-$44,999	0.023	(.040)
$45,000-$74,999	0.047	(.040)
$75,000-$124,999	0.048	(.042)
$125,000+	0.039	(.048)
Homeowner	0.019	(.024)
Length of Tenure in City	0.001	(.001)
Own Neighborhood Variables		
Demographic Characteristics		
Percent Non-Hispanic Black	0.188	(.117)
Percent Non-Hispanic Asian	-0.122	(.203)
Percent Latino	0.073	(.113)
Percent Non-Hispanic Other/Multi	1.977	(1.386)
Socio-Economic Advantage Factor^	-0.023	(.038)
Median Home Value (Logged)	-0.103*	(.051)
Residential Instability Factor^	0.007	(.014)
Physical Characteristics		
Neighborhood Amenities Factor^	-0.001	(.011)
Neighborhood Disamenities Factor^	0.018	(.013)
Square Miles of Park Land	-0.019*	(.010)
Rated Neighborhood-level Variables		
Demographic Characteristics		
Percent Non-Hispanic Black	-0.338*	(.154)
Percent Non-Hispanic Asian	-0.334	(.266)
Percent Latino	-0.606***	(.160)
Percent Non-Hispanic Other/Multi	-0.512	(1.935)
Socio-Economic Advantage Factor^	0.218***	(.047)
Median Home Value (Logged)	0.255***	(.061)
Residential Instability Factor^	-0.030	(.020)
Physical Characteristics		
Neighborhood Amenities Factor^	0.010	(.019)

Neighborhood Disamenities Factor^	-0.030	(.023)
Square Miles of Park Land	0.005	(.015)
Variance Components		
Between-neighborhood variance	0.035	
Within-neighborhood variance	0.540	
X2	704.00***	
ICC	0.061	
BIC	12007.5	

Notes: Level 1 N=5,178; Level 2 N=238. Coefficients reported from linear mixed-effects models. Standard Errors in parentheses
ICC = Intraclass correlation. BIC = Bayesian information criterion. * p<0.05, ** p<0.01, *** p<0.001 (two-tailed tests)
[a] Factor variables are standardized in models to have a mean of 0 and a standard deviation of 1 for ease of interpretation

Figure 4.2 Marginal Effects of Neighborhood Characteristics on Assessments of Own and Other Neighborhood Reputation



Chapter 5

Conclusion

In this dissertation, I examined the nature of residents' imperfect neighborhood knowledge and how people's subjective understandings of their local environments may or may not be at odds with objective measures of neighborhood characteristics. My three empirical chapters considered distinct dimensions of neighborhood knowledge that constitute, in part, what and how we know about the world around us: perceptions of levels, perceptions of change, and assessments of reputation. In the second chapter I focus on the prevalence and pattern of residents' distorted perceptions of their neighborhood's ethnoracial composition, considering how residents' perceptions compare to both objective measures and to the assessments of other residents in the same neighborhood. My third chapter takes a similar approach in measuring perceptions of change, interrogating how residents' perceptions of change in neighborhood safety reflect or fail to reflect local crime trends. In my final empirical chapter (Chapter 4) I examine the nature of neighborhood reputation and how underlying attributes of individuals and neighborhoods give shape to and are reflected by collective understandings of neighborhood identity. Below I identify a few core takeaways from these studies, their implications, and directions for future research.

First and foremost, my findings highlight the ways in which people's mental images of their neighborhoods often offer a distorted picture of local conditions. This is most clearly illustrated in my chapters on perceptions of levels and change, which, as I discuss in the introduction, are designed in part to capture the acuity of residents' neighborhood knowledge. In my second chapter my results demonstrate empirically that residents' perceptions of the racial composition of their neighborhood are often at odds with census measures of demographic composition. In fact, I find that the typical gap between perceived and objective group size is around 15 percentage points, meaning a neighborhood that is, for example, a third Black might be perceived as ranging from 15 to 45 percent Black. Similarly, in my third chapter on perceptions of change, I find that levels and change in neighborhood crime conditions explain only a small degree of variation in perceptions of change in local safety, suggesting at best a weak relationship between objective conditions often assumed to influence how safe one feels and residents' actual experience. These findings not only offer important proof of concept as to the relevance of subjective assessments of neighborhood conditions, but they also document the degree of fallibility contained in such assessments. Moreover, these findings make a powerful argument for the importance of not assuming that residents' understandings of neighborhoods map on to objective measures. Much as the Thomas Theorem suggests that subjective assessments have real consequences, these distorted perspectives of neighborhood conditions likely have real but underappreciated consequences for neighborhood processes.

A second notable finding from my research highlights the heterogenous ways in which individuals make sense of their communities. Across my studies, I find that respondents living in close proximity and exposed to similar local conditions reach considerably different conclusions about the nature of their environments. In Chapter 2, I find that residents in the same neighborhood often view the racial composition of their neighborhood very differently. Additionally, I find that how one understands their local racial composition depends greatly on their own racial identity. For example, a Latino resident is more likely to conclude their neighborhood has a larger number of other Latinos than their White neighbor, even after controlling for objective dimensions of neighborhood composition. In Chapter 3, I similarly show that residents who experience the same levels and change in crime in their block group over time often reach dramatically different conclusions about the degree to which local safety has changed. Unsurprisingly, I also find that perceptions of change in neighborhood safety are strongly influenced by personal experience with crime. Recent crime victims have half the odds of believing their neighborhood has grown safer over time compared to respondents who have not been victimized. In assessing neighborhood reputation, I also find evidence of heterogeneous evaluations of neighborhoods. While I demonstrate that collective assessments of reputation generally have a high degree of reliability across my sample, Chapter 4 also illustrates the ways in which residents' and non-residents' assessments of neighborhood reputation diverge. In keeping with past research (Permentier et al. 2008; Wileden 2019), I find that residents judge their neighborhoods' reputation more positively than non-residents, likely reflecting differences in positionality, attachment, and level and nature of neighborhood knowledge.

Documenting this variability in individuals' assessments of neighborhoods across these three studies is important in part because most quantitative scholarship on neighborhood dynamics generally assume that residents exposed to the same neighborhood context will share a consistent understanding of place. For example, while studies suggests that residential preferences vary by race (Charles 2006; Clark 1992, 2002; Krysan 2002b), they generally do not consider that perceptions of neighborhood attributes also vary by race. In standard methods meant to measure residential preference, the assumption is that a neighborhood described as 20 percent Black will be understood as 20 percent Black by all respondents, not that Black respondents might view it was 35 percent Black while White respondents view it as 15 percent Black. Similarly, studies of response to neighborhood change assume a degree of acuity and agreement about the ways in which neighborhoods have changed and don't often make space for varied understandings of the degree of change. Thus, while quantitative studies of neighborhood dynamics might allow for the effects of neighborhood conditions to vary across groups, they generally don't assume there is disagreement about the conditions themselves. This points to an opportunity for future research that considers the mutual role of objective conditions and information biases in shaping residential processes.

A third core finding of note within these studies is the way in which subjective assessments of neighborhood conditions often appear to conflate one dimension of a neighborhood with another. For example, in my third chapter, residents' perceptions of change in neighborhood safety appear to be largely driven by neighborhood composition, such that neighborhoods with greater proportions of Black residents are associated with significantly lower likelihood that one believes a neighborhood has grown safer. Similarly, in examining the underlying dimensions of neighborhood conditions that constitute neighborhood reputation, my findings in Chapter 4 suggest that socio-demographic measures of neighborhoods—including racial composition and socio-economic status—play an outsized role compared to aspects of the built environment that might offer more readily available signals of neighborhood prestige or disadvantage. These findings echo past research that similarly document instances in which people conflate two or more neighborhood attributes, for example taking racial composition as a signal for school quality, crime conditions, and home prices (Krysan et al. 2009). They also point to the ways in which subjective assessments of neighborhoods help individuals simplify and make sense of the world around them. Much like heuristics enable individuals to draw conclusions from partial information (Gigerenzer and Gaissmaier 2011), my findings suggest that subjective neighborhood assessments aid city residents in quickly making sense of their surroundings. Put simply, these studies suggest that residents' views of neighborhoods do not need to be accurate to be meaningful. More research that endeavors to disentangle when and how residents draw on distorted dimensions of neighborhood knowledge might reveal particular cases where this shorthand is especially useful to decision making.

A final consistent thread to touch on that emerges across all three studies is the importance of and need for more and better measurement of the subjective ways people make sense of their environments. In Chapters 2 and 3, I observe that traditional scholarship on residential preference and processes of neighborhood change often presume rather than measure neighborhood knowledge. Even innovative approaches like the Farley-Schuman showcard method, factorial experiments, or simulation models often assume or dictate residential knowledge of neighborhood characteristics, obscuring the fact that people generally lack precise knowledge of neighborhoods. Similarly, in studying neighborhood reputation, my survey is one of the few that can capture the collective nature of neighborhood assessments by drawing on observations from multiple types of respondents, across multiple neighborhoods within a city, and from multiple cities. Given the promising evidence of the role of subjective assessments in shaping neighborhood dynamics, future research would greatly benefit from data collection dedicated to measuring residents' subjective or distorted neighborhood knowledge. Not only is this important for exposing where subjective and objective understandings of neighborhoods diverge, it also will enable greater integration of objective and subjective data in future studies and enable continued scholarship on the symbolic nature of neighborhoods.

To date, urban scholars have largely overlooked the role of imperfect neighborhood knowledge in shaping neighborhood dynamics. Without greater attention to and integration of subjective understandings of neighborhoods, existing models of urban processes and policy efforts aimed at improving neighborhoods miss a critical component of residential experience. This dissertation offers initial evidence that by better accounting for how people make sense of place can we develop more realistic understandings of the mechanisms that shape neighborhoods and perpetuate place-based inequalities.

Appendices

Appendix A

Details of Survey Design

Data for Chapters 2 and 4 come from an online survey developed to capture residents' knowledge of and experience with neighborhoods in three US cities—Chicago, Los Angeles, and Washington D.C. The survey was conducted between January and April of 2018 via Qualtrics, an online survey platform. Qualtrics was also contracted to recruit survey participants from a pool of existing online research panel participants. A central goal of the survey was to address the general lack of available data that interrogates respondents' subjective understandings of their own and other neighborhoods in their city of residence. To that end, the survey was designed to present real, consistent, clearly delineated, and easily recognizable neighborhoods that would allow respondents to tap into their associations, mental schemas, or lived experiences with a place.

This supplementary material includes greater detail on the survey's methodology for defining neighborhoods and for identifying respondents' neighborhood of residence. Also included are descriptions of the representativeness of survey respondents in relation to each city's demographics and examples of the map tool used by respondents.

Defining Neighborhoods

It is common practice in neighborhood research to define neighborhoods as census tracts or block groups. Despite their analytical convenience and efforts by the Census Bureau to create tracts that are bounded by obvious physical markers such as major streets, bridges, or rivers, researchers have observed that census tracts may not reflect geographically salient boundaries:

residents may not be familiar with the location of tract boundaries and residents' subjective definitions of neighborhoods may not coincide with these administrative borders (Clapp and Wang 2006; Coulton et al. 2001; Sastry et al. 2002; Wong et al. 2012).

In an effort to use more salient boundaries to collect data on residents' perceptions, the survey instrument included city-specific maps developed to highlight neighborhood names and the spatial arrangement of neighborhoods within the city. Though neighborhood geographies and names can be seen as subjective, creating maps with clear boundaries and clearly labeled neighborhood names creates consistency across respondents, improves the utility of the data, and is easier to implement than other approaches that do not specify boundaries or allow respondents to define their own neighborhood geographies. For each city, a slightly different approach was taken to create a map that included a discrete number of large, identifiable neighborhoods with clearly delineated names, boundaries, and spatial configurations widely identifiable and meaningful to the general public:

- The 83 neighborhoods defined in the city of Chicago (see Figure A.1) were primarily drawn from the city's 77 community areas. Because the community areas of West Town, the Near North Side, and the Near West Side are large geographies that include multiple smaller, well-known neighborhoods, those areas were subdivided into smaller neighborhoods including the West Loop, River North, Wicker Park, etc. Boundaries and names for these smaller neighborhoods were drawn from publicly available Zillow-produced shape files.
- The 83 neighborhoods defined in the city of Los Angeles (see Figure A.2) were primarily drawn from the Los Angeles Times' Mapping LA Project (Los Angeles Times 2009), which included 87 neighborhood names and boundaries identified by Times staffers and refined through more than 1500 crowd sourced reader comments. For usability and to

reduce burden on respondents, small neighborhoods that would be difficult to select in the mapping tool were collapsed into a single geography. For example, Elysian Park and Elysian Valley were combined into Elysian; Beverlywood and Pico-Robertson were combined into Beverlywood.

- The 72 neighborhoods defined in Washington, D.C. (see Figure A.3) were created by combining data from two publicly available sources: neighborhood labels available from the municipal open data portal and neighborhood names and boundaries from Zillow-produced shape files. For usability and to reduce burden on respondents, some smaller neighborhoods were collapsed into a single geography that would be easier to select in the mapping tool. For example, Friendship Heights and Tenleytown were combined into Friendship Heights/Tenleytown; Naylor Gardens and Hillcrest were combined into Naylor Gardens/Hillcrest.

For each city, neighborhoods were determined to be broadly recognizable based on cross-referencing lists of named places included in both municipally developed geographic databases and place-based amenity websites like Zillow, OpenTable, and Airbnb.

Quality Control Measures for Identifying Respondents' Neighborhoods of Residence

Many neighborhood surveys rely on traditional address-based sampling to identify the location of residence for a respondent and link that respondent to relevant data on neighborhood characteristics. Because survey respondents were recruited from Qualtrics' online research pool and respondent addresses were not collected, a multi-stage process was employed to ensure that respondents provided quality data on their residential locations.

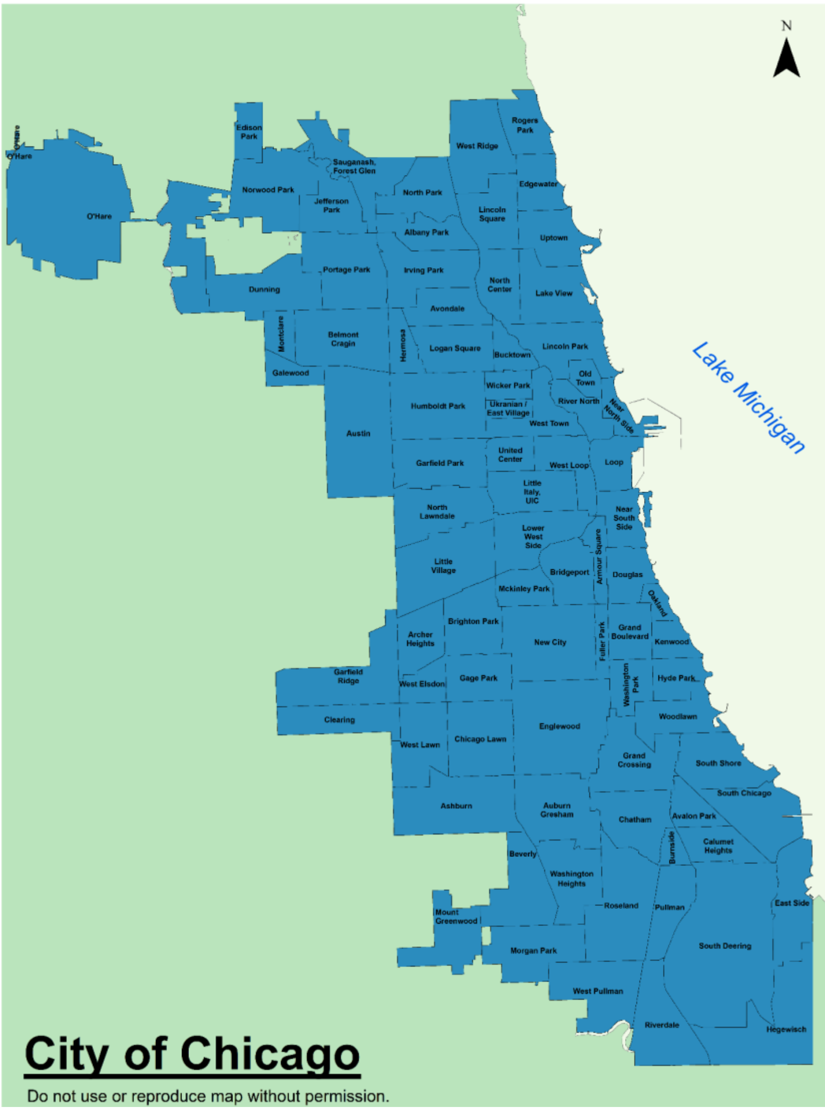
First, to identify respondents who were geographically relevant to the survey, Qualtrics screened potential respondents based on their IP locations in the recruitment phase. Only those research pool members whose IP addresses suggested they lived in the cities of Los Angeles, Chicago, or Washington D.C. were invited to participate in the survey. Second, once potential respondents had expressed interest in participating, survey logic within the instrument was used to eliminate non-city residents based on their response to the question: "Are you a resident of X city." Any negative response resulted in the termination of the survey. Third, in the data cleaning process, a thorough review of respondents' consistency across several variables was undertaken to confirm neighborhood of residence. Within the survey instrument, respondents were required to self-report the name of their neighborhood of residence and to select their neighborhood using the clickable map tool. Nonsensical responses to neighborhood name and responses indicating residence outside of the city (e.g., a Chicago survey respondent reporting their neighborhood as "Oak Park") were replaced in a second round of data collection. Additionally, comparisons of respondents' self-reported neighborhood names and the neighborhood selected on the map were used to flag questionable data. In general, there was a high degree of consistency between the name provided by the respondent and the neighborhood selected in the mapping tool. On occasions where respondents' named neighborhood was not within a half mile (per Google Maps) of the boundary of the neighborhood selected on the survey map, those responses were also replaced in a second round of data collection. Overall, 125 responses were flagged and replaced based on this data quality review.

Respondents' Representativeness of City Populations

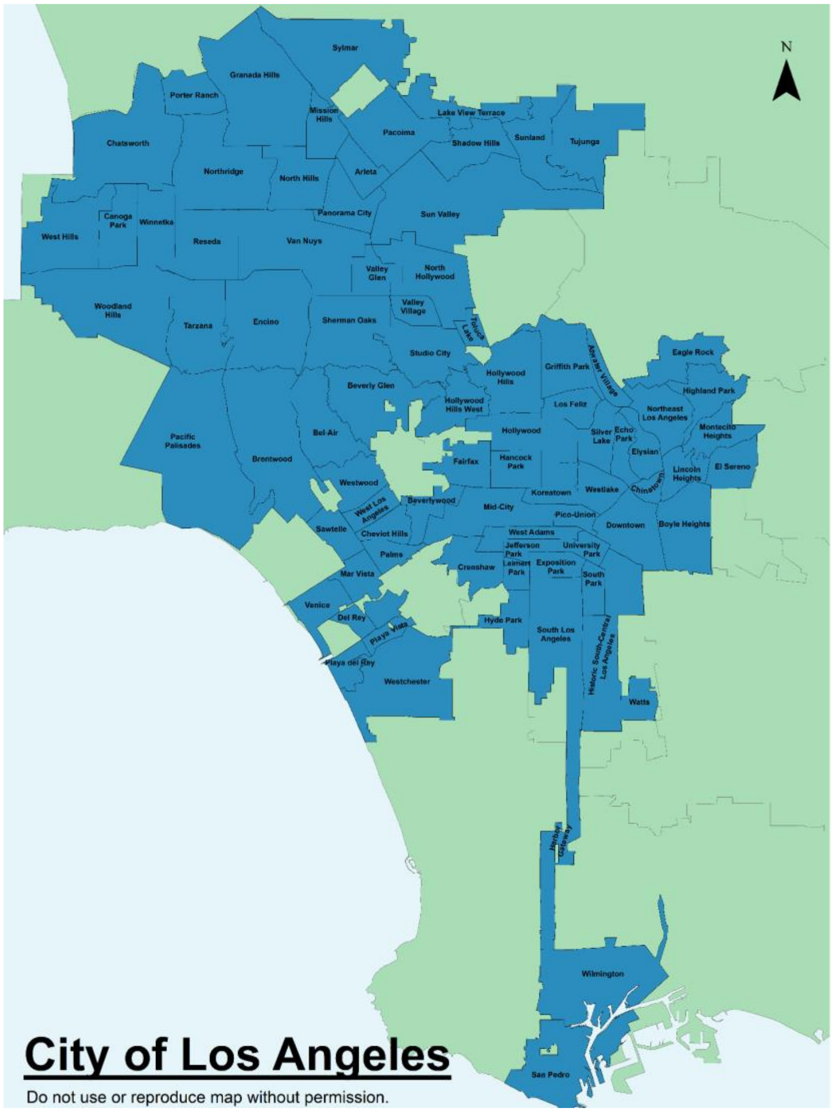
Respondent recruitment was based on quotas for gender parity and city-specific, proportionally representative quotas for respondent racial/ethnic identity based on 2016 American Community Survey (ACS) estimates. Survey responses were captured only if a respondent lived in the relevant city, reported being 18 years or older, and was either a native English speaker or self-reported proficient fluency in English. Though respondents were not recruited in a way that intentionally produced geographic distribution across neighborhoods, the resulting sample included residents of 230 of the 238 possible neighborhoods. In total, respondents in LA lived in 81 of the 83 possible neighborhoods; respondents in Chicago lived in 80 of the possible 83 neighborhoods; and respondents in DC lived in 69 of the possible 72 neighborhoods.

Table A.1 compares key demographic aspects of my survey respondents to the population of each city, as reported by the 2016 ACS. The table reveals that despite recruiting based on demographic quotas, there are some significant differences between my survey respondents and they city population. For example, in Los Angeles and Washington, D.C. my respondents are more likely to be White, whereas in Chicago my sample has a significantly higher proportion of Black respondents than the city population. Respondents were not screened based on their socio-economic status, and comparisons between my sample and the city population find that my respondents were more likely to own homes and more likely to be moderate income earners than the city population. While issues of representativeness could be addressed through the development of survey weights, because my analysis does not seek to make claims about the central tendencies of Chicago, LA, or DC residents, I leave my data unweighted. However, readers should take note that the data are drawn from a nonprobability sample and thus findings should be viewed cautiously in terms of their representativeness.

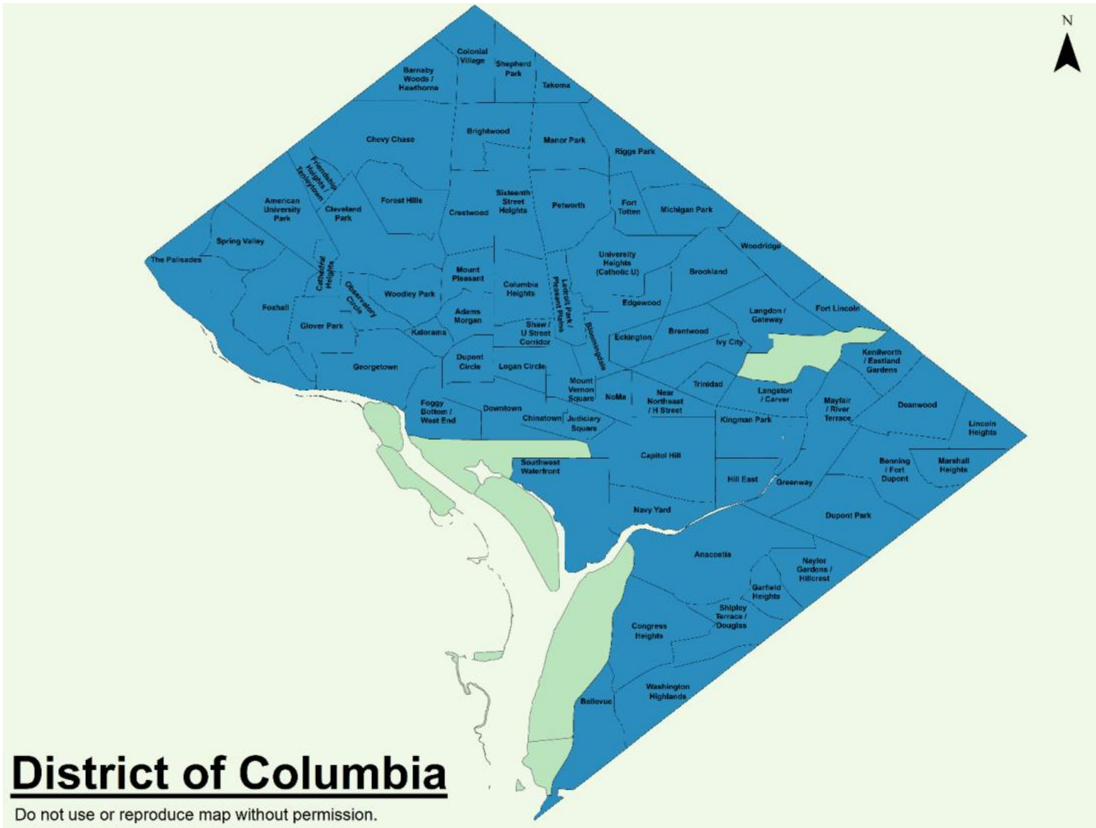
Appendix Figure A.1 Chicago Neighborhood Map



Appendix Figure A.2 Los Angeles Neighborhood Map



Appendix Figure A.3 District of Columbia Neighborhood Map



Appendix Table A.1 Comparison of Survey Sample with American Community Survey

	Chicago			Los Angeles			DC		
	Survey	ACS 2016	Sig	Survey	ACS 2016	Sig	Survey	ACS 2016	Sig
Female	52	52		52	50		52	53	
Race									
White	35	33		33	28	**	40	37	*
Black	43	29	***	8	9		43	45	
Latino	15	29	***	42	49	*	10	11	
Asian	6	7		13	11		4	4	
Multi-Race or Other	2	2		4	3		3	3	
Income									
$0 - $19,999	16	21	*	11	17	*	8	17	***
$20,000-$44,999	24	22		20	22		14	14	
$45,000-$74,999	25	19	*	26	20	*	22	16	*
$75,000-$124,999	21	19		27	20	*	34	21	**
$125,000+	15	19		16	21		20	33	***
Homeowner	50	45	**	51	37	***	48	42	**
N	552			734			480		

Notes: Significance reported from t-tests * p<0.05, ** p<0.01, *** p<0.001 (two-tailed tests)

Appendix B

Supplemental Analyses Chapter 2

Supplemental analyses were run to examine the extent to which my findings are sensitive to alternate model specifications. Specifically, I examine if modeling my results using an alternate dependent variable that captures the difference between estimated size and real size of a population yields substantively different conclusions. Results in Table B.1 show that modeling differences as the outcome variable does not produce substantively different findings, just different coefficients. Results from the null model (Model 1) estimated using difference as the dependent variable still shows that the bulk of variation in difference in perceptions lies within neighborhoods. Similarly, results from Model 2 continue to show that there is significant variation in perceptions by ethnoracial identity of the respondent.

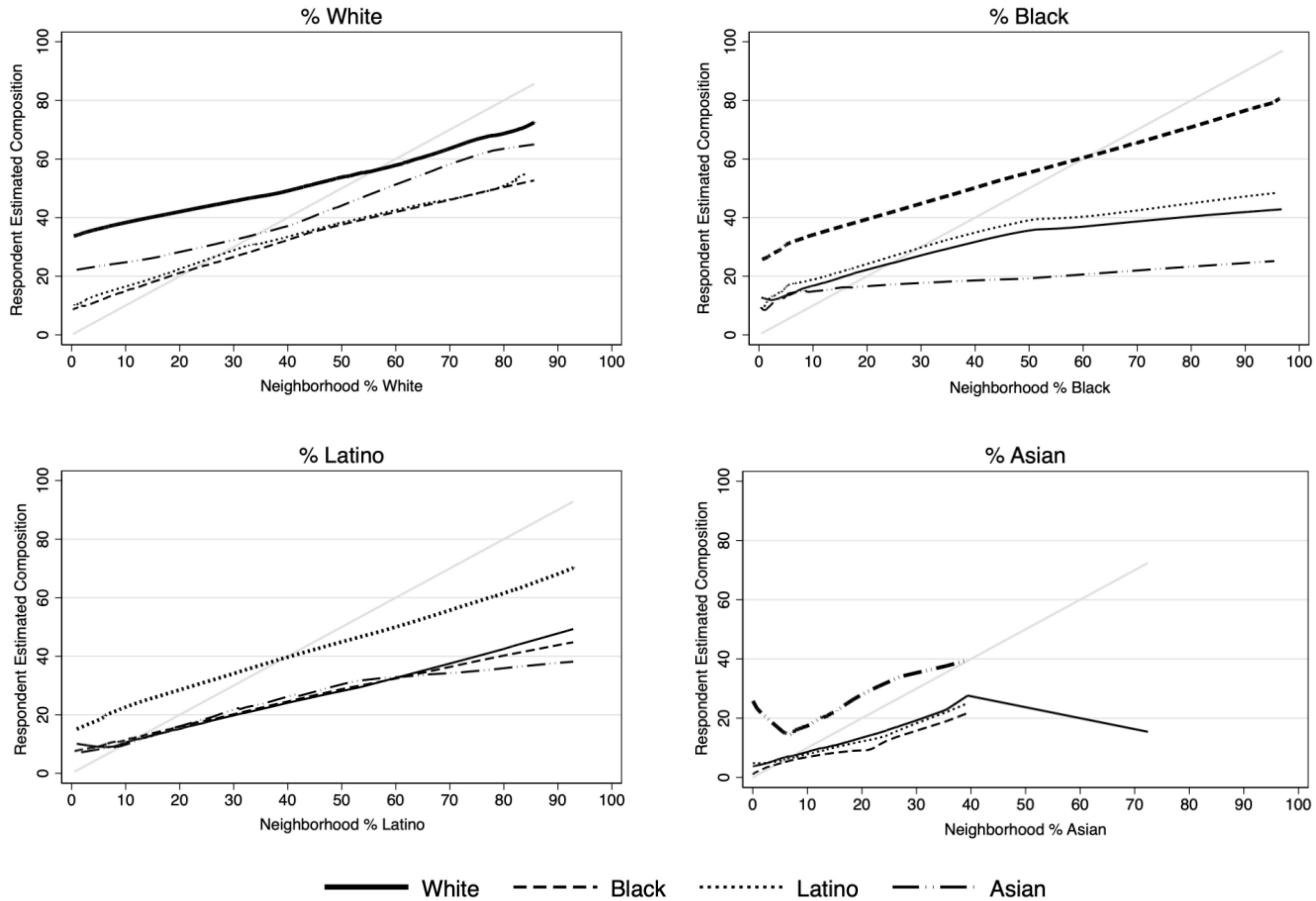
Figure B.1 illustrates with LOWESS plots the key takeaway from Model 2, that across all focal ethnoracial groups, respondents perceive their own group to make up a significantly larger portion of their neighbors than do respondents of other groups.

Appendix Table B.1 Location of Variance and Effect of Respondent Race and Objective Neighborhood Composition on Difference in Perceptions of Neighborhood Racial Composition

	Perceived % White		Perceived % Black		Perceived % Latino		Perceived % Asian	
	Model 1W	Model 2W	Model 1B	Model 2B	Model 1L	Model 2L	Model 1A	Model 2A
Intercept	0.686	12.01***	3.55**	16.41***	-4.31***	6.51***	-0.31	10.57***
	(1.00)	(.92)	(1.02)	(.94)	(0.93)	(.89)	(0.39)	(.81)
Individual-level Variables								
White		*ref*		-20.10***		-14.39***		-11.19***
				(1.25)		(1.06)		(.86)
Black		-18.88***		*ref*		-13.63***		-12.60***
		(1.34)				(1.20)		(.93)
Latino		-16.71***		-17.69***		*ref*		-11.74***
		(1.33)		(1.38)				(.89)
Asian		-9.11***		-22.09***		-15.07***		*ref*
		(2.94)		(1.85)		(1.55)		
Multi-Race or Other		-9.31**		-15.75***		-12.38***		-10.26***
		(2.94)		(2.63)		(2.34)		(1.48)
Neighborhood-level Variables (Grand Mean Centered)								
% White		-.50***						
		(.02)						
% Black				-.52***				
				(.02)				
% Latino						-.53***		
						(.02)		
% Asian								-.52***
								(.04)
Variance Components								
Between-group variance	140.97	16.66	168.17	12.32	139.03	17.48	17.53	6.36
Within-group variance	464.69	410.17	350.64	308.52	277.9	245.85	90.78	80.76
ICC	0.23	.04	0.32	.04	0.33	.07	0.16	.07
R^2 Between		.88		.93		.87		.64
R^2 Within		.12		.12		.12		.11
R^2 Total		.30		.38		.37		.20
BIC	16123.35	15755.04	15694.94	15251.31	15291.16	14884.35	13181.2	12925.82

Notes: Level 1 N=1,766; Level 2 N=230. Coefficients reported from linear mixed-effects models. Standard errors in parentheses. ICC = Intraclass correlation. BIC = Bayesian information criterion. * p<0.05, ** p<0.01, *** p<0.001 (two-tailed tests)

Appendix Figure B.1 Comparison of Perceived and Objective Neighborhood Racial Composition by Respondent Race



Notes: Locally weighted scatterplot smoother (LOWESS) plot of perceived racial composition for full sample. Grey diagonal reference line illustrates a hypothetical, perfect relationship between variables. The range for each focal ethnoracial group is limited to the maximum proportion of each group observed within neighborhoods in data.

Appendix C

Supplemental Analyses Chapter 3

Imputing Missing Data

Within the data, 129 respondents were missing data on one or more demographic variables. Table C.1 captures information on the degree of missing data for respondent demographic characteristics and the number of imputed cases. Data replacement was performed using hot deck imputation in STATA 17. While multiple imputation is the generally preferred method for replacing missing values, it is subject to limitations in its application to multi-level ordinal models. Specifically, the `meologit` command is not compatible with STATA's `mi estimate` suite, making it difficult to determine appropriate confidence intervals for ordinal coefficients. Hot deck imputation was used to overcome these limitations, and sensitivity tests find results from multiply imputed models were substantively consistent results to hot deck imputed models.

Appendix Table C.1 Imputed Variables

Imputed Variables	Complete Cases	Imputed Cases
College+	1792	29
Females	1793	28
Homeowners	1806	15
Race	1780	41
Income	1605	216
Residential Length	1800	21
Age (Centered)	1762	59

Alternative Linear Multilevel Model Specification

While I focus my findings on results from multilevel ordinal logit models, some work has argued that multilevel linear models are a preferable approach (Hipp 2013; Rodriguez and Goldman 1995). Comparisons of results from ordinal (Table 2.3) and linear models (Table C.2) finds consistent patterns across modeling approaches.

Appendix Table C.2 Effects of Crime Levels and Change, Respondent Characteristics, and Neighborhood Composition and Change on Perceived Change in Neighborhood Safety Linear Models

	Model 1		**Model 2**		**Model 3**	
Intercept	1.857***	(.144)	2.158***	(.156)	2.334***	(.186)
Crime						
2014 Violent Crime Rate	-.127**	(.042)	-.100*	(.042)	-0.044	(.044)
2014 Property Crime Rate	.145**	(.050)	.123*	(.050)	.107*	(.051)
△ Violent Crime Rate (2014-2019)	-.087**	(.031)	-.073*	(.031)	-0.042	(.032)
△ Property Crime Rate (2014-2019)	0.045	(.039)	0.047	(.038)	0.056	(.038)
Personal Characteristics						
Race/Ethnicity						
Non-Hispanic White						
Non-Hispanic Black			-0.085	(.050)	-0.034	(.052)
Latino			0.093	(.080)	0.072	(.086)
Non-Hispanic Other/Multi Race			-0.086	(.067)	-0.078	(.067)
College+			-0.009	(.040)	-0.008	(.040)
Income						
Under $10,000						
$10,000-$29,999			0.039	(.042)	0.041	(.042)
$30,000-$59,999			0.005	(.044)	0.006	(.044)
$60,000-$99,999			-0.079	(.056)	-0.08	(.056)
$100,000+			0.071	(.073)	0.078	(.074)
Age (Centered)			-0.002	(.001)	-0.001	(.001)
Female			-.112**	(.033)	-.109**	(.033)
Residential Length						
Less than 5 years						
6-10 years			-0.008	(.042)	-0.013	(.042)
11+ years			-.138**	(.041)	-.143***	(.041)
Households with children			-0.013	(.036)	-0.013	(.036)
Homeowners			0.01	(.036)	0.005	(.036)
Recent Crime Victim			-.235***	(.031)	-.237***	(.031)
Neighborhood Characteristics						
2014 % Black					-.297**	(.108)
2014 % Latino					-0.091	(.165)
2014 % Disadvantaged					-0.28	(.323)
△ % Black (2014-2019)					-0.31	(.205)
△ % Latino (2014-2019)					0.156	(.310)
△ % Disadvantaged (2014-2019)					-0.295	(.295)
Variance Components						
Between-neighborhood variance	0.025		0.021		0.017	
Within-neighborhood variance	0.411		0.390		0.389	
ICC	0.058		0.052		0.042	
R^2 Total	0.012		0.070		0.08	
R^2 Between (Level 1)	0.000		0.053		0.053	
R^2Within (Level 2)	0.178		0.309		0.444	
AIC	3652.1		3575.4		3572.7	
BIC	3690.6		3696.6		3726.9	

Notes: N=1,821 respondents clustered in 356 block groups. Coefficients reported from multi-level linear regression models. Standard errors in parentheses. ICC = Intraclass correlation. AIC = Akaike information criterion. BIC = Bayesian information criterion.
* p<0.05, ** p<0.01, *** p<0.001 (two-tailed tests)

Appendix D

Supplemental Analyses Chapter 4

Appendix Table D.1 Factor Loadings from Principal Components Analysis of Neighborhood Characteristics and Built Environment Measures

	Eigenvalue[a]	**Factor Loading**	**% Variance Explained**
Socio-Economic Advantage Factor	5.500		0.786
% Public Assistance		0.367	0.740
% Female Headed Households		0.397	0.866
% Professional or Managerial Jobs		-0.369	0.748
% Unemployed		0.351	0.678
% Population in Poverty		0.391	0.842
% Residents 25+ with a College Degree		-0.373	0.766
Median Household Income (Logged)		-0.396	0.861
Residential Instability Factor	1.343		0.672
% Renters		0.707	0.672
% New to Neighborhood		0.707	0.672
Neighborhood Amenities Factor	2.321		0.774
Count of Coffee Shops		0.614	0.876
Count of Performing Arts Organizations		0.539	0.676
Count of Museums		0.576	0.770
Neighborhood Disamenities Factor	1.394		0.465
Count of Liquor Stores		0.541	0.408
Count of Dollar Stores		0.591	0.486
Count of Polluting Sites		0.599	0.499

Notes: N=238 neighborhoods. To account for differences in the scale of variables and avoid skew in the resulting components, all variables were standardized prior to estimation.
[a] Eigenvalues measure the explanatory power of each component factor. Eigenvalues greater than one can be interpreted as possessing more explanatory power than the original variables.

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