

CLOSUP Working Paper Series  
Number 40

January 2019

**Modeling 'A Sense of Place':  
Evaluating the Roles of Knowledge and  
Reputation in Neighborhood Dynamics  
via Online Surveys**

Lydia Wileden, University of Michigan

This paper is available online at <http://closup.umich.edu>

Any opinions, findings, conclusions, or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the view of the Center for Local, State, and Urban Policy or any sponsoring agency

Center for Local, State, and Urban Policy  
Gerald R. Ford School of Public Policy  
University of Michigan

# **Modeling ‘A Sense of Place’: Evaluating the Roles of Knowledge and Reputation in Neighborhood Dynamics via Online Surveys**

**Lydia Wileden<sup>1</sup>**  
**Departments of Public Policy and Sociology**  
**Population Studies Center**  
**Institute for Social Research**  
**University of Michigan**

The processes driving neighborhood change have been of persistent interest to social scientists for decades. While researchers have developed many theories of how neighborhoods change over time – from ecological models of invasion-succession<sup>2</sup> to models of residential preference and neighborhood selection<sup>3</sup> – much of this work has relied on hypothetical neighborhoods, rather than real urban contexts, or made implausible assumptions about individual behavior to draw conclusions. As a result, these theories fail to adequately model the micro-processes underlying neighborhood change. In particular, researchers have under-theorized the importance of *(mis)perception* and *reputation* as key mechanisms driving neighborhood evolution.

In much urban research, it is assumed that individuals are omniscient and accurate observers of their environments, possessing full knowledge of local demographics and aggregate occurrences of events like crime and residential turnover. However, there is ample evidence that individuals have limited knowledge of their surroundings and are poor judges of their environments.<sup>4</sup> Given that individuals’ perceptions of their communities rarely match reality, it is important to develop more cognitively plausible models<sup>5</sup> of what individuals know, how they experience, and how they make choices about their neighborhoods. By studying one’s “sense of a place” – their neighborhood knowledge, perception of neighborhood desirability, and the gap between real and perceived neighborhood conditions – rather than focusing on objective features of neighborhoods, one can uncover latent, underlying motivations for behaviors that lead to neighborhood change over time.

This report examines three ways in which individuals’ perceptions and gaps in knowledge may influence neighborhood dynamics. All three leverage data from a newly-fielded pilot survey developed to capture residents’ knowledge of and experience with neighborhoods in three US cities – Chicago, Los Angeles, and Washington D.C. The data, described below, is some of the first to empirically measure how neighborhood information and reputation influence the changing dynamics of place, or vice versa. The first section of this report uses this unique data to

---

<sup>1</sup> This research was supported by funding from the Population Studies Center and the Center for Local State and Urban Policy at the University of Michigan. Additional support was provided through the National Science Foundation Graduate Research Fellowship Program (DGE #1256260) and an NICHD grant to the Population Studies Center at the University of Michigan (T32 HD007339).

<sup>2</sup> Duncan and Duncan 1957; McKenzie 1924; Burgess 1925; Hoover and Vernon 1959

<sup>3</sup> Krysan 2002; Charles 2003; Schelling 1971; Bruch and Mare 2006

<sup>4</sup> Alba, Rumbaut, and Marotz 2005; Hidalgo et al 2015

<sup>5</sup> Bruch and Swait n.d.; Krysan and Crowder 2017; Krysan and Bader 2009

examine systematic differences in individuals' familiarity with neighborhoods in their city of residence. The second section interrogates differences between resident and non-resident neighborhood reputations and how neighborhood demographic and socio-economic factors contribute to internal and external perceptions of neighborhood reputation. The third section examines how perceptions of neighborhood reputation shape residential mobility preferences, arguing that differences in perceptions are meaningful because they have the potential to shape individual residential behaviors, which aggregate up to create the shifting landscape of urban spaces we observe today. The report concludes by summarizing findings and discussing the implications of this work for both future urban research and urban policy.

## **A Survey Developed to Capture Neighborhood Perceptions<sup>6</sup>**

Social scientists' failure to incorporate reputation and perception into models of neighborhood evolution is in part due to a lack of available data.<sup>7</sup> In an effort to correct this data deficiency, I developed and fielded a unique, online pilot survey to capture differences in neighborhood knowledge and the salience of neighborhood reputations in three US cities. The survey was conducted between January and April of 2018 via Qualtrics, an online survey platform, and asked respondents in Los Angeles, Washington, D.C., and Chicago<sup>8,9</sup> about their knowledge of and experience with communities and neighborhoods in their city of residence. Qualtrics was also contracted to recruit survey participants from a pool of existing online research panel participants, using city-specific quotas that were proportionally representative of each city's population by race/ethnic category and gender parity.

For each city, respondents used interactive maps<sup>10</sup> (see Figure 1) to indicate their neighborhood of residence and other city neighborhoods with which they were familiar. In total, respondents could select from 83 neighborhoods in Los Angeles, 83 neighborhoods in Chicago, and 72 neighborhoods in Washington, D.C. After selecting neighborhoods on the maps, respondents

---

<sup>6</sup> 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.

<sup>7</sup> For examples of relevant studies that incorporate neighborhood reputation into their research, see Semyonov and Kraus 1982; Logan and Collver 1983; Permentier et al 2011; Permentier 2012; Permentier et al 2008

<sup>8</sup> The cities were selected because of their geographic diversity, relevance to urban research, and for the anticipated pervasiveness of neighborhood names in each city.

<sup>9</sup> Qualtrics targeted recruitment to respondents living in each target city. Additionally, the survey used three-step verification of a respondent's neighborhood of residence as a quality control measure to verify that respondents were actual city residents. 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 in the city. Nonsensical responses and responses indicating residence in a suburb of the city were replaced following the initial data collection. Finally, respondents were required to select their neighborhood of residence on the map. 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 also replaced in a second round of data collection.

<sup>10</sup> Maps for each city were developed to highlight neighborhood names and the spatial arrangement of neighborhoods within the city. Though neighborhood boundaries and names are understood by researchers to be subjective, it was important for consistency and ease of implementation to use pre-determined neighborhood names and boundaries in this research. Boundaries and neighborhood names were identified by comparing city-developed GIS shape files, other reputable place-mapping projects (such as the Mapping LA project by the Los Angeles Times), and lists on place-based amenity websites like Zillow, OpenTable and AirBnB.

Figure 1a. Chicago Neighborhood Map

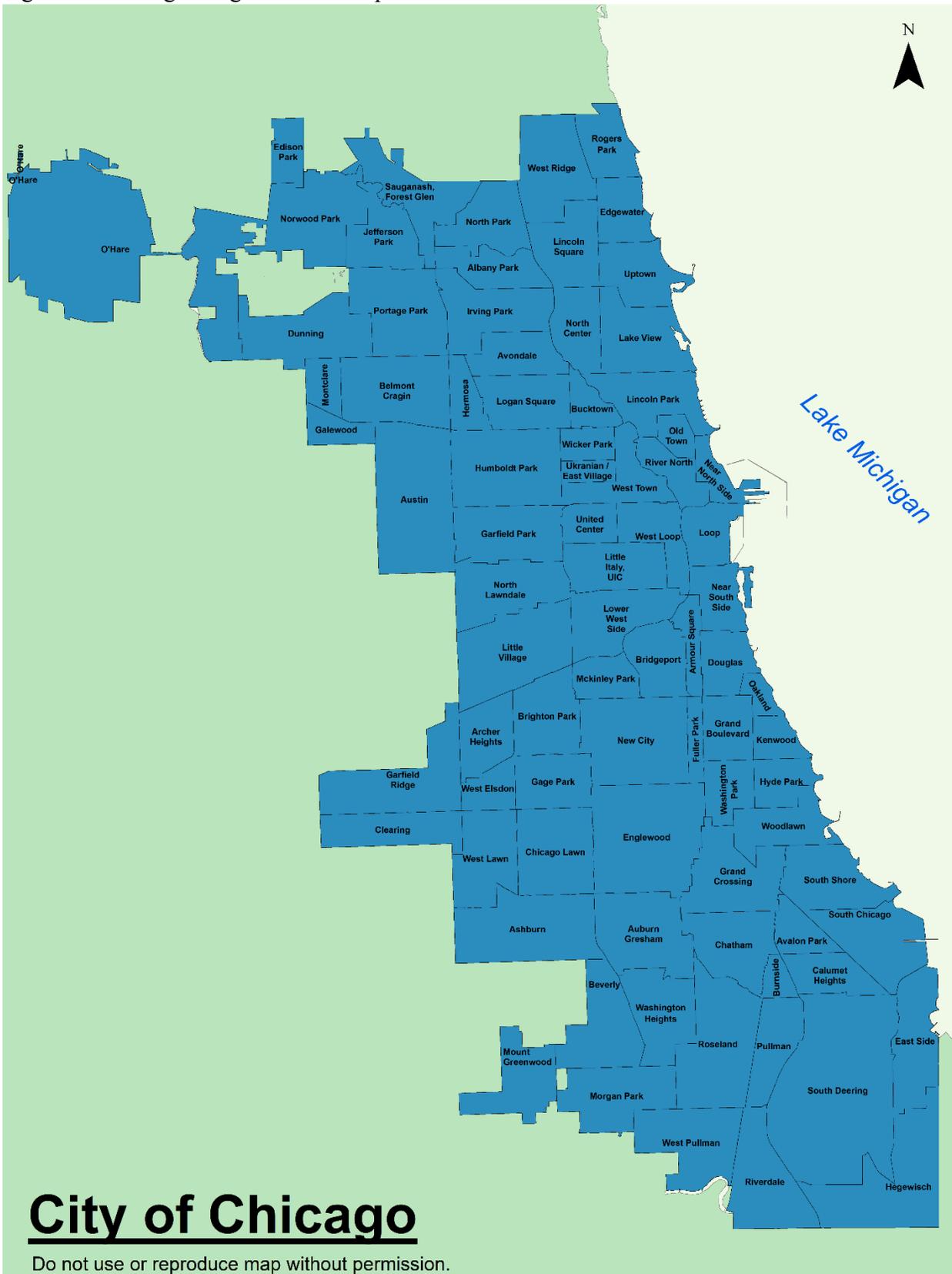


Figure 1b. District of Columbia Neighborhood Map

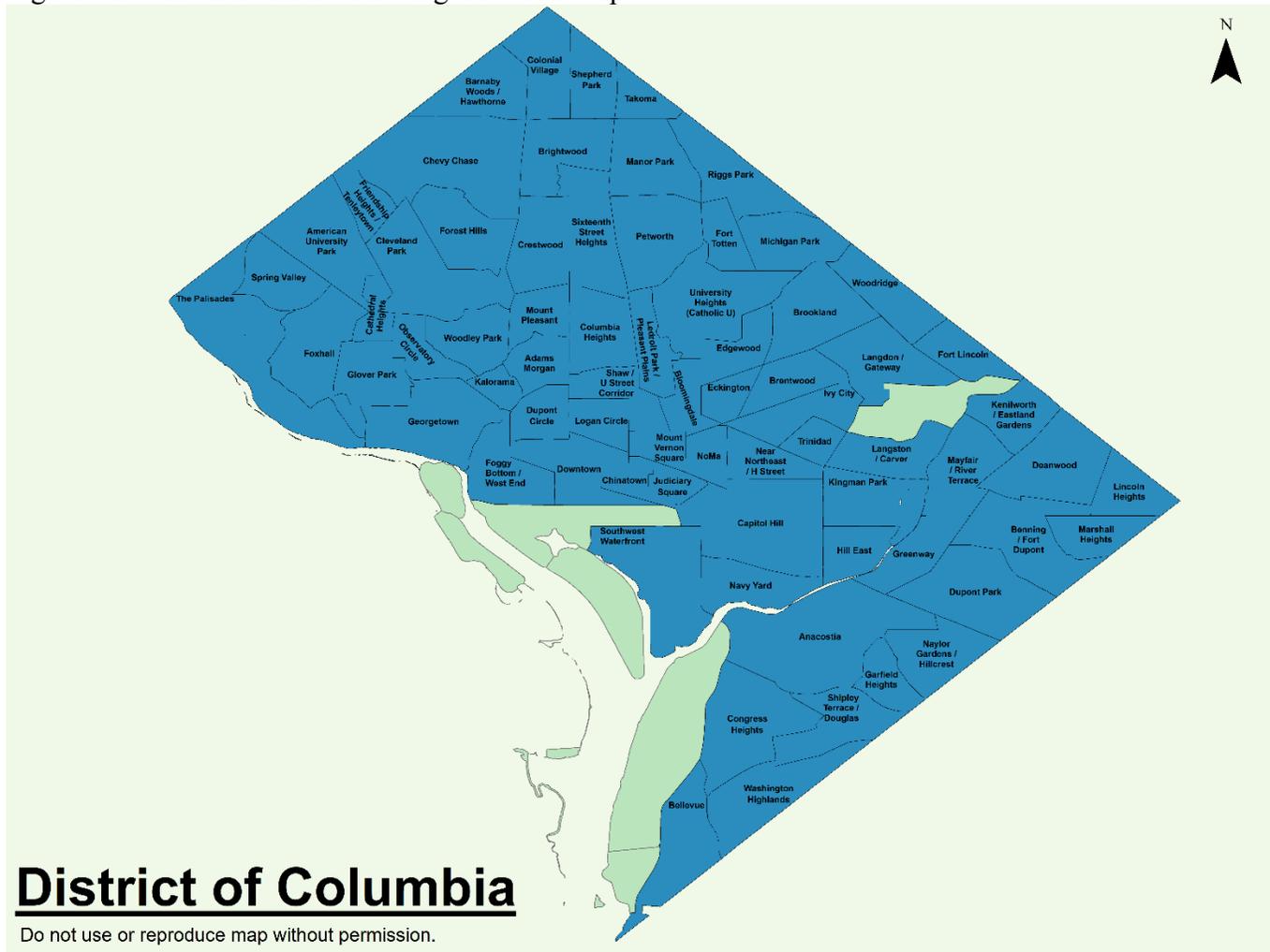
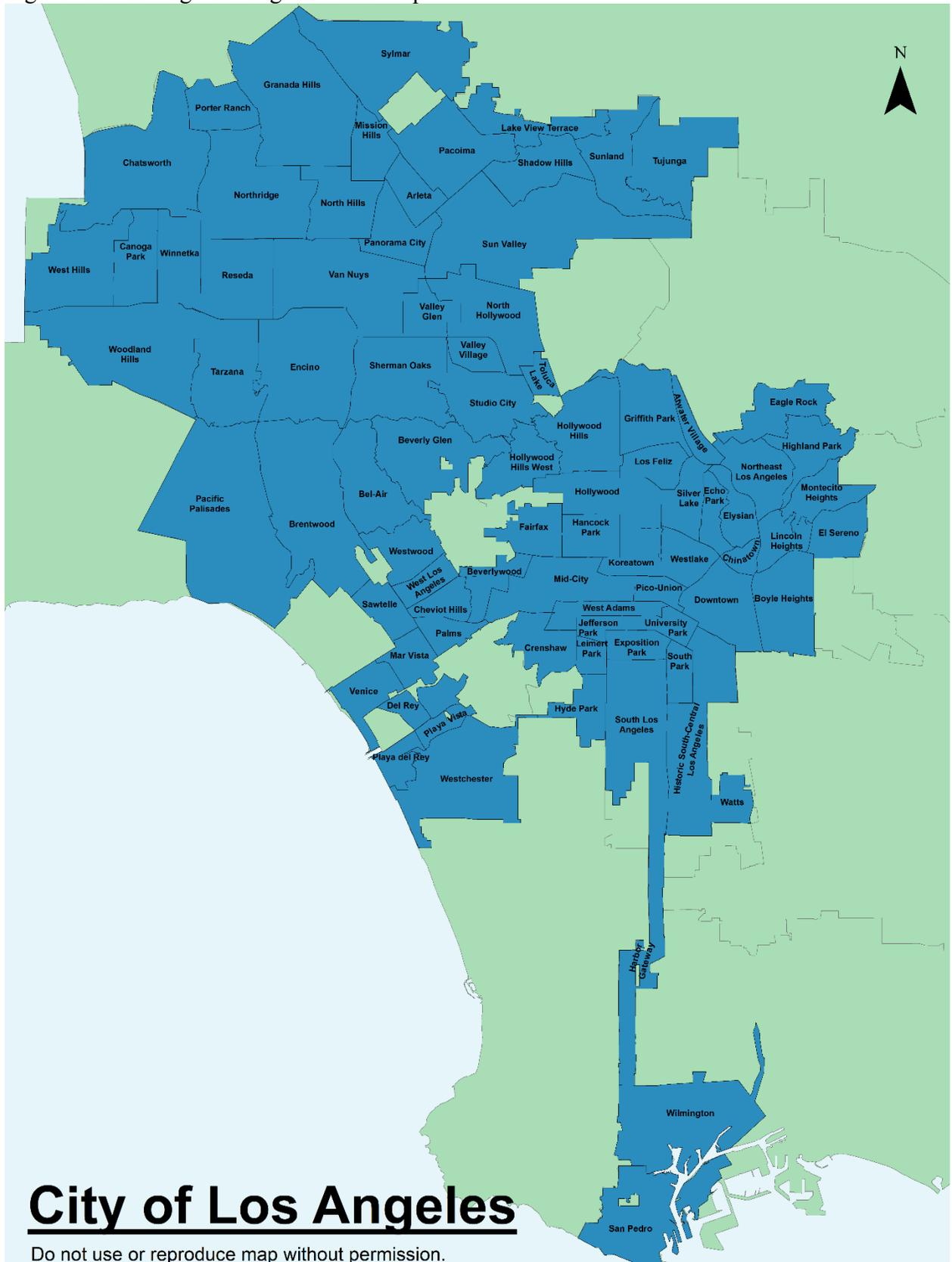


Figure 1c. Los Angeles Neighborhood Map



were surveyed about their knowledge of those neighborhoods, including how they believed the neighborhoods had changed over time and how they would assess the neighborhoods' reputations. 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 1566 responses (Los Angeles N = 614; Chicago N = 533; D.C. N = 410).

Although not a strictly representative sample, these survey data are an improvement over existing neighborhood data for a number of reasons. First, they are some of the only data to focus on neighborhood knowledge and reputation. Second, they use real – as opposed to hypothetical – neighborhoods to ask about neighborhood preference. Third, because they use these real neighborhoods, they allow respondents to tap into their associations, mental schemas, or lived experiences with a place. This enables researchers to consider real associations that may drive respondents' choice processes. Fourth, unlike some related research that focuses on and draws conclusions from a single city, the three-city design offers cross-city comparisons and the ability to control for city-specific dynamics. Finally, these data demonstrate the utility of online surveying as a fruitful methodological advancement, particularly for place-centric research. While data generated via online survey samples remains relatively rare in sociology,<sup>11</sup> recent research has highlighted the potential of such surveys to be efficient tools for social science research. Not only do these surveys require less time and money than traditional probability sampling techniques typically used in neighborhood research – making them a more accessible tool for researchers – but mounting evidence suggests that use of online samples does not sacrifice data quality.<sup>12</sup>

Despite some data tradeoffs, I find that this pilot survey captures a relatively representative sample of each city's population. Table 1 compares key demographic aspects of my survey respondents to the population of each city, as reported by the 2012-2016 American Communities Survey. While there are some significant differences between samples – for example, my respondents are more likely to be white, to own homes, and to be new to their neighborhoods – these differences can be adjusted for with survey weights in the future.<sup>13</sup> Additionally, Figure 2 shows that, though the sample recruitment method did not explicitly seek to get respondents in every neighborhood within each city, survey respondents were dispersed throughout the cities of interest, living in nearly all of the designated neighborhoods.

---

<sup>11</sup> Farrell and Petersen 2010

<sup>12</sup> Heen, Lieberman, and Miethe 2014; Goel, Obeng, Rothschild 2015

<sup>13</sup> See Goel, Obeng, Rothschild 2015



Figure 2b. Respondent Count by Neighborhood, District of Columbia

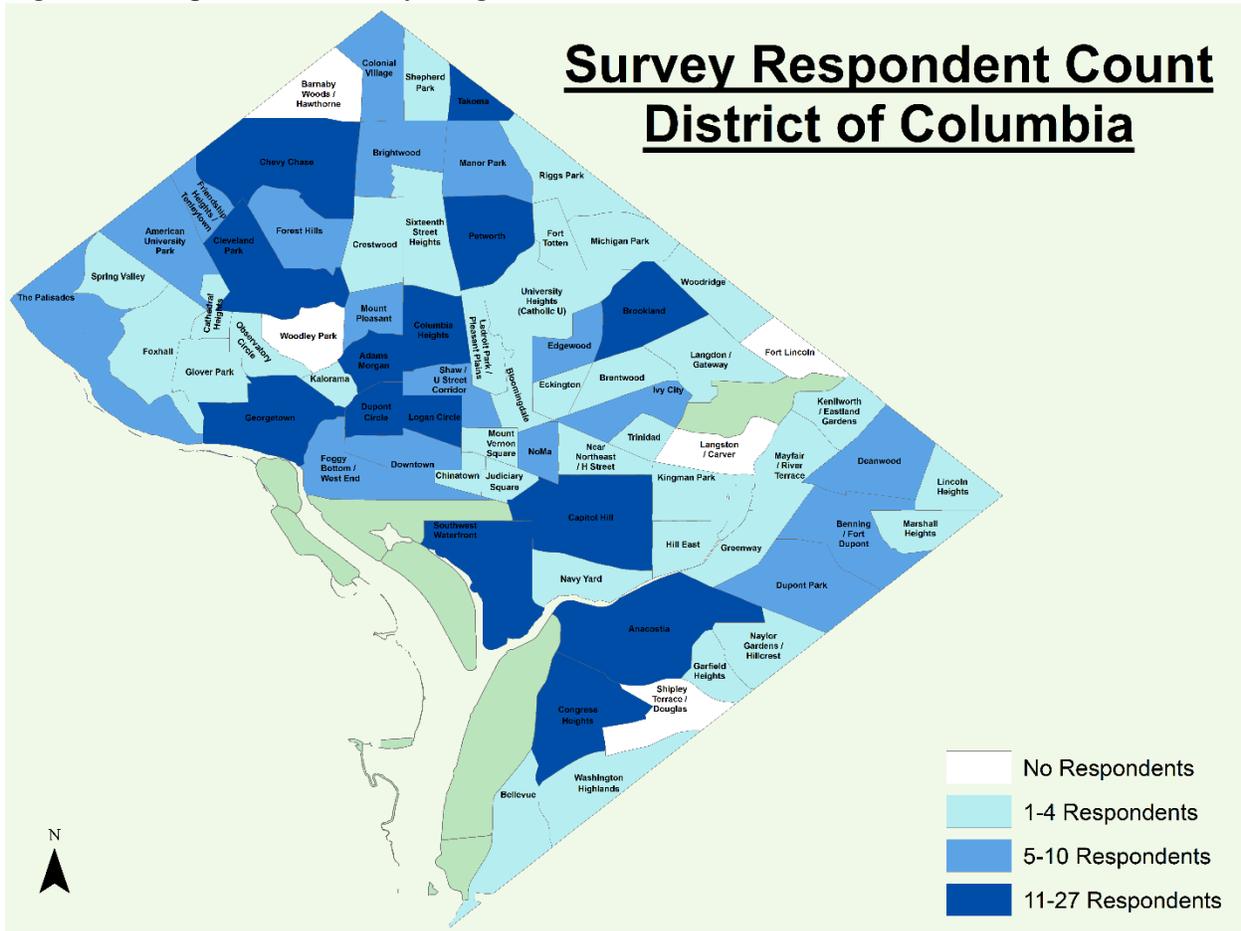


Figure 2c. Respondent Count by Neighborhood, Los Angeles

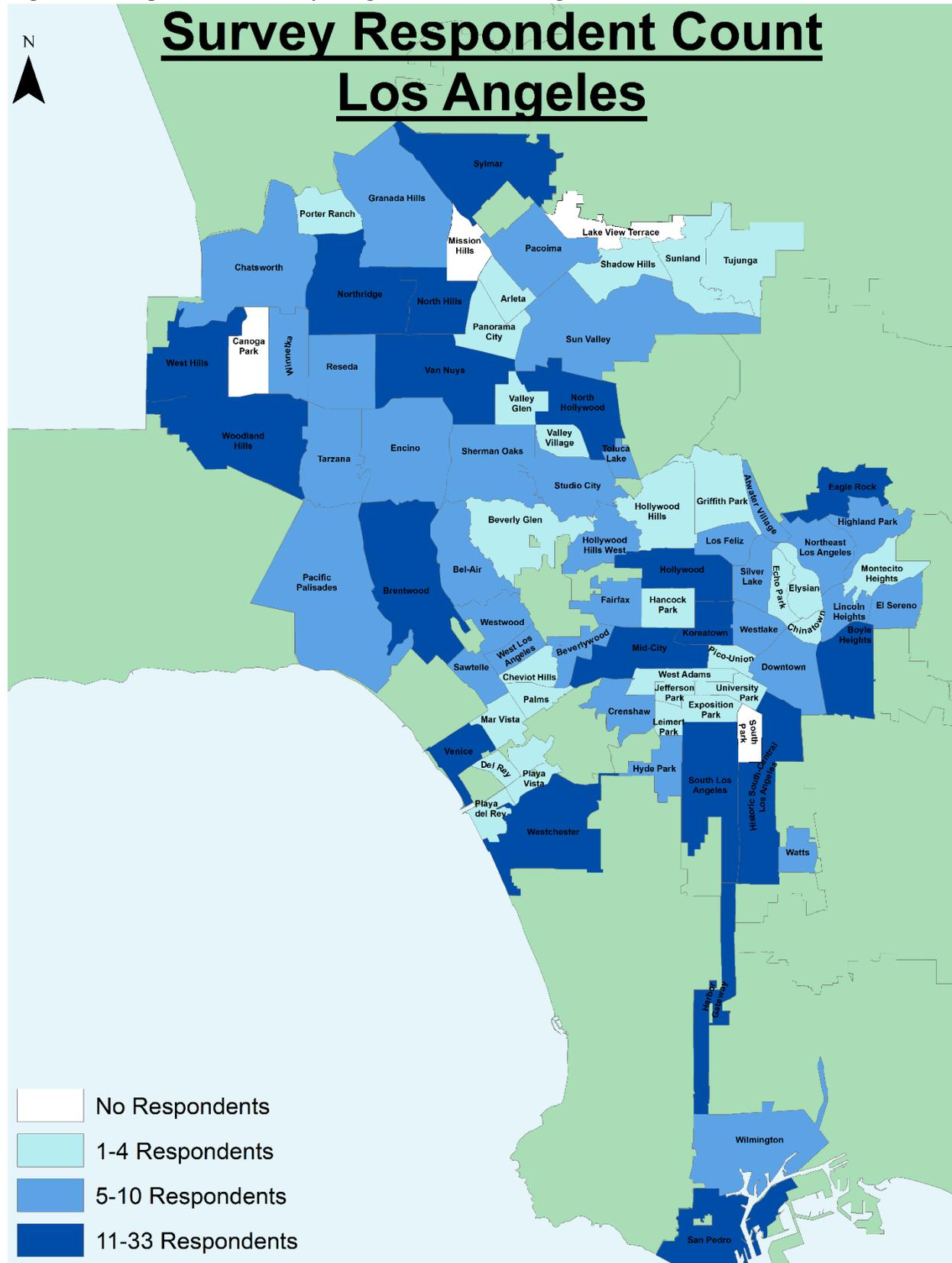


Table 1. Comparison of Survey Sample with American Community Survey

|   | Chicago |                  |     | Los Angeles |                  |     | DC     |                  |     |
|---|---------|------------------|-----|-------------|------------------|-----|--------|------------------|-----|
|   | Survey  | ACS<br>2012-2016 | Sig | Survey      | ACS<br>2012-2016 | Sig | Survey | ACS<br>2012-2016 | Sig |
| % Female  | 52      | 51.5             |     | 52.11       | 50.5             |     | 51.31  | 52.6             |     |
| % Non-Hispanic<br>White   | 34.65   | 32.3             |     | 34.2        | 28.5             | **  | 41.09  | 35.8             | *   |
| % Non-Hispanic<br>Black   | 44.07   | 30.6             | *** | 9.28        | 8.7              |     | 44.42  | 47.4             |     |
| % Hispanic  | 13.93   | 29.1             | *** | 43.16       | 48.6             | *   | 9.03   | 10.5             |     |
| % Non-Hispanic<br>Asian   | 5.84    | 6                |     | 10.75       | 11.4             |     | 3.33   | 3.6              |     |
| % New to<br>Neighborhood (less<br>than 1 yr in current<br>neighborhood) | 8.1     | 6.1              |     | 7.8         | 4.9              | **  | 10.21  | 6.6              | *   |
| % Home<br>Ownership   | 50      | 44.1             | **  | 48.86       | 36.6             | *** | 49.41  | 40.7             | *** |
| N   | 533     |                  |     | 614         |                  |     | 410    |                  |     |

### Interrogating Gaps in Neighborhood Familiarity<sup>14</sup>

To understand how neighborhood perceptions shape urban dynamics, one first must examine individuals’ degree of neighborhood knowledge – the extent to which someone is familiar with a particular neighborhood. While much urban research assumes respondents are equally familiar with every neighborhood within an urban space,<sup>15</sup> differences in familiarity may be important to understanding how and why neighborhoods change over time. Researchers have hypothesized that racial differences in neighborhood familiarity could be a contributing mechanism driving persistent segregation.<sup>16</sup> They theorize that racial blind spots – or the group-based, non-random absence of knowledge of neighborhoods – may pose a barrier to integration. If groups don’t know a neighborhood, the theory goes, then they can’t consider it in their residential choice process and thus can’t choose to move there.

Using data from the earlier described survey, I examine the degree to which systematic differences exist between racial groups’ familiarity with city neighborhoods. Neighborhood familiarity is measured based on responses to the prompt: “Using this clickable map, please select all the neighborhoods in the city of [METROAREA] with which you are familiar.”

As a first step, I examine differences in the percent of neighborhoods in a given city with which a respondent is familiar. These results are summarized in Table 2, broken out by racial group. In keeping with the assertion that neighborhood residents shouldn’t be treated as possessing complete knowledge of a city’s neighborhoods, I find that respondents on average report

<sup>14</sup> These models roughly replicate and extend the research of Krysan and Bader 2009

<sup>15</sup> Schelling 1971; Bruch and Mare 2006. For more discussion of this assumption and its pitfalls, see Krysan and Bader 2009; Bruch and Swait n.d.; Krysan and Crowder 2017.

<sup>16</sup> Krysan and Bader 2009

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 17 percent of neighborhoods or approximately 14 of the 83 neighborhoods on the map. The data also suggests that white respondents selected significantly more neighborhoods than non-white respondents. In LA and DC, I similarly find significant differences in neighborhood familiarity by racial group. For example, in both LA and DC I find that white respondents are familiar with significantly fewer neighborhoods and black respondents are familiar with significantly more neighborhoods than respondents of other racial groups. Across all three cities, I find that Asian respondents have the narrowest familiarity with neighborhoods.

Table 2. Mean Percent of Individual Neighborhood Familiarity

|          | Chicago  | LA       | DC       |
|----------|----------|----------|----------|
| All      | 0.171    | 0.197    | 0.192    |
| White    | 0.183*** | 0.184*** | 0.184*   |
| Black    | 0.171    | 0.249*** | 0.204*** |
| Hispanic | 0.176    | 0.204**  | 0.196    |
| Asian    | 0.11***  | 0.132*** | 0.135*** |

\*p<.05, \*\*p<.01, \*\*\*p<.001

Shifting from looking at individual’s neighborhood familiarity to group-based blind spots, I calculated separately the percentage of white, black, Hispanic, and Asian respondents familiar with each neighborhood in a given city. Figures 3-5 map the results. The maps highlight the differences in reported neighborhood familiarity by race of respondent, showing that within each city there is a distinctive pattern of neighborhood familiarity by racial group.<sup>17</sup> For example, in Chicago, black respondents report higher familiarity with neighborhoods on the south side while white and Hispanic respondents report greater familiarity with neighborhoods on the city’s north side. In Los Angeles, black respondents report greater familiarity with areas of South Central LA and Hispanic respondents report somewhat greater familiarity with the historically Hispanic areas of East LA. White respondents in LA report greater familiarity with the city’s west side neighborhoods and neighborhoods in the San Fernando Valley. In Washington, D.C., black respondents report greater familiarity with neighborhoods in Anacostia and in the Southeast quadrant of the city while white respondents report considerably greater familiarity with neighborhoods in the city’s Northwest quadrant. While these results highlight distinctive patterns of familiarity within cities, they are not altogether surprising. These patterns generally follow anecdotal evidence about patterns of residential segregation and ethnic stereotypes linked to the different areas of each city.

<sup>17</sup> Note that maps for Asian respondents are omitted as this group was generally comprised of very few respondents.

Figure 3. Neighborhood Familiarity by Race, Chicago

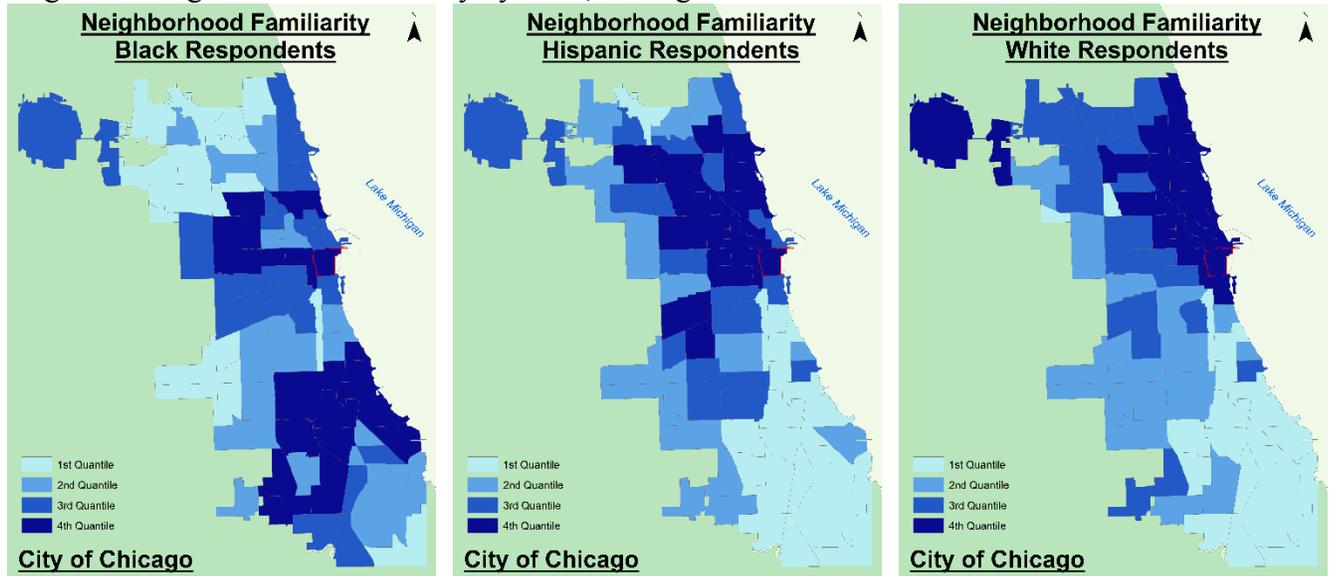


Figure 4. Neighborhood Familiarity by Race, Los Angeles

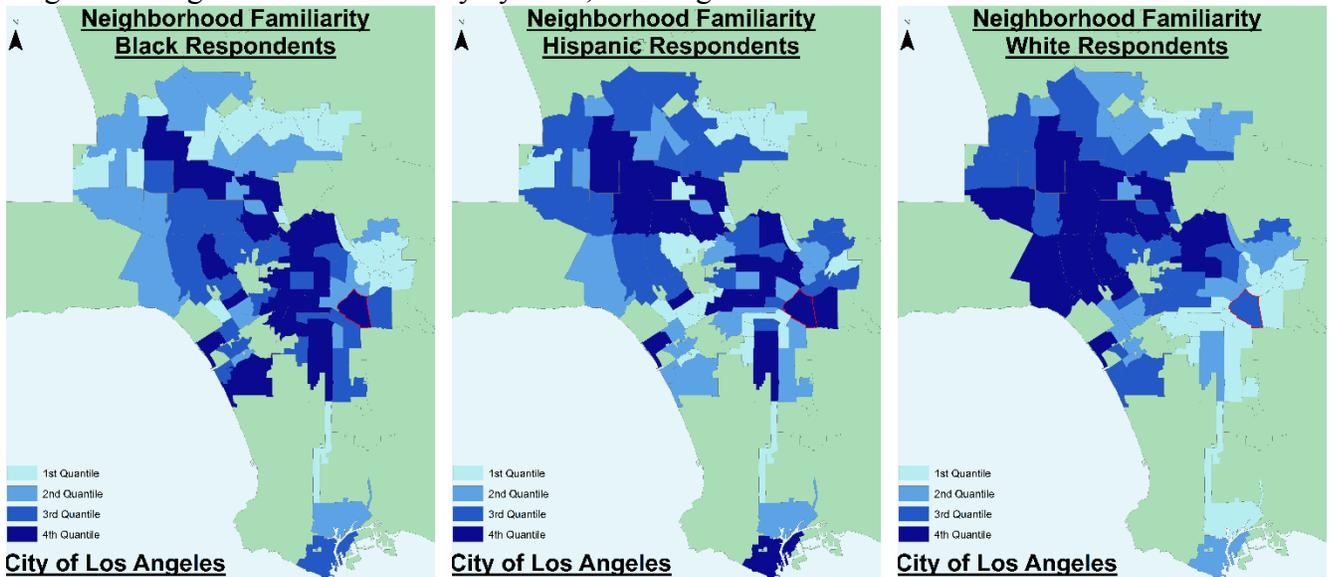
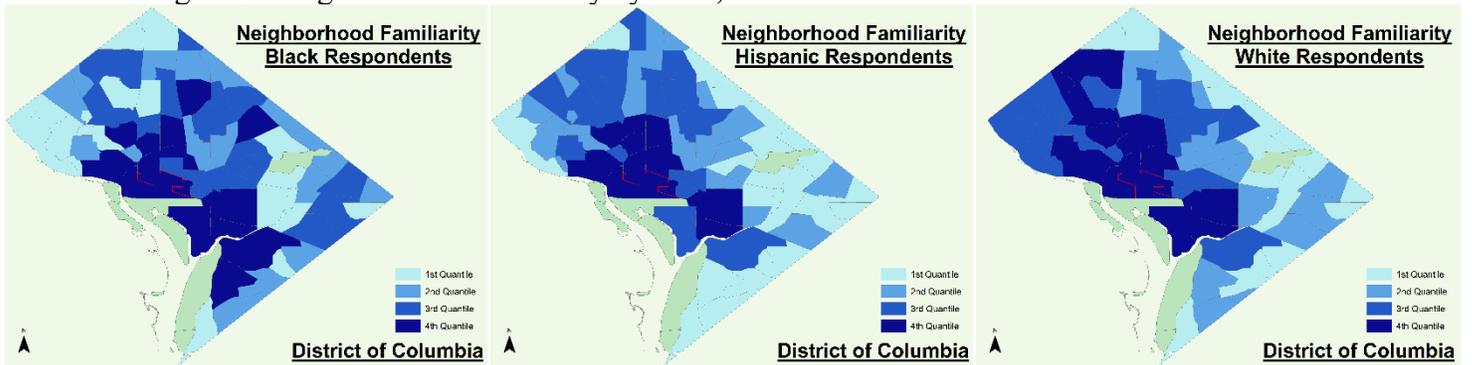


Figure 5. Neighborhood Familiarity by Race, DC



Looking beyond these graphical illustrations, I also examined differences in community familiarity for each group using rank order correlations to test neighborhoods’ relative rank of familiarity amongst racial/ethnic groups. These ranks are ordered from neighborhoods most known to those least known separately by whites, blacks, Hispanics, and Asians and test, for example, if the Loop in Chicago – a downtown neighborhood in the central business district – is equally well known across all racial/ethnic groups.

Table 3 shows that in Chicago, there is a strong relationship between the probability of neighborhood familiarity for white and Hispanic respondents. White and Asian respondents in Chicago similarly have a strongly related probability of neighborhood familiarity. By contrast, white and black respondents and black and Hispanic respondents in Chicago have low probabilities of being familiar with the same neighborhoods. This finding captures the high degree of segregation within Chicago. Interestingly, differences in neighborhood familiarity between racial groups in Washington DC and Los Angeles do not produce similarly stark divides. Unlike Chicago, neither DC nor LA reveal as clear a pattern of different neighborhood knowledge between black and non-black respondents. Instead, Spearman’s correlations for these cities suggest moderate to strong correlations between respondents of different racial groups ranging from  $\rho = .42$  to  $\rho = .87$ . This may suggest that DC and LA are somewhat less residentially segregated than Chicago, which may influence neighborhood knowledge. Alternatively, this finding may suggest that neighborhood knowledge is more generally distributed throughout the population in DC and LA even if residential patterns are segregated, perhaps because neighborhoods have more name recognition – like Hollywood – or because the daily lives of respondents of different races bring them into a greater diversity of neighborhoods than respondents in Chicago. This finding, that Chicago residents may exhibit more extreme racial blind spots than residents in other cities is important. To date, research on blind spots and resulting theories on the influence of neighborhood knowledge on persistent segregation focuses on Chicago. However, this reliance on patterns from a single, hyper-segregated city may mean researchers overstate the effects of blind spots.

Table 3. Spearman’s Rank Correlations<sup>18</sup> of Neighborhood Familiarity by Race<sup>19</sup>

|                  | Chicago | LA    | DC    |
|------------------|---------|-------|-------|
| White - Black    | 0.135   | 0.417 | 0.598 |
| White - Hispanic | 0.837   | 0.568 | 0.896 |
| White - Asian    | 0.856   | 0.614 | 0.896 |
| Black - Hispanic | 0.125   | 0.508 | 0.627 |
| Black - Asian    | 0.285   | 0.615 | 0.627 |
| Hispanic - Asian | 0.733   | 0.709 | 1     |

<sup>18</sup> Spearman’s correlations should be interpreted as indicating the degree of overlap in community knowledge between groups where a 0 means little to no overlap in community knowledge and a 1 means complete overlap in community knowledge.

<sup>19</sup> I elect to not include significance for Spearman’s correlation as I find it does not ease interpretability. Significance means that a correlation is significantly different from 0. In the case of this data, a 0 correlation is meaningful, suggesting no overlap in community knowledge. Thus, the appearance that these correlations should be ignored because of a lack of significance is misleading.

As a final step in this inquiry into the differing patterns of neighborhood familiarity, I develop multilevel logistic regression models to formally test if and how race influences neighborhood familiarity. The models, which cluster responses within respondents, examine how respondent and neighborhood characteristics predict neighborhood familiarity. For each city, I run five models. The first model includes all respondents, and provides an overview of what predicts if a neighborhood is likely one people are familiar with or not. Because I am interested in the effect of race/ethnicity in shaping neighborhood familiarity, I also estimate models separately for blacks, whites, Hispanics, and Asians. These four models each include different racial/ethnic composition variables, omitting the racial/ethnic composition of a respondent's own group to isolate the effect of the demographic composition of other racial groups on neighborhood familiarity. For example, the model of the effect of neighborhood racial composition on white respondents omits neighborhood percent white while including neighborhood percent black, Hispanic, and Asian, etc. Tables 4 - 6 show the results of these models, by city.

I find that across all three cities racial composition of a neighborhood is a strong predictor of if that neighborhood is known or not. In contrast, I do not find that neighborhood familiarity is predicted by respondent characteristics, though in some models a respondent's length of tenure in the city is marginally significant. In general, I find that for non-black respondents, the percent of African Americans living in a neighborhood is negatively associated with a respondent's familiarity with that neighborhood. I similarly find that higher percentages of Hispanic residents significantly predict if a neighborhood is unknown by non-Hispanic respondents. The effect of increasing concentrations of white populations is more mixed. While in Chicago, higher concentrations of white residents are associated with a decrease in the probability of a Hispanic respondent being familiar with a neighborhood, in Los Angeles this relationship is reversed.

Beyond race, I find that respondents across groups are less likely to be familiar with neighborhoods with higher levels of owner-occupied housing. This is curious, as nearly fifty percent of survey respondents in each city were homeowners themselves. One might expect that homeowners would have become acquainted with high homeownership neighborhoods during their housing search, but this does not appear to be the case. It is possible that lower residential turnover in neighborhoods with high levels of homeownership leads fewer non-residents to come into contact with such places. Additionally, this finding might support research that suggests that housing searches are often circumscribed by realtors and residents own identities.<sup>20</sup> Beyond a neighborhood's racial composition, I also find that if a neighborhood is gentrifying,<sup>21</sup> it is significantly more likely to be known generally and to be known by respondents across all racial/ethnic groups, particularly in Chicago and DC, than non-gentrifying neighborhoods.

---

<sup>20</sup> See for example Lacy 2007; Ross and Turner 2005; Krysan and Crowder 2017.

<sup>21</sup> To define gentrifying neighborhoods, I follow the approach used by Ding, Hwang, and Divringi 2016. This approach uses a threshold strategy to identify neighborhoods eligible to gentrify at the beginning of 2010 and then compare changes among these eligible neighborhoods between 2010 and 2016. I consider tracts to be gentrifiable if their median household income was below the citywide median household income in 2010. I consider a tract to be gentrifying if it was gentrifiable in 2010 and experienced an above citywide median percentage increase in either its median gross rent or median home value and experienced an above citywide median increase in its share of college-educated residents. For more on measures of gentrification, see Ding, Hwang, and Divringi 2016; Freeman 2005; and Newman and Wyly 2006.

Table 4. Multilevel Logit Model Predicting Neighborhood Familiarity by Individual and Neighborhood Characteristics, Chicago

|                                     | All Respondents |                  | By Race of Respondent |                     |                  |
|-------------------------------------|-----------------|------------------|-----------------------|---------------------|------------------|
|                                     | Model 1         | White<br>Model 2 | Black<br>Model 3      | Hispanic<br>Model 4 | Asian<br>Model 5 |
| <b>Neighborhood Characteristics</b> |                 |                  |                       |                     |                  |
| % NH White                          | 2.941***        | (omitted)        | 1.253                 | .471*               | 2.362            |
| % NH Black                          | (omitted)       | .049***          | (omitted)             | .132***             | .020***          |
| % Hispanic                          | .499***         | .091***          | .120***               | (omitted)           | .045***          |
| % Asian                             | .699*           | .130***          | .367***               | .128***             | (omitted)        |
| Total Pop <sup>1</sup>              | 1.013***        | 1.015***         | 1.013***              | 1.012***            | 1.014**          |
| % Owner Occupied                    | .148***         | .088***          | .163***               | .106***             | .004***          |
| Median Home Value <sup>2</sup>      | 1.002***        | 1.004***         | .999*                 | 1.005***            | 1.003*           |
| Gentrifying                         | 1.365***        | 1.214*           | 1.384***              | 1.454**             | 2.203**          |
| <b>Respondent Characteristics</b>   |                 |                  |                       |                     |                  |
| NH White                            | 1.087           |                  |                       |                     |                  |
| Hispanic                            | 1.137           |                  |                       |                     |                  |
| Asian                               | .496**          |                  |                       |                     |                  |
| Income (<\$20,000 ref category)     |                 |                  |                       |                     |                  |
| \$20,000-\$44,000                   | .968            | 1.315            | .832                  | 1.298               | 5.697            |
| \$45,000 - \$74,000                 | .928            | 1.225            | .786                  | 1.349               | 2.154            |
| \$75,000+                           | 1.279           | 1.498            | .961                  | 2.597               | 5.645            |
| Education (HS ref category)         |                 |                  |                       |                     |                  |
| < HS                                | .365*           | .320             | .271*                 | 1.461               | 1                |
| Some College                        | 1.401*          | 1.171            | 1.109                 | 2.836**             | .663             |
| BA+                                 | 1.809**         | 2.036            | 1.466                 | 1.871               | 1                |
| Owens home                          | 1.042           | 1.117            | 1.142                 | .886                | .863             |
| Age                                 | .991            | .983             | .998                  | .988                | .983             |
| Female                              | 1.074           | .961             | 1.249                 | .893                | 1.616            |
| Child in home                       | .918            | .889             | .854                  | 1.243               | .299*            |
| Coupled                             | .925            | .951             | .877                  | 1.297               | .756             |
| Years in city                       | 1.013**         | 1.015*           | 1.006                 | 1.018               | 1.032*           |
| <hr/>                               |                 |                  |                       |                     |                  |
| Intercept                           | .064***         | .290             | .310***               | .051***             | .247             |
| Respondent Variance                 | 1.345           | 1.865            | 1.414                 | 1.281               | .600             |
| N (level 1)                         | 43824           | 15189            | 19339                 | 6142                | 2490             |
| N (level 2)                         | 528             | 183              | 233                   | 74                  | 30               |
| Wald Chi <sup>2</sup>               | 2218.85***      | 1813.70***       | 885.83***             | 513.19***           | 255.08***        |

<sup>1</sup> Total Population in thousands <sup>2</sup> Median home value in thousands

Results are reported as Odds Ratios, where a value greater than 1 means an increased likelihood of a respondent being familiar with a neighborhood and a value less than 1 means a decreased likelihood of familiarity.

\*p<.05, \*\*p<.01, \*\*\*p<.001

Table 5. Multilevel Logit Model Predicting Neighborhood Familiarity by Individual and Neighborhood Characteristics, Los Angeles

|                                     | All Respondents |                  | By Race of Respondent |                     |                  |
|-------------------------------------|-----------------|------------------|-----------------------|---------------------|------------------|
|                                     | Model 1         | White<br>Model 2 | Black<br>Model 3      | Hispanic<br>Model 4 | Asian<br>Model 5 |
| <b>Neighborhood Characteristics</b> |                 |                  |                       |                     |                  |
| % NH White                          | 3.729***        | (omitted)        | .031***               | 2.533***            | .093**           |
| % NH Black                          | (omitted)       | .008***          | (omitted)             | .661                | .156**           |
| % Hispanic                          | .549**          | .034***          | .005***               | (omitted)           | .012***          |
| % Asian                             | .979            | .051***          | .003***               | 1.305               | (omitted)        |
| Total Pop <sup>1</sup>              | .972***         | .976***          | .969***               | .970***             | .969***          |
| % Owner Occupied                    | .423***         | .472***          | .158***               | .509***             | .243***          |
| Median Home Value <sup>2</sup>      | 1               | 1                | 1.000**               | 1.000*              | 1.000            |
| Gentrifying                         | 1.147**         | 1.021            | 1.046                 | 1.256***            | 1.105            |
| <b>Respondent Characteristics</b>   |                 |                  |                       |                     |                  |
| NH White                            | .502***         |                  |                       |                     |                  |
| Hispanic                            | .620**          |                  |                       |                     |                  |
| Asian                               | .324***         |                  |                       |                     |                  |
| Income (<\$20,000 ref category)     |                 |                  |                       |                     |                  |
| \$20,000-\$44,000                   | 1.134           | .819             | 1.352                 | 1.251               | .674             |
| \$45,000 - \$74,000                 | 1.182           | 1.008            | 1.050                 | 1.052               | 2.745            |
| \$75,000+                           | .824            | .571             | 1.578                 | .743                | 1.389            |
| Education (HS ref category)         |                 |                  |                       |                     |                  |
| < HS                                | .481            |                  |                       | .476                | .044             |
| Some College                        | 1.346           | 1.699            | 1.383                 | 1.311               | .129             |
| BA+                                 | 1.624*          | 1.857            | 1.240                 | 1.605               | .166             |
| Owns home                           | 1.211           | 1.491            | .504                  | 1.180               | .961             |
| Age                                 | .992            | .990             | .989                  | .996                | 1.000            |
| Female                              | 1.045           | 1.130            | .828                  | 1.106               | 1.145            |
| Child in home                       | .984            | 1.198            | 2.493                 | .824                | 1.143            |
| Coupled                             | .869            | .732             | 2.078                 | .865                | .711             |
| Years in city                       | 1.014**         | 1.019**          | 1.034                 | 1.011               | 1.005            |
| Intercept                           | .294***         | 1.160            | 14.846***             | .192***             | 12.904           |
| Respondent Variance                 | 1.688           | 1.738            | 1.473                 | 1.672               | 1.115            |
| N (level 1)                         | 50962           | 17430            | 4731                  | 21995               | 5478             |
| N (level 2)                         | 614             | 210              | 57                    | 265                 | 66               |
| Wald Chi <sup>2</sup>               | 965.18***       | 962.76***        | 240.04***             | 234.51***           | 131.67***        |

<sup>1</sup> Total Population in thousands <sup>2</sup> Median home value in thousands

Results are reported as Odds Ratios, where a value greater than 1 means an increased likelihood of a respondent being familiar with a neighborhood and a value less than 1 means a decreased likelihood of familiarity.

\*p<.05, \*\*p<.01, \*\*\*p<.001

Table 6. Multilevel Logit Model Predicting Neighborhood Familiarity by Individual and Neighborhood Characteristics, Washington D.C.

|                                     | All Respondents |                  | By Race of Respondent |                     |                  |
|-------------------------------------|-----------------|------------------|-----------------------|---------------------|------------------|
|                                     | Model 1         | White<br>Model 2 | Black<br>Model 3      | Hispanic<br>Model 4 | Asian<br>Model 5 |
| <b>Neighborhood Characteristics</b> |                 |                  |                       |                     |                  |
| % NH White                          | 9.347***        | (omitted)        | 3.218***              | .620                | 0                |
| % NH Black                          | (omitted)       | .029***          | (omitted)             | .026**              | 0                |
| % Hispanic                          | 1.261           | .095***          | .509                  | (omitted)           | 0                |
| % Asian                             | 1089.428***     | 39.542*          | 463.674***            | 48.087              | (omitted)        |
| Total Pop <sup>1</sup>              | 1.333***        | 1.340***         | 1.352***              | 1.290***            | 1.363**          |
| % Owner Occupied                    | .170***         | .103***          | .365***               | .031***             | .015***          |
| Median Home Value <sup>2</sup>      | .999***         | 1.000            | .998***               | 1.000               | 1                |
| Gentrifying                         | 1.179***        | 1.318***         | 1.144*                | 1.677**             | .790             |
| <b>Respondent Characteristics</b>   |                 |                  |                       |                     |                  |
| NH White                            | .948            |                  |                       |                     |                  |
| Hispanic                            | 1.203           |                  |                       |                     |                  |
| Asian                               | .802            |                  |                       |                     |                  |
| Income (<\$20,000 ref. category)    |                 |                  |                       |                     |                  |
| \$20,000-\$44,000                   | 1.092*          | 1.693            | 2.503*                | .477                |                  |
| \$45,000 - \$74,000                 | 1.020           | 1.524            | 1.015                 | .398                | .144**           |
| \$75,000+                           | 1.230           | 1.500            | 1.159                 | 1.750               | .729             |
| Education (HS ref category)         |                 |                  |                       |                     |                  |
| < HS                                | 1.028           |                  | 1.359                 |                     |                  |
| Some College                        | 1.294           | .662             | 1.659                 | 2.547               | 6.905            |
| BA+                                 | 1.474           | .838             | 1.886                 | 1.724               | 1.549            |
| Owns home                           | 1.057           | 1.350            | 1.081                 | .944                | .168             |
| Age                                 | 1.006           | 1.013            | .992                  | .997                | 1.002            |
| Female                              | 1.405*          | 1.574*           | 1.278                 | 1.660               | .158**           |
| Child in home                       | .964            | .666             | 1.012                 | 2.189               | .443             |
| Coupled                             | .869            | .725             | 1.051                 | .339                | 4.043**          |
| Years in city                       | 1.007           | .999             | 1.019*                | 1.022               | .983             |
| Intercept                           | .022***         | .288             | .046                  | .767                | 332733.1*        |
| Respondent Variance                 | 1.764           | 1.718            | 1.777                 | 2.204               | 0                |
| N (level 1)                         | 30312           | 12456            | 13464                 | 2736                | 1008             |
| N (level 2)                         | 421             | 173              | 187                   | 38                  | 14               |
| Wald Chi <sup>2</sup>               | 1882.43***      | 1276.60***       | 438.14***             | 256.11***           | 149.20***        |

<sup>1</sup> Total Population in thousands <sup>2</sup> Median home value in thousands

Results are reported as Odds Ratios, where a value greater than 1 means an increased likelihood of a respondent being familiar with a neighborhood and a value less than 1 means a decreased likelihood of familiarity.

\*p<.05, \*\*p<.01, \*\*\*p<.001

Chicago and D.C. also show an effect for population size. Increases in neighborhood population in these cities increase the likelihood of a neighborhood being known, though in Los Angeles population size appears to have the opposite effect.

Understanding differences in neighborhood knowledge is a first step in acknowledging the role one's "sense of place" plays in how one interacts with the city around them. From this analysis, it is clear that cities have distinct patterns of neighborhood knowledge that are shaped by the racial composition of neighborhoods. Though respondents' neighborhood familiarity doesn't differ substantially in simple counts, and I find considerable overlap in neighborhood familiarity between racial groups in most cities, the persistent effect of neighborhood knowledge gaps can have some compounding effects. If, for example, Hispanic respondents are significantly more aware of certain neighborhoods and those neighborhoods have significantly higher Hispanic populations, one can imagine that over time the Hispanic population in a city will become increasingly concentrated not because of exclusionary practices or residential preference but purely because of limited information on neighborhood options.

### **Resident and Non-Resident Ratings of Neighborhood Reputations<sup>22</sup>**

While the previous section focused on who knows which neighborhoods, this section shifts its attention to what one knows about a neighborhood. In contrast to the above analysis that argues that neighborhood evolution is driven in part by silos in neighborhood familiarity, this section puts neighborhood reputation front and center and interrogates how what a person knows about a neighborhood is shaped by their relationship to that place. Specifically, it analyzes how perceived neighborhood reputations differ between residents and non-residents and zeros in on the key drivers of perceptual difference.

A first step in this analysis is to test whether neighborhood residents assess the reputation of their neighborhood significantly differently than non-residents. To measure neighborhood reputation among residents, I group respondents by neighborhood within each city and calculate the mean response to the question, "How would you assess the reputation of your neighborhood?" Answers could range from 1 (very undesirable) to 4 (very desirable). Similarly, to measure neighborhood reputation among non-residents, I take the mean score of neighborhood desirability given by non-neighborhood residents in response to the question, "How would you assess the reputation of [NEIGHBORHOOD X]?" Again, answers could range from 1 (very undesirable) to 4 (very desirable).

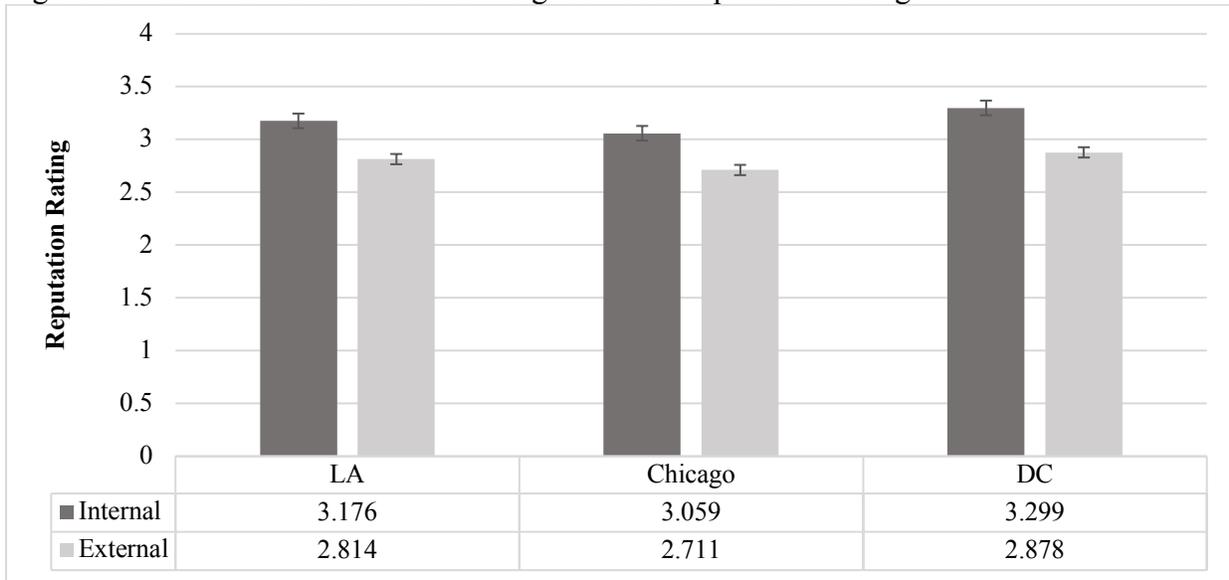
Figure 6 captures these mean reputation scores and the relationship between resident and non-resident perceptions of reputation. Within each city, I find that neighborhood residents are significantly more likely to rate their own neighborhood as more desirable than non-residents ( $p < .000$ ). In LA, Chicago, and Washington DC, I find that the average discrepancy between internal and external neighborhood reputation rating is nearly half a point (on a 4-point Likert scale). In addition to finding a consistent discrepancy between internal and external neighborhood rankings, I also find that neighborhood residents' assessments of neighborhood

---

<sup>22</sup> This section roughly replicates and extends the research of Permentier, Van Ham, and Bolt 2008

reputation tend to align more closely to one another’s— having a lower average standard deviation – than the assessments of non-residents. This agreement around a neighborhood’s status suggests that residents’ lived experience of a place yields a more consistent perspective while non-residents lack of agreement is more likely driven by second-hand or biased knowledge, which may vary more dramatically.

Figure 6. Mean Internal and External Neighborhood Reputation Ratings



Despite these difference in ratings of neighborhood reputation, Spearman’s correlations suggest that there is strong agreement between neighborhood residents’ and other city residents’ relative rankings of neighborhoods within a neighborhood hierarchy. That is, though residents evaluate their own neighborhoods more highly, the relative ranks of resident reputation scores correlate strongly with the relative ranked reputation scores of non-neighborhood residents ( $\rho > .71$ ). For example, though residents of the Kalorama neighborhood in Washington DC – an area in the city’s Northwest quadrant notable for its turn-of-the-century architecture, foreign embassies, and distinguished tenants including the Obamas, Amazon CEO Jeff Bezos, and the Trump-Kushner family – rated their neighborhood more than half a point higher than non-residents, the neighborhood ranked as among the most desirable amongst residents and non-resident alike, suggesting that there exists a latent order to neighborhood prestige shared amongst city residents.

Beyond finding agreement in reputation ranks between residents and non-residents, I also find a relationship between the difference in reputation ratings between residents and nonresidents and the relative rank of the neighborhood. Examining variation in the disparity of perceived reputations, I find that higher ranked neighborhoods have smaller differences in ratings between residents and non-residents than lower ranked neighborhoods. This pattern holds true across all cities, suggesting that there is generally more agreement amongst city residents when it comes to neighborhoods with the best reputations. One might hypothesize that the increasing gap in lower rated neighborhoods may be a result of residents’ desire for self-preservation, rating their neighborhood higher than they otherwise might to avoid the stigma of living in a disreputable neighborhood.

To further explore the neighborhood dynamics underlying reputation assessments, I developed models that examine how neighborhood demographic and socio-economic factors contribute to internal and external perceptions of neighborhood reputation. Pooling data across all three cities,<sup>23</sup> I use factor analysis to explore the effect of fourteen different neighborhood characteristics – including population size and density, dwelling type and cost, household composition, level of education, and race – conceivably related to neighborhood prestige.<sup>24</sup> The exploratory analysis yielded four factors explaining a total of 81 percent of the variance across the set of variables. Table 7 summarizes the factor-loading matrix.

Table 7. Factor loadings based on exploratory factor analysis with varimax rotation for 14 neighborhood characteristics (N = 238)

|                           | Yuppies | Minorities | Established | Urbanity |
|---------------------------|---------|------------|-------------|----------|
| Density                   |         |            |             | 0.9353   |
| Percent Foreign Born      |         | 0.9582     |             |          |
| Percent Single Households | 0.632   |            |             |          |
| Percent 18 and under      | -0.8465 |            |             |          |
| Percent Elderly           |         |            | 0.6700      |          |
| Population                |         |            |             | 0.9286   |
| Percent Owner Occupied    |         |            | 0.9364      |          |
| Household Income          | 0.7797  |            |             |          |
| Percent Black             |         | -0.8079    |             |          |
| Percent Asian             |         | 0.6259     |             |          |
| Percent Hispanic          |         | 0.7867     |             |          |
| Percent College Graduates | 0.9185  |            |             |          |
| Percent Living in Poverty | -0.7758 |            |             |          |
| Median Rent               | 0.7971  |            |             |          |
| Initial Eigen Value       | 4.598   | 2.944      | 2.231       | 1.561    |
| Percent Total Variance    | 0.3284  | 0.2103     | 0.1594      | 0.1115   |

Factor loadings < .7 are suppressed

I label Factor 1 Young Urban Professional Neighborhoods or Yuppie Neighborhoods due to the high, positive loadings on the percent of single-person households, college education, income, and median rent and the high, negative loadings on percent of residents under 18 and percent in

<sup>23</sup> I elected to combine data across cities for consistency in interpretation and to increase the ratio of cases (neighborhoods, N=238) per variable (V=14) in my factor analysis. With the combined data, I end up with a ratio of 17 cases per variable. Had I examined each city separately, I would have had much smaller ratios of cases to considered variables, between 5 and 6 per city.

<sup>24</sup> To affirm that factor analysis is an appropriate approach given this data, I examined several well-recognized criteria for the factorability of a correlation. First, 13 of the 14 items had a correlation of at least .3 with at least one other item, suggesting variables chosen for this analysis are sufficiently related with each other. Second, the Kaiser-Meyer-Olkin measure of sampling adequacy was .681, above the common cutoff of .6, and Bartlett's test of sphericity was significant ( $\chi^2(91) = 3175.809, p < .001$ ), indicating that the set of variables are adequately related for factor analysis.

poverty. This first factor explained 32.84% of the overall variance. I label the second derived factor Minority Neighborhoods due to the high, positive loadings on percent foreign born, percent Asian, and percent Hispanic and high, negative loadings on percent black. The variance explained by this factor was 21.03%. The third factor – labeled Established Neighborhoods – explained 15.94% of the variance and is derived from the high, positive percent elderly and percent owner occupied. The last factor, which I label as a neighborhood’s Urbanity, is defined by high, positive loadings on population size and population density. This fourth factor explained 11.12% of the variance.

With these components, I use multivariate linear regression to test how neighborhood types relate to internal and external reputations. Table 8 summarizes these results. I find that for both models, ‘young urban professional neighborhoods’ have the strongest effect on perceptions of reputation. A higher score on this component, suggesting neighborhoods with higher income and higher percentages of college graduates and single-person households, has a strong positive effect on reputation for both residents and non-residents. This fits with the notion that gentrifying neighborhoods, sometimes characterized by rapid increases in college-educated young professionals, often have the highest cache in terms of reputation. This finding also echoes findings in the previous section that gentrifying neighborhoods enjoy increased familiarity compared to demographically similar, non-gentrifying neighborhoods. The effect is stronger for non-residents, suggesting that they may be more swayed by the appearance of changing neighborhoods than those who actually live in them. Additionally, I find that ‘established neighborhoods’, characterized by more elderly residents and a higher percentage of owner occupancy, also have a significant positive effect on reputation. This component has a stronger effect on residents than non-residents, suggesting perhaps that neighborhood residents internalize more the value of the perceived constancy of desirable, owner-driven neighborhoods.

Table 8. Multiple Regression Analysis on Effect of Neighborhood Reputation Factors on Resident and Non-Resident Perceptions of Neighborhood Reputation (N = 238)

|                | Internal | External |
|----------------|----------|----------|
| Yuppies        | 0.265*** | 0.328*** |
| Minorities     | -0.011   | -0.018   |
| Established    | 0.100*** | 0.070**  |
| Urbanity       | -0.030   | -0.020   |
| Constant       | 3.165*** | 2.797*** |
| R <sup>2</sup> | 0.321    | 0.5217   |

In contrast to literature that suggests that neighborhoods with higher concentrations of minorities may be less desirable, I find no effect of ‘minority neighborhoods’ on neighborhood reputations for either residents or non-residents. This may imply that the racial composition of a neighborhood has been overstated as a driving force of neighborhood desirability<sup>25</sup> and instead that neighborhood reputation is driven more by the longevity of its prestige and/or by how dramatically it is upgrading, as in a gentrifying neighborhood. When coupled with earlier findings that residential familiarity is highly racialized, this finding that racial composition does

<sup>25</sup> For a full discussion on race and neighborhood preference, see Krysan and Crowder 2017

not drive desirability strengthens the claim that residential segregation may be a function of knowledge and not preference. It is also possible that the lack of effect of racial composition is an artifact of the modeling strategy, which combines data across all three cities. Given their differing demographic compositions, there is reason to believe that racial categories may mean something different amongst the three cities and that the effect of less desirable racial neighbors is muted in these combined models. While Chicago and DC are both predominantly white-black cities, Los Angeles is a white-Hispanic city. In all three cities, Asians make up 10 percent or less of the population. Note that the ‘minority neighborhood’ factor is derived from high, positive loadings on percent foreign born, percent Asian, and percent Hispanic and high, negative loadings on percent black. Thus, it is possible that the opposing directions of these loadings in effect cancel out evidence that minority populations affect neighborhood reputation. Finally, I also find that a neighborhood’s urbanity – its density and population size – has no effect on neighborhood reputation.

These predictors explain a moderate amount of a neighborhood’s perceived reputation. The models account for half of observed differences in reputation for non-residents ( $R^2 = .5217$ ), but only a third of observed differences in reputation as perceived by residents ( $R^2 = .321$ ). This discrepancy in the fit of the models suggests that there are more drivers of reputation unaccounted for when it comes to residential perceptions of reputation. This may reflect that residents’ lived experience in a place means they develop a more multi-faceted perspective on a neighborhood’s reputation that can’t be reduced to these admittedly crude measures. Future research that extends this inquiry to measures including local crime, changes in home values, commercial activity, green space, and other quality of life factors may improve our understanding of the underlying factors driving differences in perceived neighborhood reputation.

Overall, this research suggests that perceptions of neighborhood reputation between residents and non-residents differ in magnitude and consistency, but not in underlying factors. Residents more favorably rate their neighborhood’s reputation and agree more consistently in that rating than non-residents. However, there is considerable agreement between residents and non-residents on the ranking of their neighborhood’s desirability within a neighborhood hierarchy. Additionally, for both groups, factors related to a neighborhood’s draw of young, urban professionals and degree of establishment have a significant positive effect on reputation, while neighborhood racial demographics appear to be less important to a neighborhood’s prestige. That said, residents’ perceptions of neighborhood reputations may be more nuanced and complex, possibly driven more by lived experience of a place and less reducible to observable neighborhood conditions.

### **The Influence of Perception and Reputation on Residential Behavior<sup>26</sup>**

If the previous two sections revealed patterns of residential knowledge and reputation among distinct populations, this section focuses on how such differences may shape or be shaped by neighborhood change. This final set of analyses builds on the previous sections by exploring the relevance of neighborhood reputation as a mechanism driving neighborhood change. As such, it tests the theory that perception and reputation are drivers of neighborhood evolution because

---

<sup>26</sup> These models roughly replicate the research of Permentier 2012

they shape how individuals make choices about their environments, particularly via their residential behaviors.<sup>27</sup>

To test the relevance of neighborhood reputation on residential behaviors, I examine how residents' sensitivity to perceived neighborhood reputation – or “third-person effect”<sup>28</sup> – influences their desire to move. Using logistic regression, I estimate a resident's desire to move from their current neighborhood as a function of personal characteristics, neighborhood demographics, resident's neighborhood satisfaction, and perceptions of external neighborhood reputation across all three cities.<sup>29</sup> I measure the dependent variable using binary responses to the question, “If you had the choice, in the future would you like to continue to live in this neighborhood or to move to another neighborhood?” I find that within my sample of 1566 respondents, 640 respondents (41 percent), desire to move to another neighborhood. Perceived external neighborhood reputation is measured using the survey question, “How do you think other residents of the city of [METROAREA] assess the reputation of your neighborhood?” Answers could range from 1 (very undesirable) to 4 (very desirable).

Table 9 presents the results of iterative logistic regression models, with respondents clustered within neighborhoods. Results are reported using odds ratios. Model 1 shows the results of a simple bivariate logistic regression, estimating an individual's desire to leave their neighborhood as a result of their perception of the neighborhood's external reputation – or how a respondent thinks other residents of the city assess their neighborhood's reputation. It finds that as perceived external reputation increases (i.e. neighborhood reputations improve), a respondent's desire to move decreases. Specifically, predictive probabilities from this model find that while there is an 85 percent likelihood that a respondent will want to move from a neighborhood they think others find very undesirable, this drops to a 67 percent likelihood of wanting to move if they think others find the neighborhood only somewhat undesirable. The likelihood of a respondent wanting to move from a neighborhood others find very desirable is only 20 percent.

Desire to move can also be driven by personal and environmental factors. Model 2 examines how personal factors – a respondent's gender, age, race, household type, education, employment, length of residence in a neighborhood, and homeownership – affect desire to move. I find that women, black respondents, and students are more likely to report wanting to move, while more educated respondents are less likely to want to move. Model 3 examines how environmental factors – your neighborhood's racial composition and average income level – affect one's desire to move. I find strong effects for both percent non-Hispanic black and percent Hispanic, suggesting that residents in neighborhoods with higher concentrations of non-white residents are more likely to desire to move. Model 4 combines these models and finds generally that these effects still hold. Interestingly, measures of model fit suggest that these three models estimating one's intention to leave their neighborhood based on personal and environmental characteristics are not as strong as the model that only included perceived external neighborhood reputation.

---

<sup>27</sup> See also Wacquant, 1993.

<sup>28</sup> Tsfati and Cohen 2003

<sup>29</sup> I also ran these models for each city – LA, Chicago, and DC – separately and found substantively comparable results. I present the pooled results here for parsimony.

Table 9. Logistic Regression Analysis of Respondent Desire to Move (N = 1566)

|  | Model 1 <sup>1</sup> | Model 2  | Model 3  | Model 4   | Model 5   | Model 6   | Model 7   |
|--|----------------------|----------|----------|-----------|-----------|-----------|-----------|
| Perceived Neighborhood Reputation <sup>2</sup>       | .350***              |          |          |           | .372***   | .648***   | .667***   |
| Female   |                      | 1.277*   |          | 1.313*    | 1.239     | 1.289     | 1.313     |
| Age  |                      | .992     |          | .993      | .995      | .992      | 0.992     |
| Black  |                      | 1.477*   |          | 1.219     | 1.130     | 1.193     | 1.189     |
| Hispanic   |                      | 1.255    |          | 1.003     | .874      | .904      | 0.893     |
| Asian  |                      | 1.134    |          | 1.029     | 1.083     | .985      | 0.976     |
| Other  |                      | 1.450    |          | 1.235     | 1.041     | 1.050     | 1.003     |
| Household Type (ref: Single)                         |                      |          |          |           |           |           |           |
| Single parent household                              |                      | 1.443    |          | 1.390     | 1.350     | 1.575     | 1.571     |
| Couple   |                      | .993     |          | .953      | .923      | .971      | 0.979     |
| Couple w/ children                                   |                      | 1.213    |          | 1.143     | 1.102     | 1.135     | 1.130     |
| Other  |                      | 1.207    |          | 1.133     | 1.308     | 1.328     | 1.364     |
| Education  |                      | .898*    |          | .924      | .914      | .933      | 0.937     |
| Employment (ref: Employed)                           |                      |          |          |           |           |           |           |
| Unemployed   |                      | 1.173    |          | 1.156     | 1.144     | 1.093     | 1.048     |
| Student  |                      | 1.915**  |          | 2.167**   | 2.327***  | 2.332**   | 2.412**   |
| Retired  |                      | .994     |          | .959      | .929      | 1.129     | 1.122     |
| Income   |                      | .971     |          | 1.003     | 1.031     | 1.040     | 1.041     |
| Home Owner   |                      | .889     |          | .862      | .876      | 1.027     | 1.018     |
| Tenure in Neighborhood                               |                      | .998     |          | .994      | .993      | .992      | 0.991     |
| % Black  |                      |          | 2.505*   | 1.836     | 1.069     | 1.037     | 0.675     |
| % Asian  |                      |          | 1.343    | 1.092     | .884      | .935      | 0.864     |
| % Hispanic   |                      |          | 3.797**  | 3.311**   | 1.893     | 1.861     | 1.006     |
| Average Neighborhood Income                          |                      |          | .999     | .999*     | .999      | .999      | 1.000     |
| Neighborhood Satisfaction <sup>3</sup>               |                      |          |          |           |           | .566***   | .566***   |
| Actual External Neighborhood Reputation <sup>4</sup> |                      |          |          |           |           |           | .565**    |
| Wald Chi <sup>2</sup>                                | 160.18***            | 82.27*** | 64.39*** | 129.14*** | 224.51*** | 271.17*** | 276.73*** |
| AIC <sup>5</sup>                                     | 1872.531             | 2049.259 | 2048.541 | 2004.506  | 1841.59   | 1629.763  | 1624.737  |

<sup>1</sup> Coefficients are reported as odds ratios. Readers should interpret odds ratios greater than 1 as an increase in the odds of a respondent wanting to move. Odds ratios less than 1 indicate a decrease in the odds of a respondent wanting to move.

<sup>2</sup> Perceived neighborhood reputation is measured on a four category Likert scale, where 1 is very undesirable and 4 is very desirable.

<sup>3</sup> Respondents reported their neighborhood satisfaction on a 10-point sliding scale ranging from 1 (extremely dissatisfied) to 10 (extremely satisfied).

<sup>4</sup> Actual external reputation is measured as the average score given by non-neighborhood residents in response to the question, “How would you assess the reputation of [NEIGHBORHOOD X]?” Like resident’s perceptions of reputation, it is measured on a four category Likert scale, where 1 is very undesirable and 4 is very desirable.

<sup>5</sup> AIC stands for Akaike’s Information Criteria, a measure of the goodness of fit of an estimated statistical model. Smaller AIC is generally interpreted as an improvement in model fit.

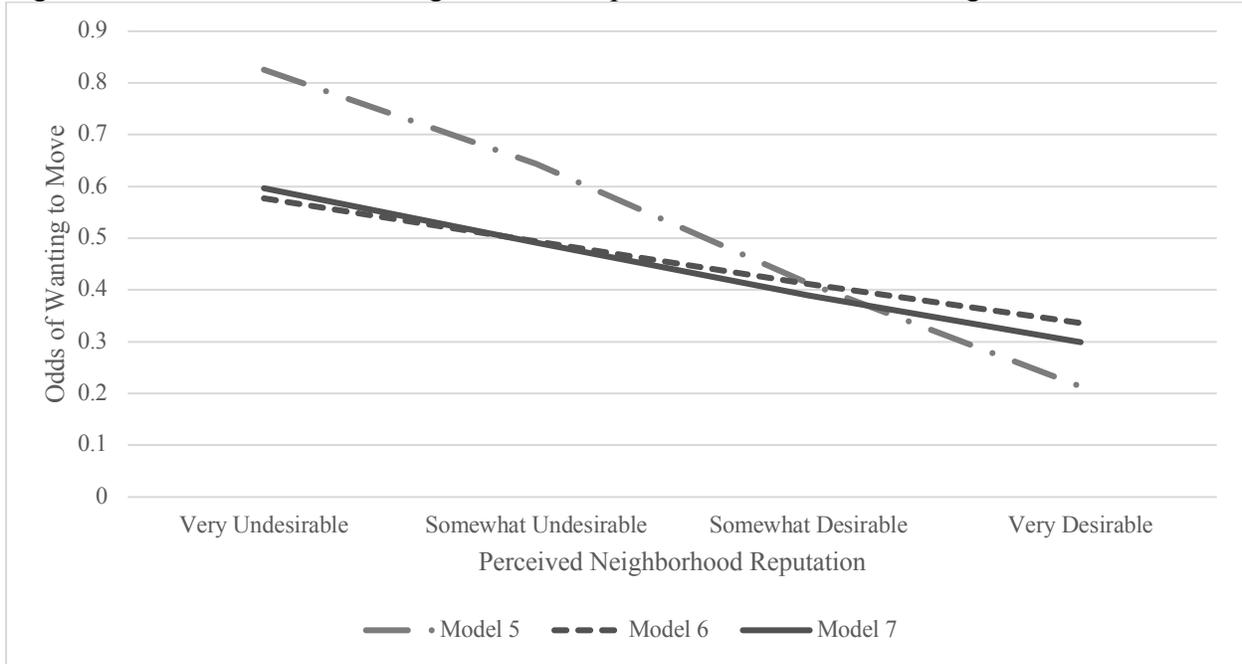
Model 5 tests the strength of neighborhood reputation as a driver of one's desire to move when personal and environmental characteristics are accounted for. It finds a nearly identical marginal effect of perceived reputation on an individual's anticipated mobility as Model 1. Model 5 suggests that including a neighborhood's perceived external reputation eliminates the effects on personal and neighborhood characteristics on desire to move. As perceived reputation increases, a respondent's desire to move decreases, dropping from an 83 percent likelihood of wanting to move from a neighborhood others find very undesirable to a 21 percent likelihood of wanting to move from a neighborhood deemed desirable.

While these models aim to measure the degree to which respondents internalize perceptions of outsider's perspectives on their neighborhood, one might think that perceived neighborhood reputation is in fact capturing how a resident feels about their own neighborhood or a base truth about collective perceptions of neighborhood desirability. That is, it is possible that perceived external reputation is masking other important variables. To test this, models 6 and 7 control for a respondent's own neighborhood satisfaction and real, measured external neighborhood reputations. Model 6 adds in a control for respondent's reported neighborhood satisfaction, measured on a 10-point sliding scale ranging from 1 (extremely dissatisfied) to 10 (extremely satisfied). It finds that while neighborhood satisfaction both decreases the effect size of perceived neighborhood reputation and is itself a significant predictor of one's desire to move, perceived reputation remains a strong and significant driver of mobility intentions. This suggests that though one's own neighborhood satisfaction is influential in their mobility decisions; satisfaction does not cancel out the influence of resident's perception of their neighborhood's desirability.

Finally, to test if the effect of perceived neighborhood reputation is driven by actual, measured external neighborhood reputation, model 7 incorporates the mean score given by non-neighborhood residents on the survey in response to the question, "How would you assess the reputation of [NEIGHBORHOOD X]?" Like resident's perceptions of reputation, it is measured on a four category Likert scale, where 1 is very undesirable and 4 is very desirable. One would expect that if residents are accurately perceiving how outsiders view their neighborhood, including this variable would nullify the effect of a respondent's perception of neighborhood reputation. However, real external neighborhood reputation is only weakly correlated with respondent's perceived external neighborhood reputation ( $\text{corr} = .459$ ). Despite this lack of accord between perceived external neighborhood reputation and measured external neighborhood reputation, model 7 shows that both aspects of reputation – real and illusory – contribute to a respondent's desire to move, as does neighborhood satisfaction.

Figure 7. illustrates these results using predicted probabilities to isolate the effect of changes in perceived neighborhood reputation. The line for Model 5 shows the effect of perceived neighborhood reputation when controlling for a respondent's personal characteristics and neighborhood environment. Models 6 and 7 show the effect of perceived neighborhood reputation when adding in neighborhood satisfaction and real external reputation, iteratively. All three reveal that improvements in perceived neighborhood reputation have a strong effect on desire to move. While this effect is diminished when you control for a respondent's reported neighborhood satisfaction and measured external neighborhood reputation, it does not disappear, suggesting that both aspects of reputation – real and perceived – contribute to a respondent's desire to move, as does neighborhood satisfaction.

Figure 7. Effect of Perceived Neighborhood Reputation on Odds of Wanting to Move



These preliminary results lend credence to the hypothesis that perception and reputation are important mechanisms driving neighborhood evolution. I find that individuals, in assessing their residential circumstances, are sensitive to the perceived desirability of their neighborhoods, internalizing not only their own lived experiences of a place but also what they perceive others think about that place.

## Summary

This report explores the ways in which individuals' perceptions and gaps in knowledge may influence neighborhood dynamics. Leveraging unique pilot survey data, it argues that perception and reputation are critical mechanisms underlying the micro-processes of neighborhood change. In particular, it examines the prevalence of differences in neighborhood familiarity, the drivers of divergent neighborhood reputations between residents and non-residents, and the influence of perceived external neighborhood reputation on individual's desire to move amongst respondents in Chicago, Los Angeles, and Washington D.C. Key results include the following:

- Urban residents have limited knowledge of neighborhoods within a city, and on average report being familiar with only one-fifth of neighborhoods. Respondents of different racial/ethnic backgrounds have significantly different levels of neighborhood familiarity.
- In each city, there are distinct – if somewhat unsurprising – patterns of neighborhood familiarity by racial group. Despite this, there are significant overlaps in the degree of familiarity by racial group, suggesting there are not absolute knowledge monopolies when it comes to neighborhoods. Compared to Los Angeles and Washington, D.C.,

Chicago has a more pronounced differences between black respondent's neighborhood knowledge and that of other racial groups.

- Across all three cities, racial composition of a neighborhood is a strong predictor of if that neighborhood is known or not. For non-black respondents, the percent of African Americans living in a neighborhood is negatively associated with a respondent's familiarity with that neighborhood. There is a similar effect for the concentration of Hispanic residents.
- Respondents are less likely to be familiar with neighborhoods with higher levels of owner-occupied housing but more likely to be familiar with gentrifying neighborhoods, particularly in Chicago and DC.
- Neighborhood residents are significantly more likely to rate their own neighborhood as more desirable – and agree more about the level of desirability – than non-residents. However, there does appear to be general agreement between residents and non-residents on neighborhood's ranked desirability within a city's urban hierarchy.
- Across all three cities, higher ranked neighborhoods have smaller differences in ratings between residents and non-residents than lower ranked neighborhoods, suggesting that there is generally more agreement amongst city residents when it comes to the neighborhoods with the best reputations.
- For residents and non-residents, neighborhood reputation is driven more by factors related to a neighborhood's draw of young, urban professionals and degree of establishment. Meanwhile, a neighborhood's racial demographics appear to be less important to its reputation.
- Perceived external reputation – how one believes others view their neighborhood's reputation – is a strong measure of a respondent's desire to move. The more positive one believes third-person perceptions of reputation are, the lower their desire to move.
- Though one's neighborhood satisfaction is a significant predictor of one's desire to move, it merely reduces but does not erase the effect of perceived external reputations. This suggests that though one's own neighborhood satisfaction is influential in their mobility decisions; satisfaction does not cancel out the influence of resident's perception of their neighborhood's desirability.
- Respondents often misjudge their neighborhood's real, external neighborhood reputation. Models suggest that both aspects of reputation – real and perceived – contribute to a respondent's desire to move.

### **Implications for Urban Research and Policy**

Researchers have thus far largely ignored the importance of neighborhood perceptions in driving neighborhood change. However, the findings detailed in this report suggest that incorporating

these mechanisms may have some important implications for urban research. First, and most importantly, the findings presented above support the argument that one's neighborhood knowledge, perception, and reputation may be consequential aspects of residential experience. In shaping that experience, these mechanisms may both drive micro-processes of behavior and aggregate up to explain macro-patterns of urban evolution. As such, it is important for urban researchers to consider how their research may be strengthened by the incorporation of these concepts.

Second, these findings challenge the assumption of omniscient neighborhood residents with thorough knowledge of their communities. Individuals' limited or imprecise knowledge about neighborhoods suggests that research on demographic trends like tipping points and white flight may over- or under-state the relationship between demographic thresholds and reactionary residential choices. If, for example, behaviors are guided by one's fallible perceptions, there is likely greater fuzziness around such thresholds than current literature suggests. Additionally, these results emphasize the importance of developing choice models that winnow the choice set of individuals to those neighborhoods with which they are familiar as a first stage of the selection process,<sup>30</sup> rather than assuming people choose neighborhoods from all possible options with equal consideration. Relatedly, given the finding that individuals are less likely to know neighborhoods with high levels of homeownership, researchers should think more deeply about how practices of residential steering<sup>31</sup> and neighborhood knowledge combine to constrict residential choice or reinforce existing patterns of residential segregation.

Third, these findings emphasize the importance of using real neighborhoods when developing models of neighborhood preference and selection. Results from the above analyses suggest that a respondent's "sense of place" strongly influences their perceptions and behaviors. Not only do we form associations with and develop stigmas about neighborhoods – which we use to make decisions – my results suggest that we also view neighborhoods within a hierarchy. Thus, evaluating neighborhoods either based on a uni-dimensional characteristic or absent of the broader urban context is likely to result in biased theories. Furthermore, this research highlights important differences in resident's neighborhood perspectives both within and between cities. Thus, it is also critical to consider in our research how urban contexts differ across cities and to develop more cross-city comparisons to decompose phenomena into local and global trends.

Finally, this research highlights the relevance of external perceptions on individual action. While psychology has examined third-person effects – or the degree to which we internalize the assumed perceptions of "others" – sociologists have generally not focused on how these external perceptions influence behavior. As researchers develop theories that incorporate perception, they must include not only individual's perceptions but those of the broader community.

In addition to their relevance to research, these findings also are relevant for urban policy. Place making, gentrification, and neighborhood branding campaigns are increasingly prevalent forces affecting urban places. Whether driven by the invisible hand of the market or by deliberate efforts by real estate developers, community development corporations, and urban governments,

---

<sup>30</sup> See Bruch and Swait, n.d

<sup>31</sup> See Lacy 2007; Ross and Turner 2005; Krysan and Crowder 2017, Besbris 2016

these neighborhood catalysts capitalize on individuals' neighborhood knowledge, perceptions, and reputation without fully understanding these mechanisms or their long-term effects.

The research outlined in this report problematizes a variety of policy avenues. For example, if enduring neighborhood segregation is the product of systematic racial blind spots, one solution may be to better disseminate information about neighborhoods throughout the urban population. However, it is possible that increasing neighborhood knowledge may lead to gentrification. Though my analysis finds an association between neighborhood familiarity and gentrifying neighborhoods, my models are descriptive, not causal. It is thus possible that gentrification is a product of increased public familiarity with a neighborhood. Urban governments should thus consider if increased neighborhood knowledge would constitute a positive or negative change for that city.

Similarly, efforts to increase resident satisfaction with their neighborhood may have mixed effects. While I find that neighborhood satisfaction is an important determinant of residential mobility desires, I also find that it is less influential than perceived neighborhood reputation. Thus, a city may do well to focus its neighborhood marketing efforts not within a neighborhood, but in disseminating positive information about a place to non-residents. These efforts may also reduce the differences between how residents and non-residents perceived a neighborhood's reputation. However, as above, improved reputation may be a double-edged sword. My analyses suggest that the most reputable places are those attracting young urban professionals, which may mean they are the same places experiencing gentrification and the displacement of lower-income residents.

Finally, the finding that neighborhoods exist in a hierarchy also may have useful policy implications. For example, if a city is trying to slow the pace of rent increases and residential displacement, governments may want to target rent control policies or landlord incentives towards neighborhoods next in the hierarchy below neighborhoods already experiencing rent hikes. Similarly, hierarchical views of neighborhoods may point community development corporations working in less desirable neighborhoods towards examples of places that have cultivated higher levels of desirability.

Ultimately, little research exists at present to make sense of the effects of place making and neighborhood branding efforts. As evaluations of these efforts and the effect of such investments are undertaken, they would do well to consider the role of neighborhood perceptions and reputation in changing neighborhood desirability and composition. More research will reveal if changing what people think about a place can catalyze or suppress neighborhood transformation.

## References

- Alba, Richard, Ruben G. Rumbaut, and Karen Marotz. 2005. "A Distorted Nation: Perceptions of Racial/Ethnic Group Sizes and Attitudes toward Immigrants and Other Minorities." *Social Forces* 84(2):901-919
- Besbris, Max. 2016. "Romancing the Home: Emotions and the Interactional Creation of Demand in the Housing Market." *Socio-Economic Review* 14, no. 3: 461–82.
- Bruch, Elizabeth, and Robert Mare. 2006. "Neighborhood Choice and Neighborhood Change." *American Journal of Sociology* 112:3
- Bruch, Elizabeth and Joffre Swait. "All Things Considered?: A Cognitively Plausible Model of Neighborhood Choice." Manuscript.
- Burgess, E.W., Park, R.E., Mackenzie, R. 1925. *The City*, Chicago: Univ. of Chicago Press.
- Charles, Camille Z. 2003. "The Dynamics of Racial Residential Segregation." *Annual Review of Sociology*. 29: 167-207
- Crowder, K., J. Pais, S.J. South. 2012. "Neighborhood Diversity, Metropolitan Constraints, and Household Migration." *American Sociological Review* 77(3):325-353
- Ding, Lei, Jackelyn Hwang, and Eileen Divringi. 2016. "Gentrification and Residential Mobility in Philadelphia." *Regional Science and Urban Economics* 61: 38–51.
- Duncan, O. D., Duncan, B. 1957. *The Negro population of Chicago: a study of residential succession*. University of Chicago Press
- Farrell, Dan, and James C. Petersen. 2010. "The Growth of Internet Research Methods and the Reluctant Sociologist\*." *Sociological Inquiry* 80, no. 1: 114–25.
- Freeman, Lance. 2005. "Displacement or Succession?: Residential Mobility in Gentrifying Neighborhoods." *Urban Affairs Review* 40, no. 4: 463–91.
- Goel, S., Obeng, A., & Rothschild, D. 2015. "Non-representative surveys: Fast, cheap, and mostly accurate." *Working Paper*.
- Heen, Miliiakeala S.J., Joel D. Lieberman, and Terance D. Miethe. 2014. "A Comparison of Different Online Sampling Approaches for Generating National Samples." University of Las Vegas Center for Crime and Justice Policy. CCJP 2014-01
- Hidalgo, Bertha, Kimberly A. Kaphingst, Jewel Stafford, Christina Lachance, and Melody Goodman. 2015. "Diagnostic Accuracy of Self-Reported Racial Composition of Residential Neighborhood." *Annals of Epidemiology*. 25(8): 597-604

- Hoover, E.M., Vernon, R. 1959. *Anatomy of a Metropolis*. Cambridge, MA: Harvard Univ. Press.
- Krysan, Maria. 2002. "Whites Who Say They'd Flee: Who Are They, and Why Would They Leave?" *Demography* 39:4
- Krysan, Maria and Michael D.M. Bader. 2009. "Racial Blind Spots: Black-White-Latino Differences in Community Knowledge." *Social Problems*. 56(4): 677-701
- Krysan, Maria and Kyle Crowder. 2017. *The Cycle of Segregation: Social Processes and the Perpetuation of Residential Stratification*. Russell Sage Foundation
- Lacy, Karyn R. 2007. *Blue-Chip Black Race, Class, and Status in the New Black Middle Class*. Berkeley: University of California Press.
- Lichter, Daniel T., Domenico Parisi, and Michael C. Taquino. 2015. "Toward a New Macro-Segregation? Decomposing Segregation within and between Metropolitan Cities and Suburbs." *American Sociological Review* 80(4): 843 – 873
- Logan, John R., and O. Andrew Collver. 1983. "Residents' Perceptions of Suburban Community Differences." *American Sociological Review*. 48(3): 428-433
- McKenzie, R.D. 1924. "The Ecological Approach to the Study of the Human Community." *American Journal of Sociology*. 30: 287-301
- Newman, Kathe, and Elvin K. Wyly. 2006. "The Right to Stay Put, Revisited: Gentrification and Resistance to Displacement in New York City." *Urban Studies* 43, no. 1: 23–57.
- Owens, A. 2012. "Neighborhoods on the Rise: A Typology of Neighborhoods Experiencing Socioeconomic Ascent," *City & Community*, 11, 4: 345-369.
- Permentier, Matthieu. 2012. "Neighbourhood Reputations, Moving Behaviour and Neighbourhood Dynamics." In *Understanding Neighbourhood Dynamics*. Dordrecht: Spring Press.
- Permentier, Matthieu, Gideon Bolt, and Maarten van Ham. 2011. "Determinants of Neighbourhood Satisfaction and Perception of Neighbourhood Reputation." *Urban Studies*. 48(5): 977-996
- Permentier, Matthieu, Maarten van Ham, and Gideon Bolt. 2008. "Same Neighbourhood ... Different Views? A Confrontation of Internal and External Neighbourhood Reputations." *Housing Studies*. 23(6): 833-855
- Ross, Stephen L. and Margery Austin Turner. 2005. "Housing Discrimination in Metropolitan America: Explaining Changes between 1989 and 2000." *Social Problems* 52(2):152–80.

Schelling, Thomas. 1971. "Dynamic Models of Segregation." *Journal of Mathematical Sociology*. 1:143-86

Semyonov, M. and V. Kraus. 1982. "The Social Hierarchies of Communities and Neighborhoods." *Social Science Quarterly* 63:780-89.

Tsfati Yariy, and Jonathan Cohen. 2006. "On the Effect of the 'Third-Person Effect': Perceived Influence of Media Coverage and Residential Mobility Intentions." *Journal of Communication* 53, no. 4: 711–27.

Wacquant, Loïc J. D. 1993. "Urban Outcasts: Stigma and Division in the Black American Ghetto and the French Urban Periphery\*." *International Journal of Urban and Regional Research* 17, no. 3: 366–83.