Chapter 6
The Micro-Level Dynamics of Racial and Ethnic Residential Segregation

6.1 Overview

Segregation is often viewed and studied as a macro-level phenomenon, described in terms of aggregate patterns across areas. Empirical analyses of segregation are typically conducted at the macro-level as well, explaining changes and variations in segregation through contextual-level factors such as population size, region, or percent White. This approach was popularized by the work of Douglas Massey and Nancy Denton (e.g. 1987, 1993) and continues to be used in more recent studies that use census summary file tabulations (e.g. Iceland, 2014; Iceland et al., 2014; Frey, 2018). Indeed, this is the approach that we have taken in previous chapters, albeit while taking precaution to only include aggregate-level predictors that do not lead us to an ecological fallacy (Fossett, 1988). However, there is an established body of literature that recognizes segregation as an outcome of micro-level processes of locational attainments and residential mobility. This work was spearheaded by Richard Alba and John Logan in the early 1990s in a series of articles that modeled segregation-relevant outcomes, such as neighborhood percent White, using household or individual-level predictors such as income, education, and nativity (Alba & Logan, 1991, 1992, 1993), which led to more locational attainment studies in the following decades (e.g. Pais et al., 2012; South et al., 2008; Yu & Myers, 2007). This work is fundamentally important for testing the dominant theoretical frameworks

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employed in segregation research, which largely emphasize that segregation is driven by micro-level characteristics and processes and center the barriers and opportunities in residential mobility. Additionally, the locational attainments approach can be linked with outcomes that are essentially consequences of segregation such as educational disparities, health disparities, and unequal exposure to crime.

Despite the contributions to come out of this past literature, this approach to studying segregation through analyzing locational attainments has fallen just short of linking the neighborhood outcomes of individual households to overall patterns of segregation. The reason for this lies in how we measure segregation, which ultimately affects how we think through drawing the link between micro- and macro-level approaches to studying segregation. Fossett (2017) emphasizes that one of the most important benefits to reformulating segregation indices as a difference of group means is that we are also called on to reconceptualize segregation, thinking of it not as an aggregate-level phenomenon but as an outcome of processes of locational attainments happening below the surface. With new methodologies described in Chap. 2 and with access to data that permits micro-level analyses, we can take on an entirely new approach to studying segregation that does not break from tradition but rather advances it, drawing a direct link between the study of locational attainments and aggregate-level patterns of segregation by simply reformulating the segregation index. By analyzing segregation through modeling individual or household-level neighborhood outcomes, the locational attainments approach to studying segregation can be directly and quantitatively linked to Fossett's (2017) reformulation of segregation indices, which situates segregation as an aggregation of individual outcomes (i.e. the difference-of-means approach). We have been successful in empirically demonstrating this approach in our recent work (Crowell & Fossett, 2018, 2020, 2022).

This final empirical chapter presents our most complex analysis of segregation thus far by rightly analyzing segregation as a dynamic and multilayered social phenomenon – one that is inherently sociological as individual actors make residential moves that are determined by both individual preferences and resources as well as structural-level factors that shape the extent to which households can convert those resources and desires into locational attainments. Disparities in these dynamics can lead to racially and economically segregated communities. In previous chapters, we examined contextual factors that correlate with patterns of segregation across areas as others have done in the past. Those analyses, while useful and informative, are ultimately simple and largely descriptive. In this chapter, we conduct a multivariate analysis of segregation that can account for a multitude of household-level factors that lead to group inequalities in residential outcomes, which at the aggregate level manifest as segregation.

While we discuss some of the dominant theoretical frameworks in this chapter, our goal is not to frame this methodological approach as the solution to engaging specifically with what has been theorized, but rather to provide a new methodological toolkit that opens up new avenues for theorizing about and analyzing segregation. What can we build on to our existing frameworks? Or perhaps the more exciting question is: What new theories and understandings can we develop about residential segregation? This chapter presents an analysis of White-Black, White-Latino, and White-Asian segregation in 25 of the largest metropolitan areas in the United States, modeling locational attainments in a way that directly and exactly predicts overall levels of segregation for any given area. The research design is determined by existing theory, but the methods are almost entirely novel to segregation research. We at times draw on our previously published research in this area, the first empirical demonstrations of these new methods, but in this chapter we take the liberty to go further into what is possible for the future of segregation research – what methodological innovations we can implement and what new questions we can ask to advance our understanding of residential segregation.

6.2 Review of Theoretical Frameworks

In Chap. 1, we gave an overview of some of the dominant theoretical frameworks in the segregation literature as well as an emergent theory of residential sorting recently set forth by Maria Krysan and Kyle Crowder (2017). Consistent with previous research in this area (Crowell & Fossett, 2018, 2020, 2022; Iceland & Scopilliti, 2008), we draw on three major theoretical perspectives – *spatial assimilation, place stratification,* and *segmented assimilation* – to frame our analysis and conclusions in this chapter. These perspectives guide demographic studies focused on racial residential segregation while considering other social factors such as socioeconomic status and immigration (e.g. Iceland & Scopilliti, 2008). Each perspective holds potential relevance for the residential segregation patterns of Black, Latino, and Asian households. One innovation in our study is that we draw on this multi-perspective framework to understand how the effects of factors operating in micro-level locational attainment processes may vary in shaping segregation across different community contexts and, in particular, across low- and high-segregation settings.

We review these three perspectives here briefly, noting first that they are not mutually exclusive and in fact can both contribute independently and complement one another to provide a more complete, nuanced understanding of the complexities of racial residential segregation processes. This point is made in Crowder and Krysan's (2016) critique of the simplicity with which these theories are often applied. Furthermore, we recognize that these three theories of segregation are not exhaustive of the perspectives that could be employed to develop a theoretical framework for residential segregation and attainments. For example, Krysan and Crowder's structural sorting perspective (2017) is an important lens for understanding the nature of household residential movements and the role of networks and information in determining residential location. However, the hypotheses of this and other theories are not testable within the scope and design of our study.

The *spatial assimilation* perspective holds that as members of a minoritized racial group acculturate towards characteristics of the majority group and experience socioeconomic mobility within and across generations, they become more likely to move away from ethnically concentrated neighborhoods and into higher-status neighborhoods with a greater presence of White households (Alba & Logan, 1991; Charles, 2003; Duncan & Lieberson, 1959; Massey & Denton, 1985). As Charles (2003) explains, this perspective emphasizes group differences in social characteristics as a primary reason for residential separation. Socioeconomic differences, typically measured by income and education, determine what neighborhoods householders are able to afford, which can lead to racial residential segregation when there is racial and economic inequality and neighborhoods are stratified on housing quality and amenities. Acculturation is also key to this perspective and is often operationalized in locational attainment models as English language ability and citizenship. The origins of this theoretical perspective are based in observations of White ethnic groups in the twentieth century, who moved away from inner-city immigrant enclaves and into suburbs where U.S.-born White households resided as they experienced social and economic mobility, intermarriage, and language assimilation, accelerated by a decline in European immigration and generational shifts along with increased economic opportunity. Thus, cultural characteristics and acculturation are also emphasized as determinants of residential location.

Spatial assimilation as a conceptual framework has persisted in residential segregation research with renewed attention following the work of Alba and Logan (1991, 1992, 1993) and is often used to guide the research design of locational attainments analysis. When applied in more contemporary research, this framework has had some useful explanatory power for understanding Latino and Asian residential trends. For example, studies show that, over time and across generations, Latino and Asian households experience residential mobility and increased contact with White households. Thus, Latino and Asian households with high socioeconomic status, where English is spoken exclusively or very well, and are several generations removed from immigration have more residential contact with White households in comparison to foreign-born Latino and Asian households with lower socioeconomic status (Alba & Logan, 1993; Alba et al., 2000; Charles, 2003; Iceland et al., 2014; Iceland & Nelson, 2008; Iceland & Scopilliti, 2008; Massey & Denton, 1985; South et al., 2008; Yu & Myers, 2007). For these groups where immigration is a major factor, newer arrivals may initially rely on enclaves where there is language support and established networks for entry into the labor market and social institutions, especially for those households with low socioeconomic status. As members of these groups acculturate and experience upward mobility, they may be less reliant on enclaves, which will be especially true for their second- and third-generation descendants (Alba et al., 1999; Charles, 2003; Massey & Denton, 1985). Their social distance from White households will be reduced and they will experience higher levels of residential integration.

The impact of spatial assimilation dynamics can potentially be seen at both the macro-level and the micro-level. As noted above, spatial assimilation theory predicts the micro-level finding that co-residence with White households will be more likely with social mobility. While this perspective also predicts that aggregate-level segregation will be greater when group differences on social and economic characteristics are more pronounced, the predicted pattern must also include evidence that segregation and group differences coincide for reasons beyond being jointly determined by discrimination and constrained opportunity. That is, there must be evidence indicating that reductions in group differences will lead to reductions in segregation. The new methods of segregation analysis we use allow us to examine this issue with quantitative precision not possible in previous research.

There is the potential for complex patterns to emerge as spatial assimilation dynamics initially emerge and play out. If group disadvantage is rooted in a pervasive web of discrimination and constrained opportunities, group disparities will be large when segregation is high but spatial assimilation at the micro-level will be weak and reducing group disparities will have little or no short-term impact on reducing segregation. Alternatively, if group differences trace discrimination that was higher in the past than in the present, as might be the case for the Black population, or if it traces to a group's historical immigration experience, as might be the case for the Latino or Asian populations, group differences might be smaller than in the former case yet have a greater potential impact on reducing segregation in the present because the micro-level spatial assimilation process is stronger. In a later section we discuss how this possibility leads us to search for evidence that the impact of group disparities on segregation will vary by context.

One notable limitation of the spatial assimilation framework is that even for U.S-born, high-socioeconomic status Latino and Asian households, segregation from White households persists, albeit at lower levels (Crowell & Fossett, 2018, 2020). Additionally, the spatial assimilation framework has had little relevance for understanding Black segregation; the predominately U.S.-born Black population experiences medium to very high levels of segregation from White households even at higher matched incomes (Alba & Logan, 1991, 1992, 1993; Iceland et al., 2005; Massey & Denton, 1987; Spivak & Monnat, 2013; Yu & Myers, 2007). Therefore, other general theoretical perspectives must be considered which can address persistent racial residential segregation.

The *place stratification* perspective is an alternative to the spatial assimilation perspective, but it is complementary, rather than mutually exclusive, in positing that discrimination based on race holds an important role in maintaining levels of segregation. Where spatial assimilation takes on greater relevance when groups begin to experience a less obstructed path to social mobility and increased residential contact with White households, place stratification takes on greater relevance when segregation primarily reflects structural racism. Place stratification stresses the persisting role of racism and group conflict in the White population's efforts to maintain power, status, and privilege by restricting access to White neighborhoods (Charles, 2003, 2006; Logan, 1978). Mechanisms include direct and covert discrimination, exclusionary zoning, steering by realtors and landlords, housing loan discrimination, and covert but perceived hostility toward minoritized families in predominately White neighborhoods. Thus, place stratification operates through both individual and institutional determinants (Massey, 2020). These dynamics are hypothesized to be effective regardless of reductions in group differences on characteristics such as socioeconomic status or acculturation.

Work by Farley and colleagues in previous decades (Farley et al., 1978, 1994) lends some support to the place stratification perspective, finding that Black families perceive greater racial discrimination in the housing market while White families remain resistant to living in neighborhoods where minoritized racial groups predominate, although White preferences have become more racially progressive over time (Farley & Frey, 1994). Additionally, direct evidence has emerged over the past several decades which would indicate continuing discrimination in the housing market, particularly that which comes from audit studies. These studies generally find that although housing market discrimination may be declining, it is still significant and, furthermore, mortgage loan discrimination shows no signs of abating (Massey & Lundy, 2001; Galster, 1990; Quillian et al., 2020; Turner et al., 2013; Yinger, 1995). The place stratification perspective is widely seen as relevant for understanding the continuing high levels of segregation for Black households but could also explain why Latino and Asian households may remain at some level of uneven distribution even though levels of segregation may be moderate or decreasing over time, as racism persists with consequences for all racially minoritized groups (Alba & Logan, 1991; Charles, 2003; Pais et al., 2012).

The final framework that informs this study is a theory positing that systems of stratification can create multiple trajectories of "assimilation," known as *segmented assimilation*. This framework holds particular relevance for understanding divergent segregation patterns by nativity and across generations and can provide insight into how locational attainment dynamics may vary by group. Assimilation can mean experiencing upward social mobility and entrance into White neighborhoods, as posited by the traditional assimilation framework that informs the spatial assimilation perspective. But it can also result in being subjected to institutional racism and discrimination, being shut out of economic opportunities, or gravitating towards ethnic communities with supportive structures for social and economic opportunities.

Segmented assimilation was first empirically explored within the context of the labor market (e.g., Portes & Zhou, 1993) but can be extended to many social outcomes that serve as indicators of social mobility and resources including residential locational outcomes (Crowell & Fossett, 2020; Iceland & Scopilliti, 2008). The implications of this framework for understanding the segregation patterns of the groups considered here is that we may not observe uniform patterns of locational attainments but may in fact find attainment patterns that run counter to what the spatial assimilation hypothesis would have us expect (South et al., 2005). For example, in our past research on the Minneapolis-St. Paul Metropolitan Statistical Area, we found that U.S.-born Black households were more likely to be segregated from White households than foreign-born Black households, counter to what we found for Latino and Asian households (Crowell & Fossett, 2020). From the segmented assimilation perspective, we argue this pattern results because Black households experience a trajectory of assimilation that is more strongly impacted by institutionalized racism and particularly an established legacy of Black residential segregation. This implies that in contrast to the traditional spatial assimilation perspective, the social and economic resources that would ease entrance into

White neighborhoods give way to other more structural dynamics including barriers that emerge from racialization and racism.

6.3 Framing Cross-context Segregation Patterns

Finally, we consider the possibility that spatial and segmented assimilation and place stratification dynamics may vary in relative salience and importance across metropolitan areas. To the extent that they do so, it will require us to take more care in assessing the quantitative importance of the different processes. Most importantly, group differences in socioeconomic characteristics and in locational attainments will have implications for reducing segregation that vary across low- to high-segregation contexts. If group differences in the effects of household social and economic characteristics on locational attainments were constant across metropolitan areas, it would be a simple matter to assess the impact of group disparities on resources and social characteristics on aggregate-level segregation. The impact of group disparities would be a simple function of the magnitude of the disparities. However, if the effects of household characteristics vary between low- and high-segregation contexts, the impact of group differences on those characteristics will vary across contexts, possibly in complex and sometimes counterintuitive ways.

Thus, we anticipate the following complexities: The role of spatial assimilation for segregation may loom largest in situations where segregation and group differences are in the middle range, spatial assimilation and place stratification dynamics are both salient, and group disparities are sizeable. In contrast the role of spatial assimilation for segregation may ironically be smaller in high segregation contexts. Group differences may be larger in such cities creating the potential for important consequences for segregation. But the differences may in fact be less consequential for segregation because place stratification dynamics and other limiting factors such as those that are central to the structural sorting perspective (Krysan & Crowder, 2017) are stronger than spatial assimilation dynamics, reinforcing observed higher levels of segregation. Similarly, the role of spatial assimilation for segregation may be higher than expected in low-to-medium segregation contexts. If group differences on social and economic characteristics are in a lower range, the consequences for segregation could rival and match the consequences in medium segregation contexts where spatial assimilation dynamics are also stronger.

These theories all carry weight in understanding the many determinants of segregation, substantiated by extensive empirical research. We do not here seek to test these theories anew or challenge the claims made by any of them. Instead, we suggest that segregation research that engages with any or all of these theories can more directly test the hypotheses posited by them by adopting our methodological approach, which permits a more thorough and dynamic demographic analysis of residential segregation. Thus, throughout this chapter we highlight opportunities and possibilities for engaging with existing questions or addressing new ones using our framework, leaving the reader to think broadly about what theories, outcomes, and sources of data they can bring in.

6.4 Previous Research in Locational Attainments Analysis and Segregation

The tradition of understanding segregation through the individual locational, or residential, attainments of households and how they vary by certain sociologically meaningful characteristics such as race or income dates back to the 1980s, exemplified by the work of Douglas Massey and Brendan Mullen (1984) and Douglas Massey and Nancy Denton (1985). This type of analysis gained more popularity in the 1990s through a series of studies published by Richard Alba and John Logan (1991, 1992, 1993) and has been a mainstay of segregation research into the twenty-first century through work by Scott South and colleagues in addition to several other researchers who have developed an interest in wanting to understand segregation in an increasingly multicultural society where multivariate analyses are really needed to answer questions about where people live, who they live among, and why (South et al., 2011; Yu & Myers, 2007).

Alba and Logan's innovating 1993 article is most often cited as an exemplar of how locational attainment analyses can be linked to segregation outcomes and inform dominant theories about segregation. In their study, they used group-specific micro-models to test theories of spatial assimilation and place stratification where the outcome was a measure of racial composition which, when measured as non-Hispanic White, can indicate low or high segregation as racial residential segregation is inherently about the level of residential contact that minoritized racial groups have with the majority group. Under this approach, independent variables in the model such as income or nativity are used to assess the spatial assimilation model, where positive effects on indicators of social mobility would be interpreted as spatial assimilation. Place stratification effects are interpreted through variations in the intercepts, or the "starting points" for each group in regard to the racial composition of their neighborhoods after all effects are controlled for.

Alba and Logan's model modernized segregation analysis to situate dynamics of segregation at the level of household locational attainments and the inequalities that shape those movements. A second major contribution of their work was their inclusion of contextual effects, circumventing the limitations of public census data that we have also reviewed throughout this book to construct correlation matrices that account for cross-area variation in contexts and their correlations with individual-level characteristics. Their work began to reframe our understanding of how the two major veins of segregation research, micro-level locational attainments and aggregate-level segregation patterns, are intricately related and demonstrated an empirical approach to drawing out this link (Alba & Logan, 1991, 1992, 1993).

While these studies argue that there is evidence of spatial assimilation dynamics and that therefore segregation may decrease as minoritized groups make gains in socioeconomic status, they also often reiterate the persistent role of place stratification which complicates what would otherwise be a simple explanation for segregation. That is, segregation can never be fully eradicated if structural racism continues to be embedded in our society and shapes housing neighborhood patterns along racial lines. Studies come to this conclusion indirectly, pointing to the unexplained component of variation in their models and bolstering their argument with existing qualitative and survey evidence that housing discrimination is still occurring. It is undoubtedly true that segregation is a product of structural racism in addition to other factors that are emphasized by the spatial assimilation model or hypotheses that focus on ethnic preference. But identifying the role of structural racism in a model of segregation has been a difficult challenge.

Additionally, even if these studies restrict their conclusions to the spatial assimilation hypothesis that is directly addressed by their models, the link between the modeled neighborhood outcomes and the pattern of segregation that exists in the area in which these neighborhoods are embedded has remained elusive. For example, many locational attainment studies model neighborhood proportion White. This decision is in recognition of the location-based resources and amenities associated with predominately White neighborhoods where White residents leverage their collective power and privilege to protect opportunity and status (Logan, 1978; Trounstine, 2018). But this choice is also made because we often use neighborhood proportion White as the building block of racial residential segregation measurement. When locational attainment models are predicting neighborhood proportion White as an outcome, they are ultimately predicting the key component for measuring segregation in the area overall. This is both conceptually true and also a methodological fact, as most indices of segregation, including the ever-popular dissimilarity index, are constructed based on neighborhood proportion White and represent group differences in residential contact with White households.

Scholars who have done this work are rightly recognizing that segregation is a collective outcome of individual residential moves that are shaped by preferences, resources, and barriers, but ultimately they have been establishing only indirect links to how these individual dynamics form and transform segregation patterns overall in a given area. We contribute directly to this literature in a substantial way by taking advantage of Fossett's (2017) difference-of-means reformulations of segregation indices which permit the disaggregation of segregation indices into individual outcomes that can then be modeled using the conventional locational attainment approach. We cannot overstate how this approach draws the locational attainments and segregation literature together with a simple, quantitative link that is established using a different, but mathematically equivalent, formula for any of the widely accepted traditional measures of segregation. Thus, we spend the remainder of this chapter describing our methodological approach and presenting empirical findings from an analysis that draws on a variety of different methodological techniques to capture the complexity of residential segregation, which is in part the product of multifaceted dynamics occurring at a micro-level. One primary benefit of what we are able to find with these new methodological innovations is that we can speak directly to the prevailing theoretical frameworks in the segregation literature, as we have done in some of our recent work (Crowell & Fossett, 2018, 2020, 2022).

6.5 Data

For the analyses in this chapter we rely on the restricted-use microdata files from the 2010 decennial census and the 2012 American Community Survey (ACS) 5-year estimates, linked together by census block identifiers. While the decennial census is a full count of the U.S. population and collects basic demographic information including race, age, gender, marital status, and household structure, the American Community Survey is an annual demographic survey conducted by the U.S. Census Bureau that collects much more detailed social, economic, and demographic information on households and persons living within the household. Each annual survey collects data on approximately 1 percent of the population, and unique samples permit the data to be pooled over 5 years to create a 5 percent nationally representative sample. The benefit of using the decennial census data is to create a measure of neighborhood racial composition that is not subject to sampling error which can be modeled and aggregated to construct a measure of segregation for the community overall. A limitation of the decennial census, however, is that it collects sparse information of persons and households, so that information relevant for testing theories that focus on how group differences on social characteristics such as education and income can contribute to residential segregation is not available. The American Community Survey does include detailed information on socioeconomic indicators, military participation, nativity, language, and other characteristics that allow us to understand much about the diversity of the U.S. population. Many of the variables identified as relevant to segregation theories, particularly spatial assimilation theory, are available in the ACS. Because the ACS is also a U.S. Census Bureau product, the data can be linked to the decennial census files using geographic identifiers. Thus, the dataset is created by merging the decennial census with the ACS using census block identifiers, creating a unique dataset that relies on a sample but draws on complete census data for the dependent variable.

Using the decennial census for the construction of the dependent variable is critical, as trying to measure segregation based on sample data can introduce bias in the segregation score. Bias that is due to small population counts can be overcome by using the unbiased segregation indices that we have used throughout this book, but it is not a solution for overcoming the measurement problems that arise from sampling error. This issue is one that has begun receiving attention, particularly as interest in economic segregation continues, because household income is a variable that can only be found in the sample survey data. Napierala and Denton (2017) identified several ways in which the dissimilarity index, and implicitly other measures of segregation, can overstate levels of segregation when using the ACS or other sample-based data. They, in addition to other scholars (e.g. Wei et al., 2023), have explored ways to account for sampling error in segregation measurement, but the issue remains largely unresolved. For this reason, we bypass the issue altogether by measuring segregation, and constructing the dependent variable that comprises the components for measuring segregation, using the decennial census.

Importantly, we also clarify our reason for relying on the restricted-use microdata files of both the decennial census and the ACS. One of the major challenges in segregation research is the limited availability of detailed social and demographic data that includes neighborhood-level geographic identifiers. There is a justifiable reason for this, because the sort of detailed information on individuals and households that we may want to access to conduct locational attainment analyses could make it easy to identify individuals if the data also comes with fine-grained information about their residential location. Thus, when it comes to public-use data, researchers have a choice: access detailed information about persons or households without information on their neighborhoods, or access information on the neighborhoods where people live but with limited data on those persons or their households. The first option is available in the form of public-use microdata, which provides researchers with deidentified individual responses to the ACS and some geographic information that rarely goes below the county level. The second option comes in the form of summary tabulations, providing population estimates from cross-tabulations of two or at most three variables at a time at levels of geography that can go as low as the block group level.

The tradeoffs that must be made using public-use data have throttled any sort of large-scale attempts at detailed segregation research, especially for conducting analyses on locational attainments. Researchers can turn to other data sources, but often this means resorting to smaller samples in comparison to the American Community Survey. Fortunately, none of these less-than-ideal alternatives have to be considered if instead one can access the restricted-use microdata files for the decennial census, the ACS, and other survey data collected and distributed by the U.S. Census Bureau. With approval from relevant agencies, these data can be accessed at Federal Statistical Research Data Centers around the country and simultaneously provide the key components needed to perform the sort of analyses that we present here: detailed social and demographic information on persons and households, and information on the neighborhoods where they live. For this chapter and other studies that we have done in the past, we accessed these restricted-use files to construct the merged dataset described above. The caveat to using these data is that disclosure of results must first undergo review, so when necessary we acknowledge the information that is not provided because data and results were not approved for disclosure.

6.6 Sample

In this chapter we present results from a selection of metropolitan areas, relying on 25 of the largest metropolitan areas in the United States with some selections made based on the representation of certain minoritized racial groups. In Table 6.1 we list

Table 6.1 Group percentages by race of householder in 25 metropolitan areas, 2010

Metropolitan area	White	Black	Latino	Asian
Atlanta-Sandy Springs-Marietta	55.5	31.9	6.7	4.0
Baltimore-Towson	63.9	27.6	3.1	3.7
Boston-Cambridge-Quincy	79.6	6.1	6.8	5.3
Chicago-Joliet-Naperville	62.6	17.0	14.2	5.0
Dallas-Ft. Worth-Arlington	58.3	15.6	19.7	4.6
Denver-Aurora-Broomfield	73.7	5.4	15.9	3.0
Detroit-Warren-Livonia	70.9	22.3	2.7	2.6
Fresno	44.3	5.4	50.3	7.5
Houston-Sugarland-Baytown	47.9	17.8	27.0	5.9
Los Angeles-Long Beach-Santa Ana	42.7	8.0	32.6	14.3
Miami-Ft. Lauderdale-Pompano Beach	43.3	16.7	36.7	1.9
Minneapolis-St. Paul-Bloomington	84.6	6.4	3.4	3.9
New York City-Northern New Jersey-Long-Island	55.3	16.0	18.4	8.5
Philadelphia-Camden-Wilmington	69.2	19.7	5.6	4.0
Phoenix-Mesa-Glendale	69.2	4.6	20.4	2.8
Pittsburgh	88.8	7.9	0.9	1.5
Portland-Vancouver-Hillsboro	82.7	2.6	6.9	4.6
Riverside-San Bernardino-Ontario	48.9	7.7	35.3	5.6
Sacramento-Arden-Arcade-Roseville	64.7	7.0	14.7	9.6
San Diego-Carlsbad-San Marcos	59.9	4.9	22.9	9.2
San Francisco-Oakland-Fremont	52.5	8.7	15.1	20.2
Seattle-Tacoma-Bellevue	74.9	5.3	6.0	9.6
St. Louis	77.9	17.3	1.8	1.8
Tampa-St. Petersburg-Clearwater	74.1	9.9	12.2	2.2
Washington-Arlington-Alexandria	54.8	25.8	9.3	7.9

these 25 metropolitan areas in addition to group percentages by racial group. While in previous chapters we have emphasized an increasing need to focus on nonmetropolitan residential segregation, the data that we use in this chapter cannot sustain analysis in nonmetropolitan communities and also present issues with confidentiality disclosure that would have prevented us from being permitted to release any results from the restricted-use data environment. Each of these 25 metropolitan areas consists of four subsamples: White, Latino, Black, and Asian householders over the age of 15.

We had previously explained our justification for measuring segregation of householders and households rather than all persons, operating on the assumption that persons are more likely to change residence as a single household unit rather than experience residential mobility individually and independent of one another. Additionally, measuring segregation of persons when household size varies by race and ethnicity can create distortions in the measure of segregation because racial groups with on average larger households will register as having more residential contact with one another when in fact it is because they live in relatively larger groups together within the same household.

6.7 Analysis Design

The central analyses of this chapter are regression models of locational attainments, where we regress neighborhood proportion White on selected characteristics of the householder including income, education, citizenship, and language, which are key independent variables within the spatial assimilation framework. The dependent variable in these models is the individual-level score, or p_i, that is used to calculate the separation index. To review, the separation index (S) is a measure of evenness that can be interpreted as the average group difference in neighborhood proportion White. Using the difference-of-means approach, the separation index is calculated by assigning each household a score, p_i, which in this case is simply the household's neighborhood pairwise proportion White. The separation index is calculated by taking the difference in the average score on p_i for White households and for the other group in the analysis. Using regression, the separation index can be estimated through group-specific models that predict p_i (described more below).

The independent variables for these models are factors relevant to spatial assimilation theory, including the following:

Socioeconomic – For socioeconomic indicators, we include measures of education and income. Education is a six-category measure that ranges from "less than high school" to "graduate degree." Income is measured as household income to which we apply a natural log transformation.

Acculturation – We include several indicators of acculturation, the first of which is a combined measure of nativity and citizenship constructed with dummy variables: U.S.-born citizen, naturalized citizen, and non-citizen. We also include a binary variable for those who are recent immigrants, defined as somebody who has arrived in the U.S. in the last 15 years. Finally, we include a measure of English-language usage which is a four-category variable that ranges from "speaks English not at all" to "speaks English very well/speaks only English."

Controls – In addition to indicators of socioeconomic status and acculturation, we also include controls for age, household family structure, and military participation.

This starting point is not unlike traditional locational attainments analysis, resembling Alba and Logan's models where positive effects of variables such as income, education, or nativity on neighborhood proportion White would indicate spatial assimilation while group differences in the intercept may be interpreted as place stratification effects (Alba & Logan, 1991, 1992, 1993). We extend beyond the conventional approach, however, with innovations that are threefold. First, the dependent variable is a direct component of an overall index of segregation which allows us to essentially model segregation at a micro-level. This allows us to link theories of segregation tested in our models with levels of segregation at the aggregate-level, aligning theory with purpose.

Second, following our regression estimations, we are able to perform regression standardization and decomposition, a core method of demographic analysis, and assess the relative roles of group differences in characteristics and group differences in the rates at which they can convert those characteristics, or resources, into residential contact with White households in producing an overall level of segregation for the area. This innovation in particular gives us the ability to more directly address place stratification dynamics in segregation outcomes. Third, using standardization we are able to isolate the effect of specific variables, such as income and education, on overall levels of segregation. This allows us to engage with multiple debates about the intersecting factors that shape racial segregation outcomes, like socioeconomic status. Importantly, because we conduct these analyses by pairing (e.g. White-Black, White-Asian, White-Latino), we can also speak to how place stratification, spatial assimilation, and other perspectives vary in relevance depending on the context and characteristics of the minoritized racial group in question.

To estimate the regression models, we use fractional regression. We have used fractional regression to analyze segregation outcomes in previous chapters, but the particular qualities of this modeling technique are especially important here. Fractional regression is a nonlinear model that restricts predicted values with the boundaries of 0 and 1, inclusively. This is important for modeling most measures of segregation at the micro-level because the individual scores are often bound between 0 and 1. For example, the dependent variable for modeling the outcome relevant for constructing the separation index is pairwise proportion White in the householder's neighborhood, adjusted to remove self-contact. This variable ranges continuously from 0 to 1, which is not appropriately handled by other estimation methods, such as ordinary least squares regression and binary logit regression (Kieschnick & McCullough, 2003; Papke & Wooldridge, 1996). The appeal of fractional regression is that it constrains the predictions to a logit curve but, unlike other nonlinear approaches, permits predictions to fall on the endpoints of 0 or 1, which are substantively meaningful in our analysis as there are observed cases of households located in neighborhoods that are either entirely White or do not have any White households at all.

For each metropolitan area, we analyze White-Black, White-Asian, and White-Latino segregation. In order to conduct regression standardization and decomposition, we must estimate a separate model for each group in the pairing (e.g., one model for White householders and one model for Black householders in the analysis of White-Black segregation). Because the measurement of neighborhood proportion White is a pairwise proportion, which means that only the two groups in the pairing are included in the calculation, this outcome is measured three separate times for White householders depending on the pairing. Neighborhood proportion White will vary for White householders depending on if the other group in the analysis is Black, Asian, or Latino. Thus, in total we estimate six models for each metropolitan area, resulting in 150 models altogether. This is admittedly an unwieldy amount of regression models to present in a single chapter, so we limit our presentation of findings to summaries of trends observed across all regression models.

Following the estimation of our regression models, we apply regression standardization and decomposition analysis techniques. This approach can be conceptually understood as asking two general questions. Within each segregation analysis pairing (i.e., White-Black, White-Asian, and White-Latino) we ask: How much residential contact would the minoritized racial group have with White households if they had the same distribution of characteristics, or resources, as White households?, and How much residential contact would the minoritized racial group have with White households if they had the same rates of return as White households on their own resources? The first question is answered by standardizing predicted outcomes for each group to White characteristics, capturing the effect of group differences that is relevant to spatial assimilation theory. The second question is answered by standardizing predicted outcomes for each group to the coefficients from the model estimated for White householders, capturing the effect of disparities in the rates of return that each group receives on their own resources in the form of residential contact with White households. Disparities in rates of return can reflect many things, with the place stratification framework emphasizing discrimination while other theoretical models, such as Krysan and Crowder's structural sorting model, may emphasize the role of disparate social networks. In addition to these separate components, we calculate a "joint" component that represents the codependency of group differences in resources and rates of return. This captures the expectation that group differences in characteristics would likely change if the two groups were matched on rates of return, or vice versa.

The predicted values are generated from the estimated group-specific regression models. Residential contact with White households for the minoritized racial group standardized to White characteristics is estimated by generated predicted values for White households out of the regression model estimated for the minoritized racial group, capturing the observed distribution on the independent variables for White householders and the estimated coefficients for householders belonging to the minoritized racial group. Residential contact with White households for the minoritized racial group standardized to White rates of return is estimated by doing the opposite – we generate predicted values for householders of the minoritized racial group using the regression model estimated for White householders. We summarize this procedure using the formulas below:

$\overline{Y}_{G1_{Re}G2_{Ra}}$ = the observed mean for Group 1 (i.e., the mean of predicted values $(\widehat{y}_i)$ for White households under the attainment model for White households)

$\overline{Y}_{G2_{Re}G2_{Ra}}$ = the observed mean for Group 2 (i.e., the mean of predicted values $(\widehat{y}_i)$ for households of the minoritized racial group under the attainment model for households of the minoritized racial group).

$\overline{Y}_{G1_{Re}G2_{Ra}}$ = the mean of Group 2 standardized to the resources of Group 1 (i.e., the mean of predicted values $(\widehat{y}_i)$ for White households under the attainment model for households of the minoritized racial group)

$\overline{Y}_{G2_{Re}G1_{Ra}}$ = the mean of Group 2 standardized to the rates of return of Group 1 (i.e., the mean of predicted values $(\widehat{y}_i)$ for households of the minoritized racial group under the attainment model for White households).

Upon estimating both the unstandardized and standardized predicted values, we can proceed to the next step in the exercise, which is to decompose the observed segregation index into the contributions made by group differences in characteristics, or resources that can be converted into movement into neighborhoods with White households, and the group differences in rates of return on those resources. This is accomplished using the general formulas presented below:

$\bar{Y}_{G1_{Re}G1_{Ra}} - \bar{Y}_{G2_{Re}G2_{Ra}}$ = (S) observed overall segregation
$\bar{Y}_{G1_{Re}G2_{Ra}} - \bar{Y}_{G2_{Re}G2_{Ra}}$ = (S_{Re}) the "resources" component
$\bar{Y}_{G2_{Re}G1_{Ra}} - \bar{Y}_{G2_{Ra}G2_{Re}}$ = (S_{Ra}) the "rates" component
S – (S_{Re} + S_{Ra}) = (S_{J}) the joint impact component

This decomposition allows us to understand more about the micro-level dynamics that shape segregation and engage with prevalent theories about segregation. For example, if the "resources" component makes up the larger share of the overall segregation score, then we would attribute segregation to the group differences in resources that are relevant for having residential contact with the majority group. This conclusion would be consistent with spatial assimilation theory, which argues that segregation is due to these group differences and will diminish over time as characteristics of the minoritized racial group converge with the majority group through acculturation and social mobility. However, if the component that represents group differences in returns on those resources contributes the larger share to overall segregation between the two groups in the analysis, then we would find support for the place stratification perspective, or perhaps other unaccounted for factors that result in White households and households who belong to minoritized racial groups converting their resources into residential contact with White households at disparate rates.

6.8 Profile Standardization

One technique that we highlight in this chapter which segregation researchers may find attractive is an extension of regression standardization where, rather than standardizing predicted values on observed distributions across independent variables, the predicted values are instead standardized on specific characteristics while only a selection of variables are permitted to vary. This technique in a sense allows one to isolate the effects of a single variable or set of factors on overall levels of segregation. For example, one could generate predicted values out of the White and Black estimated models in an analysis of White-Black segregation where all of the characteristics of the White and Black householders are specified at certain values except for household income and education for Black households. The predicted values that emerge at each income level while all other characteristics are held constant can tell us what the average difference is in neighborhood proportion White between White and Black householders at various income levels for Black households that roughly represent working-, middle-, and upper-class households. These differences produce the relevant segregation index (i.e., the separation index), and allow us to model segregation by race at different income levels while holding other factors constant. In this chapter, we demonstrate this technique to analyze the separate effects of income and education on White-Black, White-Latino, and White-Asian segregation.

6.8.1 Locational Attainment Analysis of Segregation

We begin by summarizing results from the 25 metropolitan areas included in the micro-model analysis of locational attainments. Table 6.2 presents observed levels of White-Black, White-Asian, and White-Latino segregation across the 25 metropolitan areas measured by the separation index, which has been corrected for index bias. These areas represent some of the largest and most diverse metropolitan areas across the United States, making them ideal for conducting the sort of analyses that are the primary feature of this chapter, where we ask how segregation is affected by variations in group differences in resources in addition to other factors related to structural racism. Descriptive statistics of group characteristics in these areas, such as income, education, nativity, and household structure are presented in Table 6.3, but we do not review them here other than to say that in most areas the distributions look generally similar, with higher percentages of foreign-born householders in the Latino and Asian populations and varying levels of socioeconomic status that range from highest levels for White and Asian householders and lowest levels for Black and sometimes Latino householders.

We move directly to reviewing results from the micro-models of locational attainments, where we regress pairwise neighborhood proportion White on characteristics of the householder, running separate regression models for each group. For the sake of brevity, we omit the full set of 150 regression models. In Figs. 6.1, 6.2, 6.3, 6.4, 6.5, and 6.6, we summarize the estimated regression coefficients using box plots by group and pairing across the 25 metropolitan areas in the analysis, where group refers to the racial group in the analysis and pairing refers to the combination for calculating pairwise segregation scores (e.g. White-Black, White-Latino, or White-Asian).[1] The box plots allow us to assess not only trends but also variability in the estimated effects across areas. Given that each metropolitan area has unique historical trajectories and processes of attainment, there is non-trivial variation in the

[1]Each pairing consists of a model for White households, with the dependent variable calculated based on the two groups involved. This results in three predicted outcomes for White households per area, one for each pairing.

Table 6.2 Separation index for White-Black, White-Latino, and White-Asian segregation in 25 metropolitan areas, 2010

Metropolitan area	W-B	W-L	W-A
Atlanta-Sandy Springs-Marietta	52.2	28.0	19.1
Baltimore-Towson	57.7	10.4	12.9
Boston-Cambridge-Quincy	42.5	35.2	14.7
Chicago-Joliet-Naperville	69.6	36.4	16.7
Dallas-Ft. Worth-Arlington	44.7	33.6	18.3
Denver-Aurora-Broomfield	28.5	23.7	5.5
Detroit-Warren-Livonia	68.1	17.5	13.9
Fresno	30.1	31.8	17.8
Houston-Sugarland-Baytown	53.1	38.1	25.8
Los Angeles-Long Beach-Santa Ana	55.0	46.3	30.4
Miami-Ft. Lauderdale-Pompano Beach	56.8	47.0	7.8
Minneapolis-St. Paul-Bloomington	31.3	12.7	12.3
New York City-Northern New Jersey-Long Island	69.0	47.4	28.4
Philadelphia-Camden-Wilmington	59.8	35.8	15.9
Phoenix-Mesa-Glendale	15.2	30.9	6.5
Pittsburgh	46.6	1.4	12.1
Portland-Vancouver-Hillsboro	13.4	11.4	9.0
Riverside-San Bernardino-Ontario	22.6	27.5	17.4
Sacramento-Arden-Arcade-Roseville	24.8	16.3	22.3
San Diego-Carlsbad-San Marcos	25.5	31.7	23.0
San Francisco-Oakland-Fremont	42.6	27.4	26.0
Seattle-Tacoma-Bellevue	18.3	9.4	15.7
St. Louis	61.8	6.0	9.6
Tampa-St. Petersburg-Clearwater	41.4	21.2	5.4
Washington-Arlington-Alexandria	52.7	23.9	14.4

Table 6.3 Selected descriptive statistics for regression analysis in 25 metropolitan areas

Variable	White	Black	Latino	Asian
% HS diploma or equivalent	94.2%	86.5%	65.5%	89.2%
% College degree	43.1%	23.6%	16.0%	57.7%
% Military	13.7%	9.7%	4.3%	3.0%
Median household income	$71,277	$41,187	$44,421	$73,736
% U.S. citizen	97.2%	94.3%	66.0%	71.2%
% Recent immigrant*	29.9%	38.0%	33.6%	37.7%
% Speaks English fluently	97.0%	96.7%	54.5%	61.3%
Median age	52	47	42	49
% Married couple HH	52.5%	30.8%	52.0%	65.6%
% Recent mover	88.1%	84.1%	84.5%	83.5%

Note: *Denominator is immigrants to the U.S. only

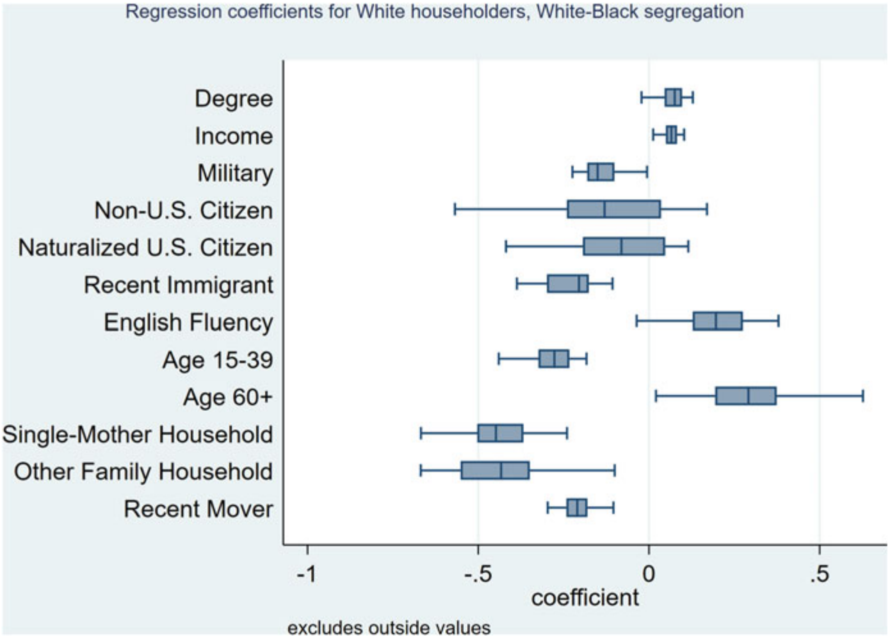

Fig. 6.1 Regression coefficients for White householders in White-Black comparison

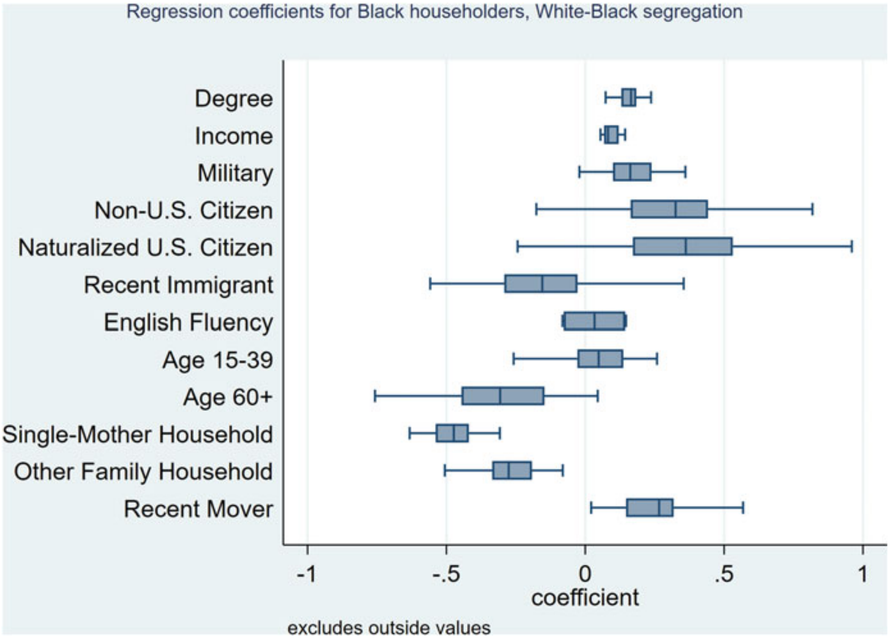

Fig. 6.2 Regression coefficients for Black householders in White-Black comparison

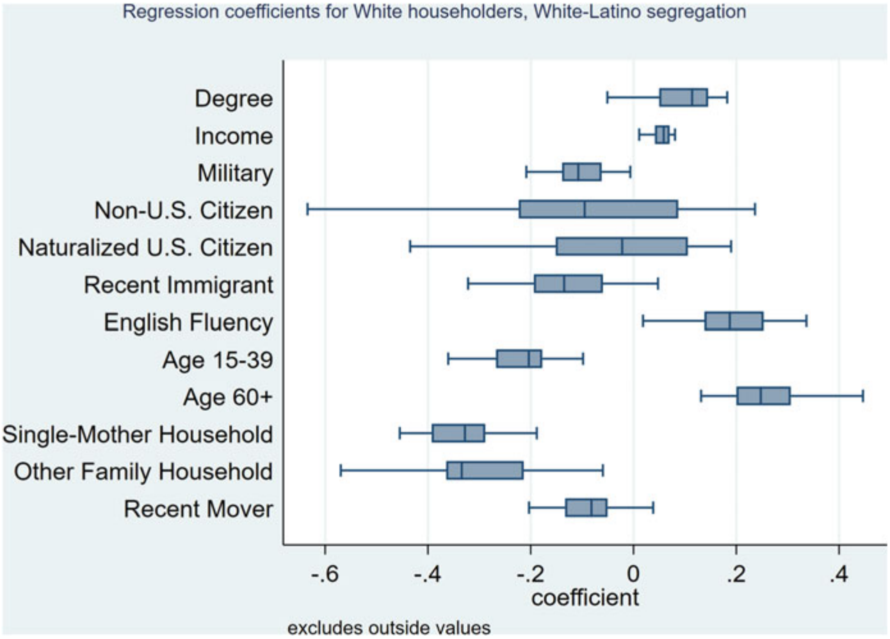

Fig. 6.3 Regression coefficients for White householders in White-Latino comparison

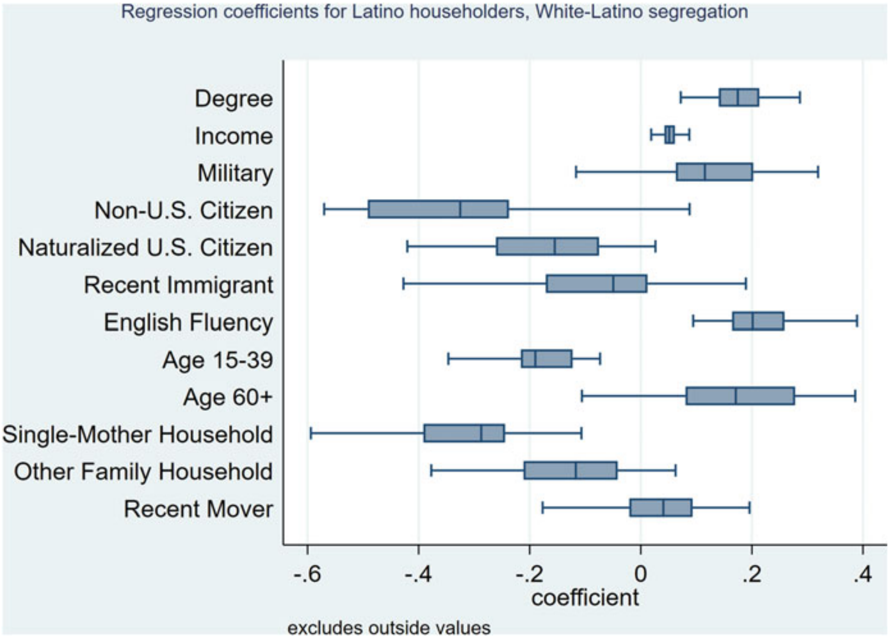

Fig. 6.4 Regression coefficients for Latino householders in White-Latino comparison

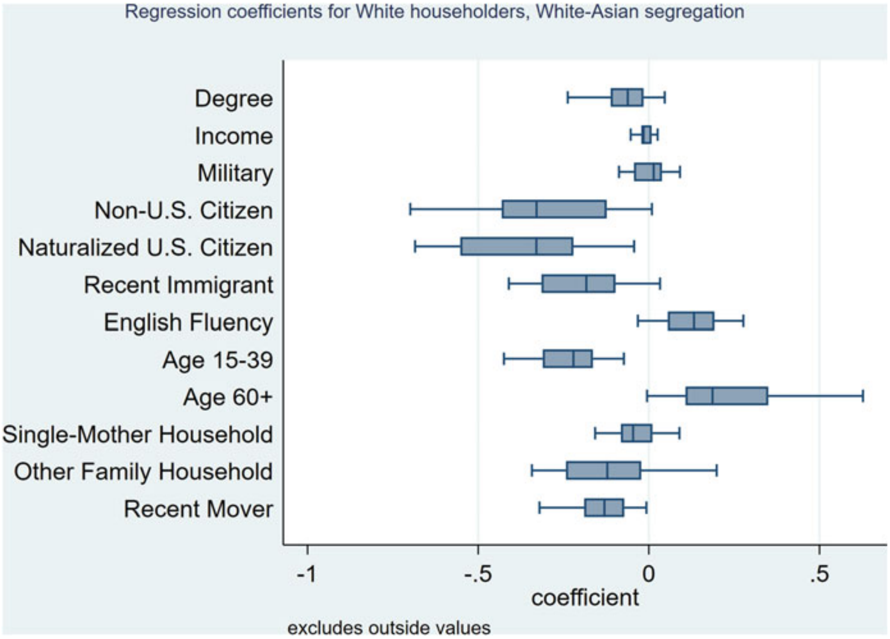

Fig. 6.5 Regression coefficients for White householders in White-Asian comparison

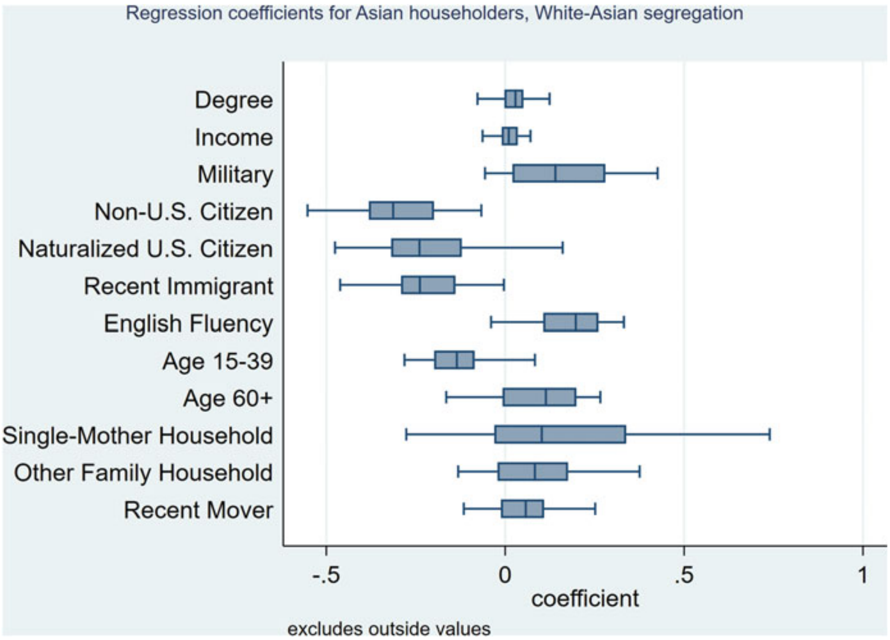

Fig. 6.6 Regression coefficients for Asian householders in White-Asian comparison

regression coefficients. For this reason, we aim to convey the typical pattern of effects found in the micro-models and limit our interpretations of these findings to the implications of the directions of the coefficients. Deeper conclusions will be drawn out from the standardization and decomposition results presented in the next tables.

The distributions of estimated coefficients in the figures document some distinct patterns aligning with the spatial assimilation hypothesis. We summarize our findings by stating that, in general, income and education are positive predictors of residential contact with White households for all groups, although these effects are very small and more mixed for Asian households. However, for Black and Latino households the effects are always positive, which means that higher incomes increase the neighborhood residential contact that Black and Latino households have with White households. From the disaggregated data we found that these positive effects of socioeconomic status were especially consistent for Black locational attainments that determine levels of White-Black segregation and were largely consistent for Latino locational attainments that determine levels of White-Latino segregation.

Also, as expected, English language ability and citizenship are typically positive predictors of residential contact with White households for Latino and Asian households, determining levels of White-Latino and White-Asian segregation. However, in the case of nativity and citizenship, these dynamics do not entirely hold true for Black households, where foreign-born Black householders generally experience greater residential contact with White households as compared to U.S.-born Black householders in nearly all of the metropolitan areas, resulting in a typical estimated coefficient that is positive for naturalized and non-citizens as compared to U.S.-born citizens. This deviation from the spatial assimilation pattern for Black households could possibly be situated in the literature on segmented assimilation which posits assimilation is not necessarily a straightforward process of upward mobility in tandem with more contact with White households, particularly for groups who experience the negative effects of racialization in the United States (Crowell & Fossett, 2020, 2022; Iceland & Scopilliti, 2008; Portes & Zhou, 1993). We conclude our discussion of the broad findings from the regression results by noting that results for White households across individual models were inconsistent and widely variable, demonstrating weaker effects that are consistent with past findings in the literature and reflecting the high levels of residential contact that White households have with one another (Pais et al., 2012; South et al., 2008).

6.9 Standardization and Decomposition Analysis

Continuing our analysis of micro-level residential segregation dynamics, we next discuss the results of performing regression standardization and decomposition analyses on the previously estimated models of locational attainments. The first step in this process is to generate predictions of neighborhood proportion White for each group in the pairing (e.g. White and Black householders in an analysis of White-Black segregation) using each group-specific model. Using the example of White-Black segregation, this produces four predictions as outlined in the methodology section above. Two predicted values represent the observed residential contact that each group has with White households, and the other two represent the predicted residential contact that the minoritized racial group would have with White households if they had the same resources or alternately the same rates of return on those resources as White householders. To put it in terms that make it clear how these predicted values are relevant for understanding the underlying factors of residential segregation, the separation index, the tool that we use to measure overall segregation, is the difference between the average residential contact that each group has with White households or, in other words, the difference between the predicted values for each group using the respective models for each group.

Using again the example of White-Black segregation, if we want to know how segregation would change if each group in the analysis were equalized on characteristics that translate into resources for locational attainment, then we would standardize predicted outcomes for each group on the characteristics of the majority group, which can be accomplished by using the model estimated for the minoritized racial group to predict values for White householders. If, however, we want to know how segregation would change if each group in the analysis were equalized on the returns that they get on their resources for locational attainment, then we would standardize predicted outcomes for each group on the rates of return, or estimated coefficients, of the majority group. This is done by generating predicted values for Black householders using the model estimated for White householders.

For each pairing, in each of the 25 metropolitan areas included in this analysis, we conducted these regression standardization exercises. It would not be feasible to present all 75 standardization results individually here, so instead we rely on summarizing the components analysis, which tells us on average the extent to which group differences in resources and group differences in returns on those resources contribute separately and jointly to the overall group difference in residential contact with White households, i.e. the separation index. In Table 6.4 we summarize these analyses by calculating the average percentage share that each component makes to the overall level of segregation measured by the separation index across all metropolitan areas by pairing. We find that for White-Latino and White-Asian segregation, the story is as complicated as past literature suggests. We find that group differences in rates of return on resources overall make the larger

Table 6.4 Summary of percentage share of each component to overall segregation, 2010

Component	White-Black	White-Latino	White-Asian
Average percentage share of resources component	9.69%	51.03%	43.84%
Average percentage share of rates component	94.69%	76.24%	76.78%
Average percentage share of joint component	−4.38%	−27.27%	−20.62%
Average level of overall segregation	43.83	26.60	16.19

contribution to White-Latino and White-Asian segregation as opposed to group differences in resources. Nonetheless, we also find that group differences in resources make sizable contributions to White-Latino and White-Asian segregation. This suggests an identifiable spatial assimilation process is at work even as place stratification is still a major factor in explaining White-Latino and White-Asian segregation. Finally, we find that the greatest moderating effect between the two components occurs with White-Latino segregation where differences in resources and in rates of return on resources interact to a greater degree in determining levels of White-Latino segregation than they do for White-Asian or White-Black segregation, highlighting the complexities underlying White-Latino segregation.

These results stand in stark contrast to White-Black segregation, where on average 94 percent of the level of segregation can be attributed to group differences in rates of return while only 10 percent on average can be attributed to group differences in resources with very little interaction between the two components. This finding suggests that even when White and Black households are matched on resources, segregation is reduced by only modest amounts because group differences in ability to convert those resources into more residential contact with White households is the dominant factor. In other words, place stratification is playing a prominent role in explaining White-Black segregation, with stronger effects than in the case of White-Latino or White-Asian segregation.

6.10 Locational Attainments Across High- and Low-Segregation Contexts

To elaborate on how locational attainment outcomes vary across communities, we summarize variations in component contributions to overall levels of segregation in a community in Table 6.5, with the metropolitan areas categorized by their level of segregation. We classify metropolitan areas using the schema laid out in Table 3.2. There is a telling pattern, which is that for all three group pairings, the contribution of group differences in rates of return to overall levels of segregation is greatest in metropolitan areas where segregation is high. In contrast, the role of group differences in resources is greatest in areas where segregation is lower. In other words, in higher segregation areas, segregation is less attributable to group differences in resources and more attributable to group differences in how those resources are converted into locational attainments. Segregation is only slightly more attributable to group differences in resources rather than rates of return in the case of White-Latino segregation in low segregation areas. Notably, for White-Black segregation group differences in rates of return is persistently and disproportionately the larger component of segregation regardless of the level of segregation in the area.

To demonstrate how segregation can be analyzed by its micro-level dynamics in specific metropolitan contexts, we highlight the Los Angeles and Portland metropolitan areas, which represent high- and low-segregation contexts, respectively. In

Table 6.5 Mean shares of resources and rates components by overall level of segregation and group pairing

	Low segregation	Medium segregation	High segregation	Very high segregation
White-Black				
% Resources	18.56%	14.78%	7.97%	7.82%
% Rates	94.69%	91.42%	95.44%	97.65%
% Joint Effect	−13.25%	−6.20%	−3.40%	−5.47%
White-Latino				
% Resources	72.89%	49.85%	37.24%	–
% Rates	72.52%	75.76%	81.28%	–
% Joint Effect	−45.41%	−25.62%	−18.51%	–
White-Asian				
% Resources	51.40%	37.91%	–	–
% Rates	74.38%	79.78%	–	–
% Joint effect	−25.78%	−17.69%	–	–

Table 6.6 Components analysis for segregation in Los Angeles and Portland, 2010

	Los Angeles			Portland		
Component	W-B	W-L	W-A	W-B	W-L	W-A
Resources	5.83	18.70	9.19	3.77	7.21	6.37
Rates	53.56	40.06	29.94	16.49	5.72	11.41
Joint	−4.38	−12.41	−8.74	−2.00	−3.50	−2.10
Dissimilarity	55.01	46.35	30.39	18.26	9.43	15.68

any given metropolitan context, regression standardization and components analysis can reveal the extent to which segregation is determined by place stratification dynamics, spatial assimilation dynamics, or both interactively. We present these results in Table 6.6. In the Los Angeles metropolitan area, regardless of the group comparison, group differences in rates of return on resources make the largest contribution to overall segregation. To clarify, in Los Angeles, place stratification plays a larger role in segregation patterns while group differences in resources make a smaller contribution. Thus, even when groups are matched on resources such as income or citizenship, they remain at least moderately segregated in Los Angeles due to place stratification factors. However, we find that for White-Latino and White-Asian segregation, there is a larger joint component, suggesting that the separate roles of place stratification and spatial assimilation covary to a greater extent for these comparisons.

Results for Portland differ in a variety of ways that reflect the need to consider the segregation context. While the contribution of group differences in rates of return to segregation is nontrivial for White-Latino and White-Asian segregation, it is now more on par with the contribution made by group differences in resources. In fact, for White-Latino segregation group differences in resources make the larger contribution. This implies that much of White-Latino and White-Asian segregation in Portland can be explained by group differences in social characteristics. However, for Black households the results remain the same as they do in many other metropolitan areas. Differences in rates of return between White and Black households are the larger determining factor in explaining segregation. Even in a low-segregation context, equalizing on resources does not drastically reduce levels of White-Black segregation because of stronger place stratification dynamics.

6.11 Estimating Segregation by Socioeconomic Status with Standardization Analysis

A benefit of micro-modeling residential segregation is that standardization techniques can be applied to not only decompose an overall segregation score but also to generate different predicted segregation outcomes based on standardizing samples on selected characteristics relevant to theories of locational attainments like income, education, nativity, and language. This can be done by holding each sample in the pairwise analysis constant on some characteristics to create a "profile" and altering one or two characteristics to generate different predicted group outcomes on neighborhood proportion White from the estimated regression models that can be used to calculate segregation scores. These scores will represent estimated levels of segregation when the two groups in the analysis are matched on all characteristics except for the characteristics of interest. This exercise allows us to see the effect of a single factor on segregation outcomes by comparing how the segregation score changes when the isolated characteristic is modified. We have previously conducted this exercise to estimate the effects of citizenship and nativity on White-Black, White-Latino, and White-Asian segregation (Crowell & Fossett, 2022) and found that segregation was lower for White-Latino and White-Asian segregation when the minoritized racial group was set to be U.S.-born versus foreign-born and that segregation was generally higher for recent immigrants and non-citizens. We found the opposite for White-Black segregation, with Black immigrant households having lower levels of segregation from White households than U.S-born Black households (Crowell & Fossett, 2022).

In this section we will use standardization to analyze the effects of education and income on White-Black, White-Latino, and White-Asian segregation, using predicted values from the regression models to compare segregation for each group comparison across different levels of education and income. For this exercise, White householders are held constant at the following profile: U.S-born, speaks English only or very well, high school education, median income of a White householder with a high school education, living in a married couple household, not a military veteran, not a recent migrant, and aged 30–59. Black, Latino, and

Table 6.7 Average predicted levels of net segregation from U.S.-born White households by education and income*

		Net segregation			
Group	Overall	Very low SES	Low SES	Middle SES	High SES
Black	43.8	48.4	43.8	35.3	34.3
Latino	26.6	22.8	18.6	11.6	11.1
Asian	16.2	12.3	11.6	10.6	10.5

*In the difference of means formulation, "overall" segregation is the majority-minority difference of means in attaining parity-level contact with White households. "Net" segregation is the expected majority-minority difference on predicted parity-level contact with White households based on a specified set of social characteristics

Asian householders are held at all of the same characteristics except for education and income. Education and income are variably set at the following values: no high school education with a household income of $15,000, high school education with a household income of $30,000, bachelor's degree with a household income of $60,000, and bachelor's degree with a household income of $100,000. We will use these values on the independent variables to generate group-specific predicted values on neighborhood proportion White that can be used to calculate the separation index by taking the difference between the predicted mean outcome for White householders at a set profile and the predicted mean outcomes for Black, Latino, and Asian households at different levels of education and income.

We begin this analysis by summarizing average levels of segregation by pairing at different levels of education and income for the minoritized racial group in Table 6.7. First, we find that average levels of White-Black segregation are somewhat reduced as Black education and income are increased, but White-Black segregation is predicted to remain at medium levels even at high socioeconomic status levels for Black households. This is consistent with our finding from the components analysis, which is that group differences on resources contribute very little to overall levels of White-Black segregation. White-Latino segregation begins at lower levels than White-Black segregation when the scores are standardized to very low socioeconomic status for Latino households and is reduced to an average low score at high socioeconomic status for Latino households. While the absolute point reduction is nearly the same as it is for White-Black segregation, the relative reduction is larger for White-Latino segregation with the predicted average score dropping from medium to low levels with increased socioeconomic status for Latino households. Finally, we observe a more mixed pattern for White-Asian segregation that indicates weak effects of Asian education and income on the predicted segregation score. This is not surprising given we observed negligible education and income effects across all areas for Asian households in our locational attainments analysis.

Because we know from our review of the estimated regression coefficients that there is some variability in the effects of education and income across areas, we also chart predicted levels of segregation by metropolitan area. In Figs. 6.7, 6.8, and 6.9, we graph the predicted levels of White-Black, White-Latino, and White-Asian

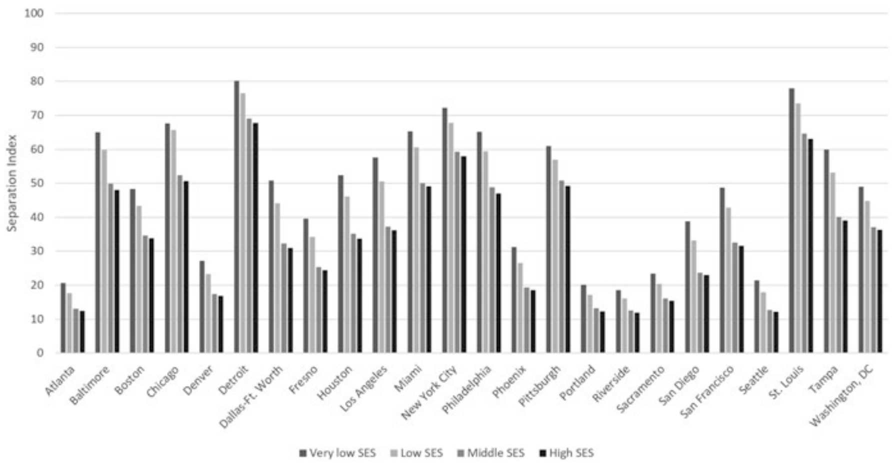

Fig. 6.7 White-Black segregation by Black socioeconomic, 25 US Metropolitan Areas

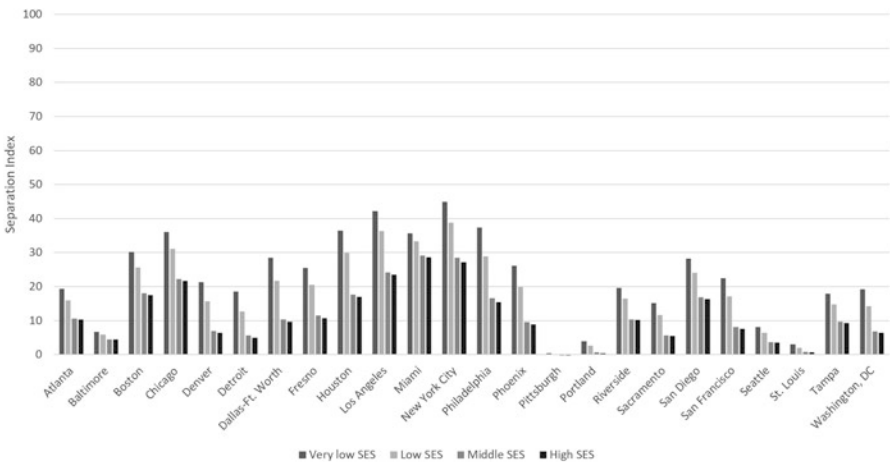

Fig. 6.8 White-Latino segregation by Latino socioeconomic status, 25 US Metropolitan Areas

segregation when White householders are standardized to the profile described above and the householders belonging to the minoritized racial group in the analysis are standardized to the profiles described above at varying levels of education and income. Across all group comparisons, it is clear that White-Black segregation remains at the highest levels even when Black households have high socioeconomic status (and White households are not set at high socioeconomic status) and are matched with White households on all other characteristics. Education and income have consistently positive effects on Black residential contact with White households, which reduces segregation as Black education and income increase. In some cases, this can result in relatively low levels of segregation, with the separation index

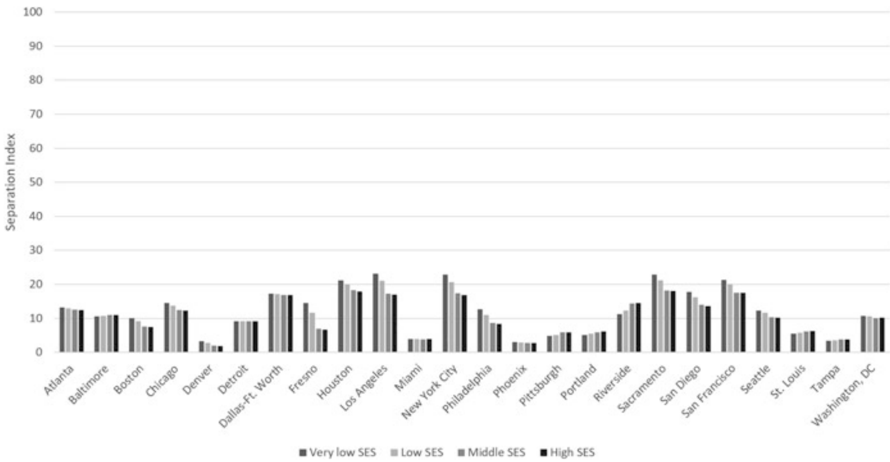

Fig. 6.9 White-Asian segregation by Asian socioeconomic status, 25 US Metropolitan Areas

score predicted to be between 11 and 13 in Atlanta, Portland, Riverside, and Seattle at the highest socioeconomic levels for Black households. But in many other metropolitan areas, White-Black segregation is predicted to remain high even at the highest levels of Black socioeconomic status, with separation index scores over 50 in Chicago, Detroit, New York City, and St. Louis.

The patterns are similar for White-Latino segregation but at much lower levels of overall segregation, with increasing education and income for Latino households resulting in increased residential contact with White households, which leads to lower predicted levels of segregation. White-Latino segregation is almost always at low to medium levels in these metropolitan areas with the exception of New York City and Los Angeles, which both begin with separation index scores over 40 at the lowest levels of socioeconomic status for Latino households. In some cases, increasing Latino socioeconomic status while also matching Latino and White households on other characteristics practically eliminates predicted levels of White-Latino segregation, which can be seen in Pittsburgh, Portland, and St. Louis. In other metropolitan areas, some level of segregation is predicted to occur at the highest levels of Latino socioeconomic status, but the scores are often below 20 and in many cases below 10. The decomposition analysis conducted previously reflects these results, with group differences in resources having more of an impact on overall levels of White-Latino segregation as compared to White-Black segregation, while group differences in rates of return on those resources remains non-trivial.

Finally, we find that there is little comment to offer on the effects of socioeconomic status on White-Asian segregation. First, White-Asian segregation is almost always very low and only just reaches medium levels in a small handful of cities including Houston, New York City, Sacramento, and San Francisco. Second, the effect of socioeconomic status is negligible and in many metropolitan areas non-significant. Changing Asian levels of education and income while holding all other variables constant at specific values, which includes being U.S.-born and English-fluent, does little to change what are already low levels of White-Asian segregation. However, where these factors do have a notable impact, it is in the predictable direction of spatial assimilation with White-Asian segregation reducing as Asian education and income increases. This can be observed in Chicago, Fresno, Houston, Los Angeles, New York City, Philadelphia, Sacramento, San Diego, San Francisco, and Seattle. What may complicate our findings in some of these cities is the ethnic diversity of the Asian population, with "Asian" being a broad panethnic label that can include ethnic groups with distinctly different experiences by immigration, reception, economic opportunity, and culture.

What we demonstrate with this exercise is a new way to explore questions about the intersecting factors that shape racial residential segregation outcomes and further develop the conversation about the dual and interacting roles that race and socioeconomic status are playing in shaping these patterns. This analysis extends beyond what has been done because we can now model household-level effects that shape overall patterns of segregation, including the effects of income and education, in a way that directly links to segregation measurement and permits the use of regression standardization analysis. Until this point, the two dominant methods for modeling the effects of income or education on racial residential segregation were to perform a locational attainments analysis with no way to link predicted outcomes to an overall measure of segregation, or to model aggregate-level effects on segregation scores with some measure of income inequality that introduces the chance of committing an ecological fallacy by failing to recognize that segregation is also a measure of group inequality (Fossett, 1988, 2017). This approach, by contrast, overcomes both limitations and allows for a more detailed analysis of the locational attainment processes that shape segregation patterns.

6.12 Summary

In this chapter, we demonstrated entirely new methods for segregation research that are based on the innovations made by Fossett (2017) which in previous chapters allowed us to refine our measurements of segregation across different groups and area types. The difference-of-means formula for segregation measurement, which can be applied to any of the more popularly used measures of segregation, reconceptualizes segregation as an inequality of individual locational outcomes. With the starting point for segregation measurement being an individual score for a household, we can establish a direct link between the tradition of locational attainments analysis and the tradition of aggregate-level segregation analysis and develop more complex research designs for understanding the micro-level factors that affect household-level locational outcomes and overall segregation patterns.

Our findings in this chapter detail the complexities of locational attainment processes that underlie segregation patterns and demand a more dynamic analytical framework. For Latino and Asian households, spatial assimilation dynamics are consistently evident, but place stratification dynamics often predominate. For Black households, the story is straightforward in some ways and not in others. In general, group differences in resources are less important to White-Black segregation, as Black locational attainments more strongly reflect place stratification effects. We also find that the classical spatial assimilation model is less applicable to understanding Black segregation, as nativity works in the opposite direction for Black households in comparison with Latino and Asian households, consistent with our past research and suggesting a pattern of segmented assimilation (Crowell & Fossett, 2020, 2022). While a deeper analysis of Black immigrant segregation is beyond the scope of this analysis, other research has offered further insight into variation in Black immigrant segregation patterns (Scopilliti & Iceland, 2008; Tesfai, 2019).

Standardization and decomposition analysis strengthens our argument that the role of race as employed by place stratification and segmented assimilation is prominent throughout, but more consistently and to a greater quantitative degree for Black households. This puts the historically rooted barriers to residential integration for Black households into sharp relief and speaks to the apparent fact that Black families in the United States encounter a far more entrenched system of segregation and oppression than other groups, while Latino and Asian households experience weaker place stratification barriers. For Black families, social disadvantages that are intrinsically linked with segregation are far more difficult to overcome and, according to Sharkey (2013), are likely inherited in a way that is parallel to how social advantages are inherited in White families.

High-segregation areas have patterns of segregation that are more resistant to any advances made by minoritized racial groups on various aspects of social status and there is likely a feedback loop, where segregation enables neighborhood disadvantage which then makes it more difficult for racially minoritized groups to achieve and maintain those social advancements (Sharkey, 2013). Segregation in these high-segregation contexts can also be reinforced through structural sorting dynamics, as theorized by Krysan and Crowder (2017). These dynamics are shaped by information networks, where locational attainments are affected by the information that households have about other neighborhoods in the area. In a highly segregated metropolitan area, groups may have knowledge about neighborhoods that is more limited by the social networks and neighborhoods that they regularly access, a manifestation of stratification which creates the structural sorting process that Krysan and Crowder (2017) describe.

A technical note to the reader about data is warranted here, because these analyses were also possible due to our ability to access the restricted-use census microdata that is only available in Federal Statistical Research Data Centers (RDCs). The barrier for access to these data is high, which may discourage researchers from adopting our approach. But we encourage researchers who may not have access to an RDC to seek out other sources of household survey data where neighborhood geography (e.g. blocks, tracts, etc.) is available which can be linked to public-use decennial census summary files. The decennial census summary files can be used to calculate neighborhood racial composition necessary for constructing the segregation index while avoiding the pitfalls of measuring segregation with sample-based estimates (Napierala & Denton, 2017), while the survey data can provide the covariates for conducting locational attainment analyses. This approach will appropriately situate segregation as a stratification outcome driven by micro-level dynamics while establishing continuity with those locational attainment analyses in the existing literature that stopped short of drawing a direct link to overall segregation outcomes.

To conclude this chapter, these findings highlight the complex nature of residential segregation in metropolitan settings in the U.S. and demonstrate the competing roles of locational attainments that reflect group differences but are also hindered by place stratification barriers. With this analysis we are able to explore new ways of understanding these complexities using innovative methodologies for identifying and explaining the micro-level factors that shape segregation patterns and how these relationships vary in different segregation contexts. We can draw the conclusion that equalizing group differences on relevant social resources does not have a uniform effect on segregation across groups or areas and the effect is markedly lower when segregation is high, reflecting the ability of residential segregation to persist once it is firmly in place. Moreover, the analyses presented in this final empirical chapter demonstrate the possibilities for segregation research when segregation is understood as a group inequality, which can be operationalized using the difference-of-means approach to measuring segregation given by Fossett (2017) and applied throughout this book. With this final empirical chapter, we show the culmination of the various methodological advancements in segregation measurement and analysis that we promote throughout this book. Understanding and measuring segregation as an aggregation of individual-level outcomes makes it possible to correct for index bias and analyze segregation as an outcome shaped by micro-level phenomena. In the concluding chapter of this book, we review these contributions and others that should influence the way researchers measure and analyze residential segregation.

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