Race and neighborhoods in the 21st century: What does segregation mean today?

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Abstract: Noting the decline in segregation between blacks and whites over the past several decades, some recent work argues that racial segregation is no longer a concern in the 21st century. In response, this paper revisits some of the concerns that John Quigley raised about racial segregation and neighborhoods to assess their relevance today. We note that while segregation levels between blacks and whites have certainly declined, they remain quite high; Hispanic and Asian segregation have meanwhile remained unchanged. Further, our analysis shows that the neighborhood environments of minorities continue to be highly unequal to those enjoyed by whites. Blacks and Hispanics continue to live among more disadvantaged neighbors, to have access to lower performing schools, and to be exposed to more violent crime. Further, these differences are amplified in more segregated metropolitan areas.

Key words: racial segregation, neighborhoods
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1. Introduction

The issue of race was central to John Quigley's work. He studied racial discrimination in housing markets as well as the potentially harmful consequences of racially segregated neighborhoods—from their centralized location in urban areas far from expanding employment opportunities to their relatively thin job networks, high cost housing and limited neighborhood amenities. Some recent work suggests that racial segregation is a thing of the past, and certainly much has changed since Quigley's early work. In this paper we revisit some of the concerns that Quigley raised about racial segregation and neighborhoods and examine their relevance today.

2. Background

Segregation across neighborhoods need not necessarily be troubling. If caused by different groups affirmatively choosing to live in different neighborhoods, with no broader negative consequences, then there might be little reason for concern. But surely segregation is troubling if it is caused by discrimination, or the actions of sellers, landlords, realtors, and lenders to restrict the choices of minority households and keep them out of white neighborhoods. Kain and Quigley (1970) provided some of the first rigorous evidence of such discrimination, demonstrating that black households paid a large premium for housing in the 'ghetto,' as lack of access to other neighborhoods inflated demand within minority neighborhoods.

Other research confirms that private housing market discrimination played a significant role in constraining the mobility of black households prior to the passage of the Fair Housing Act (Massey and Denton, 1993). Government policies were clearly discriminatory too; public housing developments were explicitly segregated by race and the Federal Housing Administration issued guidelines recommending that underwriters avoid integrated areas.

As for today, the most recent national audit study of paired testers (conducted in 2012) revealed that the blatant, overt discriminatory practices that were pervasive in housing markets in the 1950s and 1960s have dwindled.[1] Yet, the study also found that other, more subtle forms of discrimination persist, such as providing information about fewer units (Turner, Santos, Levy, Wissoker, Aranda, and Pitingolo, 2013).

While the audit studies provide the most direct evidence of shifts in the prevalence of discriminatory practices, other studies provide insights, too. For example, following Kain and Quigley (1970), Cutler, Glaeser, and Vigdor (1999) analyzed racial differentials in house prices to examine shifts over time in the roots of segregation. In brief, they argued that if discriminatory barriers were a significant cause of segregation, blacks would have to pay more for housing than whites in more segregated cities. If whites paid more for housing, by contrast, it would suggest that segregation was largely due to white preferences for largely white neighborhoods. Using this price differential approach, the authors concluded that segregation was due largely to housing market

[1] The four national audit studies conducted by the Urban Institute provide the best evidence on the prevalence of discriminatory practices. Of course, the audit studies do have limitations. Audit studies typically focus on the initial encounter between a household and an agent; they do not analyze discrimination that might occur later in the transaction (Turner, Ross, Galster, and Yinger, 2002).

discrimination in 1940, but by 1990, the decisions of individual white households to avoid black neighborhoods had become the dominant cause.

Together, these studies suggest that the discriminatory barriers limiting minority households moves into predominantly white neighborhoods have fallen to some degree. As Quigley and Raphael (2008) put it, a 'cocktail of factors' likely contribute to racial segregation today, such as racial differences in income and wealth, differences in information and search patterns, and preferences for racial composition.

Most of the studies exploring the role of income differences in driving segregation have concluded that they explain only a small portion of segregation (Farley, 1986, Kain, 1986, Gabriel and Rosenthal, 1989, Miller and Quigley, 1990, Harsman and Quigley, 1995, Ihlanfeldt and Scafidi, 2002). Bayer, McMillan, and Rueben (2004) considered a broader set of sociodemographic factors and found that they play a somewhat larger role in explaining segregation, at least in the Bay Area. Their results suggest that income, education, occupation and household composition together explained 20 percent of black segregation. But their results may be somewhat unique to the Bay Area, which enjoys only modest levels of segregation. Recent work by Jargowsky (2013) suggests that income continues to explain little of white-black segregation nationally.

Racial differences in preferences for racial composition surely play some role in sustaining segregation. Surveys of racial preferences provide little evidence of desires for self-segregation on the part of blacks (Farley, Steeh, Jackson, Krysan, and Reeves, 1993, Bobo and Zubrinsky, 1996, Charles, 2000). These same studies suggest that residential preferences of white households are far stronger and may play a more significant role in sustaining segregation. Such preferences may not always be a function of simple racial prejudice, however. Ellen (2000) argued that much of current white-black segregation is caused by the ongoing refusal of whites to move into integrated and largely-black neighborhoods, due to race-based stereotypes they hold about the quality of life in these communities.

There is far less research examining the mix of factors that drive the segregation of Asian and Hispanic households. However, the evidence that exists suggests that as compared to the drivers of white-black segregation, white avoidance generally plays a lesser role, while income differences and preferences for clustering with those who share the same language and customs appear to play a larger role (see Ellen, 2008). For example, Bayer, McMillan, and Rueben (2004) reported that sociodemographic factors collectively explained over 60 percent of the segregation of Hispanics in the San Francisco metropolitan area, as compared to just 20 percent of black segregation. Similarly, modeling differences in neighborhood choices on a national level, Quillian (2013) found that differences in observable characteristics can explain most of the spatial segregation between Hispanics and whites, but little of that between blacks and whites.

Whether driven primarily by explicit discrimination or propelled by these other, less troubling factors, segregation can still have serious consequences for minorities, in large part because it leads to the creation of separate and highly unequal communities. In their joint review of the literature that has grown out of the Moving to Opportunity (MTO) Program, Quigley and Raphael (2008) write

> "Despite the substantial decline in the degree of racial segregation in the U.S. housing

market reported in the 2000 census, most African Americans still reside in communities that are geographically separate from those of white Americans. Continued racial disparities in income, education, and employment mean that housing segregation is accompanied by the concentration of poverty and high rates of joblessness in predominantly black neighborhoods."

There is considerable empirical work demonstrating the differences in disadvantage level in minority and white neighborhoods. Most of this work has focused on the neighborhood environments faced by blacks and whites and most of it relies exclusively on measures captured by the decennial census. Massey and Denton (1993), for example, demonstrated that even affluent minorities have been found to live in communities with higher poverty rates, lower educational attainment, and higher shares of single-parent families. Quillian (2003) and Sharkey (2008) later emphasized that point-in-time measures actually understate racial differences in neighborhood disadvantage levels, as residential mobility patterns tend to compound disparities. (Black households are not only more likely to live in high poverty neighborhoods at a given point in time, but they are also much less likely to leave such neighborhoods and more likely to re-enter them if they leave.)

While the full consequences of such neighborhood conditions continue to be debated, the latest evidence from the MTO Program, together with myriad non-experimental studies, suggests that neighborhood disadvantage matters, though perhaps not in the ways that John Kain, John Quigley and other urban economists originally suspected (Ludwig, Sanbonmatsu, Gennetian, Adam, Duncan, Katz, Kessler, Kling, Lindau, Whitaker, and McDade, 2011, Burdick-Will, Ludwig, Raudenbush, Sampson, Sanbonmatsu, and Sharkey, 2011). Unfortunately, existing studies do little to help us get inside the 'black box' of neighborhood disadvantage. Socioeconomic status may matter in itself or it may instead be a proxy for the quality of neighborhood services and conditions.

There is relatively little research examining such potential disparities in these types of features across neighborhoods, in part because of the difficulty of obtaining nationally-consistent data. The research that does exist tends to show that minority households live in less accessible and lower amenity neighborhoods. Consider access to employment. John Kain (1968) first pointed to the disparities in job access between white and minority communities. Later studies confirmed this same pattern, consistently showing that black workers lived further from growing job opportunities than white workers (Raphael, 1998, Raphael and Stoll, 2002). O'Regan and Quigley (1996, 1998) highlighted not only racial disparities in physical access to jobs but also access to social networks that could connect workers to jobs. As for crime, Peterson and Krivo (2010) collected neighborhood-level crime data for 91 cities around the year 2000 and showed that largely black and largely Hispanic neighborhoods had significantly higher rates of violent crime on average than largely white areas.

Our work re-visits the nature of differences in neighborhood environments experienced by minority and white households. We extend prior work by using more recent data, considering three different minority groups (blacks, Hispanics, and Asians), analyzing neighborhood attributes rarely examined, and exploring whether disparities in exposure to neighborhood conditions within a metropolitan area vary with the level of segregation.

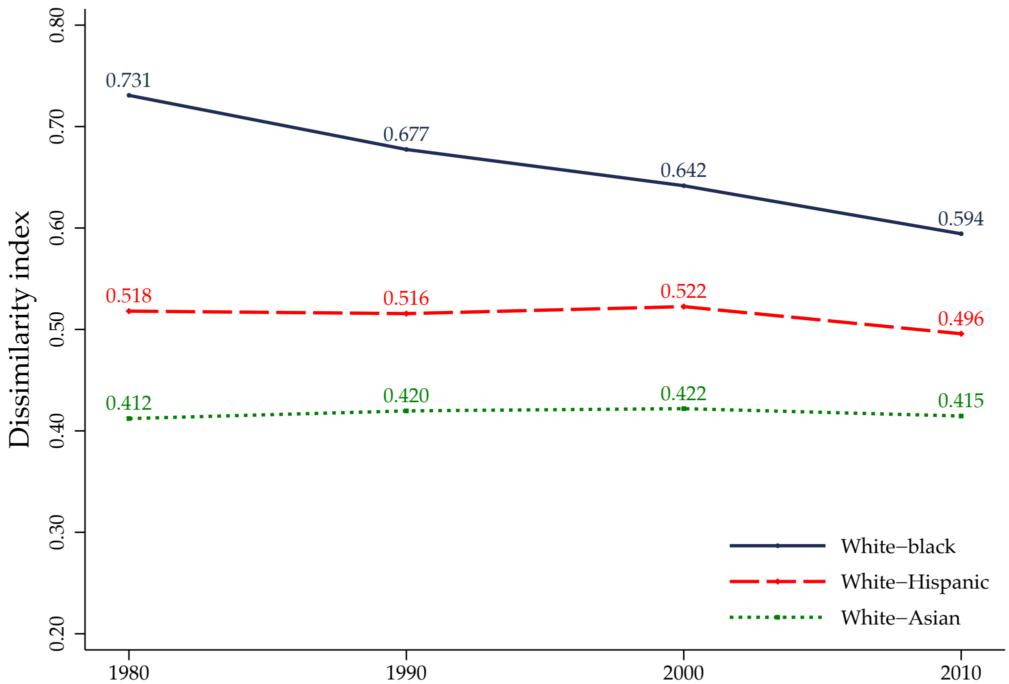

Figure 1: Metropolitan dissimilarity index 1980–2010

3. How segregated are we?

Glaeser and Vigdor (2012) provocatively titled their most recent paper on segregation, 'The End of the Segregated Century,' implying that we no longer have to worry about segregation in the United States. To be sure, the world has changed since 1970 when John Quigley first started studying the issue. Figure 1 draws on data from US2010[2], a joint project between the Russell Sage Foundation and Brown University, to show segregation levels in United States metropolitan areas from 1980 to 2010.[3] Figure 1 uses the dissimilarity index, the most common measure of segregation, to capture segregation. While flawed, the dissimilarly index is very easy to interpret; it varies from 0 to 1 and represents the share of one group that would need to move in order for the spatial distribution of both groups to be the same.[4]

Focusing first on white-black segregation, which has been a primary focus of much of the literature, we see it steadily declined from 1980 to 2010 (consistent with Glaeser and Vigdor, 2012).[5]

[2]See `http://www.s4.brown.edu/us2010/About/History.htm` and Logan and Stults (2011).

[3]1980 is the earliest year for which we can get highly consistent race and ethnicity definitions. We count any individual who self-identifies as Hispanic as Hispanic regardless of her response to the question on race. Next, we treat an individual as non-Hispanic black if she self-identifies as black and any other race; and as non-Hispanic Asian if she describes herself as Asian and any other race except black. Further, whites are non-Hispanic whites who do not report any other race. For ease of presentation, we use the term 'race' to capture both race and ethnicity.

[4]See White (1987) for an overview of measures.

[5]We weigh the dissimilarity index in each metropolitan area by the number of minority residents. As a result, the black-white dissimilarity index shows the level of segregation faced by the average black in a metropolitan area.

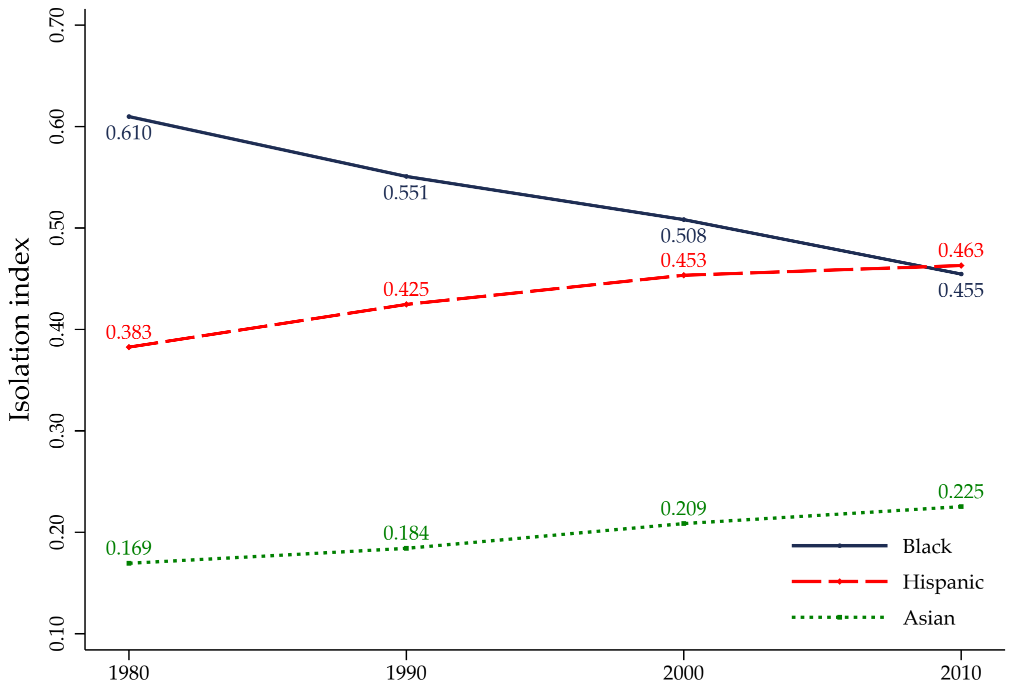

Figure 2: Metropolitan isolation index 1980–2010

At 0.59, however, white-black segregation remains quite high. Further, the steady decline in segregation observed for blacks was not seen for other minority groups. White-Hispanic segregation has shown only a slight drop and only in the most recent decade, while white-Asian segregation has been fairly constant over this 30-year period. Further, figure 2, which uses the isolation index to capture segregation levels, shows that it matters how we measure segregation. The isolation index measures the extent to which members of a given group live in neighborhoods with others from their same group, which is driven both by unevenness in the spatial distribution of a group and its size. Specifically, it captures, for the typical member of a racial or ethnic group, the proportion of her neighborhood's population that belongs to her same group. By this measure, Hispanics and Asians have actually grown steadily more isolated since 1980, although isolation remains much lower among Asians given that they make up a much smaller share of the population than Hispanics and blacks.

These figures show clearly that by focusing solely on white-black segregation, as much of the literature has done, mischaracterizes the broader trends in segregation. While it might have been reasonable to focus on the residential patterns of whites and blacks in 1980, by 2010, Hispanics had become the largest ethnic minority group in the U.S., representing 16 percent of the overall population, as compared to 12 percent for blacks and roughly 5 percent for Asians. A distinguishing feature of our paper is that we focus on segregation for this broader set of minority groups, and test all of our results with an alternative measure of segregation.

4. Data and empirical approach

We rely on a variety of different data sources to capture neighborhood conditions and environment. We use census tracts throughout to proxy for neighborhoods. Census tracts include an average of approximately 4,000 people, with most tracts including between 2,000 and 7,000 people. We omit any census tract with fewer than 100 residents or with a majority of residents living in group quarters, and we limit our analysis to census tracts located in metropolitan areas, which we define using core-based statistical areas (CBSAs).[6]

Our first set of neighborhood measures, capturing the socioeconomic status of residents, is drawn from census data. To avoid capturing changes driven by census tract definitions, we first rely on the longitudinal file of the Neighborhood Change Database (NCDB) developed by GeoLytics and the Urban Institute, which provides fixed-boundary census tracts for all metropolitan areas in the country. In particular, 1980 and 1990 decennial census data are remapped to 2000 census tract boundaries. Subsequently, we crosswalk these data to 2010 census tract boundaries and combine them with 2010 census data from the Longitudinal Tract Data Base (LTDB).[7] Using these data, we can revisit the neighborhood attributes typically examined in past studies, such as poverty rates and educational attainment, and examine whether the composition of residents in neighborhoods lived in by different groups changes from 1980 to 2010.

In addition to these census measures, we consider two key neighborhood attributes often noted as important by researchers but rarely examined due to data limitations: the performance of nearby elementary schools and safety levels. We can only examine these two important attributes through single cross-sections, and in the case of crime, we are restricted to the 91 central cities where neighborhood crime rates are available.

We rely on two data sources for schools. Data from the Department of Education (DOE) report the proficiency rates in math and English for students in all public schools in the country for the 2008–2009 school year, and data from the Common Core of Data (a product of the DOE's National Center for Education Statistics) provide the share of students who are eligible for free and reduced-price lunch as well as the location of each elementary school. Although we do not have actual school attendance zones for every school district in the country, we use GIS to match each census block group in the country to the public elementary school in its district that is nearest to its centroid. It is of course possible that some students residing in a block group are not zoned for the school nearest to the block group's centroid. But the analysis in Ellen and Horn (2011) suggests that the nearest school is also the zoned school in the overwhelming majority of cases.[8]

[6] Core Based Statistical Areas (CBSA) are defined by the Office of Management and Budget. In particular, we focus on the 363 Metropolitan Statistical Areas which have an urban core population of at least 50,000 and exclude Micropolitan Statistical Areas. These CBSA metro areas have replaced metropolitan areas defined based on the 1990 census. We use the terms MSA and metropolitan area interchangeably throughout the paper.

[7] The most recent version of the LTDB provides information on the 2010 census and the American Community Survey 2006-2010. While the 2010 census provides point-in-time estimates of population counts and basic characteristics, the ACS 2006–2010 provides period estimates of demographic, housing and economic characteristics for very small populations like census tracts. See appendix A for further details on the crosswalk process between NCDB and LTDB.

[8] When mapping schools to larger geographic units, census tract centroids in New York City, Ellen and Horn (2011) found that approximately 74 percent of households were correctly matched to their zoned schools. In smaller school districts (many of which have only one or a few elementary schools), and relying on block groups, the nearest school within the school district is even more likely to be the zoned school.

We then aggregate this block-group-level data set up to the census tract by calculating a weighted average of the characteristics of the elementary schools nearest to each of the constituent block groups within a census tract.

For crime, we use data from the National Neighborhood Crime Study, a nationally representative sample of crime data for 9,583 census tracts in 91 U.S. cities, collected by Peterson and Krivo (2000). Local police departments provided crime counts by category from 1999 to 2001. The data set includes an average of the Part I (violent and property) crime categories over the entire three years for each census tract. The researchers originally chose a random sample of cities, stratified by region, from all cities with at least 100,000 persons as of the 2000 census. In the event that police departments were not able to provide crime data, they replaced the city with one of "similar size, racial/ethnic composition, and level of poverty" (Peterson and Krivo, 2010).

To sketch our basic empirical approach, we begin by calculating weighted averages of all these neighborhood attributes to capture the characteristics of the 'average' neighborhoods lived in by people of different races. (The weights in each case are the number of residents of a given race in a neighborhood divided by the total number of people of that race across the full population.) These weighted average characteristics are often called 'exposure rates,' because they show the degree to which the average person of a particular race is exposed to a particular neighborhood characteristic (see appendix B for the formula and additional explanation).

These weighted averages permit us to compare neighborhood attributes across racial groups, assess the extent of any disparities by race ('racial gaps'), and for census-based data, explore whether those gaps have changed over time. We then examine how any racial gaps vary with levels of racial segregation, testing whether racial gaps are greater in more highly segregated metropolitan areas than in less segregated metropolitan areas. We begin with simple comparisons across metropolitan areas, stratified by segregation levels, and then move to a regression framework to test whether any association between racial differences in neighborhood environments and segregation persists after controlling for other metropolitan characteristics. Of course, there is some concern that minority households who live in more segregated metropolitan areas are simply different in unobserved ways from the minority households who live in less segregated areas and, therefore, more apt to live in more disadvantaged neighborhoods. We attempt to control for potential selection in two ways. First, where data permit, we introduce metropolitan area fixed-effects to examine the relationship between changes in racial disparities and levels of segregation within a metropolitan area. This strategy allows us to get rid of time-invariant, unobserved characteristics in a metropolitan area. Second, we instrument for the segregation level of the metropolitan area using a set of instruments used in earlier studies (Cutler and Glaeser, 1997).

5. Exposure to neighborhood conditions and services

Characteristics of neighbors

Table 1 compares the characteristics of the average neighborhood lived in by people of different races for 1980 and for 2010 and highlights white-minority differentials or gaps. The first three attributes (poverty rates, share of adults employed, and the share of the adult population with

Table 1: Average neighborhood characteristics by race

	1980 share of neighborhood residents				2010 share of neighborhood residents			
	in poverty status	employed (adults)	with college degree	in central city	in poverty status	employed (adults)	with college degree	in central city
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
All	11.5%	75.4%	17.5%	46.2%	13.4%	72.7%	29.6%	39.4%
White	8.8%	76.5%	19.0%	39.8%	10.5%	73.1%	32.9%	31.3%
Black	24.1%	69.2%	10.5%	73.7%	20.3%	69.7%	22.3%	55.7%
White-black gap	*-15.3%*	*7.3%*	*8.5%*	*-33.9%*	*-9.7%*	*3.5%*	*10.6%*	*-24.4%*
Hispanic	18.9%	73.6%	12.0%	62.8%	18.5%	73.0%	21.0%	50.5%
White-Hispanic gap	*-10.1%*	*2.9%*	*7.0%*	*-23.0%*	*-8.0%*	*0.2%*	*11.9%*	*-19.2%*
Asian	11.4%	78.0%	21.7%	60.1%	11.5%	74.9%	38.2%	49.3%
White-Asian gap	*-2.6%*	*-1.5%*	*-2.7%*	*-20.3%*	*-1.0%*	*-1.7%*	*-5.3%*	*-18.0%*

Notes: Units of analysis are census tracts as in 2010. Data on columns (1)–(4) are obtained from the 1980 census. Data on columns (5), (6) and (7) are obtained from a population sample surveyed throughout 2006–2010 (ACS 5-year estimates). Central city location in column (8) is obtained from the 2010 census.

a college degree) capture the level of disadvantage of a neighborhood's residents and the social networks they provide. The final columns for each decade show the share of the population living in the central city, which may suggest differences in public services.

Beginning with columns (4) and (8), we see that a smaller proportion of individuals of all races are living in central city rather than suburban environments today than they were in 1980. While all minority groups are more centralized than whites, gaps have closed to some degree over time, particularly for blacks.

Racial gaps in exposure to neighborhood poverty have also closed over time for blacks and Hispanics, though more so for blacks. While the typical person, and the typical white person, found herself in a higher poverty neighborhood in 2010 than in 1980, blacks on average found themselves in lower poverty neighborhoods, decreasing the white-black gap in average neighborhood poverty from 15 to 10 percentage points. The white-Hispanic gaps declined by 2 percentage points, all of which is due to the increase in neighborhood poverty rates for the average white person. There was also a decline in the white-black and white-Hispanic gaps in neighborhood employment rates, but in both cases, the decline was driven by a reduction in the employment rate in the average neighborhood lived in by whites. Racial gaps in the share of residents with college degrees widened in absolute terms for these two groups, although college attainment in neighborhoods increased across the board, so in percentage terms, the gaps did not change.

Of course, some of the shifts in black and Hispanic racial gaps may be driven by trends in demographic differences across racial groups that affect sorting across neighborhoods, perhaps most importantly, differences in income. To attempt to control, at least partially, for income differences across races, we also examined how racial gaps in neighborhood environment changed among poor people of different races (not shown). The reductions in the gaps in neighborhood

Table 2: Exposure to high or extreme neighborhood poverty by race

	1980 share of residents in neighborhoods of		2010 share of residents in neighborhoods of	
	high poverty (⩾ 30% poor)	extreme poverty (⩾ 40% poor)	high poverty (⩾ 30% poor)	extreme poverty (⩾ 40% poor)
	(1)	(2)	(3)	(4)
All	7.3%	3.0%	9.6%	3.9%
White	2.3%	0.8%	4.4%	1.8%
Black	32.0%	14.5%	23.0%	10.2%
White-black gap	*-29.8%*	*-13.8%*	*-18.7%*	*-8.4%*
Hispanic	19.0%	8.0%	17.8%	6.7%
White-Hispanic gap	*-16.7%*	*-7.2%*	*-13.4%*	*-4.9%*
Asian	5.5%	1.7%	6.8%	2.7%
White-Asian gap	*-3.2%*	*-0.9%*	*-2.4%*	*-0.9%*

Notes: Units of analysis are census tracts as in 2010. Data on columns (1) and (2) are obtained from the 1980 census. Data on columns (3) and (4) are obtained from a population sample surveyed throughout 2006–2010 (ACS 5-year estimates).

conditions between poor blacks and poor whites were slightly smaller than those seen for the full population of blacks and whites, but the patterns are basically the same.

Table 1 reveals a very different pattern for Asians. The white-Asian gap in exposure to neighborhood poverty is quite small in both decades, and the white-Asian gap for share of adults employed or with a college degree is actually negative, so to the advantage of Asians. One root of the distinct Asian pattern lies in the lower segregation level of Asians, shown in figure 1. Asians are much more likely to live among white neighbors: more than half of the average Asian's neighbors were white in 2005–2009, compared to less than 40 percent for the typical black or Hispanic (Logan, 2011). Moreover, Asian socioeconomic status tends to be similar to that of whites (Logan and Zhang, 2013), so exposure to own-group need not bring disadvantage. Indeed, Asians have a slight advantage in terms of educational attainment relative to whites (Logan and Zhang, 2013). Hence we should expect very different relationships between segregation and neighborhood environments for this group.

Table 1 captures racial gaps in the average neighborhood characteristics, including average poverty rates. We are also interested in changes in the share of residents of different races living in high poverty (more than 30% poor) and extremely high poverty (more than 40% poor) neighborhoods, as it is arguably these highly disadvantaged environments that potentially undermine individual life chances. Table 2 shows that racial gaps in exposure to high and extremely high poverty neighborhoods have closed over time for both blacks and Hispanics, but (again) especially for blacks, who unlike Hispanics, experienced a decline in segregation during this time period. That said, the gaps between blacks and whites remain quite large. White-black gaps in 2010 are larger than white-Hispanic gaps in 1980. As is the case with average poverty rates, white-Asian gaps are small in both decades.

Quality of nearest school

While concern with access to jobs and concentrated poverty have dominated most previous work on segregation, households more typically report concerns about quality of schools and the level of safety when choosing their neighborhoods. The first two columns in table 3 show racial differences in two key attributes of the neighborhood elementary school—the relative ranking with respect to mean proficiency or passing rates on standardized tests (averaged across math and reading) and the share of the students who qualify for free or reduced-price lunch, our best proxy for poor and near poor students. We translate school measures into percentiles within the metropolitan area in order to control for differences in standardized tests, proficiency standards, and poverty rates across states and areas.[9]

Focusing first on proficiency rankings of the neighborhood school, we see that the average white person lives in a census tract where the nearest elementary school within the district ranks at the 58^{th} percentile in the metropolitan area. In contrast, the average black person lives in a tract associated with an elementary school scoring at the 37^{th} percentile, resulting in a 22 percentage point racial gap in proficiency ranking. The white-Hispanic gap is only a bit smaller, at 16 percentage points, while the white-Asian gap is only 2 percentage points. The second column reveals a similar pattern. The average white person lives near an elementary school ranked at the 43^{rd} percentile with respect to the percentage of students eligible for free or reduced-price lunch. Blacks and Hispanics, by contrast, live near schools above the 60^{th} percentile, with resulting racial gaps of 23 and 21 percentage points (respectively). These differences are large and substantially greater than the observed small white-Asian gap.

Higher poverty rates among minorities do not explain these racial gaps. While the poor live near more disadvantaged schools than the full population (bottom panel of table 3), controlling for poverty status does almost nothing to narrow the white-black and white-Hispanic gaps. Indeed, white-black gaps are so large that the average poor white person lives near a school with a higher proficiency ranking than the average *non-poor* black person.

We also examine differences in the characteristics of schools nearest to children of different races and ethnicities (not shown). After all, we should care most about children's access to schools, not the full population. We find that white-black and white-Hispanic gaps in characteristics of the nearest school are even more pronounced for children under the age of 15. These larger gaps are due to fact that the schools near to the census tracts where white children under 15 reside are ranked more highly than the schools near to the full white population.

Neighborhood crime

Table 3 also shows exposure to violent and property crime by race and ethnicity, for 91 cities located in 60 metropolitan areas in 2000. As shown, we find very large white-black and white-Hispanic

[9]For the relative ranking with respect to mean proficiency on standardized tests, we have also calculated percentiles separately for those metropolitan areas that cross state boundaries, by treating the share of each MSA within a state as a different geographic unit. The racial gaps we obtain are very similar, generally greater by a magnitude of one percentage point.

Table 3: Percentile rankings of school attributes and neighborhood crime by race

	Schools ranked by		Neighborhood ranked by	
	proficiency in test scores	free/reduced-price eligibility	violent crime	property crime
	(1)	(2)	(3)	(4)
Full population				
All	52.2	50.3	48.8	47.8
White	58.3	42.9	36.8	42.3
Black	36.6	66.0	66.2	57.5
White-black gap	*21.7*	*-23.1*	*-29.4*	*-15.2*
Hispanic	42.1	63.5	58.2	50.5
White-Hispanic gap	*16.2*	*-20.6*	*-21.4*	*-8.2*
Asian	56.5	47.7	42.6	45.2
White-Asian gap	*1.9*	*-4.8*	*-5.8*	*-2.9*
Poor population				
All	41.0	64.0	64.2	57.1
White	50.0	53.8	55.5	54.2
Black	30.1	73.4	74.5	62.4
White-black gap	*19.9*	*-19.6*	*-19.0*	*-8.3*
Hispanic	36.2	71.0	65.9	54.2
White-Hispanic gap	*13.8*	*-17.2*	*-10.5*	*0.0*
Asian	48.1	60.8	52.3	52.9
White-Asian gap	*1.9*	*-7.0*	*3.2*	*1.3*

Notes: Units of analysis are census tracts as in 2010. Sample of school attributes includes 360 metropolitan areas. Sample of crime exposure includes 91 cities in 60 metropolitan areas. Due to the smaller sample of neighborhoods in cities, we have calculated percentiles for crime exposure at the deciles and multiplied by ten.

gaps, at least in terms of violent crime. While the average white person lives in a tract with a violent crime rate at the 37th percentile in their city, the average black person and average Hispanic person live in a tract with a violent crime rate at the 66th and 58th percentiles, respectively, resulting in racial gaps of 29 percentage points for blacks and 21 percentage points for Hispanics. Racial gaps are small between whites and Asians, and for all groups, racial gaps in exposure to property crime tend to be far smaller than those for violent crime. This is perhaps not surprising given that past research has found that violent crime is far more associated with neighborhood disadvantage than property crime (Krivo and Peterson, 1996). There are fewer attractive targets to steal in more disadvantaged neighborhoods, and reporting rates may also be lower, while violent crime is less likely to go unreported, regardless of neighborhood advantage.

Differences in income, or at least poverty, appear to explain about a third of the white-black gap and almost half of the white-Hispanic gap. But large gaps remain in the violent crime rates of the neighborhoods lived in by poor whites compared to poor blacks and poor Hispanics. Indeed, in our sample of cities, the average poor white person lived in a neighborhood with a lower violent crime rate than the average *non-poor* black person. It is worth emphasizing that we only have crime data for a selected set of cities rather than for entire metropolitan areas. As a result, these racial gaps may greatly understate the full racial gaps in metropolitan areas, given the greater suburbanization of whites and lower crime rates in the suburbs.

In sum, these series of analyses reveal continued large gaps in the neighborhood environments experienced by whites and Asians on the one hand and blacks and Hispanics on the other. Large gaps remain even after controlling for poverty. We consider next whether these racial gaps vary by level of segregation.

6. Racial segregation and racial gaps in environments

To analyze the degree to which racial gaps in exposure to neighborhood conditions widen in more segregated metropolitan areas, we first conduct a simple assessment by dividing all metropolitan areas in our sample into segregation quartiles based on their relevant dissimilarity index in that year, i.e., the white-black dissimilarity index when examining white-black gaps, the white-Hispanic dissimilarity index for white-Hispanic gaps, and the white-Asian dissimilarity index for white-Asian gaps. We then calculate racial gaps in exposure rates to neighborhood characteristics for each metropolitan area quartile: areas with very low segregation (bottom quartile), low (second quartile), high (third quartile) and very high (top quartile).

Table 4 presents results for two of the neighborhood characteristics we examine, the share of residents who are poor and the share with a college degree in 2010, broken out by MSA segregation quartiles. For both attributes, and for both blacks and Hispanics, racial gaps increase monotonically moving from the least to the most segregated MSAs. While white-black and white-Hispanic gaps still exist in metropolitan areas with very low levels of segregation, they are far smaller—on the order of the gaps between whites and Asians. We find remarkably similar results when we consider the relative ranking of a neighborhood within an MSA rather than absolute percentages and when we restrict our analysis to the poor. Further, we find qualitatively similar results when we use the isolation index to capture segregation rather than the dissimilarity index.

We also find the same pattern of increased white-black and white-Hispanic racial gaps by metropolitan segregation when we examine racial gaps in the share of the population living in high and extremely high poverty neighborhoods, gaps in the proficiency and poverty ranking of the nearest school, and gaps in neighborhood crime (see appendix tables C.10 through C.12).[10] Finally, we also see similar patterns in each of the earlier decades. White-black and white-Hispanic gaps in neighborhood environment are modest in metropolitan areas with very low levels of segregation and widen as segregation increases, in all decades and with both measures of segregation. To shed additional light on these relationships, we next move to a regression framework analysis.

Regression models of neighborhood exposure

Our basic model regresses the exposure of a specific racial minority group in a metropolitan area to a particular neighborhood characteristic or amenity as a function of segregation in that metropoli-

[10]Racial gaps in the share of adults employed in the neighborhood are less consistently associated with segregation levels.

Table 4: Racial gaps in neighborhood SES by metropolitan area segregation 2010

	Share of neighborhood residents in poverty				Share of neighborhood residents with college degree			
	Very low	Low	High	Very high	Very low	Low	High	Very high
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
White	13.1%	12.3%	11.0%	9.4%	29.7%	28.3%	30.7%	35.7%
Black	18.4%	19.1%	19.6%	20.7%	24.0%	20.9%	22.5%	22.4%
White-black gap	*-5.3%*	*-6.7%*	*-8.5%*	*-11.3%*	*5.7%*	*7.5%*	*8.2%*	*13.3%*
White	13.4%	12.1%	11.3%	9.2%	26.3%	28.9%	30.3%	36.5%
Hispanic	16.2%	17.9%	19.1%	18.5%	23.2%	21.2%	19.4%	21.4%
White-Hispanic gap	*-2.8%*	*-5.8%*	*-7.8%*	*-9.2%*	*3.1%*	*7.7%*	*10.9%*	*15.1%*
White	11.8%	11.3%	11.1%	9.7%	26.9%	30.3%	31.0%	36.2%
Asian	12.3%	11.8%	11.2%	11.5%	28.4%	33.1%	38.7%	39.5%
White-Asian gap	*-0.5%*	*-0.6%*	*-0.1%*	*-1.8%*	*-1.5%*	*-2.9%*	*-7.7%*	*-3.3%*

Notes: Units of analysis are census tracts as in 2010. Information is obtained from a population sample surveyed throughout 2006–2010 (ACS 5-year estimates).

tan area and other MSA attributes. Specifically, our basic regression model can be represented as:

$$\text{Exp}_{jt} = \alpha_1 + \beta_1 \,\text{Seg}_{jt} + \beta_2 \,\text{White Exp}_{jt} + \beta_3 \, X_{jt} + T_t + \varepsilon_{jt} \;, \tag{1}$$

where Exp_{jt} represents the average neighborhood exposure for a racial group in MSA_j in time period t, Seg_{jt} is the dissimilarity index between whites and the given minority group for MSA_j in decade t, White Exp_{jt} is the exposure of white residents in MSA_j to that attribute in decade t, X_{jt} is a vector of metropolitan level characteristics described below, and T_t is a decade time control (for multi-decade models). We estimate separate regressions for black exposure, Hispanic exposure, and Asian exposure. Because we include the exposure of whites to the given neighborhood feature or amenity, our estimated coefficients can be interpreted as indicating the association of a given variable with a change in exposure to the feature or amenity experienced by the minority group *relative* to whites living in the same metropolitan area.[11]

For the neighborhood attributes that we can capture in multiple decades, we exploit the variation over time to estimate two additional models:

$$\begin{aligned} \text{Exp}_{jt} = \; & \alpha_2 + \gamma_1 \,\text{Seg}_{jt} + \gamma_{1,1} \,\text{Seg}_{jt} \times \text{Year 1990} + \gamma_{1,2} \,\text{Seg}_{jt} \times \text{Year 2000} + \\ & \gamma_{1,3} \,\text{Seg}_{jt} \times \text{Year 2010} + \gamma_2 \,\text{White Exp}_{jt} + \gamma_3 \, X_{jt} + T_t + \mu_{jt} \;, \end{aligned} \tag{2}$$

$$\text{Exp}_{jt} = \alpha_3 + \delta_1 \,\text{Seg}_{jt} + \delta_2 \,\text{White Exp}_{jt} + \delta_3 \, X_{jt} + T_t + \text{MSA}_j + \eta_{jt} \;, \tag{3}$$

Equation (2) includes interactions between MSA segregation and year indicator variables to test whether the relationship between segregation and neighborhood exposure has changed over time. Equation (3) includes MSA fixed-effects to control for non-varying metropolitan characteristics that might drive both segregation and exposure.

[11]We have run all models without this control with essentially the same results. Inclusion of white exposure permits us to more directly assess the relationship between segregation and the white-minority racial gap in exposure.

We also include a number of metropolitan control variables that are frequently cited in the literature on causes of racial segregation, such as demographic characteristics of the population, MSA population and income, industry mix, and occupational characteristics (see full list in table 5).

7. Results

Characteristics of neighbors

Table 5 presents results for exposure to neighborhood poverty for blacks, Hispanics and Asians, for each of the three regression models. In our baseline model (columns 1, 4 and 7), exposure to neighborhood poverty is significantly higher for each racial group in metropolitan areas with higher segregation, controlling for other metro area characteristics, though the coefficient on segregation is nearly twice as large for blacks and Hispanics as for Asians. Again, because we control for the degree to which white residents of the metropolitan area are exposed to neighborhood poverty, the positive coefficients on segregation can be interpreted as indicating that the racial gaps in poverty exposure are larger in more segregated metropolitan areas. In other words, segregation is not creating separate but equal environments.

When we allow the coefficient on segregation to vary across decades (columns 2, 5 and 8), we find evidence that the association between segregation and exposure to neighborhood poverty was highest for all racial groups in 1990. Since 1990, the relationship between segregation and relative exposure to poverty has declined for all three groups, although only Asians have seen an improvement since 2000. Finally, the results of regressions with MSA fixed effects (columns 3, 6, and 9) show that increases in segregation over time within a metropolitan area are associated with exposure to higher poverty relative to whites for all three racial groups. The coefficients on segregation are smaller, however, in the models with MSA fixed-effects.

When we estimate these same regressions using the isolation index to capture segregation, we obtain very similar results.[12] Once again, racial gaps in exposure to poverty are larger in metropolitan areas with higher levels of segregation, and the magnitude of the association was largest in 1990, with only Asians gaining in the most recent decade. The one difference is that the coefficient on isolation is actually larger for Asians than it is for blacks and Hispanics.[13] We find that the association between segregation and racial gaps in exposure to poverty also peaked in the 1990s when we consider residence in high poverty neighborhoods (more than 30 percent poor) rather than average poverty rate.[14]

Table 6 presents similar results for exposure to college-educated neighbors. The broad brush findings of larger gaps where segregation is higher are the same for blacks and Hispanics as they were for neighborhood poverty: across all three model specifications, blacks and Hispanics are less exposed to college educated neighbors relative to whites in more segregated metropolitan areas. However, the temporal patterns are quite different. Using the dissimilarity index, we find

[12] Results available from authors.

[13] Unlike educational attainment and income, which are higher among Asians than whites, poverty rates are higher among Asians (Logan and Zhang, 2013).

[14] Results available from authors.

Table 5: Exposure to neighborhood poverty by race

Dependent variable:	Share of neighborhood residents in poverty								
	Blacks			Hispanics			Asians		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
White-black DI	0.282 (0.016)***	0.298 (0.022)***	0.195 (0.028)***						
White-Hispanic DI				0.256 (0.017)***	0.257 (0.020)***	0.176 (0.014)***			
White-Asian DI							0.148 (0.019)***	0.097 (0.024)***	0.104 (0.022)***
White-black DI × 1990		0.030 (0.015)**							
White-black DI × 2000		-0.047 (0.015)***							
White-black DI × 2010		-0.047 (0.017)***							
White-Hisp DI × 1990					0.028 (0.014)**				
White-Hisp DI × 2000					-0.028 (0.016)*				
White-Hisp DI × 2010					-0.014 (0.017)				
White-Asian DI × 1990								0.085 (0.023)***	
White-Asian DI × 2000								0.068 (0.022)***	
White-Asian DI × 2010								0.024 (0.026)	
White poverty exposure	1.120 (0.061)***	1.122 (0.061)***	1.445 (0.064)***	1.107 (0.046)***	1.111 (0.046)***	1.264 (0.056)***	1.259 (0.048)***	1.257 (0.048)***	1.169 (0.072)***
Log population	0.005 (0.002)**	0.005 (0.002)**	-0.012 (0.009)	0.004 (0.001)***	0.005 (0.001)***	-0.006 (0.006)	0.000 (0.001)	0.000 (0.001)	-0.002 (0.007)
% black	0.084 (0.015)***	0.088 (0.015)***	-0.140 (0.073)*	-0.020 (0.011)*	-0.019 (0.011)*	0.061 (0.057)	-0.100 (0.013)***	-0.098 (0.013)***	-0.149 (0.062)**
% Hispanic	0.046 (0.017)***	0.045 (0.017)***	0.055 (0.053)	0.054 (0.019)***	0.052 (0.019)***	0.060 (0.044)	-0.078 (0.017)***	-0.078 (0.017)***	-0.157 (0.050)***
% Asian	-0.035 (0.017)**	-0.036 (0.017)**	0.224 (0.130)*	-0.015 (0.018)	-0.018 (0.019)	0.062 (0.091)	-0.053 (0.018)***	-0.052 (0.018)***	-0.103 (0.092)
% over 65	0.167 (0.056)***	0.169 (0.057)***	0.007 (0.098)	0.094 (0.041)**	0.096 (0.041)**	-0.024 (0.082)	-0.097 (0.029)***	-0.095 (0.029)***	-0.016 (0.111)
% under 15	0.073 (0.052)	0.079 (0.053)	0.011 (0.030)	0.042 (0.026)*	0.049 (0.028)*	0.039 (0.020)*	-0.046 (0.031)	-0.045 (0.031)	0.043 (0.029)
% foreign-born	-0.210 (0.041)***	-0.205 (0.041)***	-0.246 (0.143)*	-0.165 (0.044)***	-0.157 (0.045)***	-0.136 (0.101)	0.098 (0.033)***	0.101 (0.033)***	0.179 (0.092)*
% unemployed	0.046 (0.078)	0.053 (0.079)	-0.274 (0.060)***	0.143 (0.057)**	0.137 (0.056)**	-0.100 (0.050)**	-0.072 (0.050)	-0.073 (0.049)	-0.148 (0.054)***
% manufacturing	-0.007 (0.028)	-0.007 (0.028)	-0.071 (0.037)*	0.023 (0.018)	0.026 (0.018)	-0.065 (0.026)**	-0.050 (0.019)**	-0.048 (0.019)**	-0.045 (0.032)
% professional	-0.208 (0.088)**	-0.196 (0.087)**	0.068 (0.063)	0.071 (0.070)	0.070 (0.071)	0.033 (0.044)	-0.150 (0.060)**	-0.143 (0.061)**	-0.072 (0.055)
% college	0.186 (0.057)***	0.184 (0.057)***	-0.123 (0.071)*	0.050 (0.047)	0.051 (0.048)	-0.064 (0.053)	0.239 (0.041)***	0.235 (0.041)***	-0.068 (0.061)
Median income	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)**	0.000 (0.001)	0.000 (0.001)	-0.002 (0.001)***	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)
MSA fixed-effects	No	No	Yes	No	No	Yes	No	No	Yes
Observations	1,417	1,417	1,417	1,417	1,417	1,417	1,417	1,417	1,417
R^2	0.705	0.710	0.593	0.761	0.763	0.699	0.773	0.775	0.550

Notes: All specifications include a constant term and year indicators. Coefficients are reported with robust standard errors in parenthesis, which are clustered by MSA. ***, **, and * indicate significance at the 1, 5, and 10 percent levels. DI stands for dissimilarity index which is not available for 35 MSAs in 1980. Median income is expressed in tens of thousands of dollars.

Table 6: Exposure to neighborhood college attainment by race

Dependent variable:	Share of neighborhood residents with college degree								
	Blacks			Hispanics			Asians		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
White-black DI	-0.163 (0.014)***	-0.162 (0.017)***	-0.062 (0.021)***						
White-Hispanic DI				-0.199 (0.014)***	-0.176 (0.016)***	-0.125 (0.013)***			
White-Asian DI							0.226 (0.037)***	0.228 (0.041)***	0.111 (0.025)***
White-black DI × 1990		0.013 (0.012)							
White-black DI × 2000		-0.004 (0.014)							
White-black DI × 2010		-0.010 (0.015)							
White-Hisp DI × 1990					-0.006 (0.012)				
White-Hisp DI × 2000					-0.041 (0.014)***				
White-Hisp DI × 2010					-0.057 (0.015)***				
White-Asian DI × 1990								0.008 (0.032)	
White-Asian DI × 2000								-0.001 (0.030)	
White-Asian DI × 2010								-0.014 (0.036)	
White college exposure	0.746 (0.070)***	0.747 (0.069)***	0.534 (0.073)***	0.706 (0.054)***	0.712 (0.054)***	0.813 (0.066)***	1.129 (0.060)***	1.128 (0.060)***	0.983 (0.069)***
MSA fixed-effects	No	No	Yes	No	No	Yes	No	No	Yes
Observations	1,417	1,417	1,417	1,417	1,417	1,417	1,417	1,417	1,417
R^2	0.836	0.836	0.854	0.855	0.856	0.822	0.870	0.870	0.854

Notes: All specifications include a constant term and year indicators. Coefficients are reported with robust standard errors in parenthesis, which are clustered by MSA. ***, **, and * indicate significance at the 1, 5, and 10 percent levels. Additional controls included for MSAs are the following: log population, median household income and shares of population that are black, Hispanic, Asian, over 65 years, under 15 years, foreign-born, unemployed, working in manufacturing, working in professional occupations and in poverty status. DI stands for dissimilarity index which is not available for 35 MSAs in 1980.

no evidence that the relationship between segregation and racial gaps has improved for blacks over time, and it has actually gotten worse (more negative) since 1980 for Hispanics. Using the isolation index (results not shown), segregation has a stronger, negative association with exposure to college-educated neighbors over time for both blacks and Hispanics. Finally, once MSA fixed effects are included, the coefficients on segregation decline in magnitude but remain significant, just as they do in table 5.

Notably, the coefficients on segregation in the Asian exposure models are positive and significant, suggesting that Asians actually live in neighborhoods with more highly educated neighbors in metropolitan areas where they are more segregated from whites.[15] Throughout, Asians appear to be less disadvantaged by segregation from whites than blacks and Hispanics, but here, they even appear to benefit. This is consistent with the higher levels of education among Asians and a steep rise in college attainment rates noted previously (see table 1), such that greater segregation and hence contact with other Asians would actually increase exposure to college attainment.

We see a story similar to that for college attainment when we examine exposure to employed neighbors. These results confirm that segregation is associated with significantly higher (lower) exposure to neighborhood disadvantage (advantage) level for blacks and Hispanics relative to whites living in the same metropolitan areas. There is also no consistent sign of improvement in the exposure to employed neighbors over time. For blacks, the coefficient on segregation is larger (more negative) after 1980, with no signs of recent improvement, for each measure of segregation. For Hispanics, trends are less consistent, with signs of improvement in some decades post 1980, while for Asians, there is no change over time.

In sum, the association between racial gaps and segregation revealed in table 4 hold when controlling for other metropolitan area characteristics. While we see some reduction in the association between segregation and poverty exposure since 1990, the link between segregation and racial gaps in neighborhood environment does not appear to be weakening across the board. Indeed, we see some signs of stronger associations between segregation and other human capital characteristics of neighbors. Segregation continues to mean that blacks and Hispanics live in less advantaged communities, as blacks and Hispanics continue to lag behind whites in their income and education levels.

Quality of nearest school

For our single cross-section of school data, we estimate scaled-back versions of model 1 with no time indicators. Table 7 presents results for regression models with two dependent variables: the share of students in the local school who test at proficient levels; and the share of students in the local school who qualify for free or reduced-price lunch, each for the average minority resident. After controlling for a variety of metropolitan area characteristics including the proficiency rate or poverty rate of the school nearest to the average white resident of the metropolitan area, we find that blacks and Hispanics in more segregated areas live near schools with significantly lower proficiency rates relative to schools near to whites and significantly higher relative shares of students on free and reduced-price lunch.[16] We find no relationship between segregation and the school attributes for Asians. We obtain the same results when we use the isolation index to capture segregation levels.

[15] Again, when using the isolation index to measure segregation, we obtain similar results.

[16] Our results are very similar when we exclude white exposure rates, which imply that higher segregation is associated with exposure to lower quality schools for blacks and Hispanics, relative to minorities of the same race in less segregated MSAs.

Table 7: Exposure to neighborhood school attributes by race

Dependent variable:	Proficiency rate			Free/reduced-price lunch eligibility share		
	Blacks	Hispanics	Asians	Blacks	Hispanics	Asians
	(1)	(2)	(3)	(4)	(5)	(6)
White-black DI	-0.280 (0.026)***			0.536 (0.037)***		
White-Hispanic DI		-0.284 (0.023)***			0.692 (0.035)***	
White-Asian DI			-0.017 (0.023)			0.087 (0.058)
White proficiency exposure	1.100 (0.023)***	1.094 (0.016)***	1.026 (0.014)***			
White free lunch exposure				0.955 (0.063)***	0.996 (0.039)***	0.986 (0.030)***
Observations	360	360	360	360	360	360
R^2	0.910	0.949	0.960	0.830	0.874	0.859

Notes: All specifications include a constant term. Coefficients are reported with robust standard errors in parenthesis. ***, **, and * indicate significance at the 1, 5, and 10 percent levels. Additional controls included for MSAs are the following: log population, median household income and shares of population that are black, Hispanic, Asian, over 65 years, under 15 years, foreign-born, unemployed, working in manufacturing, working in professional occupations, in poverty status and with college degree. DI stands for dissimilarity index.

Neighborhood crime

Table 8 presents results for exposure to violent crime and property crime using similar models. Controlling for other metropolitan area characteristics, blacks and Hispanics in more segregated metropolitan areas are exposed to significantly more violent crime in their neighborhoods relative to whites in the same metropolitan area (and to blacks or Hispanics in less segregated areas). Relative exposure to property crime, however, is not significantly higher once controls are included, perhaps not surprising given the weaker association found in table 3.[17] The relationship between segregation and the relative exposure of Asians to crime is insignificant throughout. Again, results are the same when using the isolation index rather than the dissimilarity index as our measure of segregation.

When examining exposure to neighborhood schools and crime, we only have one year of data and are thus unable to include MSA fixed-effects to control for unobservable differences in populations across metropolitan areas. Such unobserved differences might drive both the spatial patterns (segregation) and observed differences in neighborhood environments. As a second strategy, we instrument for segregation.

Instrumental variables estimation

We employ two instruments: (1) the log of the number of municipal and township governments present in the metropolitan area in 1962 and (2) the share of local revenue from state and federal

[17] Prior research has also found that controlling for demographic and spatial differences, white-black racial gaps in crime remain only for violent crime (Logan and Stults, 1999).

Table 8: Exposure to neighborhood crime by race

Dependent variable:	Violent crime			Property crime		
	Blacks	Hispanics	Asians	Blacks	Hispanics	Asians
	(1)	(2)	(3)	(4)	(5)	(6)
White-black DI	0.111 (0.043)**			0.109 (0.142)		
White-Hispanic DI		0.068 (0.026)**			0.033 (0.107)	
White-Asian DI			0.039 (0.038)			-0.002 (0.186)
White violent crime exposure	1.844 (0.199)***	1.315 (0.122)***	1.263 (0.103)***			
White property crime exposure				1.061 (0.157)***	1.048 (0.094)***	1.078 (0.112)***
Observations	60	60	60	60	60	60
R^2	0.834	0.853	0.887	0.825	0.872	0.891

Notes: All specifications include a constant term. Coefficients are reported with robust standard errors in parenthesis. ***, **, and * indicate significance at the 1, 5, and 10 percent levels. Additional controls included for MSAs are the following: log population, median household income and shares of population that are black, Hispanic, Asian, over 65 years, under 15 years, foreign-born, unemployed, working in manufacturing, working in professional occupations, in poverty status and with college degree. DI stands for dissimilarity index.

transfers at the state level, again in 1962. The number of municipal and township governments likely affects segregation because more governments allow for more Tiebout sorting. Similarly, the share of local revenue from intergovernmental transfers could also affect sorting if lower shares result in higher local taxes, which in turn invites more Tiebout sorting. Both instruments satisfy the inclusion restriction and plausibly satisfy the exclusion restriction by affecting our outcomes only through their effect on segregation.

These two political instruments from the 1962 Census of Governments were first used by Cutler and Glaeser (1997) and are made available by the Inter-university Consortium for Political and Social Research at the University of Michigan.[18] As in Cutler and Glaeser (1997), we calculate the share of local revenue from intergovernmental transfers at the state level, not the MSA level, in order to exclude local, endogenous factors. Using data from 1962 further reduces the possibility of endogeneity for both instruments.

Unlike Cutler and Glaeser, we are examining the segregation of multiple racial groups, not just blacks, and we find that first stage results differ by racial group. For white-black segregation, coefficients for both instruments are statistically significant and of the expected signs (see appendix table D.13).[19] For Hispanics, however, the coefficient on neither instrument is significant in the first stage, and for Asians, only the coefficient on the number of governments is significant. This suggests that while these historical indicators of fiscal division correlate well with white-black segregation, they have less independent predictive power for spatial patterns among minority groups who have more recently arrived in the United States. This is particularly true for Hispanics. Given

[18]United States Department of Commerce (2001), https://doi.org/10.3886/ICPSR00017.v1.

[19]Our results are remarkably similar to Cutler and Glaeser (1997).

Table 9: Exposure models for blacks: OLS and IV

Exposure to	Coefficient on white-black dissimilarity index	
	OLS	IV
	(1)	(2)
neighborhood poverty, 2010	0.279 (0.015)***	0.317 (0.032)***
neighborhood poverty, 1990	0.335 (0.024)***	0.360 (0.064)***
neighborhood college attainment, 2010	-0.187 (0.016)***	-0.163 (0.031)***
neighborhood college attainment, 1990	-0.146 (0.019)***	-0.019 (0.062)
proficiency rate in local school, 2008	-0.283 (0.026)***	-0.366 (0.046)***
free/reduced-price lunch eligibility share in local school, 2008	0.544 (0.037)***	0.663 (0.066)***

Notes: All specifications include a constant term. Coefficients are reported with robust standard errors in parenthesis. ***, **, and * indicate significance at the 1, 5, and 10 percent levels. Additional controls included for MSAs are the following: log population, median household income and shares of population that are black, Hispanic, Asian, over 65 years, under 15 years, foreign-born, unemployed, working in manufacturing, working in professional occupations, in poverty status and with college degree. Number of MSA observations is 358 in first four rows and 357 in the last two.

this, and the consistently small (or reversed) white-Asian racial gaps, we restrict our instrumental variable estimation to the association between white-black segregation and white-black gaps in neighborhood environments.

Table 9 presents a summary of OLS and IV results for models of black exposure to four distinct neighborhood attributes: share of residents in the neighborhood who are poor (2010 and 1990), share with a college degree (again, 2010 and 1990), share of the students in the local school who test at proficient levels and share of students who qualify for free or reduced-price lunch.[20] For ease, we only highlight coefficients on our variable of interest, MSA segregation, as measured by the dissimilarity index, but all models include the full list of metropolitan area controls from tables 5 to 7.

Our instrumental variable results are highly similar to the OLS estimates. In five of six models, the instrumented coefficient on segregation remains statistically significant and of similar magnitude to that estimated through OLS. For the exposure to poverty models, the coefficient on segregation is highest in both OLS and IV models in 1990, consistent with results in table 5 (although the differences are not statistically significant). For both measures of school quality, the coefficient on segregation remains significant when instrumented, with larger coefficients. The one notable difference between the OLS and IV results emerges in the models of exposure to neighbors with college degrees. In this one model, the coefficient on segregation falls in magnitude and loses significance in the IV estimation. But in general, results from IV estimations suggest that our

[20]We do not carry out IV estimations for crime exposure indicators given the reduced sample of 60 MSAs.

baseline results are not driven by unobserved differences across metropolitan areas that drive both white-black segregation and differences in neighborhood environments.

Notably, we find that the association between white-black segregation and racial differences in neighborhood environments are largest in 1990, the year in which the impacts of segregation were studied by Cutler and Glaeser (1997) and Ellen (2000). But even in 2010, we continue to find an independent association between white-black segregation and racial gaps in key features of neighborhood environments. This suggests that there is still reason for concern about segregation.

8. Conclusions

Much has changed since John Quigley initially examined issues of race and neighborhoods. While still quite high, white-black segregation continues to decline, as does the centralization of blacks in urban cores. Given the diversification of the non-white population in the U.S., however, these changes in spatial patterns for blacks provide only a limited view of what segregation means today. And residential segregation from whites is not on the decline for these other, growing minority groups.

Looking at a broader set of minorities than have been examined by previous research, as well as over a wider set of environmental attributes, our results suggest large variation in the experiences of different minority groups. Our analysis shows that the neighborhood environments of minorities remain unequal to those of whites, at least for blacks and Hispanics. Blacks and Hispanics continue to live among more disadvantaged neighbors, to have access to lower performing schools, and to be exposed to more violent crime. Further, these differences are amplified in more segregated metropolitan areas. In contrast, we find little evidence of neighborhood disadvantages for Asians.

Focusing on perhaps the most hopeful dimension of our findings, we find a reduction in white-black and white-Hispanic gaps in exposure to various measures of neighborhood poverty. This is evidence of relative improvement in one key dimension of neighborhood environment for the two minority groups who face significant racial gaps. We also find a weaker relationship between segregation and these racial gaps since 1990, at least suggesting the potential for improvement in exposure to poverty even with continued high levels of segregation.

On a less hopeful note, the relationship between segregation and other neighborhood attributes, such as exposure to employed or college-educated neighbors, appears to have worsened over time, at least for blacks. To be sure, we are not able to examine individual outcomes, the ultimate test for how much segregation still matters. Future research should try to find exogenous variation in segregation patterns to test the continued impact of this segregation on individual outcomes—and not just for blacks but for non-black minorities as well.

Certainly our results here raise a flag, however. To the extent that these neighborhood features matter to quality of life, our results suggest we still have reason to be concerned about segregation, even at the start of the 21^{st} century.

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Appendix A. Combining NCDB and LTDB data sets

In order to examine neighborhood changes in outcomes over time, we need to hold constant the boundaries of geographic units for different periods. We start with the Neighborhood Change Database (NCDB), a proprietary product developed by GeoLytics and the Urban Institute (Tatian, 2003), that provides longitudinal census tract data for 1980, 1990 and 2000 adjusted to 2000 boundaries for all metropolitan areas in the U.S. We then exploit the 2000–2010 Longitudinal Tract Data Base (LTDB) crosswalk developed by Logan, Xu, and Stults (2012) so that we are able to bridge NCDB data to 2010 census tract boundaries. This is the most reliable way to harmonize data collected prior to 2000, particularly 1990, given that the NCDB interpolation strategy between 1990 and 2000 is based on block population and on the distribution on population within blocks.

Next, we combine 1980-2000 NCDB (fixed at 2010 tract boundaries) with LTDB 2010 data from full- and sample-count files. 'Full count' data include essential variables such as race and ethnicity collected in the 2010 census, while 'sample count' data include other demographic and economic variables based on sample data from the American Community Survey 2006–2010.

Appendix B. Calculating exposure rates

The exposure index, or exposure of individuals of one race to a particular neighborhood attribute or service is calculated as follows:

$$\sum_{j=1}^{J} \left(N_j \times \frac{r_j}{R} \right) ,$$

where N_j is the neighborhood attribute (such as crime rate) in census tract j, r_j is the number of residents of a given race in census tract j, and R is the number of total population of a given race in all (or a subset of) metropolitan areas. Thus, this ratio weighs the neighborhood attribute by the share of people of a given race in the neighborhood. The resulting value is essentially a weighted average neighborhood crime rate or the crime rate faced by the typical person in that group.

Appendix C. Racial gaps in neighborhood conditions by metropolitan area segregation

Table C.10: Racial gaps in neighborhood poverty by metropolitan area segregation 2010

	Share of residents living in high poverty neighborhood				Share of residents living in extremely high poverty neighborhood			
	Very low	Low	High	Very high	Very low	Low	High	Very high
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
White	6.9	5.4	4.6	3.6	3.0	2.3	1.9	1.4
Black	14.4	18.2	20.5	24.7	5.4	7.8	9.5	11.0
White-black gap	*-7.5*	*-12.8*	*-15.9*	*-21.2*	*-2.5*	*-5.5*	*-7.5*	*-9.6*
White	6.5	5.5	4.9	3.4	3.0	2.5	2.1	1.3
Hispanic	9.7	16.5	19.7	17.6	4.0	6.5	8.1	6.3
White-Hispanic gap	*-3.2*	*-11.0*	*-14.8*	*-14.2*	*-1.1*	*-4.0*	*-6.0*	*-5.1*
White	4.5	4.4	5.1	4.0	1.7	1.6	2.2	1.7
Asian	6.4	6.2	7.0	6.8	2.6	2.6	3.4	2.5
White-Asian gap	*-1.9*	*-1.7*	*-2.0*	*-2.9*	*-0.9*	*-1.0*	*-1.2*	*-0.8*

Notes: Units of analysis are census tracts as in 2010. Information is obtained from a population sample surveyed throughout 2006–2010 (ACS 5-year estimates).

Table C.11: Racial gaps in school attributes by metropolitan area segregation 2010

	Schools ranked by proficiency in test scores				Schools ranked by free/ reduced-price eligibility			
	Very low	Low	High	Very high	Very low	Low	High	Very high
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
White	57.0	57.4	57.9	59.0	46.8	43.5	43.4	41.9
Black	52.3	46.4	40.6	33.5	49.6	53.6	62.4	69.4
White-black gap	*4.7*	*11.0*	*17.3*	*25.6*	*-2.8*	*-10.0*	*-19.0*	*-27.5*
White	56.9	56.8	57.6	59.4	47.9	43.8	42.6	41.9
Hispanic	53.0	49.0	47.2	39.4	53.8	55.6	58.1	66.2
White-Hispanic gap	*3.9*	*7.8*	*10.3*	*19.9*	*-5.8*	*-11.8*	*-15.5*	*-24.4*
White	56.8	58.1	58.5	58.7	46.3	43.5	43.1	41.8
Asian	54.3	57.1	58.4	56.0	46.1	44.3	44.4	49.1
White-Asian gap	*2.5*	*1.0*	*0.1*	*2.7*	*0.2*	*-0.8*	*-1.2*	*-7.3*

Notes: Units of analysis are census tracts as in 2010. Sample of school attributes includes 360 metropolitan areas.

Table C.12: Racial gaps in neighborhood crime by metropolitan area segregation 2000

	Neighborhood ranked by violent crime			Neighborhood ranked by property crime		
	Very low/ Low	High	Very high	Very low/ Low	High	Very high
	(1) + (2)	(3)	(4)	(5) + (6)	(7)	(8)
White	44.1	40.9	32.3	46.5	44.2	39.9
Black	62.6	68.4	66.2	57.3	59.9	57.1
White-black gap	*-18.5*	*-27.5*	*-33.9*	*-10.8*	*-15.7*	*-17.2*
White	41.3	42.4	34.3	43.4	44.2	41.6
Hispanic	54.7	55.8	58.6	51.9	52.3	50.3
White-Hispanic gap	*-13.5*	*-13.5*	*-24.2*	*-8.5*	*-8.2*	*-8.7*
White	42.3	37.7	33.4	45.1	42.0	40.9
Asian	48.2	42.4	41.2	47.6	46.5	44.4
White-Asian gap	*-6.0*	*-4.7*	*-7.8*	*-2.5*	*-4.6*	*-3.5*

Notes: Units of analysis are census tracts as in 2010. Sample of crime exposure includes 91 cities in 60 metropolitan areas. We have pooled categories for 'very low' and 'low' levels of segregation given the small number of metropolitan areas (5) with 'very low' segregation. Due to the smaller sample of neighborhoods in cities, we have calculated percentiles for crime exposure at the deciles and multiplied by ten.

Appendix D. First stage results

Table D.13: First stage regression of white-black dissimilarity index

Second stage dependent variable:	Poverty, 2010	Poverty, 1990	College, 2010	College, 1990	Proficiency rate	Free/red. lunch
	(1)	(2)	(3)	(4)	(5)	(6)
Log of local governments 1962	0.039	0.028	0.041	0.025	0.040	0.044
	(0.007)***	(0.008)***	(0.007)***	(0.008)***	(0.007)***	(0.007)***
Share of local revenue from transfers	-0.266	-0.274	-0.279	-0.297	-0.280	-0.289
	(0.066)***	(0.079)***	(0.066)***	(0.077)***	(0.066)***	(0.066)***
White poverty exposure	-0.584	-0.280				
	(0.315)*	(0.205)				
White college exposure			-0.258	0.024		
			(0.182)	(0.217)		
White test proficiency exposure					0.003	
					(0.049)	
White free lunch exposure						0.128
						(0.060)**
Log population	0.034	0.054	0.041	0.060	0.040	0.039
	(0.009)***	(0.009)***	(0.009)***	(0.009)***	(0.009)***	(0.009)***
% black	0.537	0.261	0.569	0.224	0.523	0.513
	(0.072)***	(0.064)***	(0.069)***	(0.075)***	(0.071)***	(0.068)***
% Hispanic	0.155	0.017	0.154	-0.061	0.087	0.103
	(0.065)**	(0.067)	(0.068)**	(0.074)	(0.070)	(0.067)
% Asian	-0.051	0.016	-0.063	0.011	-0.339	-0.387
	(0.101)	(0.077)	(0.081)	(0.075)	(0.215)	(0.215)*
% over 65	0.031	0.996	0.460	1.204	0.341	0.355
	(0.241)	(0.321)***	(0.219)**	(0.301)***	(0.229)	(0.221)
% under 15	-1.389	0.145	-1.074	0.402	-1.189	-1.223
	(0.307)***	(0.293)	(0.306)***	(0.271)	(0.308)***	(0.300)***
% foreign-born	0.060	-0.375	-0.194	-0.318	-0.039	-0.081
	(0.172)	(0.164)**	(0.162)	(0.167)*	(0.190)	(0.189)
% unemployed	0.349	0.825	-0.056	0.511	0.091	0.039
	(0.363)	(0.538)	(0.372)	(0.572)	(0.403)	(0.385)
% manufacturing	0.423	0.248	0.489	0.349	0.482	0.513
	(0.114)***	(0.120)**	(0.114)***	(0.115)***	(0.117)***	(0.115)***
% professional	0.240	0.201	-0.289	-0.192	0.198	0.237
	(0.344)	(0.352)	(0.306)	(0.329)	(0.351)	(0.349)
% college	-0.471	-0.239			-0.627	-0.587
	(0.208)**	(0.251)			(0.208)***	(0.203)***
% in poverty status			0.647	0.223	0.653	0.686
			(0.293)**	(0.215)	(0.286)**	(0.268)**
Median income	-0.010	-0.002	0.039	0.001	0.042	0.050
	(0.018)	(0.004)	(0.015)***	(0.004)	(0.014)***	(0.014)***
Observations	358	358	358	358	357	357
R^2	0.583	0.513	0.576	0.511	0.585	0.591
F-test weak identification	45.485	20.859	49.760	20.762	49.095	50.974
P-value endogeneity test	0.141	0.354	0.202	0.085	0.031	0.100
P-value J test	0.117	0.062	0.004	0.000	0.714	0.047

Notes: All specifications include a constant term. Coefficients are reported with robust standard errors in parenthesis. ***, **, and * indicate significance at the 1, 5, and 10 percent levels. Each column is the first stage regression of the white-black dissimilarity index on specified controls for each second stage dependent variable.