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What Explains Neighborhood Sorting by Income and Race?

Dionissi Aliprantis, Daniel R. Carroll, and Eric R. Young

Why do high-income black households live in neighborhoods with characteristics similar to those of low-income white households? We find that neighborhood sorting by income and race cannot be explained by financial constraints: High-income, high-wealth black households live in similar-quality neighborhoods as low-income, low-wealth white households. We provide evidence that black households sort across neighborhoods according to some non-pecuniary factor(s) correlated with the racial composition of neighborhoods. Black households sorting into black neighborhoods can explain the racial gap in neighborhood quality at all income levels. The supply of high-quality black neighborhoods drives the neighborhood quality of black households.

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1 Introduction

High-income black households live in neighborhoods with rates of unemployment, educational attainment, poverty, and single-headed households that are similar to those of low-income white households (Pattillo (2005), Logan (2011), Reardon et al. (2015), Intrator et al. (2016)). Figure 1a shows this fact after combining several characteristics into an index of neighborhood quality. In the presence of neighborhood effects, neighborhood sorting could help explain why black children have lower incomes than white children, even conditional on parents’ income (Figure 1b, Chetty et al. (2018), Mazumder (2018)).

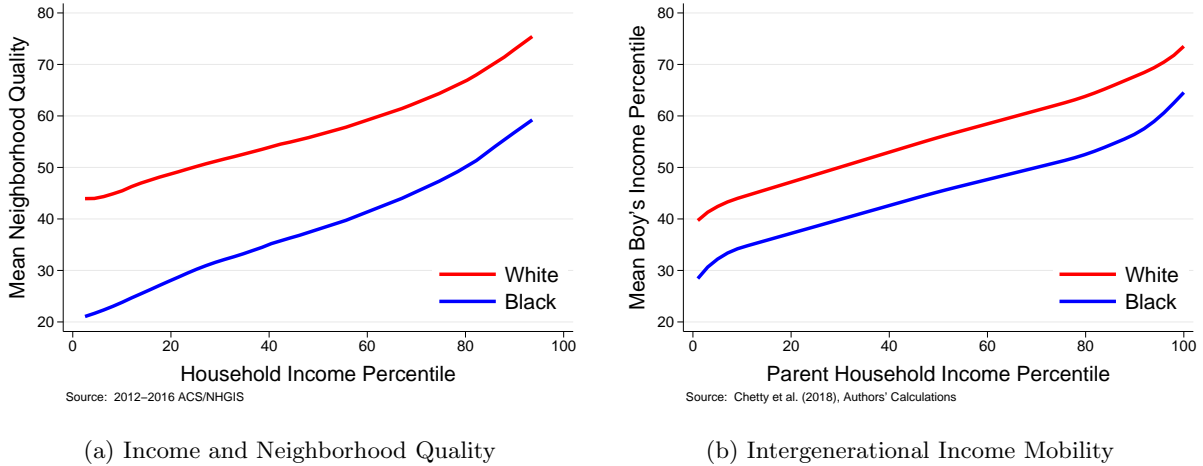


Figure 1: Black-White Gaps in Neighborhood Quality and Child’s Income, by Income
Note: The left panel displays 2012-2016 American Community Survey (ACS) data from both IPUMS-USA and the NHGIS. Our measure of neighborhood quality is defined in Appendix A as an index capturing the poverty rate, labor market outcomes, educational attainment, and the share of single-headed households in each census tract. The right panel is Figure V-A in Chetty et al. (2018), showing mean boy’s individual income percentile.

If neighborhood sorting contributes to racial inequality, one question seems obvious: Why do black households with high incomes live in neighborhoods of lower quality than white households of comparable incomes? Financial limitations related to wealth and the price of housing are natural places to look for the answer, as black households at all levels of income hold substantially less wealth than white households (Barsky et al. (2002), Aliprantis et al. (2019)) and are over-represented in urban areas where housing tends to be more expensive (Parker et al. (2018), Murray and Schuetz (2018)).¹ Alternatively, neighborhood sorting by income and race might be driven by non-pecuniary factors (Bayer and McMillan (2005)). Relative to their white peers, black households may have access to different information about the stock of available housing (ie, steering; Christensen and Timmins (2018)), face different levels of discrimination in rental markets (Yinger (1998)), have family and social networks residing in lower-quality neighborhoods (Büchel et al. (2019), van der Klaauw et al. (2019)), and experience different levels of

¹Discrimination in the mortgage market is another place to look, although we do not investigate it in this paper. The best evidence on the pricing of mortgages (Bhutta and Hizmo (2019), Hanson et al. (2019)) and houses (Bayer et al. (2017), Early et al. (2018)) finds small effects of discrimination.

hostility from prospective neighbors (Harriot (2019), Jensen et al. (2018)) or local institutions (Harris and Yelowitz (2018)).

We show that financial constraints are not the reason black families live in lower-quality neighborhoods than white families with similar incomes. Combining data from the 2015 Panel Study of Income Dynamics (PSID) with tract-level data from the 2012-2016 American Community Survey (ACS), we regress neighborhood quality on race, income, and wealth. We find that high-income, high-wealth black households live in similar-quality neighborhoods as low-income, low-wealth white households. Wealth has almost no predictive power for neighborhood quality within racial groups, but there is a 22 percentile point gap in quality between black and white households.² Moreover, high housing prices in high-quality neighborhoods do not explain black households living in lower-quality neighborhoods: Black and white households are distributed across metros with similar housing price-quality gradients.

In contrast, we find that non-pecuniary factors correlated with race do explain neighborhood sorting by income and race. At all income levels, the racial gap in neighborhood quality can be explained by black households sorting into black neighborhoods. We show that this sorting is driven not by wealth but by the supply of high-quality black neighborhoods. The neighborhood quality of black residents in a metro increases as the supply of high-quality *black* neighborhoods increases, but is unresponsive to the overall supply of high-quality neighborhoods. As well, the metro-level quality differences decline as the supply of high-quality black neighborhoods increases relative to high-quality white neighborhoods.

The importance of race in determining how households select into neighborhoods has implications for policies aiming to improve outcomes by exploiting neighborhood externalities. This includes new approaches to the Housing Choice Voucher program, such as tenant counseling with information (Bergman et al. (2019), Darrah and DeLuca (2014)) and neighborhood-specific voucher values (Collinson and Ganong (2018), Aliprantis et al. (2019)); public subsidies for the construction of affordable housing (Diamond and McQuade (2019)); school choice and magnet school programs (Epplé and Romano (2003), Ellison and Pathak (2016), Owens (2018)); geographically tied college scholarships (LeGower and Walsh (2017)); locally provided universal pre-K (Horn (2019)); and tax credits for new employment or capital investment (Neumark (2018), Slattery (2019), Hanson and Rohlin (2011)).

Beyond racial inequality, our results have broader implications in favor of place-making policies. Persistent spatial inequality has generated interest in policies that can support local economies (Schweitzer (2017), Austin et al. (2018)). Our results give urgency to understanding what aspects of place-making policies make them effective in creating long-run gains (Neumark and Simpson (2015)). The existence of racial differences in mobility within cities suggests the existence of frictions to mobility across larger regions.

²We show that this result is robust, not being driven by the sample period, our approaches to measuring neighborhood quality or wealth, the age of household head, the presence of children, housing tenure, differences in within wealth×race-bin distributions of wealth or home equity, or issues related to common support and functional form assumptions.

The remainder of the paper is organized as follows: Section 2 specifies a simple model to illustrate how we think about financial constraints and non-pecuniary factors in a household's choice of neighborhood. Section 3 investigates whether financial constraints can explain neighborhood sorting, and Section 4 investigates whether non-pecuniary factors correlated with race can explain neighborhood sorting. Section 5 concludes.

2 Model

We guide our analysis by specifying a static, partial equilibrium model of a household's choice of neighborhood in which to reside. We suppose that the household will buy/rent the same quantity of housing services in each neighborhood. In this case we can write the household's problem as:

$$\max_{n_t \in \{1_j, \dots, N_j\}} u(n_t | n_{t-1}, q_n, \Psi_n(r_i)) - h(n_t | n_{t-1}, p_n, W_i, I_i) \quad (1)$$

We assume household i at time t in city j can choose between neighborhoods n_t in the set $\{1, \dots, N_j\}$. The household gets utility from the quality of the neighborhood in which it resides, which we measure in terms of the neighborhood characteristics thought to generate externalities on labor market outcomes. The $h(\cdot)$ function captures the pecuniary costs, in terms of utils, of moving to neighborhood n that are driven by the price of housing in neighborhood n , the household's wealth, and the household's income. The utility function $u(\cdot)$ captures the non-pecuniary/psychic costs and benefits, in terms of utils, of moving to neighborhood n that are driven by neighborhood amenities Ψ_n . Ψ_n is thought to capture social networks and institutions in addition to standard neighborhood amenities. The presence of a household's race r_i as an argument of Ψ_n captures the effects of discrimination in the housing market, race-specific psychic costs to living in a neighborhood due to racial hostility, or a taste for living near others of one's race. We note that race-specific preferences over neighborhoods could arise even if households have, for example, the same preferences for residing near family and friends, but family and friends are distributed differently conditional on race. We also note that while our analysis is focused on the choices of black households, the choices of white households also help to determine the set of Ψ_n .

Our empirical analysis is focused on understanding which factors enter as arguments of $u(\cdot)$ and $h(\cdot)$, and then we focus on understanding the relative importance of each of those arguments. Because we do not have data with direct measures of $\Psi_n(r_i)$, we instead look at data with some combination of the variables q_n, r_n, p_n, r_i, W_i , and I_i . We begin by looking at these variables across the neighborhoods in all metros, $\{1_j, \dots, N_j\}_{j=1}^J$, and then we look at how these variables are distributed within the neighborhoods in specific metros, $\{1_j, \dots, N_j\}$, as well as across metros.

3 Can Financial Constraints Explain Neighborhood Sorting?

3.1 Data

We use two versions of the 5 percent sample from the 2012-2016 American Community Survey (ACS) of the US Census. We obtain individual-level data from the Integrated Public Use Microdata Series (IPUMS-USA, Ruggles et al. (2018)) and tract-level data from the National Historical Geographic Information System (NHGIS, Manson et al. (2017)). We also use individual-level survey data from the Panel Study of Income Dynamics (PSID, ISR (2019)).

The first part of our analysis features extensive use of the net worth variable provided in the PSID. The constructed net worth variable in the PSID, ER65408, is defined as the sum of total assets net of debt value plus the value of home equity. Total assets are the sum of the values of farm/businesses, checking and savings accounts, real estate holdings other than one’s main home, stocks, vehicles, other assets like life insurance policies or rights in a trust, and annuities/IRAs. Debt value is the sum of debt toward farm/businesses, real estate debt for holdings other than one’s main home, credit card debt, student loan debt, medical debt, legal debt, loans from relatives, and other debts. We measure income using the total family income variable, ER65349, that is the sum of all taxable income, transfer income, and Social Security income of the head, his/her spouse/partner, and other family members. We prefer this measure of income relative to a labor income variable due to the importance of transfers (Meyer et al. (2019), Meyer and Sullivan (2012)), and our results are qualitatively similar when measuring income using labor income.

Following Aliprantis and Richter (2019), we define neighborhood quality in terms of a neighborhood’s poverty rate, employment to population ratio, unemployment rate, high school attainment rate, BA attainment rate, and the share of households with children under 18 that are single-headed. We measure these variables in terms of the percentiles of their national distributions, and then define neighborhood quality as the percentile of the first principal component of these variables. These neighborhood characteristics are strongly correlated with a neighborhood’s upward mobility as estimated in Chetty et al. (2018), and are chosen to capture the mechanisms described in Wilson (1987) and Galster (2019). Appendix A discusses this measure of neighborhood quality in detail.

In several parts of the analysis we look at tract-level outcomes by household income quintiles. Although the tract-level NHGIS data only provide counts of households that have incomes within bins, we can obtain approximate counts of households in income quintiles by matching the NHGIS bins to the quintile cutoffs of the household income distribution in the individual-level IPUMS-USA data. The person-weighted household income quintiles in the IPUMS-USA 2012-2016 ACS data are $(-\infty, 29)$, $[29, 53)$, $[53, 83)$, $[83, 132)$, $[132, \infty)$, and we map these to the NHGIS bins as $[0, 30)$, $[30, 50)$, $[50, 75)$, $[75, 125)$, $[125, \infty)$.

3.2 Sorting by Wealth

Recalling the $h(\cdot)$ component of the household’s problem in Equation 1, we suspect that wealth could be a major factor determining how households sort into neighborhoods of different levels of quality. To investigate, we combine our index of neighborhood quality from the 2012-2016 ACS, as described in Appendix A, with data from the 2015 wave of the PSID. We estimate the regression

$$Q_i = \alpha + \alpha^B B_i + \beta_1 I_i + \beta_2 I_i^2 + \beta_1^B I_i \times B_i + \beta_2^B I_i^2 \times B_i + \gamma I_i \times W_i + \delta_1 W_i + \delta_2 W_i^2 + \delta_1^B W_i \times B_i + \delta_2^B W_i^2 \times B_i + \varepsilon_i \quad (2)$$

where the unit i is families, Q_i is neighborhood quality as measured at the tract level, B_i is an indicator for the head of the family being black versus non-Hispanic white, I_i is total family income, and W_i is family net worth. In an attempt to impose common support, the estimation sample is restricted to families with incomes between the 10th and 90th percentiles of the income distribution within each wealth quintile×race bin. The regression is estimated on the sample of all families in the 2015 PSID with a black or non-Hispanic white head, and weights are used to obtain all of our PSID estimates.

Table 1 displays estimated regression coefficients. The coefficient on having a black head of household is −22, indicating that black families live in neighborhoods that are 22 percentile points worse than white families conditional on income and wealth. Income matters more than wealth, with the coefficient on family income more than an order of magnitude higher than the coefficient on family wealth. And finally, neighborhood quality is more strongly related to family income and wealth for blacks than for whites, although the difference for wealth is minor.

Table 1: Neighborhood Quality Regression

All Households			
Constant	39.9 (0.9)	Black Head of Household	−21.8 (2.0)
Family Income	2.0e-4 (2.4e-5)	Black×Family Income	9.2e-5 (7.5e-5)
Family Income ²	−1.6e-10 (1.2e-10)	Black×Family Income ²	−8.7e-10 (5.9e-10)
Family Wealth	1.2e-5 (1.4e-6)	Black×Family Wealth	1.6e-6 (9.1e-6)
Family Wealth ²	−8.1e-13 (1.2e-13)	Black×Family Wealth ²	−1.4e-12 (2.6e-12)
		Family Income×Family Wealth	−4.6e-11 (8.8e-12)
R^2	0.22	N	6,600-6,700

Figure 2 illustrates just how small the differences in neighborhood quality are across wealth levels once income and race are accounted for. High- and low-wealth families, or 4th and 1st quintile families, live in neighborhoods of similar quality after accounting for income and race.

If income and wealth were driving neighborhood sorting, then the dashed lines representing low-wealth families would be on top of each other. Similarly, the solid lines representing high-wealth families would be on top of each other. Instead, the lines we see on top of each other are the red lines representing white families and the blue lines representing black families.

It is worth noting that even within race, wealth appears unimportant at both low levels of income and high levels of income. As a stylized fact, we might characterize these estimation results as indicating that neighborhood quality is (mean) independent of wealth conditional on income and race. If credit constraints were a barrier to accessing high-quality neighborhoods, then one would expect a larger gap between high- and low-wealth groups at low levels of income.

We use the 1st and 4th quintiles of the overall wealth distribution to represent, respectively, low and high wealth for two reasons. First, there are simply not many African American households in the 5th quintile of the overall distribution of wealth. Second, the right tail of the wealth distribution is extremely long, and there are differences across race in the distribution within the 5th quintile. The mean wealth of white households in the 5th quintile of the overall distribution is \$1.97 million, compared to \$0.18 million for white households in the 4th quintile. In contrast, discrepancies across race within bins are not large enough to drive our results when focusing on the 1st and 4th quintiles.³ In the 4th quintile of wealth, mean white and black wealth is, respectively, \$180,000 versus \$155,000. In the 1st quintile of wealth, mean white and black wealth is, respectively, −\$51,000 and −\$36,000.

The result that wealth does not predict neighborhood quality after conditioning on income and race is robust. Appendix B shows that this result is not driven by the age of household heads or the absence of children in the families in our sample, assumptions about how to measure neighborhood quality, or the functional form assumptions made about the relationship between quality and family characteristics. We also look at issues related to measuring wealth. Appendix C repeats this analysis with the 1990 Census and 1989 PSID and finds very similar results.

3.3 Neighborhood Quality and the Price of Housing

The previous section presented evidence that household wealth W_i is not an argument of $h(\cdot)$ in Equation 1. We might still be concerned that the price of housing could be a financial constraint differentially affecting black and white households.

In most metros, the price of housing does not increase sharply as a function of quality. In most metros it is also the case that the price of housing is not so strongly correlated with quality that there are no “affordable” high-quality neighborhoods. Figure 3a illustrates this general pattern by plotting a random sample of 1,000 tracts from the 54 metros with at least 1 million residents in the 2012-2016 ACS.

Neighborhood choices are made at the metro level, though, and so the general picture in Figure

³See Auerback and Gelman (2016) for an example of how different within-bin distributions can drive inferences. In our case, the concern would be that black families in the 4th quintile would be disproportionately near to the 3rd quintile of wealth while white families would be nearer to the 5th quintile. In such a scenario, comparing families within the 4th quintile would not be a comparison between families with similar levels of wealth.

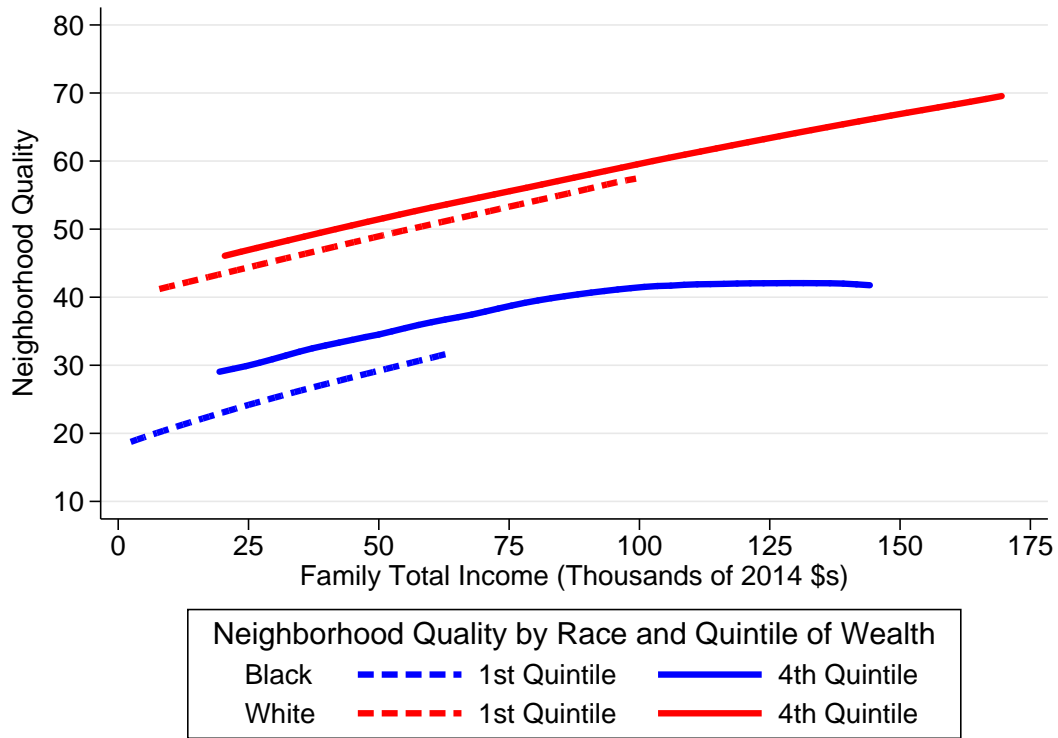


Figure 2: Neighborhood Quality by Income, Race, and Wealth

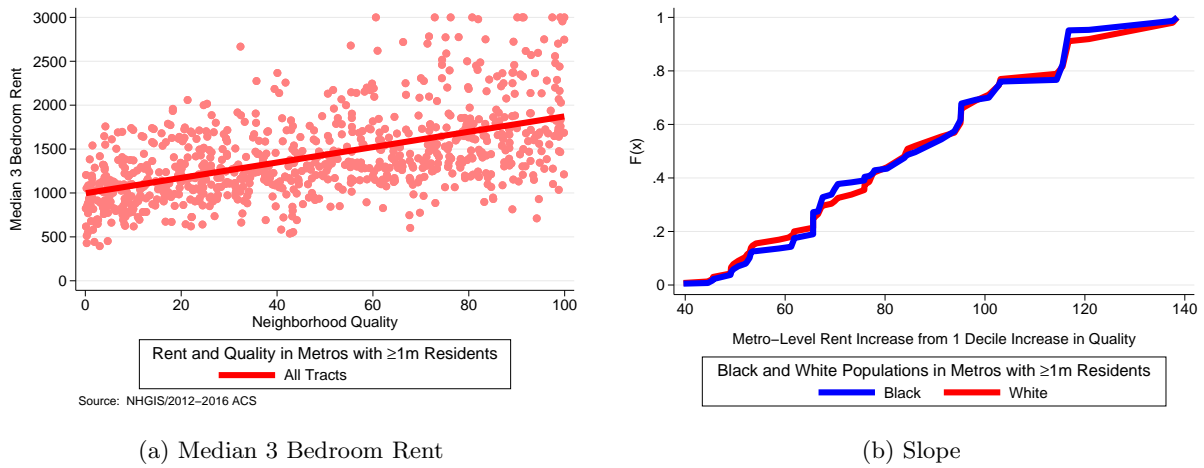


Figure 3: Neighborhood Quality and the Price of Housing

3a could mask heterogeneity in housing prices in the metros where black or white households are more likely to reside. It could be the case that black households tend to live in more expensive metros than white households, and this price differential could help drive differences in neighborhood sorting by income and race. Figure 3b shows that this is not the case, as black and white households are distributed in metros with similar housing price-neighborhood quality elasticities. A related analysis is replicated in Appendix E showing similar results with housing prices measured using median house values. Appendix E also shows the data from several metros and shows that black and white households reside in cities where the strength of the correlation between price and quality is similar.

4 Can Non-Pecuniary Factors Explain Neighborhood Sorting?

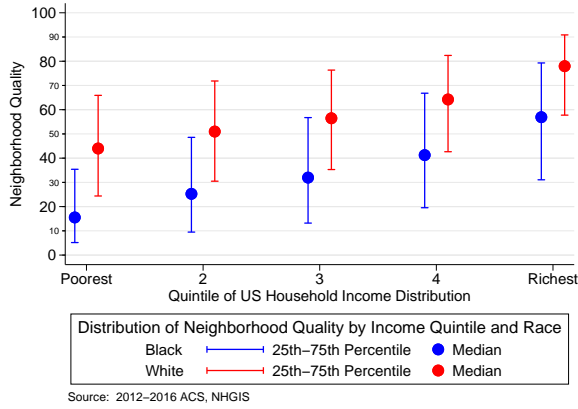
4.1 Sorting by Neighborhood Racial Composition

We have shown that wealth predicts little difference in neighborhood quality conditional on income and race, and that black and white households live in cities with similar housing prices. These facts point to an alternative to financial constraints as an explanation for why black and white households of similar incomes live in different quality neighborhoods. Recalling the utility function in Equation 1, one such explanation has to do with race-specific preferences. We think of race-specific preferences very broadly. In addition to preferences over the racial composition of one's neighborhood, we think these could include race-specific preferences over neighborhood amenities, race-specific costs to living in a neighborhood, race-specific costs to searching for housing in a neighborhood, as well as black and white households facing different distributions of amenities across neighborhoods (say, in the case of social or family networks). We cannot measure these factors separately. Instead, we measure the racial composition of neighborhoods and are agnostic about precisely what factors drive race-specific preferences $u(\Psi_n(r_i))$.

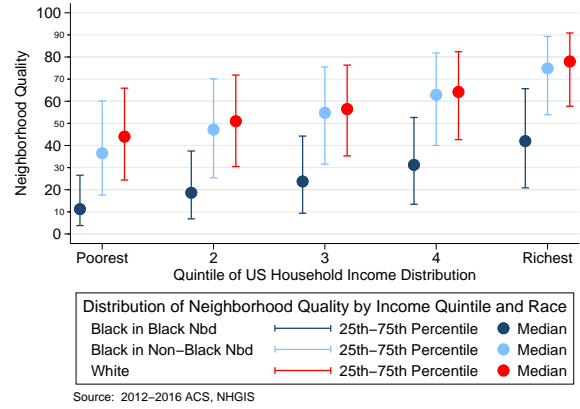
If broadly defined race-specific preferences drive neighborhood sorting, we would expect to see that black households would live in neighborhoods of similar quality to those of white households when not residing in black neighborhoods. This expected pattern is the one we observe in the data. Figure 4b shows the following fact: At all income levels, the racial gap in neighborhood quality can be explained by black households sorting into black neighborhoods.⁴

The neighborhood sorting counterfactuals delineated in Aliprantis and Carroll (2018) provide some context for Figure 4b. That the percent of blacks in black neighborhoods is, by income quintile, 64, 59, 56, 52, and 45, suggests that the US is in the Wilson counterfactual. In the Wilson counterfactual, enough high-income African Americans leave segregated neighborhoods after the victories of the Civil Rights movement that the externalities in black neighborhoods decline. This lies between the Malcolm X counterfactual, in which all African Americans would remain in black neighborhoods while working to build up the institutions in those neighborhoods, and the Martin

⁴Differences in the number of children, home equity, and housing services across those in black and non-black neighborhoods are relatively small.



(a) Quality by Income and Race



(b) Quality by Income, Race, and Racial Composition

Figure 4: Neighborhood Quality by Income, Race, and Neighborhood Racial Composition

Luther King, Jr. counterfactual, in which the US would achieve racial and economic integration.

To be sure that the neighborhood sorting patterns in Figure 4b are not driven by financial constraints, we estimate an analogue to Equation 2 where the dependent variable is the share of black residents rather than quality. Figure 5 shows the results: High-wealth black households sort into neighborhoods with the same high share of black residents as low-wealth black households. Similarly, low-wealth white households sort into neighborhoods with the same (lower) share of black residents as high-wealth white households. The share of black residents in one's neighborhood also appears independent of income; among wealth, income, and race, a household's race is the only variable predictive of the share of black residents in one's neighborhood, with the gap between black and white households being 42 percentage points.

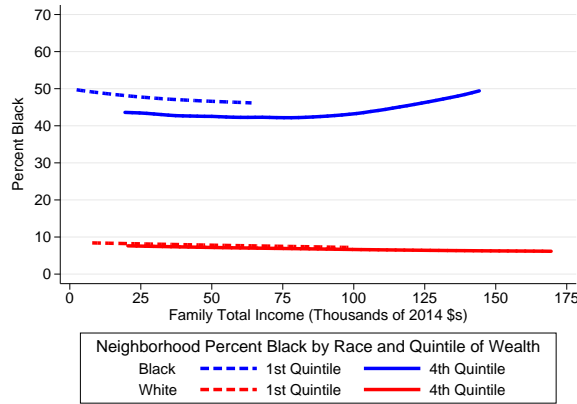


Figure 5: Neighborhood Racial Composition by Income, Race, and Wealth

4.2 Metro-Level Data

We now conduct a metro-level analysis. We start with the 2012-2016 ACS sample of residents in the 53 largest metropolitan statistical areas (metros) in the US in 2017, each of which has a population of at least 1 million residents. We define a neighborhood as being “black” if at least 20 percent of its residents are black. While the precise cutoff used in this definition is arbitrary, we choose 20 percent because Ellen (2000) finds that 10 percent is an inflection point for the willingness of black residents to move into a neighborhood, and the Gautreaux program defined neighborhood eligibility in terms of a 30 percent cutoff (Polikoff (2006)). We define “white” neighborhoods analogously.

We define a neighborhood as being high quality if it is above the median of the national distribution. We consider a resident of a metro as being high income if he/she is in a household with above-median household income. Since [Census tracts](#) have 4,000 residents on average, we define:

$$\text{Supply of High-Quality Black Neighborhoods in a Metro} \equiv \frac{\# \text{ of High-Quality Black Neighborhoods}}{4,000 \text{ Black High-Income Residents}}.$$

We define the supply of high-quality white and any-race neighborhoods in a metro analogously. This measure of the supply of high-quality neighborhoods takes two issues into account: First, different sorting patterns across metros have led to a distribution in the number of black neighborhoods per black residents. Second, some cities have higher-income residents than others. Thus, a metro might have many high-quality black neighborhoods per black resident, but few per high-income black resident. Likewise, a metro might have few high-quality black neighborhoods per black resident, but many per high-income black resident.

We drop several metros from our analysis. We drop two metros because they have no black neighborhoods: Salt Lake City and Tucson. We drop 11 metros because they have less than one black neighborhood per 4,000 residents: Austin, Las Vegas, Orlando, Phoenix, Portland, Riverside, Sacramento, San Antonio, San Diego, San Jose, and Seattle.⁵ The remaining sample has 40 metros with 91 percent of the black population in the original 53 metros.

4.3 Sorting by the Supply of High-Quality Neighborhoods

The relationship between rent and quality for black neighborhoods is not remarkably different from the relationship between rent and quality for other neighborhoods in the US. What is different about quality and black neighborhoods in the US is simply the scarcity of high-quality black neighborhoods (Bayer and McMillan (2005), Bayer et al. (2014)). Figure 6a shows that in Chicago, a metro with over 2,200 Census tracts and a black population of 1.6 million people, there are 11 black neighborhoods in the top quintile of quality. This translates into 0.028 top-quintile black neighborhoods per 4,000 black residents, compared with 0.29 top-quintile non-black neighborhoods

⁵The analysis yields qualitatively similar but noisier results when including these 11 metros.

per 4,000 non-black residents.⁶

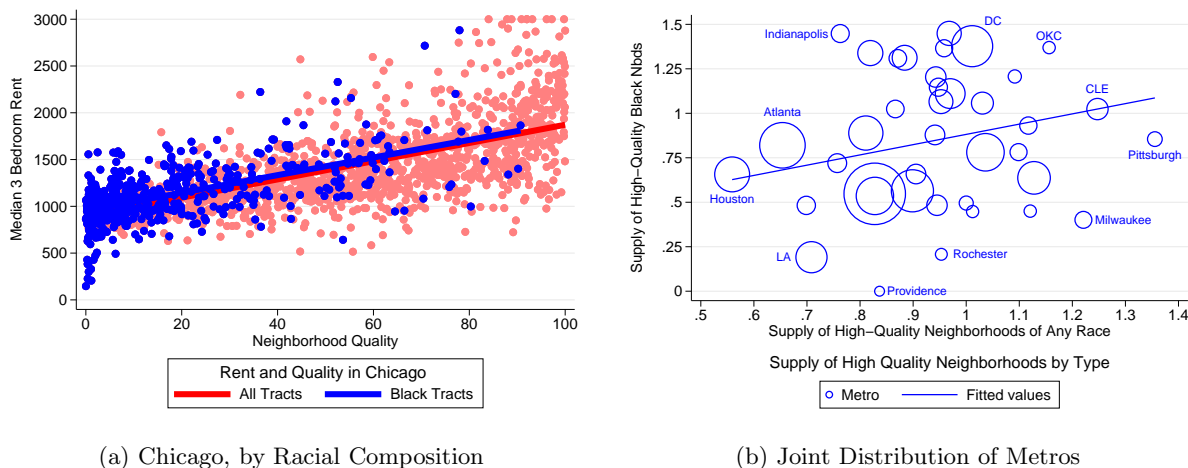


Figure 6: The Supply of High-Quality Neighborhoods

There is variation in the supply of high-quality neighborhoods in a metro, and Figure 6b shows that there is independent variation in the supply of high-quality black neighborhoods and high-quality any-race neighborhoods. While there is a positive relationship between black and any-race supply, the R^2 of a regression of the supply of high-quality black neighborhoods on the supply of high-quality any-race neighborhoods is 0.13. To give an example of the type of variation this allows for, consider Washington, DC and Rochester, NY. Washington, DC and Rochester have similar supplies of high-quality any-race neighborhoods. However, Washington, DC has a very high supply of high-quality black neighborhoods, while Rochester has an extremely low supply of high quality black neighborhoods. High-income black households in these metros face quite different neighborhood choice sets.

We use the orthogonal variation in the supply of high-quality neighborhoods shown in Figure 6b to test how the neighborhood sorting of black residents depends on the supply of high-quality neighborhoods. Looking at the grey bubbles in Figure 7a, we can see that there is no correlation between the supply of high-quality any-race neighborhoods and the neighborhood quality of high-income black residents. However, looking at the blue bubbles in Figure 7a, we can see that there is a positive correlation between the supply of high-quality black neighborhoods and the neighborhood quality of high-income black residents. These patterns indicate that race-specific preferences play an important role in the neighborhood choices of high-income black households.

⁶Los Angeles is even more extreme than Chicago. LA has 2,929 Census tracts and 880,000 black residents, but only *one* top-quintile black neighborhood. This gives LA 0.005 top-quintile black neighborhoods per 4,000 black residents, compared with 0.14 top-quintile non-black neighborhoods per 4,000 non-black residents.

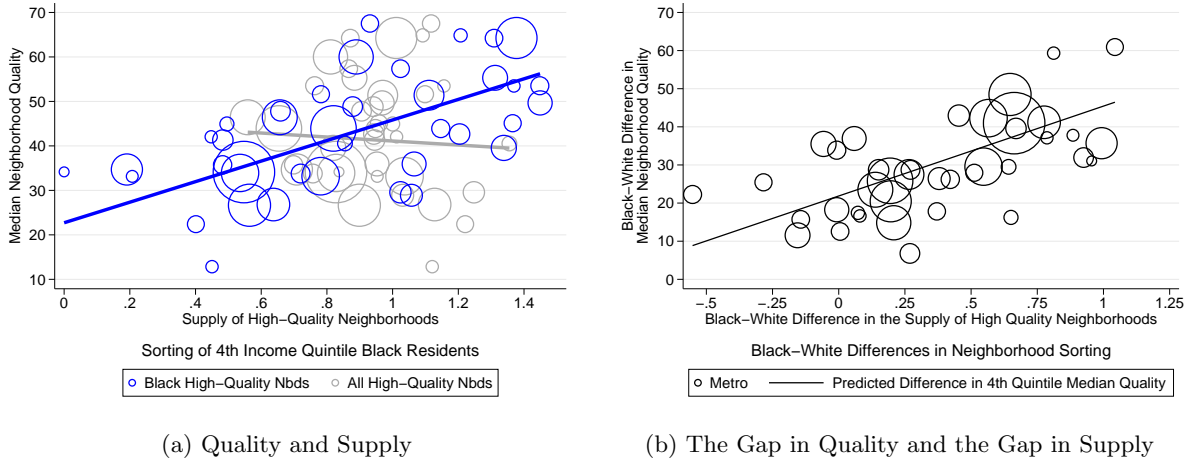


Figure 7: Sorting and the Supply of High-Quality Neighborhoods by Metro

Table 2 presents results similar to those displayed in Figure 7a, expanding to include each race \times income quintile group. Looking at the first three rows of Table 2, we see that the pattern from Figure 7a extends from black households in the 4th quintile of income to black households at all incomes: Neighborhood quality is not related to the overall supply of high-quality neighborhoods. Looking at the last three rows of Table 2, we see that black households do respond to an increase in the supply of high-quality *black* neighborhoods by sorting into higher-quality neighborhoods.

Table 2: Regressions of Median Neighborhood Quality

Coefficient on Supply of HQ Nbds	Median Neighborhood Quality									
	Black by					White by				
	HH Income Quintile					HH Income Quintile				
	1	2	3	4	5	1	2	3	4	5
Any-Race	-7	-10	-12	-4	2	14	14	10	11	7
p-value	0.50	0.37	0.32	0.72	0.84	0.15	0.09	0.16	0.09	0.19
R^2	0.01	0.02	0.03	0.00	0.00	0.06	0.07	0.05	0.08	0.04
Own-Race	14	17	20	23	22	27	23	16	14	6
p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.25
R^2	0.25	0.31	0.35	0.43	0.38	0.25	0.23	0.17	0.15	0.04

Returning to the household’s problem in Section 2, one could imagine that sorting into metros has resulted in differences in income across metros with different levels of neighborhood supply that correlate with racial composition. This issue appears both possible and unlikely given the results in Section 3.3. One way to attempt to deal with this issue is to use white households as a “control” group by looking at differences in the supply of high-quality neighborhoods. Using this approach, we define the black-white difference in the supply of high-quality neighborhoods as the supply of high-quality white neighborhoods in a metro minus the supply of high-quality black

neighborhoods in the metro. Figure 7b shows that the black-white difference in the supply of high quality neighborhoods predicts the black-white difference in the median neighborhood quality of households in the 4th quintile of income.

5 Conclusion

This paper documented facts about neighborhood sorting in the US. It was previously known that black and white households of similar incomes live in neighborhoods of much different quality. We have presented a set of results that make it very difficult to explain this fact in terms of financial constraints related to wealth or the price of housing. We have presented another set of empirical results showing that this fact can be explained by non-pecuniary factors correlated with the racial composition of neighborhoods.⁷

We speculate that racial discrimination in the housing market, while present and non-trivial, is not large enough to generate the sorting patterns we observe.⁸ This speculation is partly informed by the literature (Ross (2010), Bhutta and Hizmo (2019)), partly informed by recent studies finding discrimination priced in terms of a 1 or 2 percent premium (Bayer et al. (2017), Early et al. (2018)), and partly informed by the existence of websites like [Zillow](#) and [realtor.com](#), which equalize access to information.

In contrast, our results are more readily interpreted in terms of recent evidence on the types of push (Harris and Yelowitz (2018)) and pull (Hanson et al. (2018)) factors that would drive preferences over neighborhoods. One explanation for our results is that living in predominantly white neighborhoods imposes large psychic costs on black households, and that these costs are enough to outweigh any educational, labor market, or safety benefits one might experience due to living in a higher-quality neighborhood. Alternatively, the desire to reside near family and friends (Büchel et al. (2019), van der Klaauw et al. (2019)), when combined with the history of racial segregation in the US, could be the source of persistent black enclaves.

Our results highlight that the spatial component of public policy should not be focused entirely on access, say, through wealth building, but should also be designed with attention given to non-pecuniary factors. An important subject for future research will be providing evidence that allows us to move beyond speculation about these factors. The success or failure of related policies will hinge on understanding precisely *which* non-pecuniary factors matter the most in determining neighborhood choices. The preferred policy might be very different depending on whether neighborhood choices are driven more by information (Bergman et al. (2019), Christensen and Timmins (2018)), family and social networks (Büchel et al. (2019), van der Klaauw et al. (2019)), racial hostility (Harriot (2019)), or preferences for same-race neighbors (Shertzer and Walsh (2019), Derenoncourt

⁷The nearest related results on wealth of which we are aware are in Woldoff and Ovadia (2009), Crowder et al. (2006), and Freeman (2000), and the nearest related results on stated-race preferences are in Ihlanfeldt and Scafidi (2002) and Vigdor (2003). Bayer et al. (2014) is also related, but focused more on racial segregation than neighborhood quality.

⁸For related evidence see Edelman et al. (2017), Christensen and Timmins (2018), Nowak and Smith (2018), Hanson et al. (2016), Ihlanfeldt and Mayock (2009), or Yinger (1986).

(2018), Bayer and Blair (2019)).

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Appendix to “What Explains Neighborhood Sorting by Income and Race?”

Dionissi Aliprantis Daniel Carroll Eric Young

A Measuring Neighborhood Quality

There are reasons to exercise caution when focusing on a single dimension to characterize neighborhood quality (Chetty et al. (2018)). Important neighborhood characteristics are not perfectly collinear, and this can generate surprising implications for sorting patterns. An important example is that black low-poverty neighborhoods in Moving to Opportunity (MTO) cities looked like white high-poverty neighborhoods in terms of characteristics such as educational attainment, unemployment, and the share of single-headed households (Aliprantis and Kolliner (2015)).

With this consideration in mind, we now consider our measure of neighborhood quality. To begin, we note that each of the variables we use in our measure of neighborhood quality is motivated by Wilson (1987)’s original discussion of the mechanisms driving neighborhood effects. These mechanisms include the concentration of poverty generating social isolation (Chapter 2); the importance of educational attainment in the face of secular changes in the labor market (Chapter 2); the importance of black males’ labor market outcomes such as employment and participation in terms of role models and household formation (Chapters 2 and 3); and the importance of single-headed households in driving child poverty (Chapter 3). A more recent discussion of related mechanisms can be found in Chapter 8 of Galster (2019).

Figure 1 and Table 1 show that if we were to summarize the neighborhood variables poverty rate, high school graduation rate, BA attainment rate, employment-to-population ratio, unemployment rate, and share of single-headed households, a principal components analysis would indicate that these variables can be summarized by a univariate index. In other words, it appears reasonable to focus on the first principal component of these variables alone, and to define this univariate index as neighborhood quality. Table 2 shows that the coefficients on the variables are relatively similar.

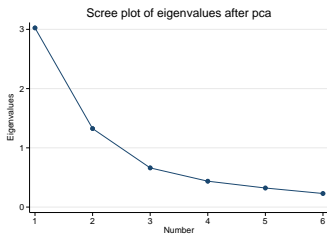


Figure 1: Scree Plot of Eigenvalues

Table 1: Percent of Variance Explained

Principal Component	Marginal Contribution of Single Vector	Cumulative
1st	64	64
2nd	12	76
3rd	10	86
4th	7	92
5th	5	97
6th	3	100

Note: See the text for further details.

Table 2: Coefficient for First Principal Component

Characteristic	Princ Comp	Characteristic	Princ Comp
Poverty Rate	0.45	Emp-to-Pop Ratio	0.35
HS Grad Rate	0.44	Unemp Rate	0.39
BA Attainment Rate	0.43	Share Single-Headed HHs	0.39

Note: See the text for further details.

It is important to be mindful that our measure of neighborhood quality will sometimes miss in its univariate summary of a multivariate world, as well as the fact that many criteria would define neighborhood quality in terms of additional neighborhood characteristics. Nevertheless, we find our univariate index to be a useful abstraction; it summarizes information in a way that allows us to conduct an analysis in terms of the types of neighborhood effects discussed in Wilson (1987).

Figure 2 uses the NHGIS data to replicate the result from the literature that neighborhood quality is lower for blacks than whites at all levels of income (Pattillo (2005), Reardon et al. (2015)). Note that the gap is large enough so that high-income black households live in neighborhoods with characteristics similar to those of low-income white households. Whites in the first (poorest) quintile of household income live in neighborhoods of similar quality to those of blacks in the fourth quintile of household income.

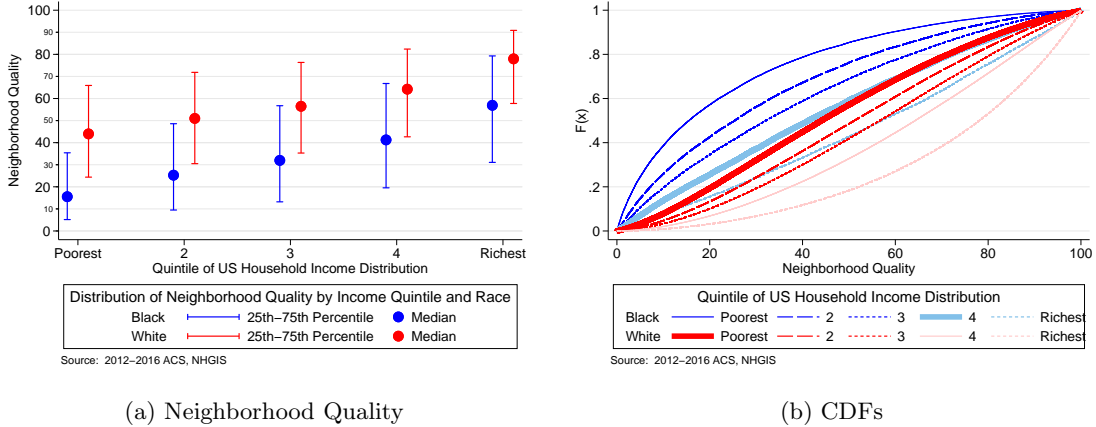


Figure 2: Household Income and Neighborhood Quality in the 2012-2016 ACS, by Race

Empirically, the components of our index are also the neighborhood characteristics found to be highly correlated with neighborhood opportunity as estimated in Chetty et al. (2018): the employment rate of the local residents, poverty rate, share of college graduates, and share of single-headed households. Here we compare neighborhood quality with a few measures of intergenerational outcomes from Chetty et al. (2018). Chetty et al. (2018) analyze data for children born between 1978 and 1983. In Census tracts with sufficient data, they provide publicly available estimates of mean outcomes for children of a specific race and gender given parents at several percentiles of the national household income distribution. These estimates represent the expectation of each outcome conditional on growing up from birth in a given tract, where each tract-level regression weights children by the fraction of their childhood (up to age 23) spent in that tract.

Figure 3 shows mean income estimates pooled across race/ethnicity and gender for children whose parents had incomes at the 50th percentile of the US distribution. Figure 4 shows mean income estimates for black boys whose parents had incomes at the 25th percentile of the US distribution. We see that the intergenerational income level in a neighborhood is positively correlated with neighborhood quality, although the relationship is different by subgroups and is noisier as the sample size for estimation declines.

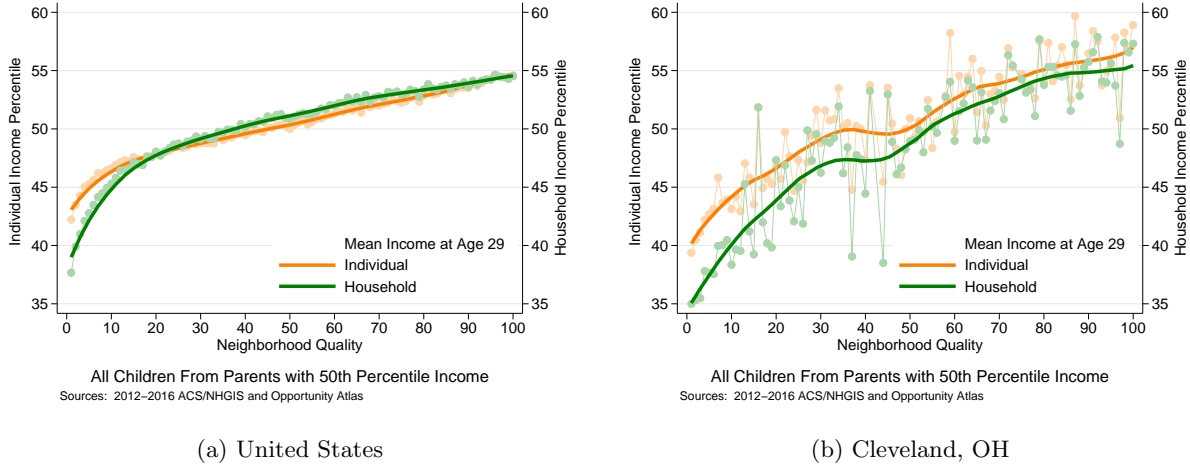


Figure 3: All Children with 50th Percentile Parents

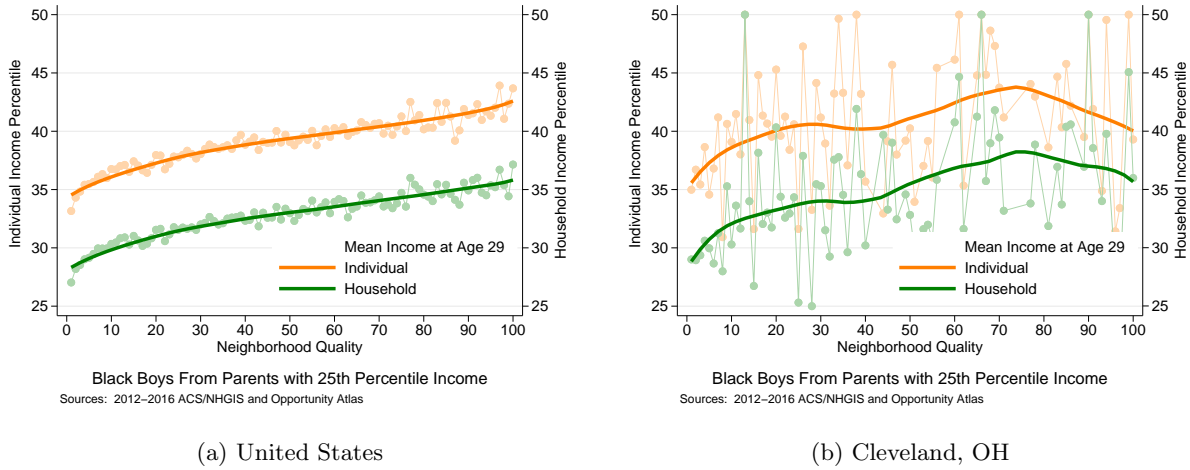


Figure 4: Black Boys with 25th Percentile Parents

B Robustness: The 2015 Wave of the PSID

It might come as a surprise to find that wealth only weakly predicts neighborhood quality after conditioning on race and income. There are several reasons we might see such a result that are not related to the explanation that neighborhood sorting is driven by race and income.

For this reason we now consider the robustness of our result that sorting into neighborhood quality is not driven by wealth once income and race are taken into account. We first present evidence on whether our result is driven by family composition of our sample, assumptions about how to measure neighborhood quality, or the functional form assumptions made about the relationship between quality and family characteristics. We also look at issues related to measuring wealth.

B.1 Family Composition

One possibility is that black households in the 4th quintile of wealth are older, less likely to have children than their white counterparts, or less likely to be homeowners. We test this possibility by estimating versions of Equation 2 on our estimation sample that also include a quadratic in the age of the head of the household, a dummy for the presence of children 18 or younger, a dummy for homeownership, and each of these controls. These estimates are shown in Table 3, with there being two main findings. The first is that the coefficient on having a black head of household is stable, and the second is that the R^2 does not increase after including the additional controls. Both of these findings indicate that the main results in the text are not driven by compositional issues across race.

Table 3: Neighborhood Quality Regressions

Black Head of Household	-21.8 (2.0)	-21.2 (2.0)	-21.0 (2.0)	-22.7 (2.1)	-21.5 (2.1)
Child ≤ 18 in Household		X			X
Quadratic in Age of Head			X		X
Rent/Own Dummy				X	X
R^2	0.22	0.22	0.23	0.23	0.23

We run a similar set of regressions where the dependent variable is the percentage of black residents in the household's neighborhoods, where again we progressively add a quadratic in the age of the head of the household, a dummy for the presence of children 18 or younger, a dummy for homeownership, and each of these controls. These estimates are shown in Table 4, with there again being two main findings. The first is that the coefficient on having a black head of household is stable, and the second is that the R^2 does not increase after adding more controls. Both of these findings indicate that the main results in the text are not driven by compositional issues across race.

Table 4: Racial Composition Regressions

Black Head of Household	41.5 (1.3)	41.5 (1.3)	41.2 (1.3)	41.1 (1.4)	41.0 (1.4)
Child ≤ 18 in Household		X			X
Quadratic in Age of Head			X		X
Rent/Own Dummy				X	X
\overline{R}^2	0.46	0.46	0.46	0.46	0.46

B.2 Measuring Neighborhood Quality

We also investigate whether one variable in our neighborhood quality index is by itself driving our results. Table 5 shows the coefficient on the black indicator when Equation 2 is estimated with Q_i measured as each individual component of our index.

No single variable drives our results on the relationship between neighborhood quality, race, income, and wealth. Most of the neighborhood characteristics yield results similar to the penalty of 22 percentile points in neighborhood quality for having a black family head. The coefficient on the black indicator is -20 percentile points or more for the poverty rate, unemployment, and the share of single-headed household; -16 percentile points for the employment-to-population ratio and the share of high school graduates; and smallest in magnitude for the BA attainment rate at -12 percentile points. These results are not surprising given the relatively even coefficients across characteristics under our definition of quality (Table 1 in Appendix A), and the relatively higher value given to the educational attainment of neighbors is consistent with the recent hedonic results in Bishop and Murphy (2019).

Table 5: Neighborhood Characteristic Regressions

Coefficient on Black Household Head			
	for Percentile of	Coefficient	s.e.
Poverty Rate		-19.5	(2.1)
Share of Single-Headed HHs		-25.6	(2.1)
Unemployment Rate		-23.0	(2.2)
Employment-to-Population Ratio		-15.8	(2.3)
HS Attainment Rate		-16.0	(2.1)
BA Attainment Rate		-11.9	(2.2)

B.3 Functional Form Assumptions

Another possibility is that black families with high wealth actually do sort into higher-quality neighborhoods than those without wealth, but that this relationship is blurred by the limited number of high-income and high-wealth black families we observe in the data. As highlighted in

Barsky et al. (2002), this could mean that our results are being driven by functional form assumptions over the parts of the income and wealth distribution where there is not common support between black and white households.

Figure 5 presents evidence on this issue by showing means within \$10,000 income bins by race and wealth quintile. Figure 5b shows the area of concern for having a limited sample size, high-income and high-wealth black families. Each \$10,000 income bin with a dot shown has at least 15 families to prevent indirect data disclosure. When the cell size is decreased to 10 families, which is not shown here, we see that the variance of neighborhood quality for high-income, high-wealth black families is higher than it is for their white counterparts. However, the relationship characterized by the curve in Figure 5b accurately characterizes the mean relationship. Most importantly, there remains a clear gap between means across black- and white-headed families that are high income and high wealth.

Related analyses using the propensity score to relax functional form assumptions imposed by OLS regression (Imbens (2015)), both to impose common support (Heckman et al. (1998)) and to conduct nearest neighbor matching, produce similar results.

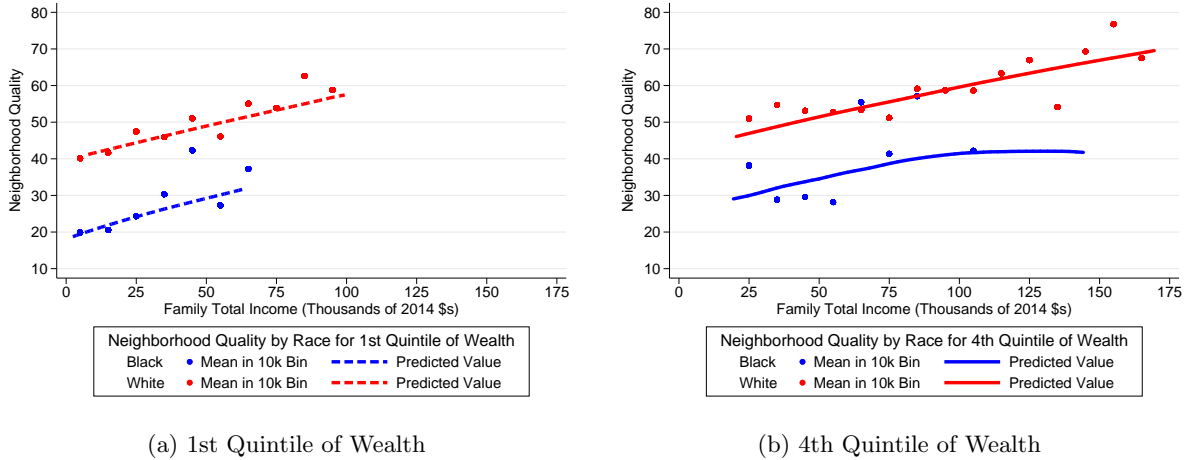


Figure 5: Neighborhood Quality by Income and Race, 2015 PSID

B.4 Measuring Wealth

Turning to the issue of measuring wealth, net worth might be less informative for a family's credit constraints than either total assets or liquid wealth. Two households with identical net worth but different levels of total assets, and therefore debt, might have different access to credit, just based on past access. Similarly, two households with identical net worth but different levels of liquid wealth have different needs for credit. We measure total assets as net worth plus total debt, and we measure liquid wealth as the sum of two asset classes; checking/savings accounts and stocks. We do not show the results here, but the qualitative results are almost identical regardless of whether we measure wealth as net worth, total assets, or liquid wealth.

It could also be the case that families within quintiles of wealth are too heterogeneous to be

compared, especially across race. Figure 6a shows the distribution of wealth across race in the 4th quintile of wealth, which we use as our high-wealth category. The means for black and white families are, respectively, \$155,000 and \$180,000.

One might also suspect that high-wealth households of different races make different investments in home equity, and that this is somehow driving neighborhood sorting patterns. Figure 6 shows that the distribution of home equity is very similar for black- and white-headed families in the 4th wealth quintile. Homeownership rates are very high among the 4th wealth quintile, and the rates are (statistically) identical by race.

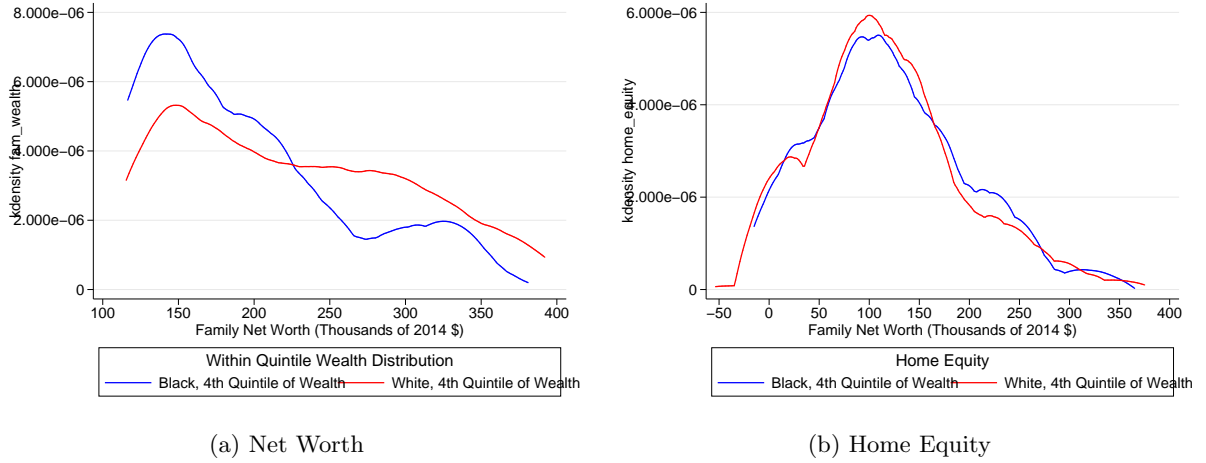


Figure 6: Net Worth and Home Equity by Income and Race, 2015 PSID

C Robustness: The 1989 Wave of the PSID

In order to test whether our result reflects a new trend in sorting due to the Great Recession, we replicate the previous analysis using the 1990 decennial Census together with the 1989 wave of the PSID. We find almost identical results to those using the 2012-2016 ACS and 2015 wave of the PSID: In the 1989 wave of the PSID wealth had little role in sorting into neighborhood quality once race and income are accounted for.

Table 6 shows results from estimating Equation 2 using the 1990 decennial Census and the 1989 wave of the PSID, where the estimation sample is all families in the 1989 PSID with a black or non-Hispanic white head. To impose common support, the sample is restricted to families with incomes between the 10th and 90th percentiles of the within-wealth-quintile black income distribution. The coefficient on black head of household is -25 , which indicates that black families live in neighborhoods that are, on average, 25 percentile points worse than those of white families. Figure 7 displays these results graphically.

Table 6: Neighborhood Quality Regression, 1989 PSID

All Households			
Constant	39.9 (0.9)	Black Head of Household	-25.1 (2.1)
Family Income	$5.1\text{e-}4$ ($6.1\text{e-}5$)	Black \times Family Income	$-1.6\text{e-}4$ ($1.5\text{e-}4$)
Family Income ²	$-1.5\text{e-}9$ ($6.8\text{e-}10$)	Black \times Family Income ²	$2.2\text{e-}9$ ($2.4\text{e-}9$)
Family Wealth	$3.7\text{e-}5$ ($5.2\text{e-}6$)	Black \times Family Wealth	$3.3\text{e-}5$ ($1.9\text{e-}5$)
Family Wealth ²	$-5.8\text{e-}12$ ($9.8\text{e-}13$)	Black \times Family Wealth ²	$-5.3\text{e-}12$ ($4.0\text{e-}12$)
		Family Income \times Family Wealth	$-2.7\text{e-}10$ ($6.9\text{e-}11$)
R^2	0.29	N	4,400-4,500

Tables 7 and 8 again investigate whether differences in family composition or homeownership can explain the main results in the 1989 PSID. We again find that the coefficient on black head of household is stable and that explanatory power does not increase when adding these covariates.

Table 9 shows the coefficient on the black indicator when Equation 2 is estimated with Q_i measured as each individual component of our index. Again for the 1989 wave, just as we saw in the 2015 wave of the PSID, no single variable drives our results on the relationship between neighborhood quality, race, income, and wealth. Most of the neighborhood characteristics yield results similar to the penalty of 25 percentile points in neighborhood quality for having a black family head.

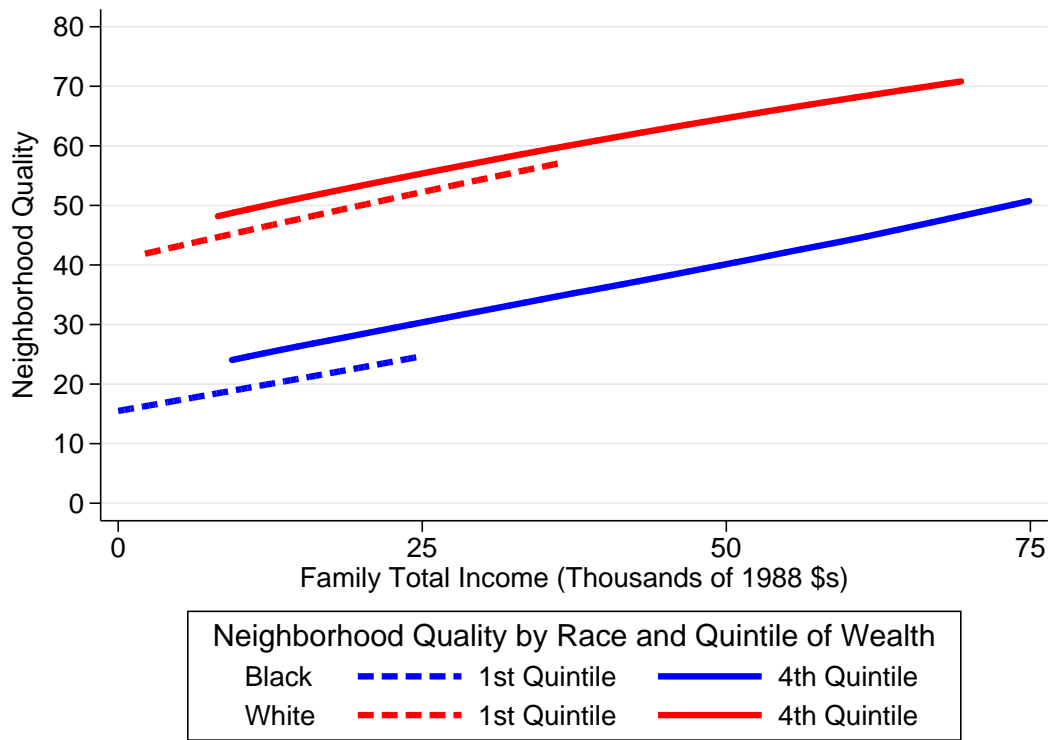


Figure 7: Neighborhood Quality by Income, Race, and Wealth, 1989 PSID

Table 7: Neighborhood Quality Regressions, 1989 PSID

Black Head of Household	-25.1 (2.1)	-22.5 (2.1)	-26.0 (2.1)	-24.9 (2.2)	-23.0 (2.2)
Child ≤ 18 in Household		X			X
Quadratic in Age of Head			X		X
Rent/Own Dummy				X	X
R^2	0.29	0.29	0.29	0.29	0.31

Table 8: Racial Composition Regressions, 1989 PSID

Black Head of Household	56.5 (1.3)	56.7 (1.4)	56.8 (1.4)	56.4 (1.4)	57.0 (1.4)
Child ≤ 18 in Household		X			X
Quadratic in Age of Head			X		X
Rent/Own Dummy				X	X
R^2	0.61	0.61	0.61	0.61	0.61

Table 9: Neighborhood Characteristic Regressions,
1989 PSID

Coefficient on Black Household Head		
for Percentile of	Coefficient	s.e.
Poverty Rate	−24.4	(2.1)
Share of Single-Headed HHs	−25.4	(2.1)
Unemployment Rate	−27.8	(2.1)
Employment-to-Population Ratio	−22.7	(2.2)
HS Attainment Rate	−22.5	(2.1)
BA Attainment Rate	−16.4	(2.2)

Turning to the possibility that the relationship between race, income, wealth, and neighborhood quality is blurred by the limited number of high-income and high-wealth black families we observe in the data, Figure 8 shows means within \$10,000 income bins by race and wealth quintile. Figure 8b shows the area of concern for having a limited sample size, high-income and high-wealth black families. Each \$10,000 income bin with a dot shown has at least 15 families to prevent indirect data disclosure. When the cell size is decreased to 10 families, which is not shown here, we see that the variance of neighborhood quality for high-income, high-wealth black families is higher than it is for their white counterparts. However, the relationship characterized by the curve in Figure 8b accurately characterizes the mean relationship.

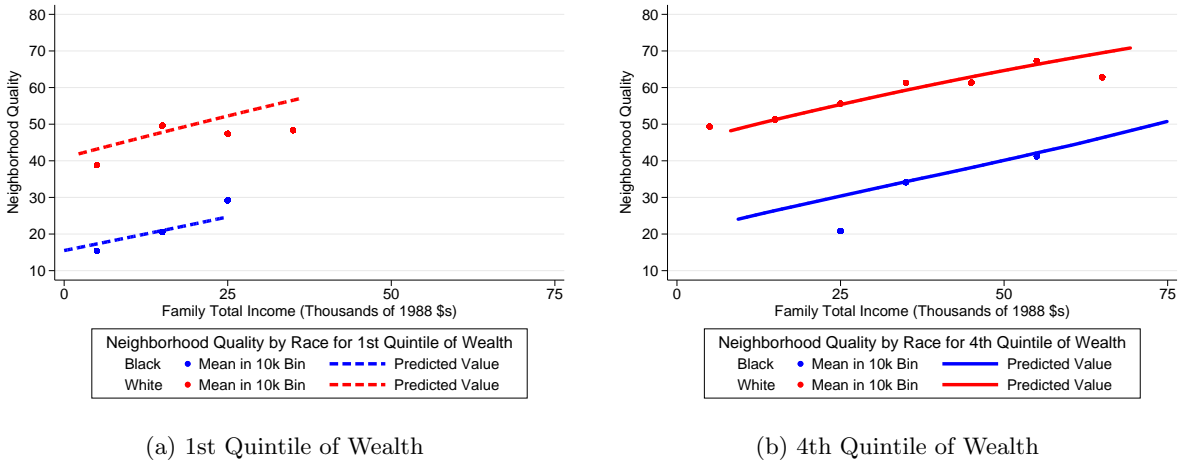
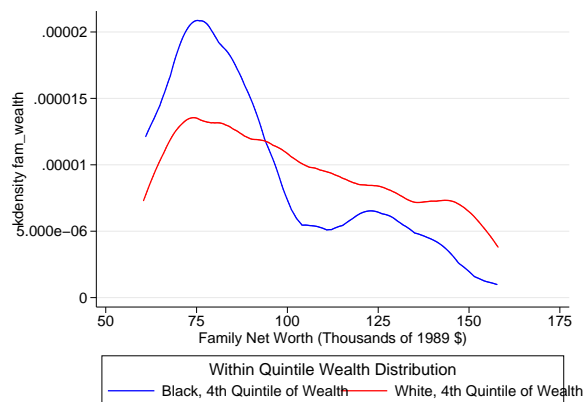
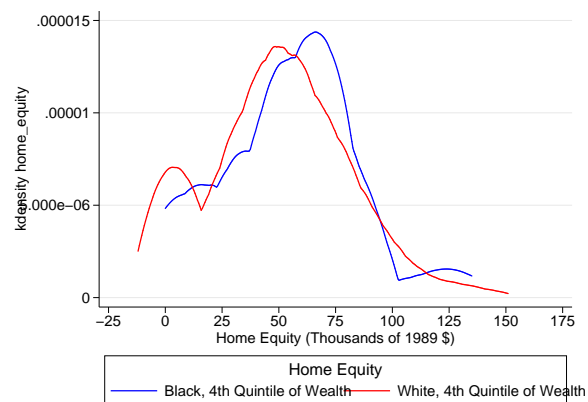


Figure 8: Neighborhood Quality by Race, Income, and Wealth, 1989 PSID

Figure 9a shows again that within wealth quintile differences in wealth across race are unlikely to drive our results. Homeownership rates are very high among the 4th wealth quintile and (statistically) identical across race. Figure 9b shows that in the 1989 wave of the PSID, just as in the 2015 wave, home equity was very similar across race in the 4th quintile of wealth.



(a) Net Worth



(b) Home Equity

Figure 9: Net Worth and Home Equity by Race, Income, and Wealth, 1989 PSID

D Additional Evidence on Race-Specific Location Preferences

D.1 The National Longitudinal Survey of Youth 1997 (NLSY97)

We present further evidence that conditional on income and wealth, blacks and whites have different locational preferences. We look first at data from the National Longitudinal Survey of Youth 1997 (NLSY97), a nationally representative longitudinal survey of individuals born between 1980 and 1984. Figure 10a shows that at age 25 in the NLSY97, black respondents were more likely than their white counterparts to live within five miles of their mothers. Figure 10b shows that this fact is not driven by financial constraints, as it remains true conditional on both income and wealth.

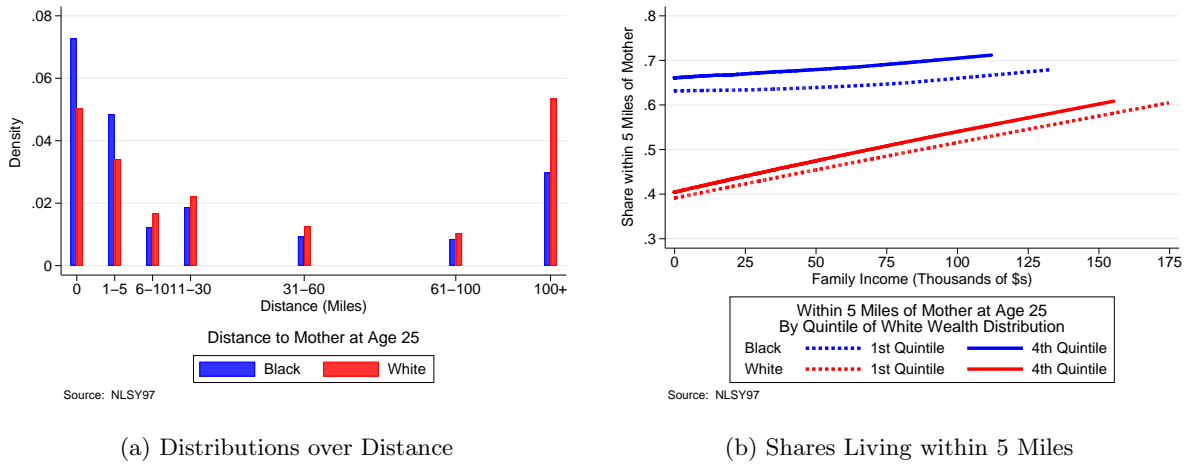


Figure 10: Distance to Mother at Age 25, NLSY97

D.2 2012-2016 American Community Survey (ACS)

We next look at anonymized individual-level data from the 2012-2016 wave of the ACS drawn from IPUMS-USA. Figure 11 shows that black individuals “pay” for the locational preference, including that of being near their mothers, by spending more time traveling to work, even conditional on income. This result provides suggestive evidence that high-income households’ neighborhood sorting is not driven by access to employment (Ellen et al. (2013)). The estimates in Figure 11 are precise, even for high-income African Americans, since the IPUMS ACS sample has more than 15 million individuals.

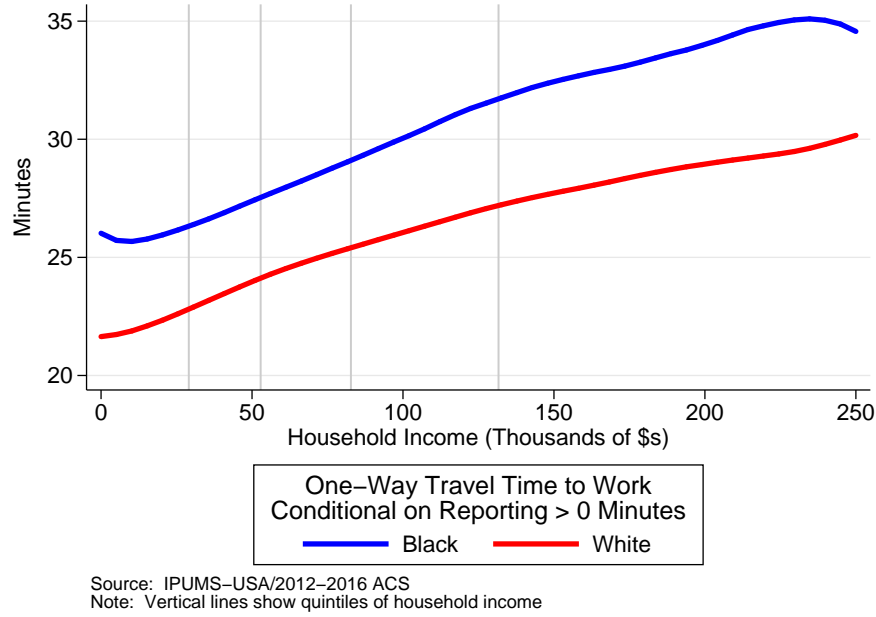


Figure 11: One-Way Travel Time to Work, 2012-2016 ACS

Digging into the cross section of travel to work times in Figure 11, Figure 12a shows the empirical CDFs of travel to work times for black and white households within \$2,500 of the income separating 3rd and 4th quintile households, \$78,000. To more clearly show where differences in black and white distributions occur, Figure 12b shows differences between the white and black CDFs in \$5,000 bins centered at each of the incomes separating quintiles. This figure shows, for a given income, a value on the y -axis indicating the additional share of black households with a longer travel time than the time on the x -axis.

The qualitative patterns in Figure 12b are similar across income levels. The big increases around 5 and 10 minutes, combined with the drop-off at 30 minutes, indicate that many more African Americans than white Americans have travel times of 30 minutes rather than 5 or 10 minutes. We might interpret the drop-offs at 45 and 60 minutes similarly; many more African Americans have commutes of 45 or 60 minutes rather than 30 minutes.

The levels in Figure 12b, however, are clearly differences across income levels. The largest differences in travel time are seen for the highest income households. The highest income households are also clear exceptions between 30-60 minutes, with larger differences in CDFs than for any other income level. There is also variation in differences between 0-30 minutes that is not monotonic in income. Figure 13 shows more detail on precisely how differences in travel time are increasing in income.

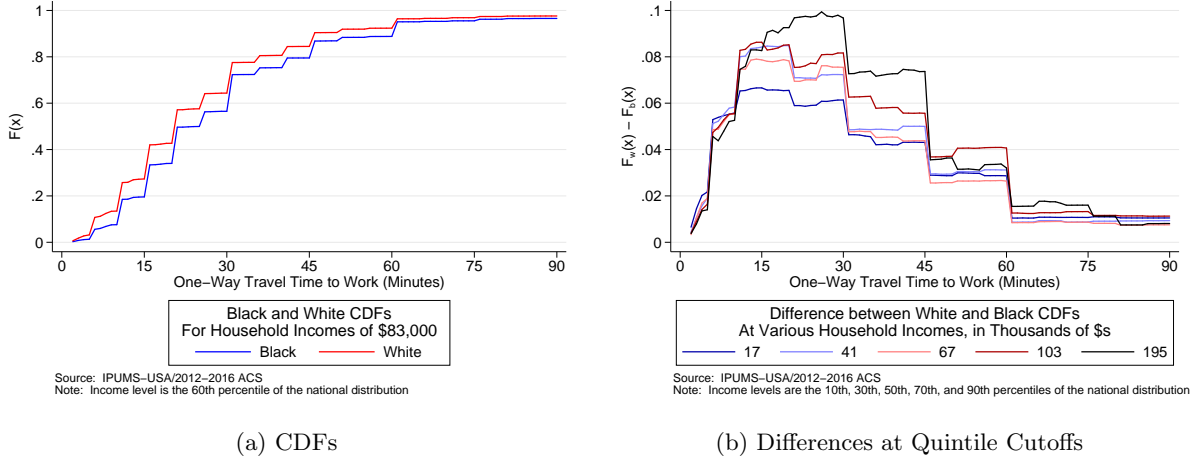


Figure 12: Census Data

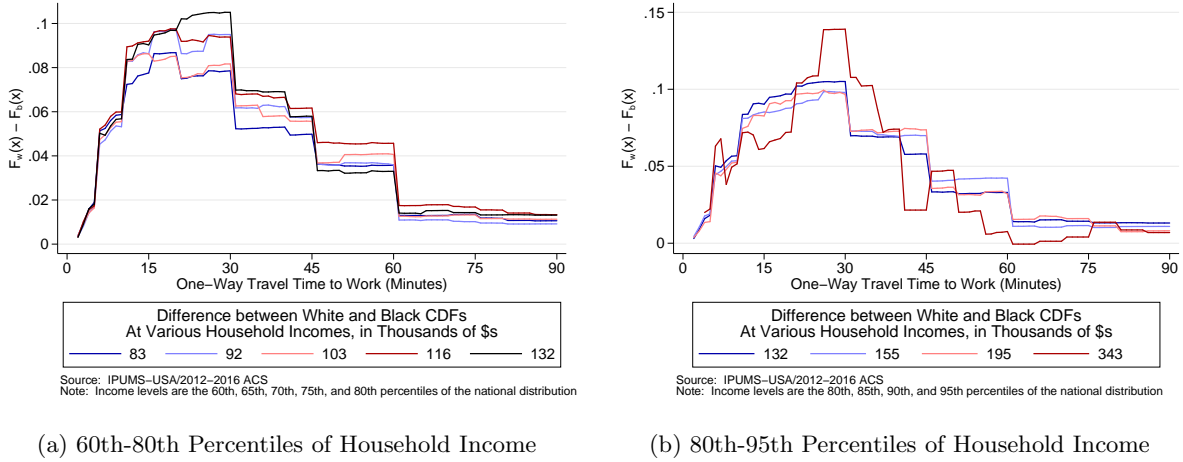
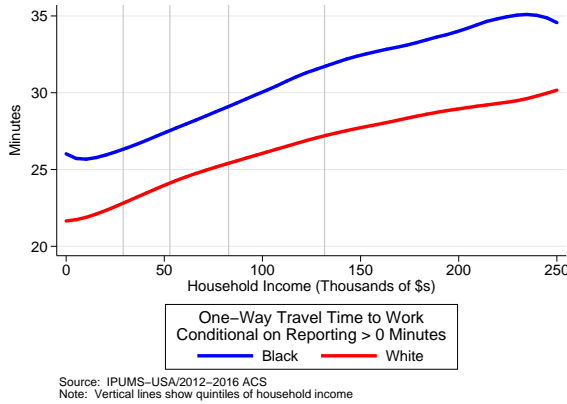


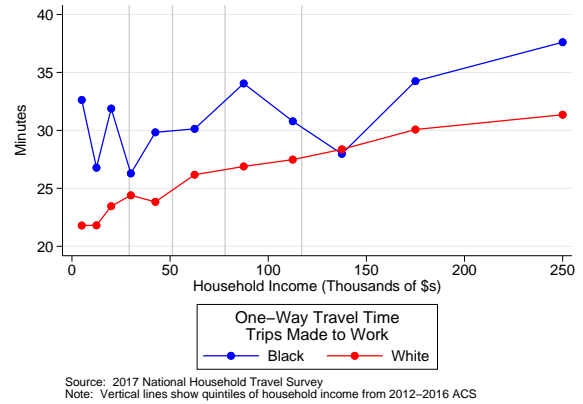
Figure 13: Census Data

D.3 2017 National Household Travel Survey (NHTS)

Finally, we look at data from the 2017 National Household Travel Survey (NHTS). The evidence from the NHTS is noisier than either the NLSY97 or the IPUMS 2012-2016 ACS, and this is one reason for the difficulty of using these data to test for the relationship between neighborhood sorting and social isolation (Wang et al. (2018)) or consumption segregation (Davis et al. (2019)). We first compare results from the 2017 NHTS with the IPUMS Census data in Figure 14, and find that the NHTS is noisier but qualitatively similar. Figures 15a - 16b show that black and white respondents in the NHTS tend to spend similar amounts of time on trips made for doing household chores, picking up meals, buying goods or services, and picking someone up. This is especially true within the first 4 quintiles of income. One notable exception is that black respondents in the fifth quintile of income tend to spend much more time on trips picking someone up.

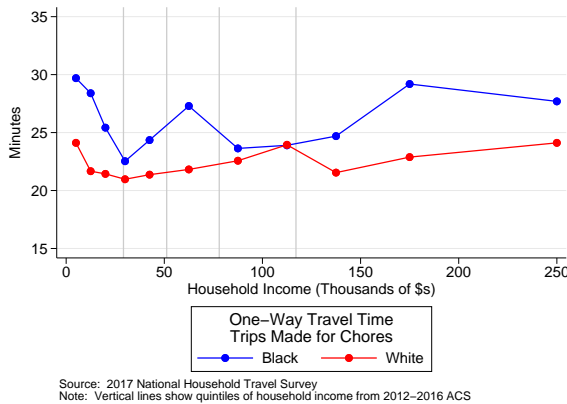


(a) IPUMS/ACS 2012-2016

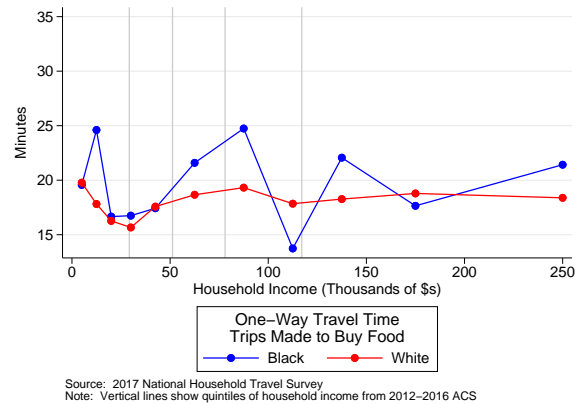


(b) NHTS

Figure 14: Travel Times to Work

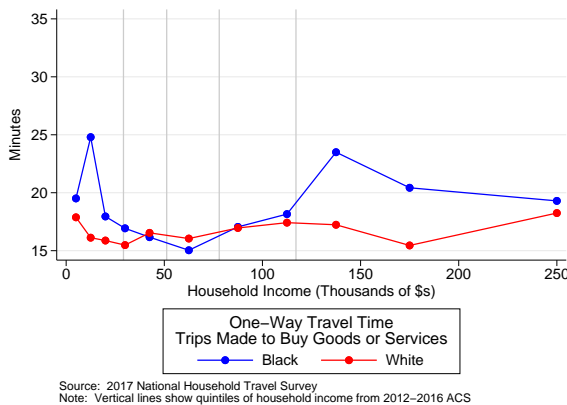


(a) Trips Made for Chores

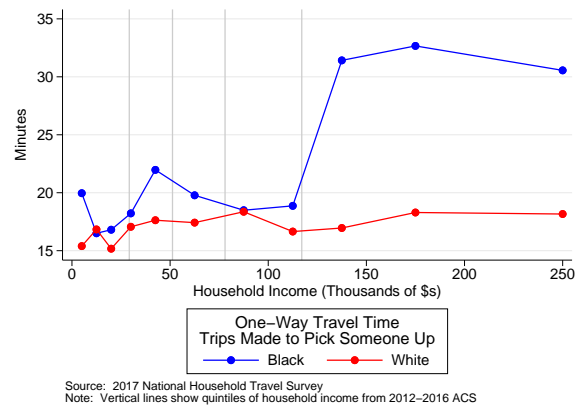


(b) Trips Made to Buy Food

Figure 15: Travel Times in the 2017 NHTS



(a) Trips Made to Buy Goods or Services



(b) Trips Made to Pick Someone Up

Figure 16: Travel Times in the 2017 NHTS

E Neighborhood Quality and the Price of Housing

Figures 17 and 18 confirm the result noted in Section 3: Black and white households are distributed across metros where the relationship between neighborhood-level housing prices and quality is similar. This result does not depend on whether we measure price using the median three-bedroom rent in a neighborhood or using the median house value in the neighborhood. Moreover, if we run a metro-level regression of neighborhood housing price on neighborhood quality, we find that this result is true both for the slope of the regression coefficients (Figures 17b and 18b) and for the R^2 of the regression (Figures 17c and 18c).

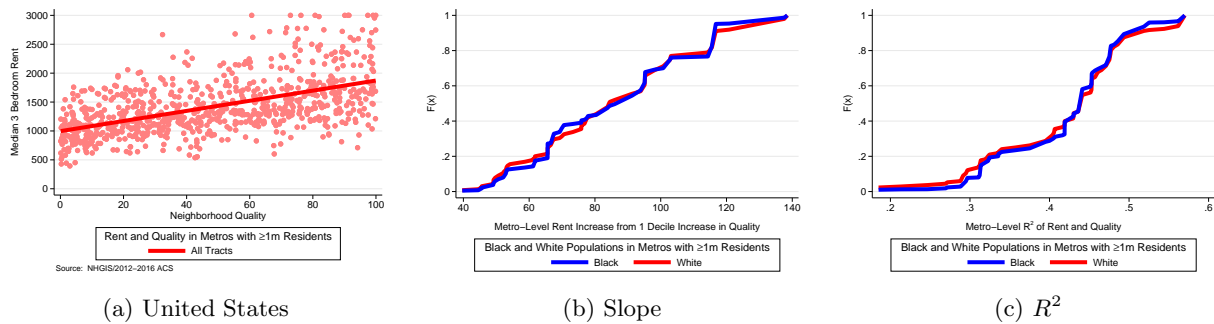


Figure 17: Neighborhood Quality and Median 3-Bedroom Rent

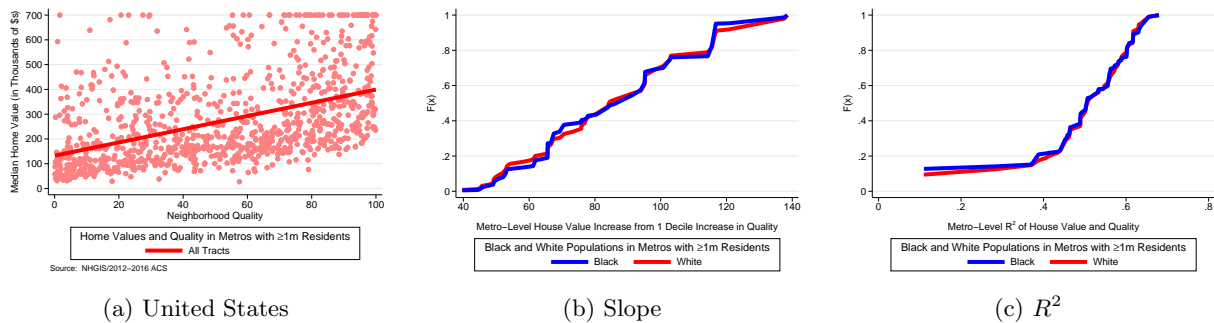
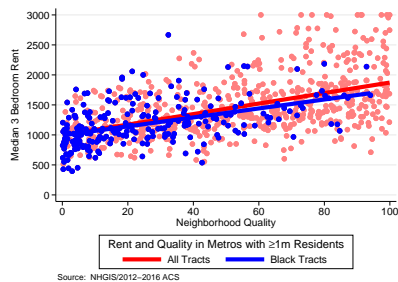
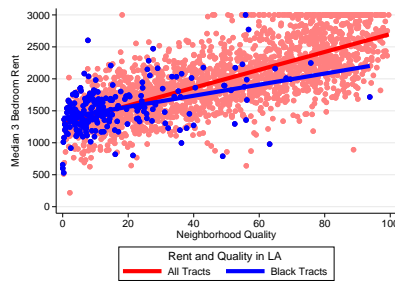


Figure 18: Neighborhood Quality and Median House Value

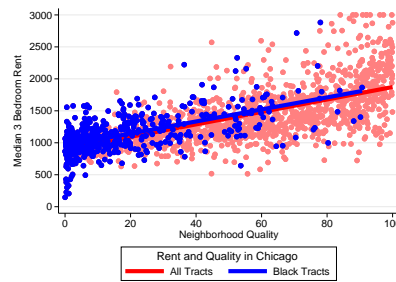
Figures 17a and 18a display a random sample of 1,000 tracts from the 53 MSAs with populations of at least 1 million in the 2012-2016 ACS. Because the subject of our interest here is understanding the variation across metros in the relationship between price and quality, Figures 19-22 plot the data on housing prices and neighborhood quality for several metros.



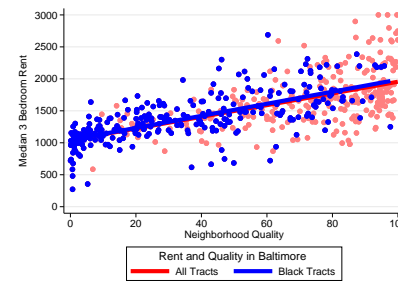
(a) United States



(b) Los Angeles

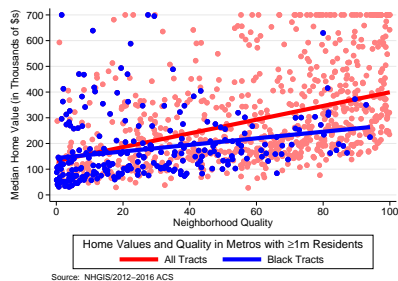


(c) Chicago

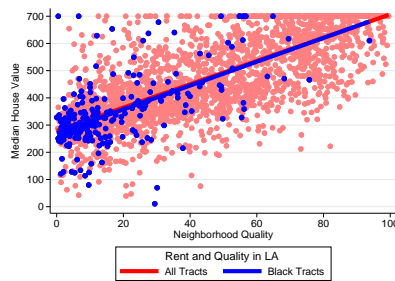


(d) Baltimore

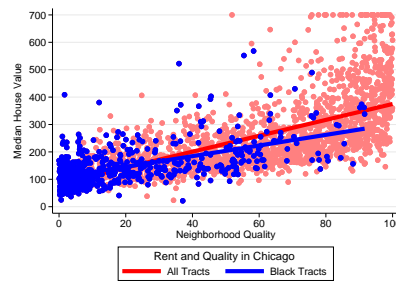
Figure 19: Median 3 Bedroom Rent



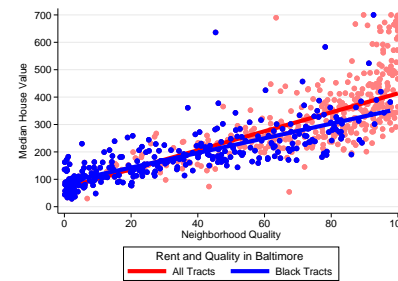
(a) United States



(b) Los Angeles

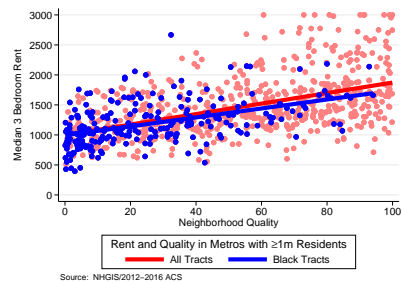


(c) Chicago

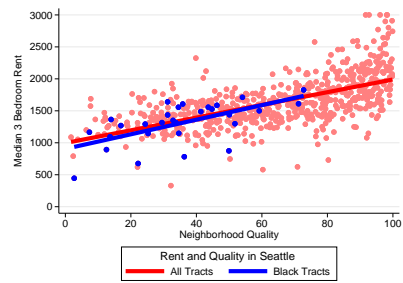


(d) Baltimore

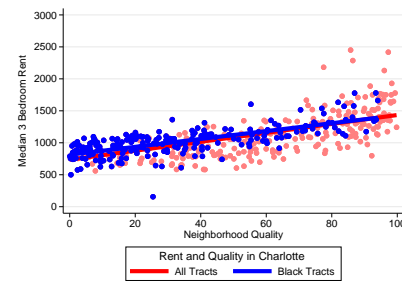
Figure 20: Median House Value



(a) United States

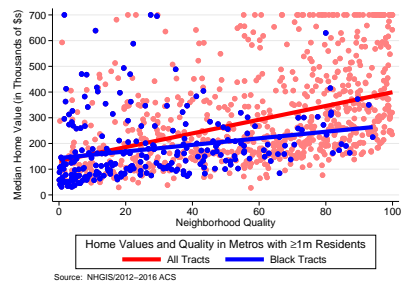


(b) Seattle

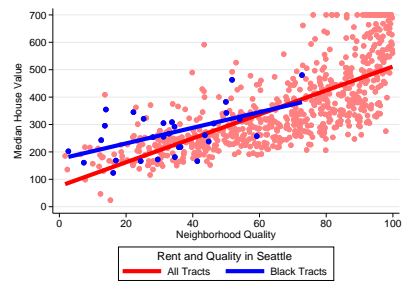


(c) Charlotte

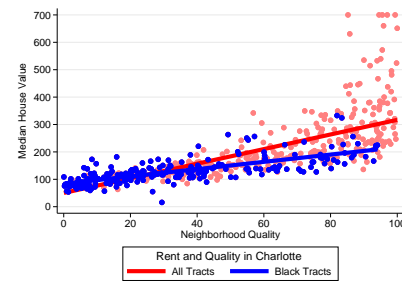
Figure 21: Median 3 Bedroom Rent



(a) United States



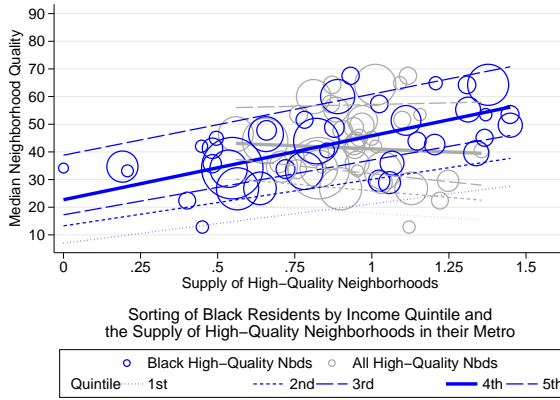
(b) Seattle



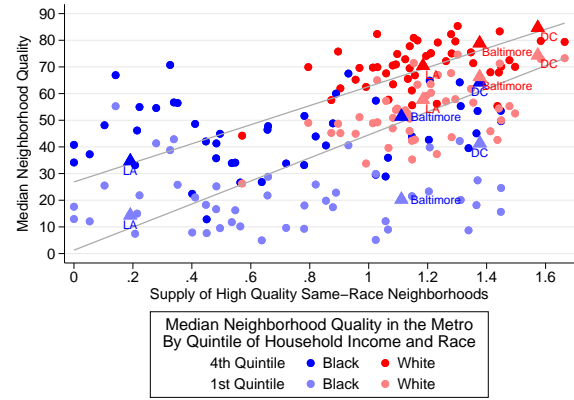
(c) Charlotte

Figure 22: Median House Value

F Additional Figures



(a) Sorting by Supply, All Income Quintiles



(b) Sorting by Supply, Black and White

Figure 23: Sorting by the Supply of High Quality Neighborhoods

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