What Explains Neighborhood Sorting by Income and Race?

Dionissi Aliprantis* Daniel R. Carroll* Eric R. Young**

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Abstract: 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 is not explained by wealth: High-income, high-wealth Black households live in similar-socioeconomic status (SES) neighborhoods as low-income, low-wealth white households. Instead, we show that race outweighs economic factors in neighborhood sorting. Black households residing in Black neighborhoods explains the racial gap in neighborhood SES at all income levels. Absent high-SES Black neighborhoods in their metro, Black households reside in Black neighborhoods rather than high-SES ones.

Keywords: Neighborhood, Income, Wealth, Race
JEL Classification Codes: J15, J18, R11, R23

*: Federal Reserve Bank of Cleveland, +1(216)579-3021, *dionissi.aliprantis@clev.frb.org*.
*: Federal Reserve Bank of Cleveland, +1(216)579-2417, *daniel.carroll@clev.frb.org*.
**: University of Virginia, Zhejiang University, and Federal Reserve Bank of Cleveland, *ey2d@virginia.edu*.

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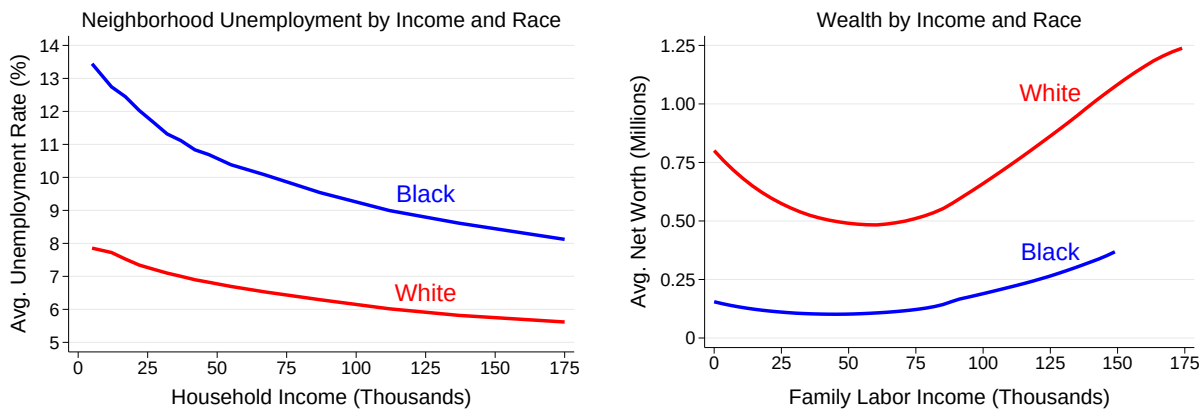
1 Introduction

High-income Black households live in neighborhoods of similar socioeconomic status (SES) as low-income white households. This fact is true whether one measures SES in terms of a neighborhood's unemployment rate (Figure 1a), its rate of poverty, educational attainment, or single-headed households (Pattillo (2005), Logan (2011), Reardon et al. (2015), Intrator et al. (2016)), or an index of all of these factors like the one we use below. In the presence of neighborhood effects, this sorting pattern could help explain the persistence of racial inequality.[1]



(a) Income and Neighborhood Unemployment Rates

(b) Income and Wealth

Figure 1: Black-White Gaps in Neighborhood Unemployment Rates and Wealth, by Income
Note: The left panel displays 2012-2016 American Community Survey (ACS) data from the NHGIS. The right panel displays local regressions using data from the 2016 Survey of Consumer Finances.

If neighborhood sorting contributes to racial inequality, one question seems obvious: Why do Black households with high incomes live in neighborhoods of lower SES than white households of comparable incomes? Financial constraints related to wealth and the price of housing are natural places to look for the answer. Figure 1b shows that Black households at all levels of income hold substantially less wealth than white households (Barsky et al. (2002), Aliprantis et al. (2019)). Black households are also over-represented in urban areas where housing tends to be more expensive (Parker et al. (2018), Murray and Schuetz (2018)), which would require larger down payments when purchasing a house.

We test the importance of these financial factors for explaining neighborhood sorting patterns by race. We first create an index of neighborhood SES that combines labor market outcomes, educational attainment, poverty, and the share of single-headed households. Matching 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 SES on race, income, and wealth and find no

[1] For example, Black children have lower incomes than white children, even conditional on parents' income (Mazumder (2012), Chetty et al. (2020)). The precise share of racial inequality in intergenerational mobility explained by neighborhoods is an open question; for relevant analyses see Chetty et al. (2020), Aliprantis and Martin (2021), Wodtke et al. (2016), and Wodtke et al. (2011).

evidence that financial constraints are the reason Black families live in lower-SES neighborhoods than white families with similar incomes. Instead, high-income, high-wealth Black households live in similar-SES neighborhoods as low-income, low-wealth white households. Wealth has almost no predictive power for neighborhood SES within racial groups, but there is a 22 percentile point gap in SES rank between Black and white households. This result is robust to the sample period, the measurement of neighborhood SES or household wealth, the age of household head, the presence of children, housing tenure, differences in within wealth×race-bin distributions of wealth or home equity, and issues related to common support and functional form assumptions. Moreover, high housing prices in high-SES neighborhoods do not explain Black households living in lower-SES neighborhoods: Black and white households are distributed similarly across metros by housing price-SES gradient.

In contrast to the lack of evidence on financial constraints, we find extensive evidence that Black households trade off large amounts of neighborhood SES in exchange for residing in a Black neighborhood. We show that the racial gap in neighborhood SES can be explained at all income levels by Black households residing in Black neighborhoods. When compared at the medians, a Black household living in a neighborhood that is at least 20 percent Black is associated with a decline of 33 percentile points in neighborhood SES. To translate this result in terms of neighborhood characteristics, Black households in the 6th decile of income live in Census tracts with a mean poverty rate of 22.0 percent when living in Black neighborhoods, compared with 13.5 percent when living in non-Black neighborhoods. The analogous comparison for unemployment rates is 11.5 percent versus 7.0 percent. We establish that this result is robust to alternative measures of neighborhood SES, including the homicide rate (Rich et al. (2018)) and estimates of intergenerational income mobility (Chetty et al. (2018)).

We investigate how the neighborhood SES of Black households responds to the supply of high-SES neighborhoods by looking across metros. We find that the neighborhood SES of Black households is unresponsive to the supply of high-SES neighborhoods; however, it *is* increasing in the supply of high-SES *Black* neighborhoods. As well, the metro-level neighborhood SES gap declines as the supply of high-SES Black neighborhoods increases relative to the supply of high-SES white neighborhoods. These patterns hold for all income levels.

The neighborhood sorting patterns documented in this paper demonstrate the enduring significance of race in American life and serve as evidence that effects of *de jure* racial segregation persist into the present. There are many ways that race could matter more than economics for neighborhood sorting. For instance, relative to their white peers, Black households may have stronger attachments to communities located in lower-SES neighborhoods (Eligon and Gebeloff (2016)) or experience higher levels of hostility from prospective neighbors and institutions in higher-SES neighborhoods (Anderson (2020), Harriot (2019), Jensen et al. (2018), Harris and Yelowitz (2018)). Also, the preferences of white households could result in white flight upon the arrival of Black households (Shertzer and Walsh (2019), Derenoncourt (2018)). And racial discrimination in the housing market (Turner et al. (2013)) could operate through mortgage mar-

kets (Bhutta and Hizmo (2019), Willen and Zhang (2020)), landlords (Hanson and Hawley (2011), Christensen and Timmins (2020)), or real-estate agents (Christensen and Timmins (2018)).

Our findings extend the literature on racial segregation by examining its connection to neighborhood SES. While segregation might be helpful or harmful for a group depending on the broader context (Cutler and Glaeser (1997), Cutler et al. (2008)), one of the main reasons for concern about racial segregation in the United States is that it can lead to racial gaps in neighborhood externalities, which can then generate racial inequality of opportunity. Previous studies have shown that race matters for neighborhood sorting (Bayer et al. (2007), Bayer et al. (2004), Gabriel and Rosenthal (1989)) and can interact with economics to generate residential segregation (Sethi and Somanathan (2004), Bayer et al. (2014)). The implications for neighborhood externalities are ambiguous, however, as they depend on both the supply of neighborhoods and the marginal rate of substitution between racial composition and characteristics like SES that determine externalities.

Our findings also inform the design of policies in the US that target economics while ignoring race or that operate through space. Housing mobility programs are a prominent example (Bergman et al. (2020)) and our results suggest that a race-conscious design is critical for success (Aliprantis et al. (2020)). Turning the focus more directly on space, the finding of large racial frictions to mobility within cities suggests the importance of frictions across larger regions (Zabek (2019)). Regional frictions to mobility would point in favor of place-making policies that can support local economies in the face of persistent spatial inequality (Schweitzer (2017), Austin et al. (2018)).[2]

Finally, our findings inform our interpretation of the racial wealth gap, which serves as both a barometer of progress toward racial equality and a potential mechanism for perpetuating racial inequality. Recent evidence points toward wealth being more of a consequence than a cause (Kaymak et al. (2020), Black et al. (2020), Bulman et al. (2021), Chetty et al. (2020)). However, the available data are not perfect, and there are still reasons to believe that wealth could itself cause racial inequality in economic mobility. Low levels of wealth could serve as an obstacle to African-Americans' educational attainment, business formation, capacity for job search, and access to high-externality neighborhoods. Our results are evidence against the neighborhood effects channel.

2 Data

We 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

[2] Another implication is that spatial equilibrium models of racial inequality should include some accounting for race bias in location (Kuminoff et al. (2013), Badel (2015), Aliprantis and Carroll (2018)).

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)), although our results are qualitatively similar when measuring income using labor income.

We use tract-level data from the 5 percent sample from the 2012-2016 American Community Survey (ACS) of the US Census, obtained from the National Historical Geographic Information System (NHGIS, Manson et al. (2017)). To measure the externality in a neighborhood we follow Aliprantis and Richter (2019) and define neighborhood socioeconomic status (SES) in terms of a tract'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.[3] We measure these variables in terms of the percentiles of their national distributions, and then define neighborhood SES 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 neighborhood externality mechanisms described in Wilson (1987) and Galster (2019). Appendix A discusses this measure of neighborhood SES in greater detail.

We employ two data sets that include alternative measures of neighborhood SES. For tract-level homicide rates, we use data from the Washington Post Unsolved Homicide Database (Rich et al. (2018)). This database contains criminal homicides that occurred between 2007 and 2017 in the main county or counties of 55 of the largest American cities, and we are able to calculate tract-level homicide rates because the database contains the exact coordinates of each killing. For intergenerational mobility, we use publicly-available estimates from the Opportunity Atlas (Chetty et al. (2018)). The tract-level estimates we use are the average child's household income percentile when growing up in a household with median-income.

In several parts of the analysis we look at tract-level outcomes by household income quintiles or deciles. 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 and deciles by matching the NHGIS bins to the quintile cutoffs of the household income distribution in the individual-level 2012-2016 ACS data from the Integrated Public Use Microdata Series (IPUMS-USA, Ruggles et al. (2018)). The person-weighted household income deciles in terms of thousands of dollars in the IPUMS-USA 2012-2016 ACS data are $(-\infty, 17), [17, 29), [29, 41), [41, 53), [53, 67), [67, 83), [83, 103), [103, 132), [132, 193), [193, \infty)$, and we map these to the NHGIS bins as $[-\infty, 15), [15, 30), [30, 40), [40, 50), [50, 60), [60, 75), [75, 100), [100, 125), [125, 200), [200, \infty)$.

Finally, we construct metro-level data from the 2012-2016 ACS sample of residents in the 53

[3] To be clear, our SES measure is chosen to capture a neighborhood's externalities on labor market outcomes. We do not interpret households sorting along other neighborhood characteristics as evidence that they are "irrational," but rather as evidence that they are sorting for other reasons.

largest metropolitan statistical areas (metros) in the US, each of which has a population of at least 1 million residents in the 2016 ACS. We define several variables to characterize the neighborhoods in each metro. We define a neighborhood as being "Black" if at least 20 percent of its residents are Black. While the precise cutoff is arbitrary, we choose 20 percent as a compromise between alternatives. 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)).[4] Our results are qualitatively similar when using a 10 or 30 percent threshold to define neighborhoods; Appendix Figure 25 shows the distribution of the US entire and Black populations in terms of their Census tract percent of residents who are Black. "White" neighborhoods are defined analogously, as those that are more than 20 percent white.

We create a measure of the supply of high-SES neighborhoods that takes two issues into account: First, different sorting across metros has 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 few high-SES Black neighborhoods per Black resident, but many per high-income Black residents. To address these issues, we define a neighborhood as being high SES 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. And finally, since Census tracts tend to have about 4,000 residents, we define:

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

The supply of high-SES white and any-race neighborhoods in a metro are defined analogously.

3 Wealth and Prices Do Not Explain Neighborhood Sorting

3.1 Wealth Does Not Explain Neighborhood Sorting by Income and Race

After combining our index of neighborhood SES from the 2012-2016 ACS with data from the 2015 wave of the PSID, we estimate the regression

$$\begin{aligned} SES_i = \quad & \alpha + \alpha^B B_i \quad && +\beta_1 I_i + \beta_2 I_i^2 + \beta_1^B I_i \times B_i + \beta_2^B I_i^2 \times B_i \\ & +\gamma I_i \times NW_i && +\delta_1 NW_i + \delta_2 NW_i^2 + \delta_1^B NW_i \times B_i + \delta_2^B NW_i^2 \times B_i + \varepsilon_i \end{aligned} \tag{1}$$

where the unit i is families, SES_i is neighborhood SES 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 NW_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

[4] Caetano and Maheshri (2018) find that 20 percent Black is a stable equilibrium for schools.

the 2015 PSID with a Black or non-Hispanic white head, and weights are used to obtain all of our PSID estimates.

Table 2 displays estimated regression coefficients. The coefficient on having a Black head of household is –22, indicating that Black families live in neighborhoods that are ranked 22 percentile points lower than white families conditional on income and wealth. The coefficient on income indicates that as income increases by $10,000, rank of neighborhood SES increases by 2 percentile points on average. 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 SES is more strongly related to family income and wealth for Blacks than for whites, although the difference for wealth is minor.

Table 1: Neighborhood SES Regression Coefficients

All Households			
Constant	39.9	Black Head of Household	–21.8
	(0.9)		(2.0)
Family Income	2.0	Black×Family Income	0.9
	(0.2)		(0.8)
Family Income^2	–1.6e-6	Black×Family Income^2	–8.7e-6
	(1.2e-6)		(5.9e-6)
Family Wealth	0.1	Black×Family Wealth	1.6e-2
	(0.1)		(9.1e-2)
Family Wealth^2	–8.1e-9	Black×Family Wealth^2	–1.4e-8
	(1.2e-9)		(2.6e-8)
		Family Income×Family Wealth	–4.6e-7
			(8.8e-8)
R^2	0.22	N	6,600-6,700

Note: This table reports coefficients from a family-level OLS regression of neighborhood SES ranking on an indicator for having a Black head, a quadratic in income (interacted with Black head), a quadratic in net worth (interacted with Black household head), and an interaction of income and net worth. Income and wealth coefficients are scaled to represent the change in neighborhood SES rank per change of $10,000. The sample is taken from the 2015 PSID and joined with tract-level data from the 2012-2016 ACS.

Figure 2 summarizes the regression results. Although estimation uses raw measures of both income and wealth, Figure 2 focuses on two quintiles of wealth for clarity of exposition. High- and low-wealth families, or 4th and 1st quintile families, live in neighborhoods of similar SES 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. One way of seeing the role of wealth is that the intercept for fourth wealth quintile Black families is lower than the intercept for the first wealth quintile white families.

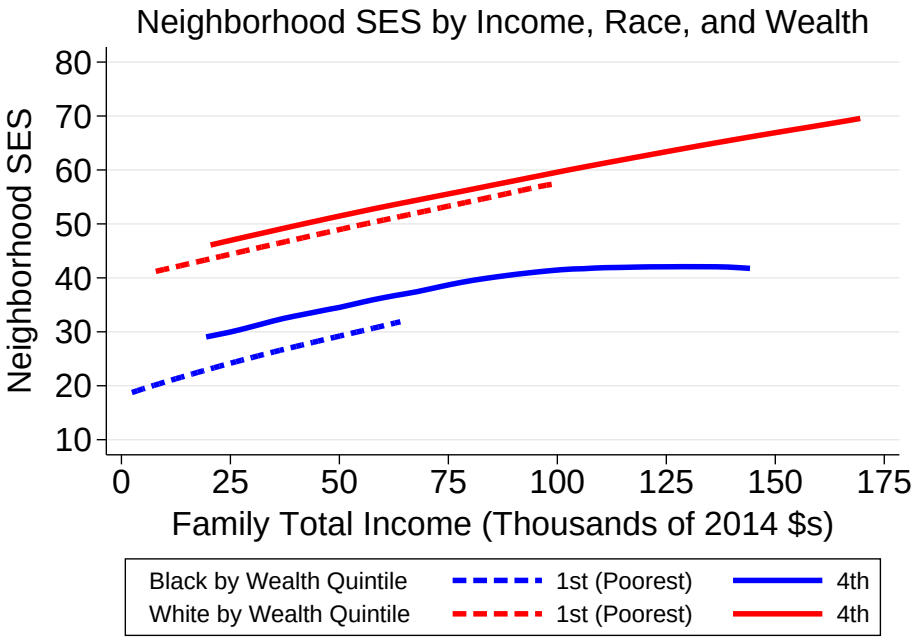


Figure 2: Neighborhood SES by Income, Race, and Wealth
Note: This figure reports results from a family-level OLS regression of neighborhood SES ranking on an indicator for having a Black head, a quadratic in income (interacted with Black head), a quadratic in net worth (interacted with Black household head), and an interaction of income and wealth. Note that results are reported in this figure by income and wealth rankings, but estimation uses raw measures of income and wealth. The sample is taken from the 2015 PSID and joined with tract-level data from the 2012-2016 ACS.

Although the gap between the dashed and solid blue lines is small, it is larger than the analogous gap between the red lines. We interpret the gap between the dashed and solid blue lines as more likely reflecting income volatility rather than discrimination. The reason is that when we make a similar figure using the 2011, 2013, and 2015 waves of the PSID to construct a three-year average of income to account for the greater income volatility of Black households (Ganong et al. (2020), Darity et al. (2019)), the dashed and solid lines for Black families lie on top of one another (Appendix Figure 5).

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 SES is (mean) independent of wealth conditional on income and race. If credit constraints were a barrier to accessing high-SES 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.[5] In the 4th quintile of wealth for our trimmed sample, 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. While these within-bin differences in wealth are not large, to check that they are not driving our results, we also make a similar figure comparing the 2nd decile of wealth to the 8th decile of wealth, and find identical results.

The result that wealth does not predict neighborhood SES 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 SES, the functional form assumptions made about the relationship between SES and family characteristics, or heterogeneity across race in income or wealth volatility. We also look at issues related to measuring wealth and find identical results when measuring wealth only in terms of financial assets; financial assets minus the value of annuities and individual retirement accounts; net worth minus student loan debt of all family in the household; or home equity.[6] Appendix C repeats this analysis with the 1990 Census and 1989 PSID and finds very similar results.

3.2 The Price of Neighborhood SES Does Not Explain Neighborhood Sorting by Income and Race

The price of housing represents another financial constraint that could be differentially affecting Black and white households. 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.

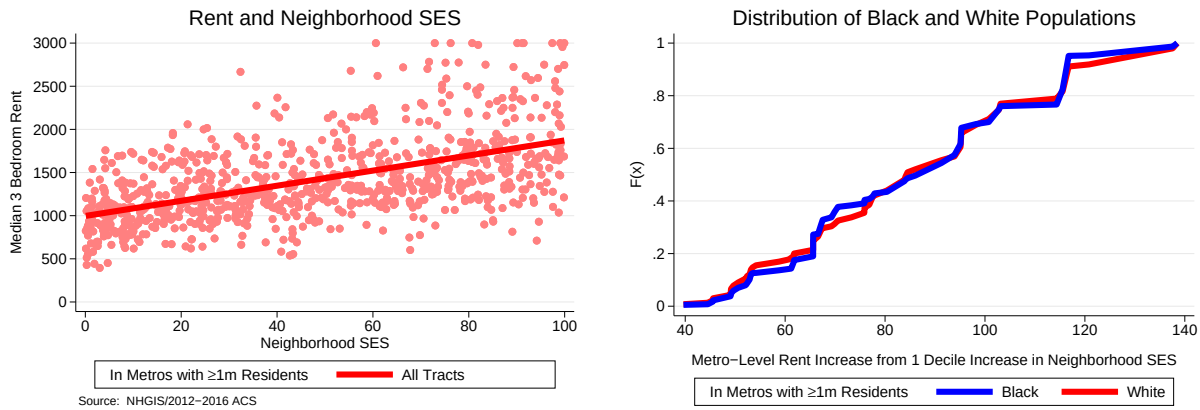
The general relationship between price and neighborhood SES is illustrated in Figure 3a as the plot of a random sample of 1,000 tracts from the 53 metros with at least 1 million residents in the 2012-2016 ACS.[7] In most metros, the price of housing increases as a function of SES, but not steeply. It is also the case in most metros that while the price of housing is correlated with SES, this correlation is not so strong as to eliminate "affordable" high-SES neighborhoods. The metro-level average (population-weighted) R^2 of median three-bedroom rent and quality is 0.43.

Neighborhood choices are made at the metro level, though, and so the general picture in Figure 3a could mask heterogeneity in housing prices in the metros where Black or white households are more likely to reside. Do Black households live in metros where neighborhood SES is more expensive

[5] See 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.

[6] We define financial assets as (farm/business assets) plus (the value of all checking and savings accounts) plus (the value of real estate other than main home minus debt owed on that real estate) plus (the value of stocks) plus (the value of vehicles minus debt on vehicles) plus (the value of life insurance and other assets) plus (the value of private annuities or Individual Retirment Accounts (IRAs) (ie, ER65352+ER65358+ER65362-ER65364+ER65368+ER65370+ER65374+ER65378), and home equity as ER65404.

[7] We abstract from the dimension of housing unit quality, which itself can generate important neighborhood effects (Ioannides and Zabel (2003), Brock and Durlauf (2001)).



(a) Median 3 Bedroom Rent

(b) Slope

Figure 3: Neighborhood SES and the Price of Housing
Note: The left panel illustrates the price of neighborhood SES by plotting a random sample of 1,000 tracts from the 53 metros with at least 1 million residents in the 2012-2016 ACS. The right panel displays the CDF of the Black population in those 53 metros over the metro-level slope of an OLS linear regression of price on neighborhood SES.

than the metros in which white households live? Figure 3b shows that this is not the case, as Black and white households are distributed in metros with similar housing price-neighborhood SES elasticities. A related analysis is conducted in Appendix E and shows similar results when housing prices are measured using median house values. Appendix E also shows that Black and white households reside in cities where the strength of the correlation between price and neighborhood SES is similar.

We have shown that wealth predicts little difference in neighborhood SES 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 SES neighborhoods.

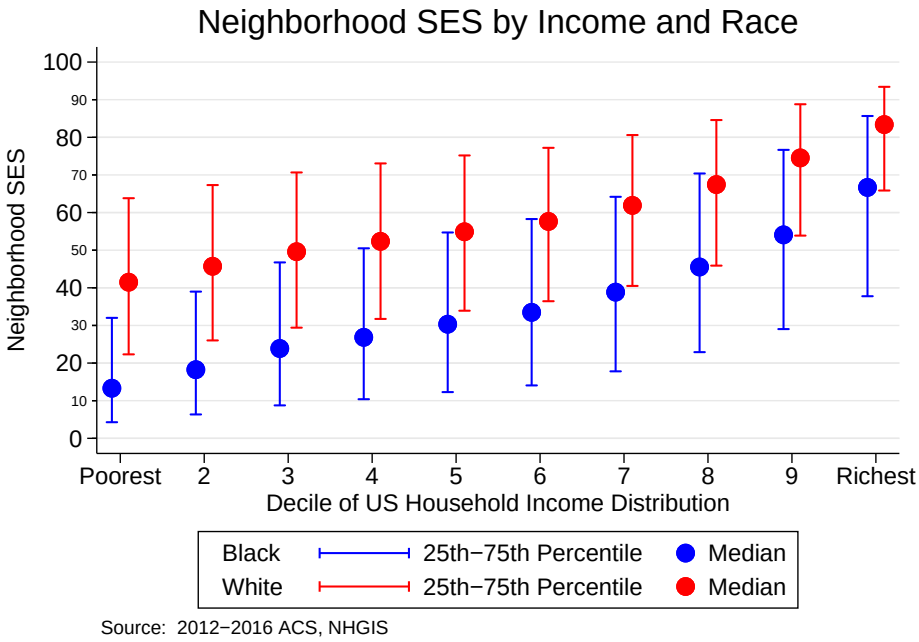
4 What Does Explain Neighborhood Sorting?

4.1 Neighborhood Racial Composition Explains Sorting by Income and Race

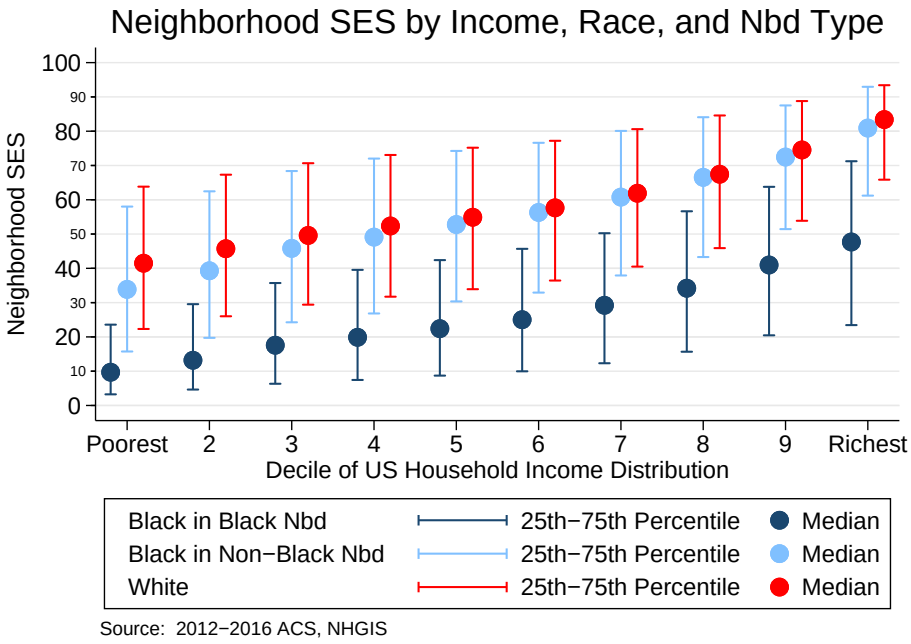
An alternative explanation for neighborhood sorting patterns in the data is that race outweighs economic factors. We know from the literature that the racial composition of neighborhoods affects location choices (Bayer et al. (2007), Bayer et al. (2004), Gabriel and Rosenthal (1989)) and that this mechanism can generate residential segregation (Sethi and Somanathan (2004), Bayer et al. (2014)). The implications for racial gaps in neighborhood SES are not clear, though, as they depend on both the supply of neighborhoods and the marginal rate of substitution between racial composition and SES. We now investigate the link between neighborhood racial composition and neighborhood SES.

If Black households face a tradeoff between neighborhood racial composition and neighborhood SES, then we would expect to find that Black households not residing in Black neighborhoods

would live in neighborhoods of similar SES to those of white households. The predicted pattern is the one we observe in the data. Figure 4a shows the known result that at all income levels, Black households tend to reside in neighborhoods of lower SES than their white counterparts. Figure 4b shows the new result that at all income levels, the racial gap in neighborhood SES can be explained by Black households residing in Black neighborhoods.



(a) Neighborhood SES by Income and Race



(b) Neighborhood SES by Income, Race, and Racial Composition

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

Note: The top panel shows the distribution of neighborhood SES conditional on household income decile and race. The bottom panel shows the distribution of neighborhood SES conditional on household income decile, race, and, for Black households, whether they live in a Census tract that is at least 20 percent Black. Both panels use tract-level data from the 2012-2016 ACS/NHGIS.

We do not know if these sorting patterns reflect preferences or constraints. If they reflect preferences, however, we can measure the compensating differential of living in a Black neighborhood in terms of the amount of neighborhood SES that households are willing to tradeoff. Under the assumption that these sorting patterns reflect preferences, the compensating differential can be seen by looking at the gap in neighborhood SES at each income decile for Black households living in Black neighborhoods as compared to the neighborhood SES of Black households living in non-Black neighborhoods. Figure 5 plots this compensating differential for the medians in each income decile; this is the difference between the light blue and dark blue dots in Figure 4b. This figure highlights that the actual tradeoff faced by households is about 30 percentile points of neighborhood SES, which is considerably larger than the 22 percentile points that is implied by the regression coefficient on a Black household head reported in Table 2. To put the 30 percentile point gap in SES into perspective, the median Black households in the 6th decile of household income living in a Black and non-Black neighborhood live in neighborhoods with, respectively, unemployment rates of 10.3 and 6.3 percent; poverty rates of 20.2 and 11.1 percent; and BA attainment rates of 19.7 and 29.2 percent.

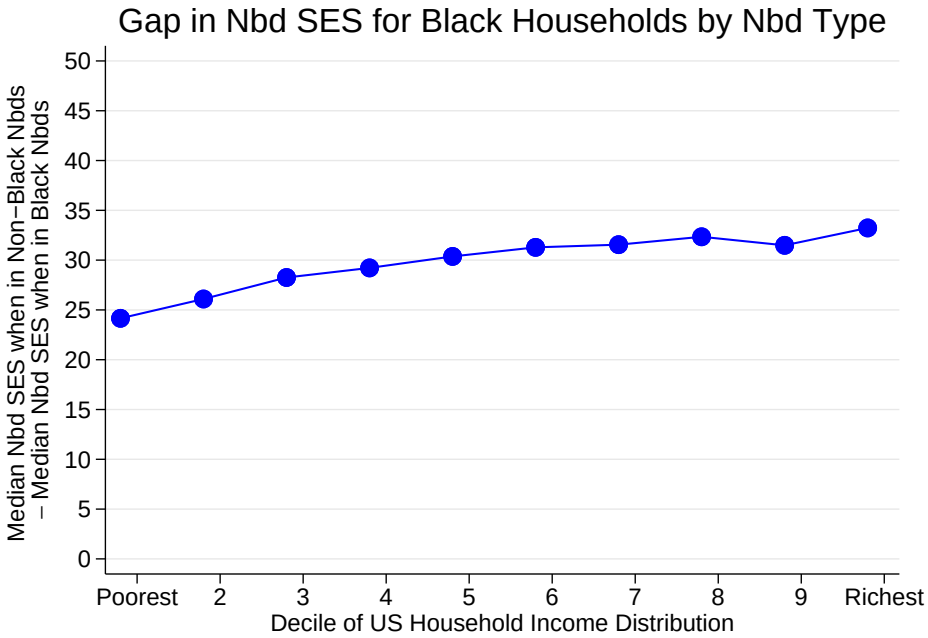
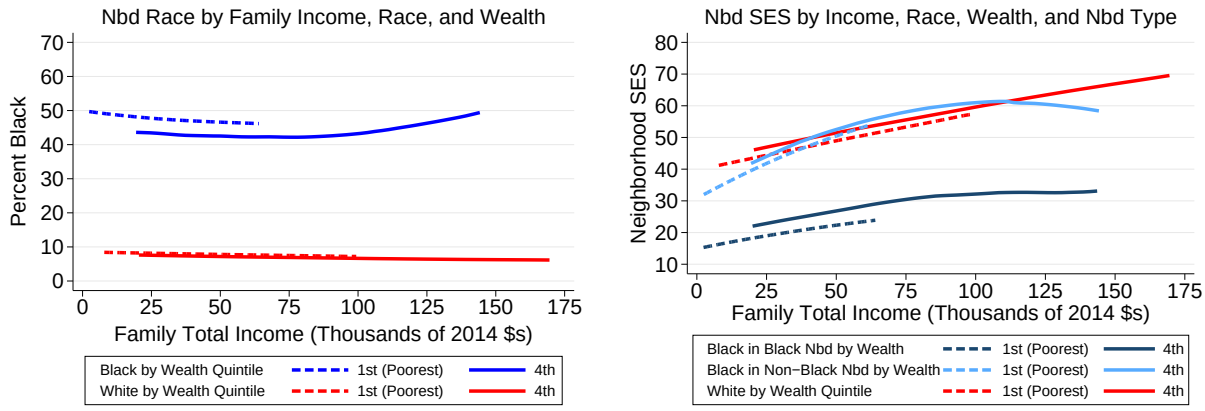


Figure 5: Neighborhood SES of Black Households by Income and Neighborhood Racial Composition
Note: This figure shows the difference, conditional on household income decile, in the neighborhood SES of the median Black household in a neighborhood that is non-Black (<20 percent) versus Black (≥20 percent). This figure uses tract-level data from the 2012-2016 ACS/NHGIS.

The neighborhood sorting patterns in Figure 4 are not driven by wealth. We estimate an analogue to Equation 1 where the dependent variable is the share of Black residents rather than SES. Figure 6a 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. We also estimate a version of Equation 1 that conditions on whether a Black household is residing in a Black neighborhood. Figure 6b shows that conditional on income and wealth, Black households residing in non-Black neighborhoods sort into neighborhoods of SES comparable to their white counterparts, while Black households residing in Black neighborhoods sort into neighborhoods of significantly lower SES ranking than those of their white counterparts.



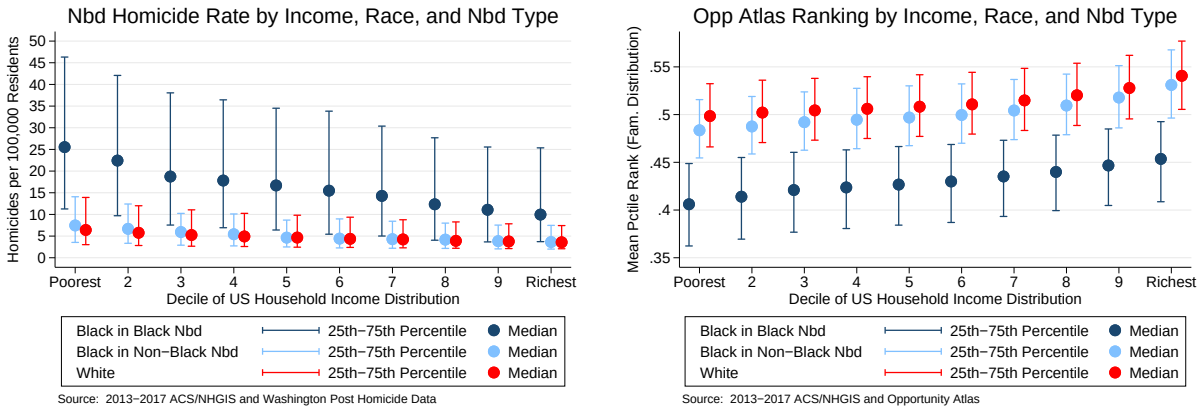
(a) Neighborhood Racial Composition

(b) Neighborhood SES

Figure 6: Neighborhood Sorting

Note: The left panel reports results from a family-level OLS regression of neighborhood racial composition on an indicator for having a Black head, a quadratic in income (interacted with Black head), a quadratic in net worth (interacted with Black household head), and an interaction of income and wealth. The sample is taken from the 2015 PSID and joined with tract-level data from the 2012-2016 ACS. The right panel shows results from an identical regression in which the dependent variable is neighborhood SES and the sample of Black families is split by whether they live in a Census tract that is at least 20 percent Black.

Nor are the neighborhood sorting patterns in Figure 4 driven by our measure of neighborhood SES. Identical results obtain when measuring neighborhood externalities in terms of a Census tract's homicide rate (Figure 7a) or intergenerational income coefficient (Figure 7b). These results indicate that our measure of neighborhood SES is generating meaningful results, given the importance of exposure to violence for outcomes (Aliprantis (2017), Sharkey and Friedson (2019)) and the importance of racial segregation for intergenerational income mobility (Andrews et al. (2017)).



(a) Homicide Rate

(b) Intergenerational Correlation of Income

Figure 7: Alternative Measures of Neighborhood Externalities

Note: Both panels show the distribution of neighborhood SES conditional on household income quintile, race, and, for Black households, whether they live in a Census tract that is at least 20 percent Black. The left panel measures neighborhood SES using the tract-level homicide rate calculated from the Washington Post Unsolved Homicide Database and the right panel measures neighborhood SES using the tract-level intergenerational income correlation for 50th income-percentile parents in the Opportunity Atlas.

4.2 Black Households' Expected Neighborhood SES Is Explained by the Black Neighborhoods in their Choice Set

We now examine the importance of Black neighborhoods in a given metro for the expected neighborhood SES of Black households in that metro. We define a metro as having no Black neighborhoods if it has less than one Black neighborhood per 4,000 residents. Appendix Figure 24 shows that these metros contain a small share of the Black population in our sample of 53 metros (9 percent). The metros without Black neighborhoods in the 2012-2016 ACS are Austin, Las Vegas, Orlando, Phoenix, Portland, Riverside, Sacramento, Salt Lake City, San Antonio, San Diego, San Jose, Seattle, and Tucson.

Figure 8 shows the neighborhood SES of high-income (4th quintile of the population distribution) Black households in a metro as a function of the supply of high-SES any-race neighborhoods in the metro, conditional on the presence or lack thereof of Black neighborhoods in the metro. The light blue metros show that when no Black neighborhoods are in the choice set, Black households' neighborhood SES increases as the supply of high-SES any-race neighborhoods increases. In contrast, the gold metros shows that when Black neighborhoods are in the choice set, the neighborhood SES of Black households does not change as the supply of high-SES any-race neighborhoods increases.

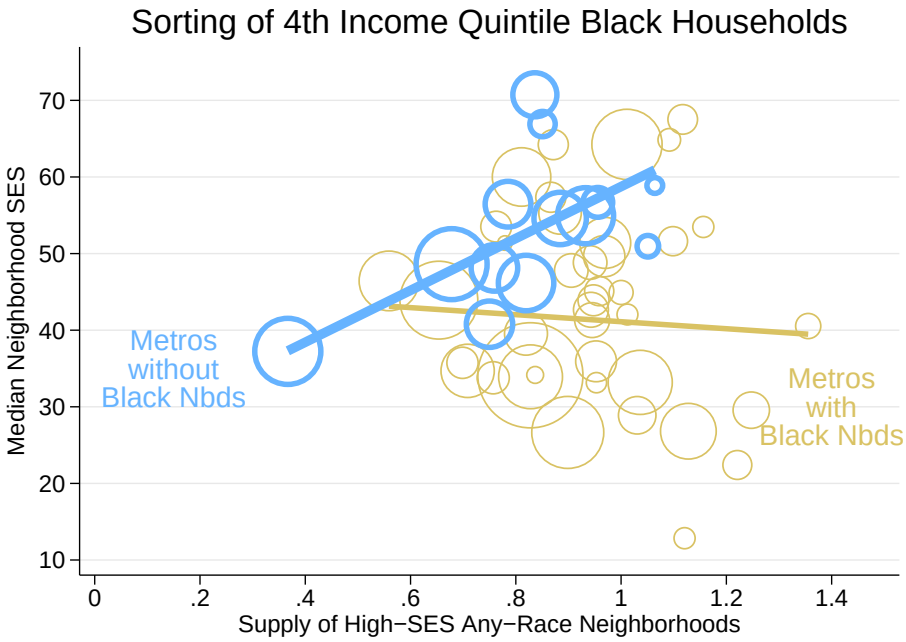
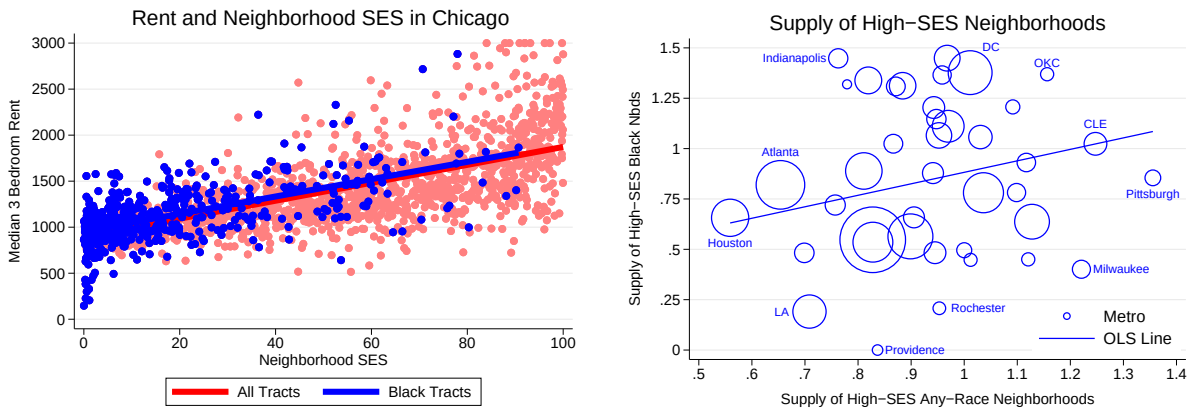


Figure 8: Neighborhood SES by Metro Type
Note: This figure shows the mean neighborhood SES of 4th income quintile Black households as a function of the supply of high SES any-race neighborhoods, separated by households living in metros with Black neighborhoods versus households living in metros without Black neighborhoods.

The relationship between rent and SES for Black neighborhoods is not remarkably different from the relationship between rent and SES for other neighborhoods in the US (See Appendix E.). What is different about SES and Black neighborhoods in the US is simply the scarcity of high-SES Black neighborhoods (Bayer and McMillan (2005), Bayer et al. (2014)). Figure 9a 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 our SES ranking. This translates into 0.028 top-quintile Black neighborhoods per 4,000 Black residents, compared with 0.29 top-quintile non-Black neighborhoods per 4,000 non-Black residents.[8]

Figure 9b shows that across metros there is variation in the supply of high-SES Black neighborhoods conditional on the supply of high-SES 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-SES Black neighborhoods on the supply of high-SES 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-SES any-race neighborhoods. However, Washington, DC has a very high supply of high-SES Black neighborhoods, while Rochester has an extremely low supply of high-SES Black neighborhoods. High-income Black households in these metros face quite different neighborhood choice sets.

[8]Los 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.



(a) Chicago, by Racial Composition

(b) Joint Distribution of Metros

Figure 9: The Supply of High-SES Neighborhoods

Note: The left panel shows the supply of neighborhoods in Chicago by SES and price, separated by whether those neighborhoods are at least 20 percent Black. The right panel shows the joint distribution of metros' supply of high-SES Black neighborhoods and high-SES any-race neighborhoods.

We use the orthogonal variation in the supply of high-SES neighborhoods shown in Figure 9b to test how the neighborhood sorting of Black residents depends on the supply of high-SES neighborhoods. Recall that the gold bubbles in Figure 8 show that the neighborhood SES of high-income Black households does not change as the supply of high SES any-race neighborhoods in their metro increases. The blue bubbles in Figure 10a show a different story when looking at the supply of high-SES Black neighborhoods. These data show that there is a strong, positive correlation between the supply of high-SES Black neighborhoods and the neighborhood SES of high-income Black residents.

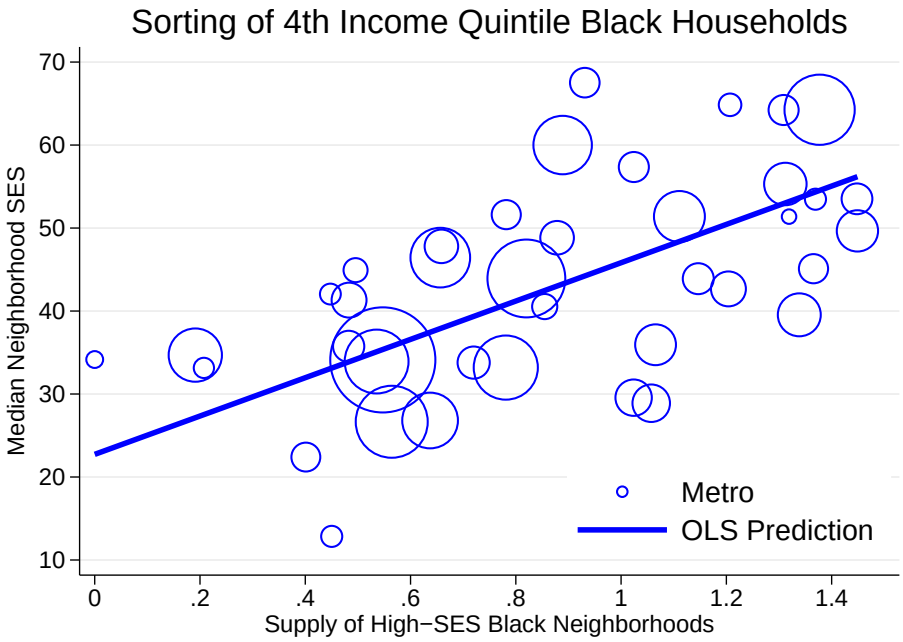
Table 2 quantifies the results from Figures 8 and 10a and expands the analysis to include each race×income quintile group. Looking at the first three rows of Table 2, we see that the pattern from the figures extends from Black households in the 4th quintile of income to Black households at all incomes: Neighborhood SES is not related to the supply of high-SES any-race neighborhoods. Looking at the last three rows of Table 2, we see that Black household locations do respond to an increase in the supply of high-SES *Black* neighborhoods by sorting into higher-SES neighborhoods.

Table 2: Regressions of Median Neighborhood SES

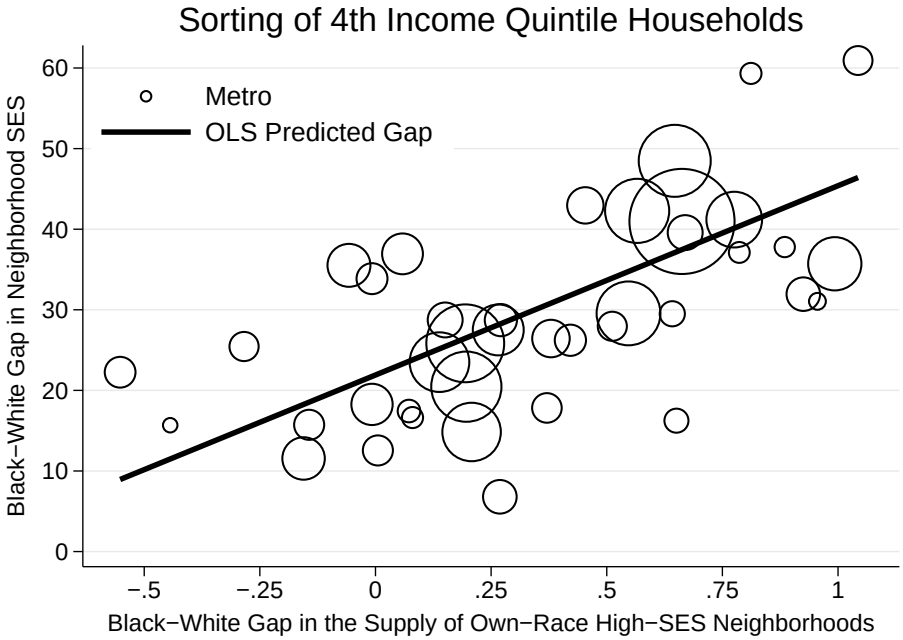
	Median Neighborhood SES									
	Black Households by					White Households by				
Coefficient on	HH Income Quintile					HH Income Quintile				
Supply of HQ Nbds	1	2	3	4	5	1	2	3	4	5
Any-Race	–7	–10	–12	**–5**	2	14	14	10	11	7
p-value	0.49	0.36	0.31	**0.71**	0.84	0.14	0.09	0.15	0.08	0.18
R^2	0.01	0.02	0.03	**0.00**	0.00	0.06	0.07	0.05	0.08	0.05
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	0.23
R^2	0.25	0.31	0.35	**0.43**	0.38	0.25	0.23	0.18	0.16	0.04

Note: This table reports regression results where the dependent variable is the median neighborhood SES ranking of a metro's Black or white households, estimated separately by income quintile, and the independent variable is the metro's supply of high-SES Black, white, or any-race neighborhoods. The table uses data from the 2012-2016 ACS/NHGIS and the estimation sample only includes metros with Black neighborhoods (having at least one Black neighborhood per 4,000 Black residents). The bold column reports the regression results from the gold line in Figure 8 and the blue line in Figure 10a. Income quintiles are defined in terms of the population distribution of household income in the US.

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 possible albeit unlikely given the results in Section 3.2. One way to deal with this issue is to use white households as a "control" group by looking at differences in the supply of own-race high-SES neighborhoods. Using this approach, we define the Black-white gap in the supply of high-SES neighborhoods as the supply of high-SES white neighborhoods in a metro minus the supply of high-SES Black neighborhoods in the metro. We also define the metro-level Black-white gap in neighborhood SES as the median neighborhood SES of white households in the 4th quintile of income minus the median neighborhood SES of Black households in the 4th quintile of income. Figure 10b shows that the Black-white gap in the supply of high-SES neighborhoods predicts the Black-white gap neighborhood SES. In a regression of the gap in neighborhood SES on the gap in supply the coefficient is 24, the relevant p-value is 0.000, and the R^2 is 0.47.



(a) Neighborhood SES and Supply



(b) The Gap in Neighborhood SES and the Gap in Supply

Figure 10: Sorting and the Supply of High-SES Neighborhoods by Metro

Note: The top panel shows the median neighborhood SES of a metro's 4th income quintile Black households as a function of the metro's supply of high SES Black neighborhoods. The bottom panel shows a metro's gap in the median neighborhood SES of 4th income quintile Black households relative to the metro's 4th income quintile white households as a function of the metro's gap in the supply of high SES Black neighborhoods versus high SES white neighborhoods. Both panels use data from the 2012-2016 ACS/NHGIS and are estimated on the sample of metros with Black neighborhoods (with at least one Black neighborhood per 4,000 Black residents).

5 Conclusion

This paper documented new facts about neighborhood sorting in the US. It was previously known that Black and white households of similar incomes live in neighborhoods with different levels of socioeconomic status (SES). It was also previously known that the racial composition of neighborhoods affects location choices. What was not known before this paper was whether wealth or the price of neighborhood SES were omitted variables that could explain racial differences in neighborhood SES, and the extent to which racial composition affects African Americans' neighborhood SES.[9] We have shown that financial constraints related to wealth or the price of housing do not explain neighborhood sorting by income and race, and that race is a central determinant of the neighborhood externalities experienced by African Americans. Future research will be needed to quantify the relative importance of psychological costs and benefits, white flight, and racial discrimination.

Our results draw attention to what we consider to be an under-appreciated phenomenon, the psychological costs of being "Black in white space" (Anderson (2020)). The psychological costs of living in predominantly-white neighborhoods are large enough for many African Americans to outweigh any educational, labor market, or safety benefits they might experience due to living in a higher-SES neighborhood. Interpreted in terms of this mechanism, our results provide one way of quantifying how costly it is for Black people to interact with white people. As suggested here at the level of neighborhoods, and in other studies at the levels of schools and workplaces (Fletcher et al. (2020), Ananat et al. (2020), Hellerstein and Neumark (2008)), making "white spaces" more welcoming for Black people appears to be an important step in achieving racial equality.

By showing that race outweighs economic factors for neighborhood sorting in the US, this paper highlights that public policy should not be focused entirely on access and economics, but should also be designed with attention to race. In the case of generating integrated neighborhoods, the success or failure of policies will hinge on understanding precisely which factors matter the most in determining neighborhood choices. The preferred policy might be very different depending on whether neighborhood choices are driven more by discrimination in the housing market (Turner et al. (2013), Ross and Yinger (2002)); the related inertia of past practices (Courchane and Ross (2019), Nowak and Smith (2018)); information (Bergman et al. (2020)); family and social networks (Büchel et al. (2019), van der Klaauw et al. (2019)); racial hostility (Harriot (2019)); white flight (Shertzer and Walsh (2019), Derenoncourt (2018), Card et al. (2008), Ellen (2000)); amenities (Caetano and Maheshri (2019)); preferences for same-race neighbors or communities (Bayer and Blair (2019), Wong (2013)); or the supply of new housing (Monkkonen et al. (2020)); and the extent to which these mechanisms have changed over time (Blair (2019), Mallach (2019)).

[9] The nearest published 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).

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Appendix to
"What Explains Neighborhood Sorting by Income and Race?"

Dionissi Aliprantis Daniel Carroll Eric Young

A Measuring Neighborhood SES

There are reasons to exercise caution when focusing on a single dimension to characterize neighborhood SES (Chetty et al. (2020)). 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 SES. To begin, we note that each of the variables we use in our measure of neighborhood SES 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 SES. Table 2 shows that the coefficients on the variables are relatively similar.

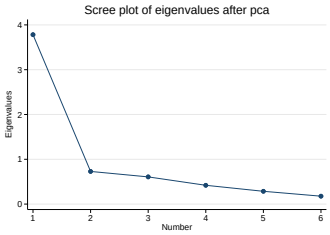


Figure 1: Scree Plot of Eigenvalues

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.

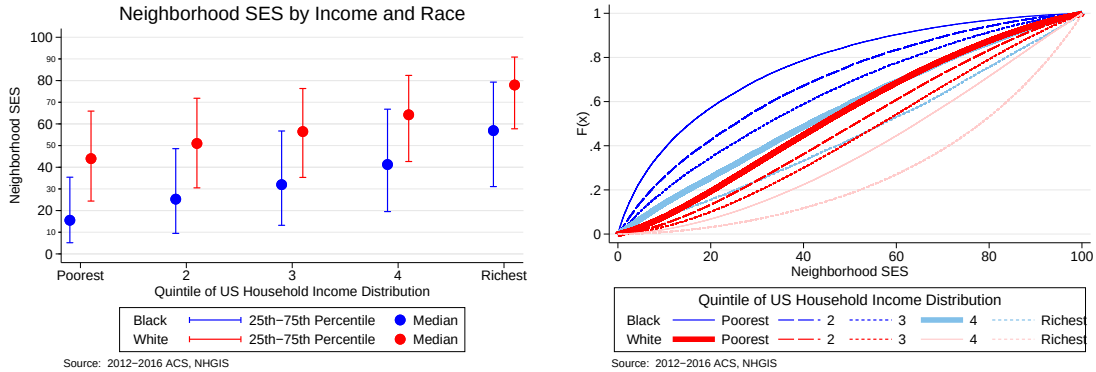
Table 2: Coefficient for First Principal Component

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 SES will sometimes miss in its univariate summary of a multivariate world, as well as the fact that many criteria would define neighborhood externalities 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 SES 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 SES to those of Blacks in the fourth quintile of household income.



(a) Neighborhood SES

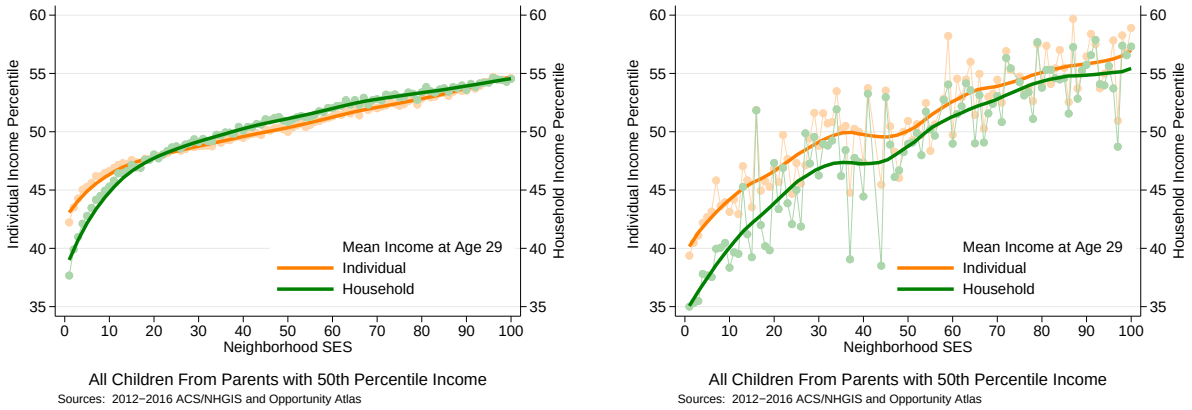
(b) CDFs

Figure 2: Household Income and Neighborhood SES 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 SES 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

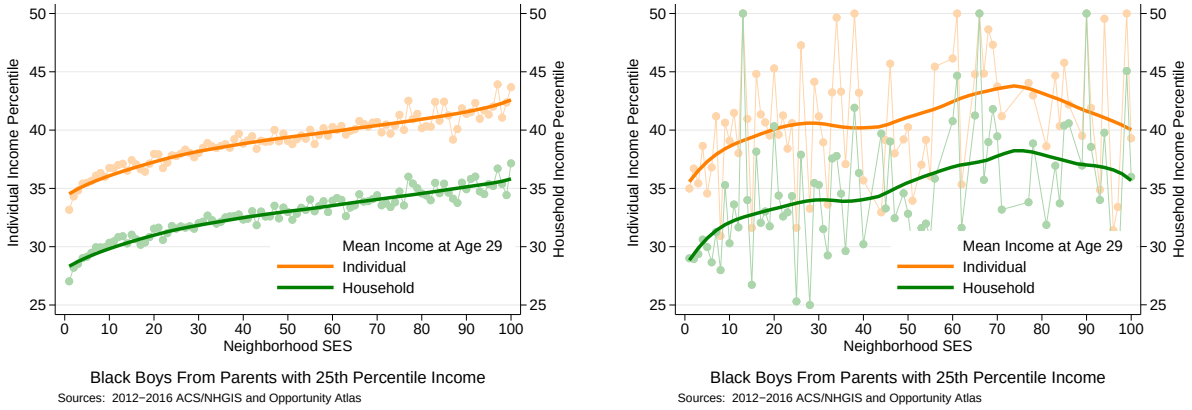
children by the fraction of their childhood (up to age 23) spent in that tract.

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 SES, although the relationship is different by subgroups and is noisier as the sample size for estimation declines.



(a) United States (b) Cleveland, OH

Figure 3: All Children with 50th Percentile Parents



(a) United States (b) Cleveland, OH

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 SES 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 SES 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 SES, or the functional form assumptions made about the relationship between SES 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 1 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 SES Regressions

Black Head of Household	–21.8	–21.2	–21.0	–22.7	–21.5	–21.2
	(2.0)	(2.0)	(2.0)	(2.1)	(2.1)	(4.7)
Child $\leq$ 18 in Household		X			X	
Quadratic in Age of Head			X		X	
Rent/Own Dummy				X	X	
'11+'13+'15 Avg I, NW						X
R^2	0.22	0.22	0.23	0.23	0.23	0.17

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	41.5	41.2	41.1	41.0
	(1.3)	(1.3)	(1.3)	(1.4)	(1.4)
Child $\leq$ 18 in Household		X			X
Quadratic in Age of Head			X		X
Rent/Own Dummy				X	X
R^2	0.46	0.46	0.46	0.46	0.46

B.2 Income Volatility

The last column in Table 3 shows evidence from a similar regression investigating whether the higher income volatility of Black families documented in the PSID in Darity et al. (2019) is driving our results. We find that the coefficient on having a Black head of household is stable when measuring income and wealth as the average of 2011, 2013, and 2015 income and net worth.

Figure 5 shows an analogue to the main text's Figure 2 where the 2015 measurements of income and net worth are replaced by their three year averages over the waves 2011, 2013, and 2015.

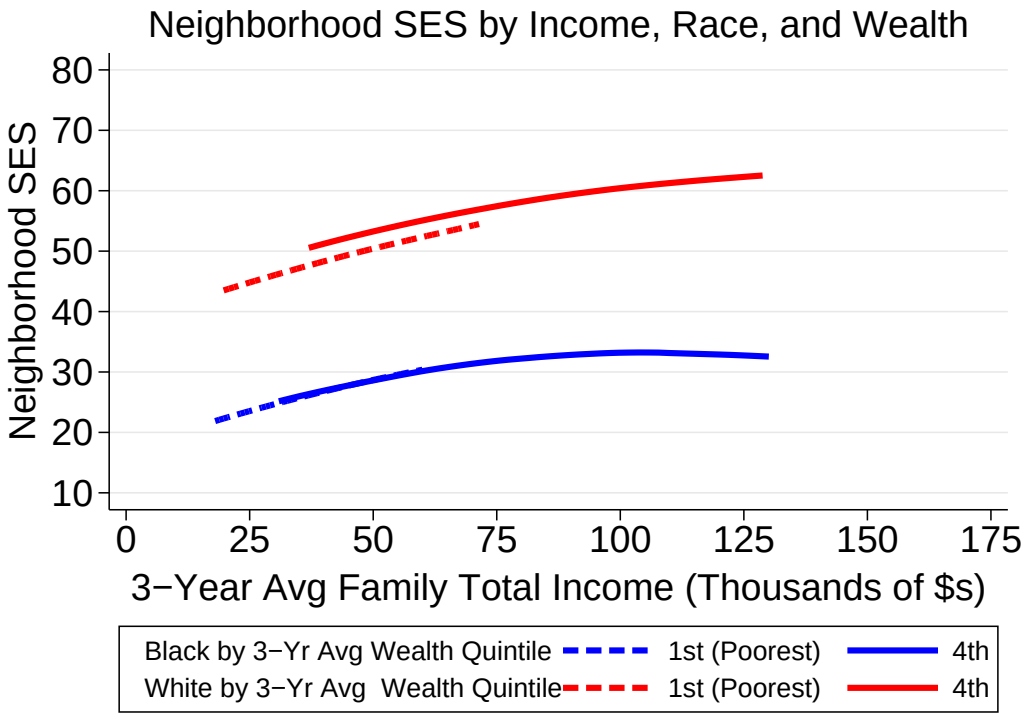


Figure 5: Neighborhood SES by Income, Race, and Wealth
Note: This figure reports results from a family-level OLS regression of neighborhood SES ranking on an indicator for having a Black head, a quadratic in three-year average income (interacted with Black head), a quadratic in three-year net worth (interacted with Black household head), and an interaction of average income and average wealth. Note that results are reported in this figure by income and wealth rankings, but estimation uses raw measures of these variables. The sample is taken from the 2011, 2013, and 2015 PSID and joined with tract-level data from the 2012-2016 ACS.

B.3 Measuring Neighborhood SES

We also investigate whether one variable in our neighborhood SES index is by itself driving our results. Table 5 shows the coefficient on the Black indicator when Equation 1 is estimated with SES_i measured as each individual component of our index.

No single variable drives our results on the relationship between neighborhood SES, race, income, and wealth. Most of the neighborhood characteristics yield results similar to the penalty of 22 percentile points in neighborhood SES ranking 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 SES (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)

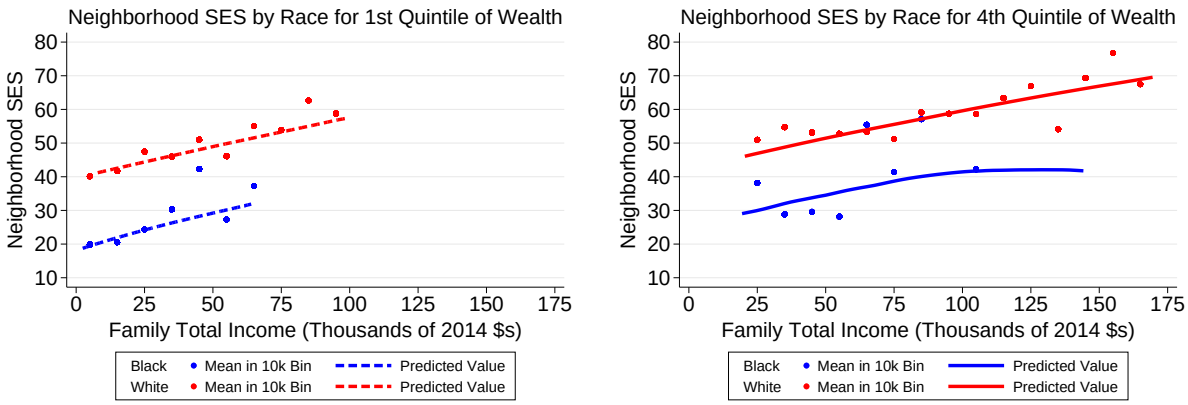
B.4 Functional Form Assumptions

Another possibility is that Black families with high wealth actually do sort into higher-SES 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 6 presents evidence on this issue by showing means within $10,000 income bins by race and wealth quintile. Figure 6b 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 SES 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 6b 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.



(a) 1st Quintile of Wealth

(b) 4th Quintile of Wealth

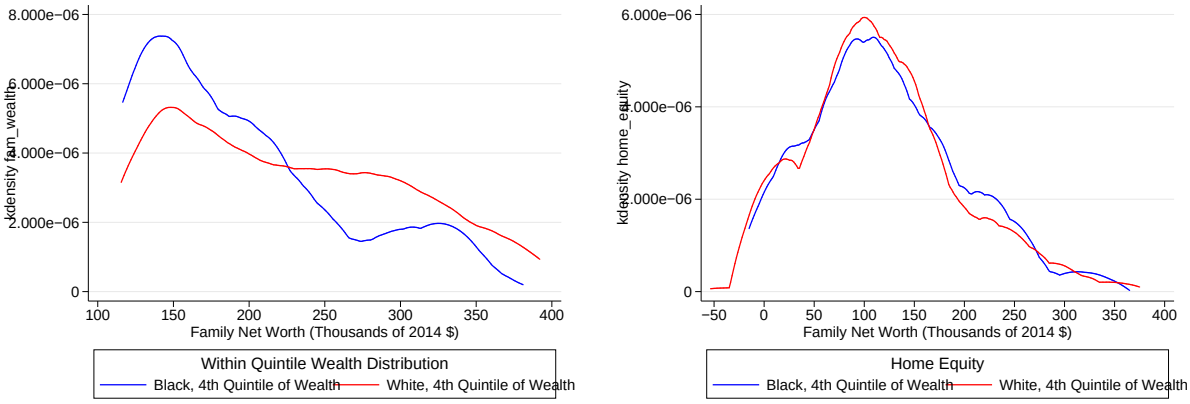
Figure 6: Neighborhood SES by Income and Race, 2015 PSID

B.5 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 7a 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 7 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.



(a) Net Worth

(b) Home Equity

Figure 7: 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 SES once race and income are accounted for.

Table 6 shows results from estimating Equation 1 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 ranked, on average, 25 percentile points lower than those of white families. Figure 8 displays these results graphically.

Table 6: Neighborhood SES Regression, 1989 PSID

		All Households	
Constant	39.9	Black Head of Household	–25.1
	(0.9)		(2.1)
Family Income	5.1e-4	Black×Family Income	–1.6e-4
	(6.1e-5)		(1.5e-4)
Family Income^2	–1.5e-9	Black×Family Income^2	2.2e-9
	(6.8e-10)		(2.4e-9)
Family Wealth	3.7e-5	Black×Family Wealth	3.3e-5
	(5.2e-6)		(1.9e-5)
Family Wealth^2	–5.8e-12	Black×Family Wealth^2	–5.3e-12
	(9.8e-13)		(4.0e-12)
		Family Income×Family Wealth	–2.7e-10
			(6.9e-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 1 is estimated with SES_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 SES, race, income, and wealth. Most of the neighborhood characteristics yield results similar to the penalty of 25 percentile points in neighborhood SES ranking for having a Black family head.

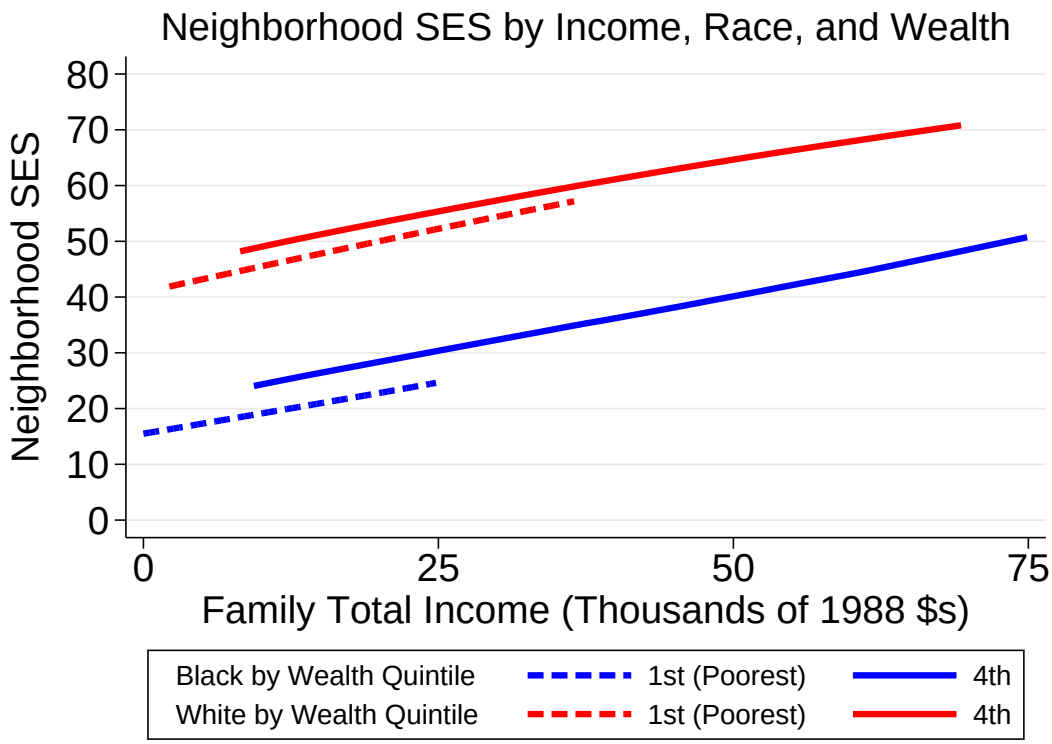


Figure 8: Neighborhood SES by Income, Race, and Wealth, 1989 PSID

Table 7: Neighborhood SES Regressions, 1989 PSID

Black Head of Household	–25.1	–22.5	–26.0	–24.9	–23.0
	(2.1)	(2.1)	(2.1)	(2.2)	(2.2)
Child $\leq$ 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

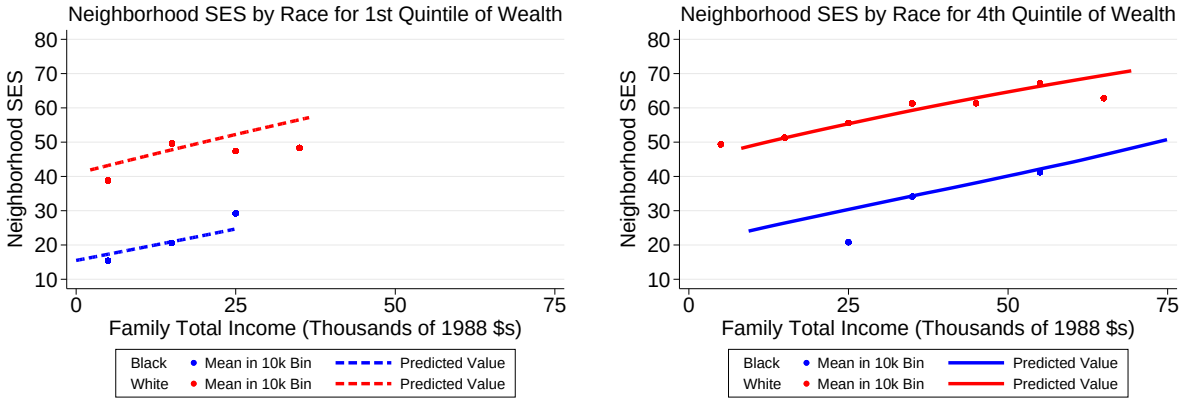
Table 8: Racial Composition Regressions, 1989 PSID

Black Head of Household	56.5	56.7	56.8	56.4	57.0
	(1.3)	(1.4)	(1.4)	(1.4)	(1.4)
Child $\leq$ 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 SES is blurred by the limited number of high-income and high-wealth Black families we observe in the data, Figure 9 shows means within $10,000 income bins by race and wealth quintile. Figure 9b 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 SES 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 9b accurately characterizes the mean relationship.

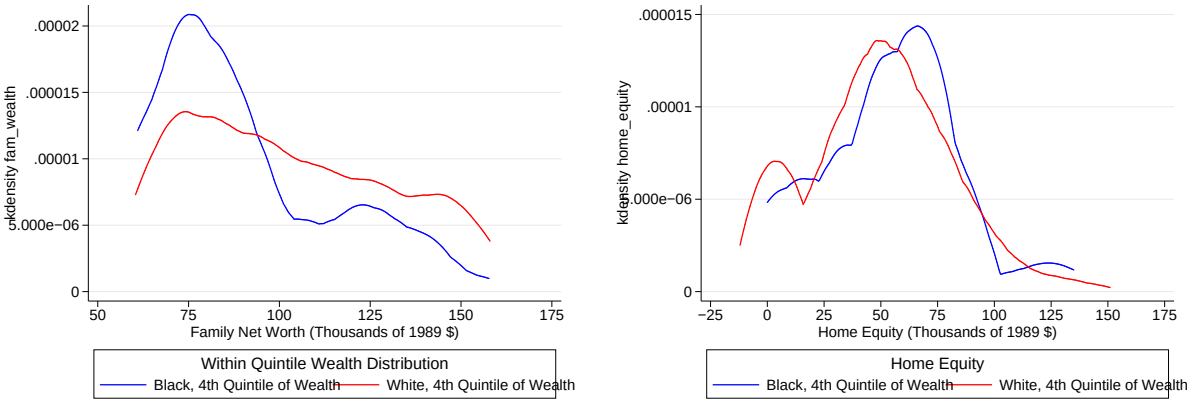


(a) 1st Quintile of Wealth

(b) 4th Quintile of Wealth

Figure 9: Neighborhood SES by Race, Income, and Wealth, 1989 PSID

Figure 10a 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 10b 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

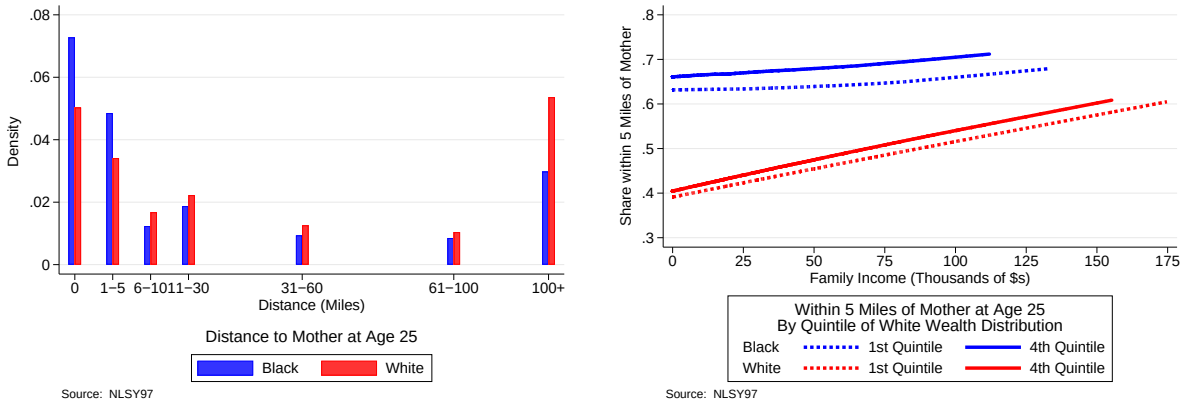
(b) Home Equity

Figure 10: Net Worth and Home Equity by Race, Income, and Wealth, 1989 PSID

D Additional Evidence on Race-Specific Locations

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 11a 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 11b shows that this fact is not driven by financial constraints, as it remains true conditional on both income and wealth.



(a) Distributions over Distance

(b) Shares Living within 5 Miles

Figure 11: 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 12 shows that Black individuals "pay" for their locational characteristics, 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 12 are precise, even for high-income African Americans, since the IPUMS ACS sample has more than 15 million individuals.

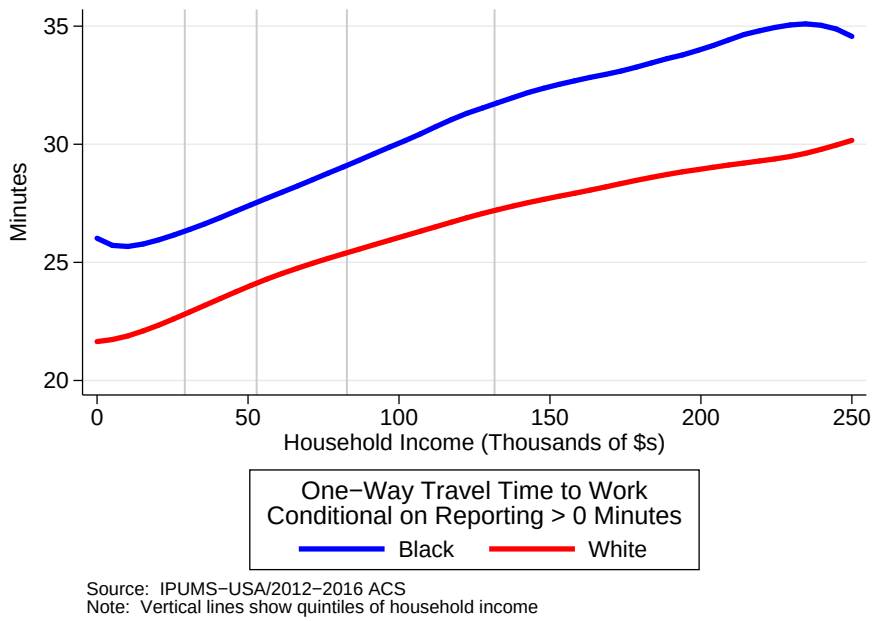
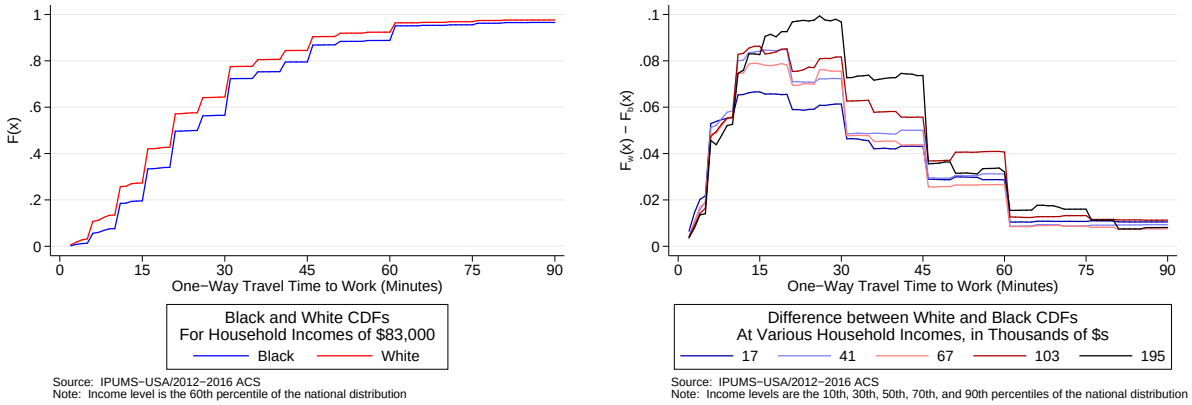


Figure 12: One-Way Travel Time to Work, 2012-2016 ACS

Digging into the cross section of travel to work times in Figure 12, Figure 13a 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 13b 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 13b 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.

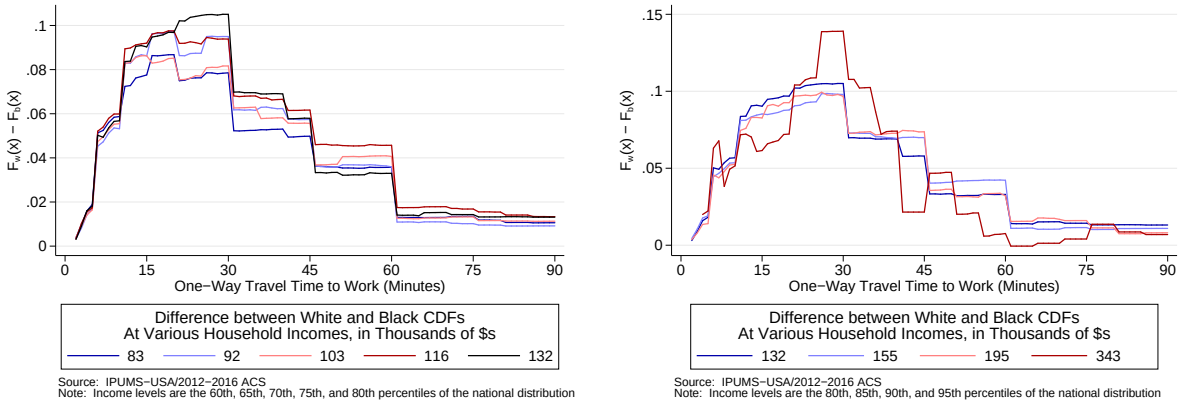
The levels in Figure 13b, however, are clearly differences across income levels. The largest differences in travel time are seen for the highest income households. The highest income households are also clear exceptions between 30-60 minutes, with larger differences in CDFs than for any other income level. There is also variation in differences between 0-30 minutes that is not monotonic in income. Figure 14 shows more detail on precisely how differences in travel time are increasing in income.



(a) CDFs

(b) Differences at Quintile Cutoffs

Figure 13: Census Data



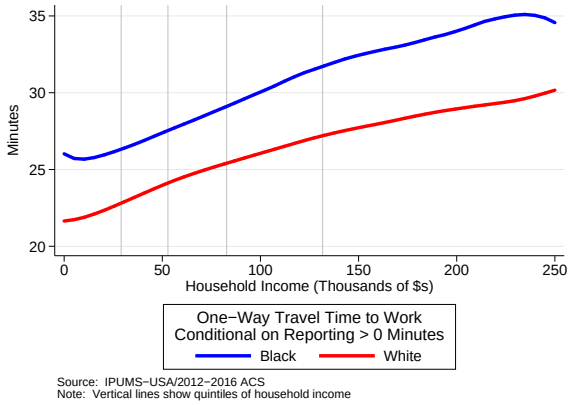
(a) 60th-80th Percentiles of Household Income

(b) 80th-95th Percentiles of Household Income

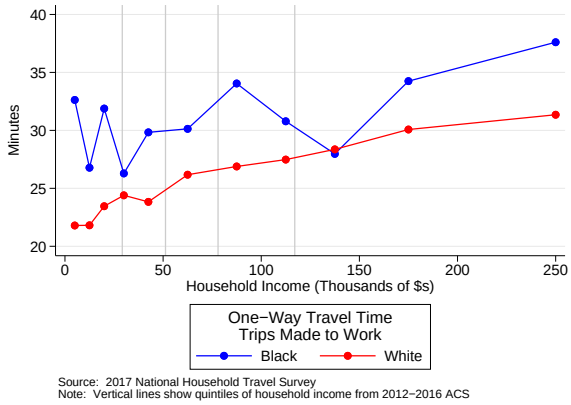
Figure 14: Census Data

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 15, and find that the NHTS is noisier but qualitatively similar. Figures 16a - 17b 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.

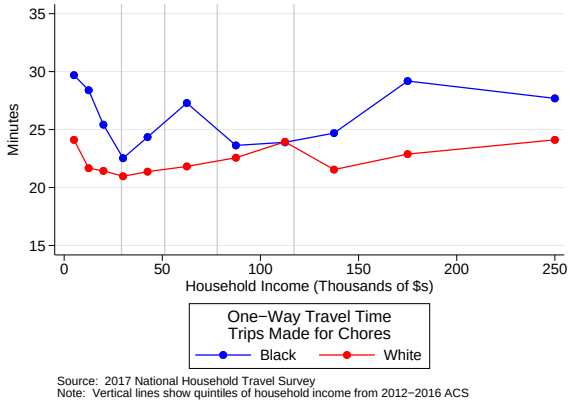


(a) IPUMS/ACS 2012-2016

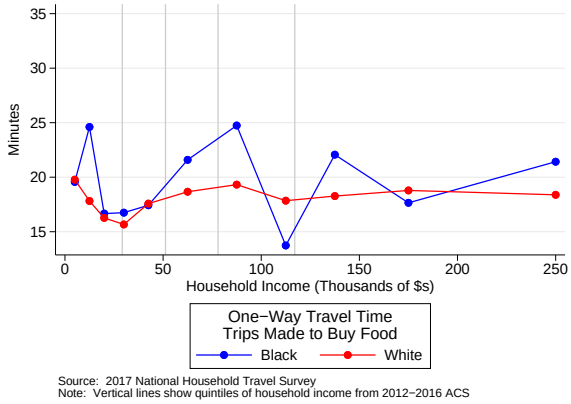


(b) NHTS

Figure 15: Travel Times to Work

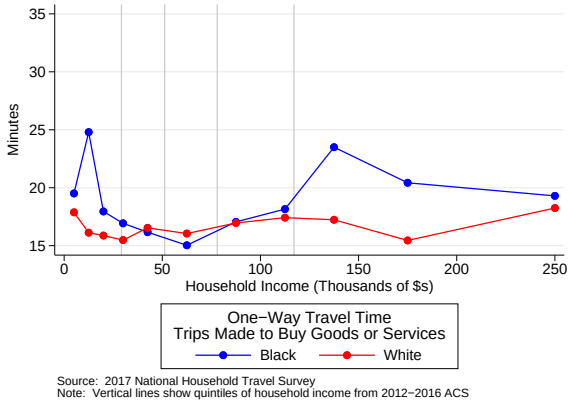


(a) Trips Made for Chores

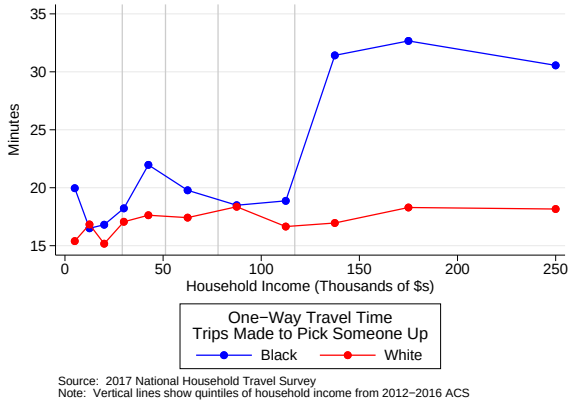


(b) Trips Made to Buy Food

Figure 16: Travel Times in the 2017 NHTS



(a) Trips Made to Buy Goods or Services

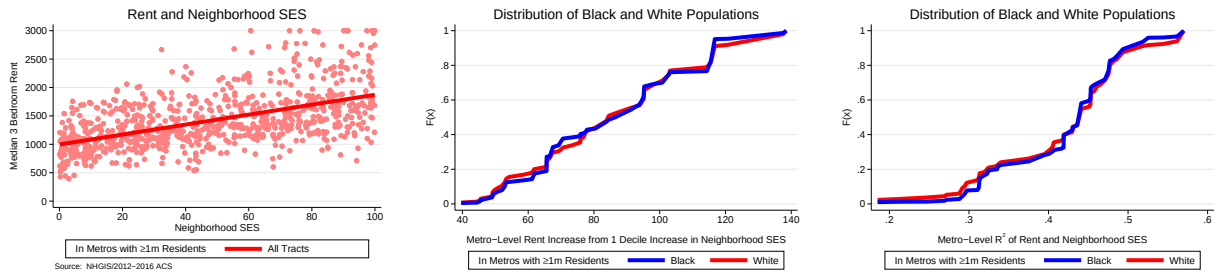


(b) Trips Made to Pick Someone Up

Figure 17: Travel Times in the 2017 NHTS

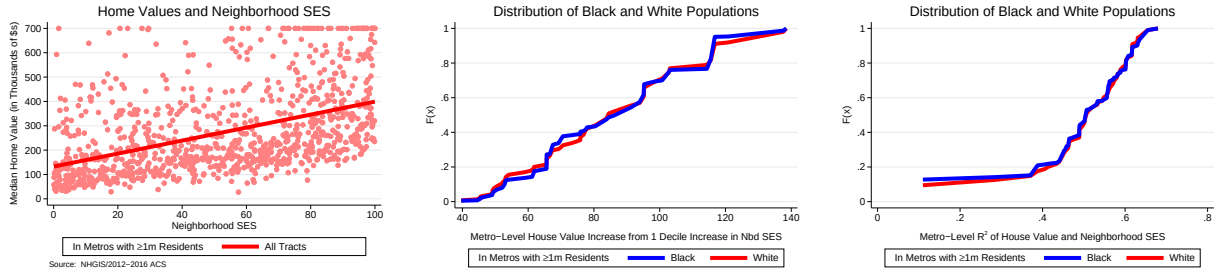
E Neighborhood SES and the Price of Housing

Figures 18 and 19 confirm the result noted in Section 3: Black and white households are distributed across metros where the relationship between neighborhood-level housing prices and SES 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 SES, we find that this result is true both for the slope of the regression coefficients (Figures 18b and 19b) and for the R^2 of the regression (Figures 18c and 19c).



(a) United States (b) Slope (c) R^2

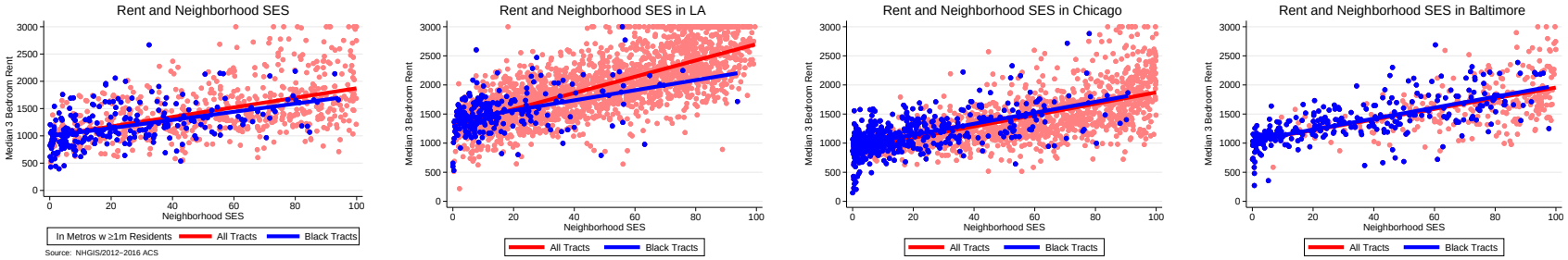
Figure 18: Neighborhood SES and Median 3-Bedroom Rent



(a) United States (b) Slope (c) R^2

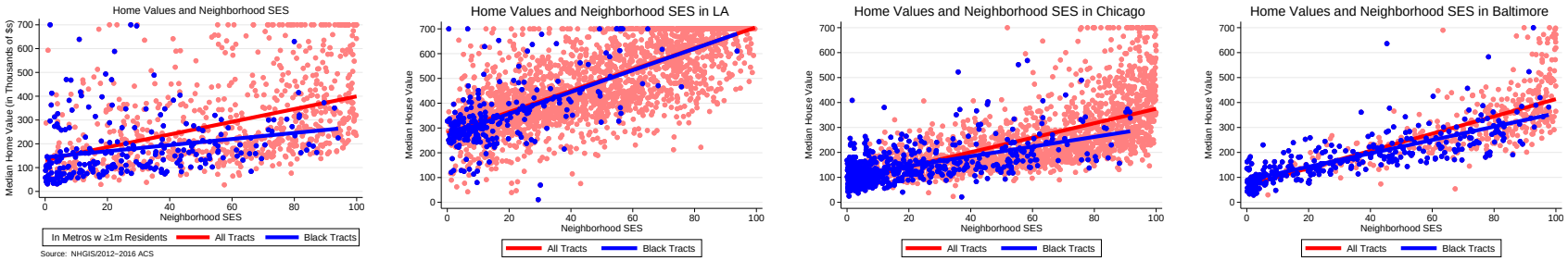
Figure 19: Neighborhood SES and Median House Value

Figures 18a and 19a 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 SES, Figures 20-23 plot the data on housing prices and neighborhood SES for several metros.



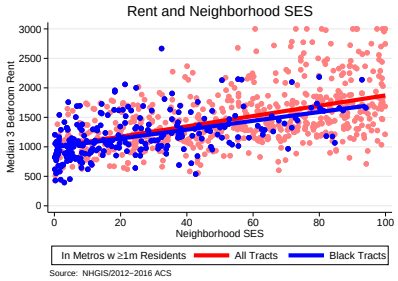
(a) United States (b) Los Angeles (c) Chicago (d) Baltimore

Figure 20: Median 3 Bedroom Rent

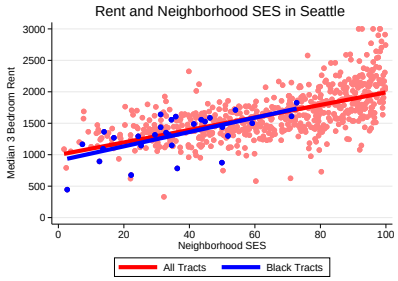


(a) United States (b) Los Angeles (c) Chicago (d) Baltimore

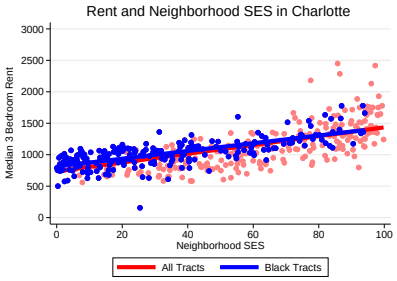
Figure 21: Median House Value



(a) United States

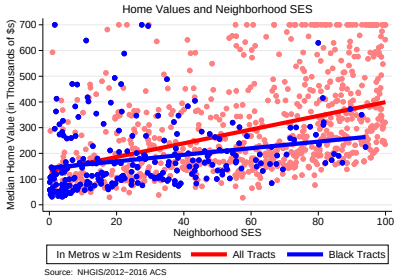


(b) Seattle

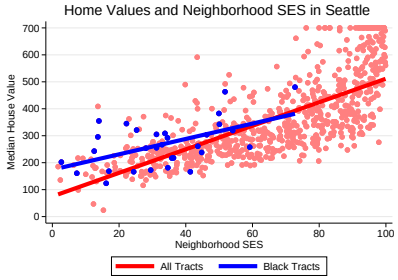


(c) Charlotte

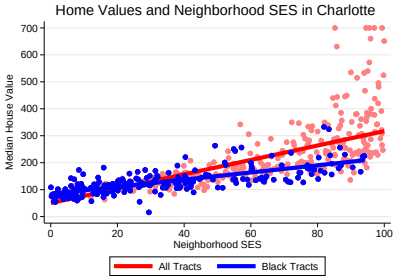
Figure 22: Median 3 Bedroom Rent



(a) United States



(b) Seattle



(c) Charlotte

Figure 23: Median House Value

F Additional Figures

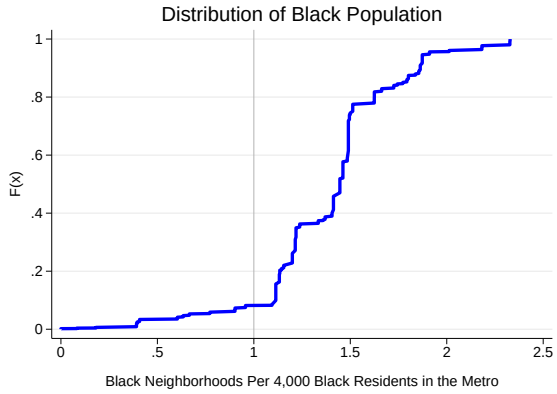


Figure 24: Metros With and Without Black Neighborhoods
Note: This figure shows the distribution of Black residents over the supply of Black neighborhoods in their metro (per 4,000 Black residents). Metros without Black neighborhoods are defined as metros with less than 1 Black neighborhoods per 4,000 Black residents.

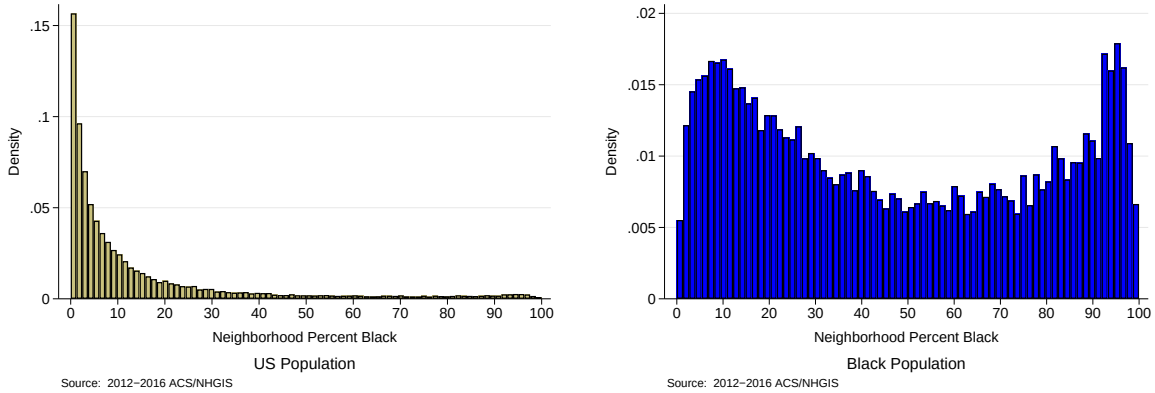


Figure 25: Share of Tract Residents Who are Black

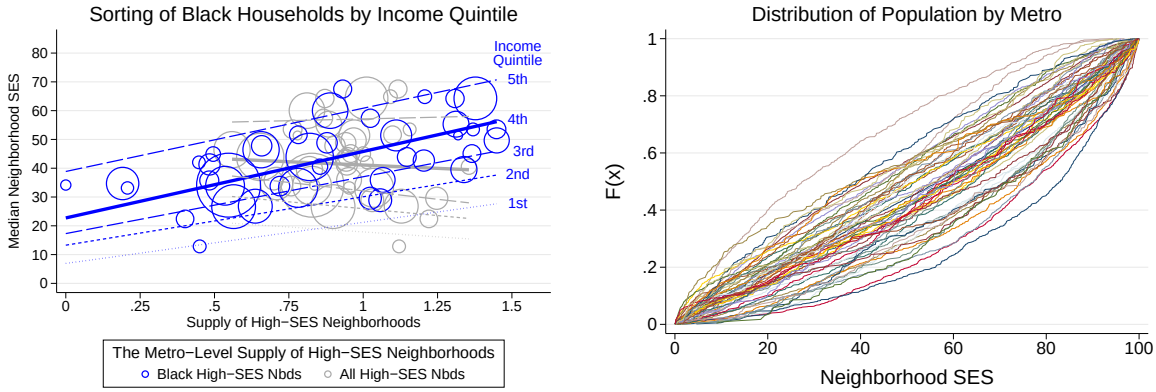


Figure 26: Sorting

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