What Determines the Success of Housing Mobility Programs?

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Abstract: Housing Mobility Programs (HMPs) support residential mobility to reduce economic segregation. One design feature of HMPs requires identifying areas to which moving will most improve outcomes. We show that ranking neighborhoods' effects using current residents' outcomes has strengths over using previous residents' outcomes due to statistical uncertainty, bias from sorting over time, and lack of support. We simulate how the choice of neighborhood ranking and others affect an originally-intended outcome of HMPs: reducing racial segregation. HMP success on this dimension depends on the ability to port vouchers across jurisdictions, access to cars, and the range of neighborhoods targeted.

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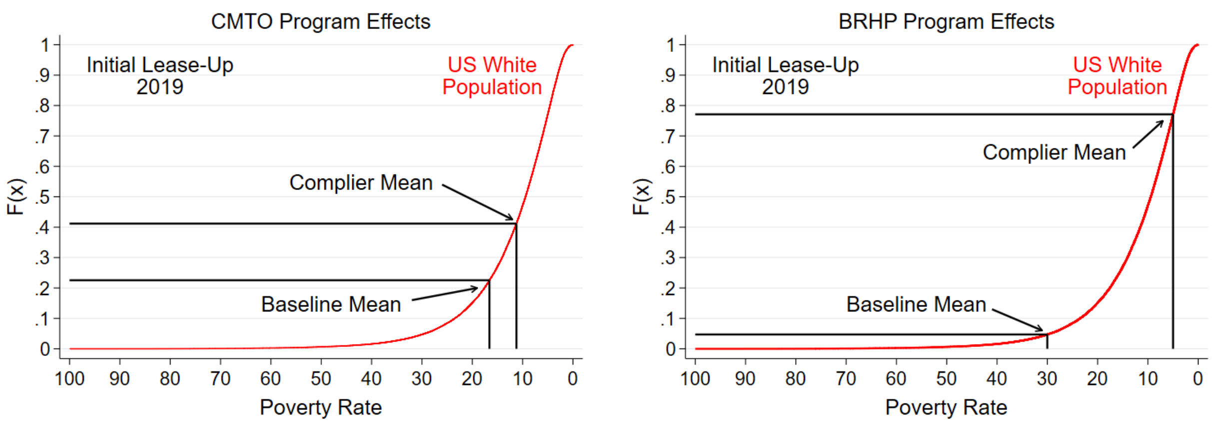
1 Introduction

Housing mobility programs (HMPs) are a model that is receiving renewed attention in the design of public housing policy. The first HMP, Gautreaux, began in 1976 and supported Black households in Chicago moving from public housing to suburban neighborhoods with a low share of Black residents (Polikoff (2006)). Subsequent HMPs have encouraged moves to higher-income neighborhoods with varying degrees of focus on racial segregation.

The success of HMPs in empowering moves to opportunity has varied widely. Figure 1 shows the 2019 results of two prominent HMPs, Creating Moves to Opportunity (CMTO) and the Baltimore Regional Housing Partnership (BRHP). While both of these HMPs are regarded as being very successful, they have clearly resulted in different levels of success in moving their participants to lower poverty neighborhoods. CMTO moved the typical participant from the 23rd percentile to the 41st percentile of neighborhood poverty rates for non-Hispanic whites, but those who moved in the BRHP typically increased from the 5th to the 77th percentile.



(a) Creating Moves to Opportunity (b) Baltimore Regional Housing Partnership

Figure 1: Program Effects on Participants' Tract-Level Poverty Rates
Note: Both figures display the Cumulative Distribution Functions of tract-level poverty for the United States' population of non-Hispanic whites in the 2014-2018 American Community Survey/NHGIS. The left panel shows the pre-program and post-move means of BRHP program participants in 2019. The right panel shows the baseline mean and treatment group complier mean for CMTO participants in April 2019, where the complier mean is calculated as the control mean plus the treatment on the treated (TOT) effect.

What determines the success of such HMPs? This paper breaks the question into two parts, the first of which is an econometric question: How can we identify the areas to which moving will most improve the outcomes of participants? The second question is about implementation: How can policy best support moves to those areas identified as offering the greatest opportunity for participants?

The best approach to identifying neighborhood effects is a remarkably open question. While one approach to identifying neighborhood effects is to compare average outcomes across neighborhoods, uncontrolled differences in means may owe more to selection bias than to causal effects. The literature on school effectiveness has made considerable progress in addressing this issue, moving beyond simply comparing observed outcomes to identify school effects (Angrist et al. (2022)). The literature on identifying neighborhood effects has made much less progress (Graham (2018)).

Step 1 of canonical approaches to understanding neighborhood effects is measuring the neighborhood characteristics that theory suggests affect residents' outcomes. Two examples are neighborhood quality (Aliprantis (2017)) and the Child Opportunity Index (COI, Noelke et al. (2020)). Neighborhood quality ranks Census tracts according the socioeconomic characteristics of current residents, including poverty rates, educational attainment, labor market outcomes, and household composition. The COI supplements the outcomes of current residents with information on additional neighborhood amenities, such as public school performance, access to public transportation and employment, and environmental conditions. After ordering neighborhoods, Step 2 of canonical approaches is to use exogenous variation and/or a model of sorting to identify the effects of those characteristics on outcomes (recent examples include Altonji and Mansfield (2018) and Aliprantis and Richter (2020)).

A new approach to identifying neighborhood effects is made possible by an administrative data set, the Opportunity Atlas (OA, Chetty et al. (2020a)). The OA combines Steps 1 and 2 and orders neighborhoods by estimating the mean adult outcomes of a tract's *previous* residents rather than the outcomes of its current residents, both overall and conditional on race or parental income. The OA has been used both to rank and to predict neighborhoods' effects while eschewing the canonical approach's search for exogenous variation or modeling.

The first contribution of this paper is to show that using the outcomes of contemporaneous residents has several strengths over using the outcomes of previous residents for the ranking of neighborhood effects.

We document that the OA has many large disagreements with contemporaneous rankings of neighborhoods, and we present evidence that these large disagreements are driven by bias and noise in the OA. We show that disagreement between the OA and neighborhood quality is steeply related to the sample size used to estimate the OA. We also show that time bias is paramount for understanding "opportunity bargains," or tracts with both highly-ranked neighborhood effects and low rents. Chetty et al. (2020a) interpret this additional variation in the OA ranking in terms of neighborhood effects. Under this interpretation, low-rent tracts ranked highly by the OA represent relative bargains for accessing opportunity. We find evidence that suggests caution when using the OA to identify opportunity bargains: such places have tended to show declines in canonical rankings since 1990, when OA's children were being treated by a neighborhood's effect. While opportunity bargains may exist, those identified by the OA appear to be driven by neighborhood change. Low prices may instead convey information about *current* neighborhood conditions, reflecting a "time bias" in the OA estimates.

Contemporaneous rankings like neighborhood quality or COI themselves are only rankings on observable characteristics; they satisfy only Step 1 as described above and do not identify causal neighborhood effects in a structural sense. However, they also do not introduce the time bias or small sample issues that appear to plague the OA. Beyond the part of the sample that is susceptible to these issues, OA does not appear to provide substantially different information over contemporaneous rankings. We show this point by looking at disagreement in rankings after dropping tracts that experienced large changes over time or that had small sample sizes for OA estimates. We find that disagreements between OA and quality rankings of tracts are negligible in the tracts for which we are confident that this disagreement is not driven by bias or noise in the OA estimates.

A potential strength of the OA is the ability to measure outcomes by certain demographic characteristics like race. We find that this strength is not operational for the design of HMPs. We show that in most highly-ranked tracts we have not observed *any* Black boys grow up. This finding also highlights that purely empirical exercises, such as that conducted in Chetty et al. (2020b), cannot measure how much outcomes would converge if Black and white boys grew up in the same neighborhoods. Theory must be invoked to make predictions outside the support of the data.

The second contribution of this paper is to quantify the relative importance of design features in reducing racial inequality by helping program participants move to areas designated as high opportunity. Our approach to quantifying the importance of design features is to simulate residential locations in a reference HMP and compare how simulated locations would change in HMPs with alternative design features. In the reference HMP, poor residents living in neighborhoods of concentrated poverty are encouraged to move to tracts in the top third of their metro area as ranked by neighborhood quality, the index used earlier that aggregates six rankings of current residents' socioeconomic status. While the number of moves into a given tract is constrained by the supply of rental housing units there, we also assume that the number of moves into a tract is constrained so as to be low enough to avoid incumbent households from sorting in response to the arrival of program participants.[1]

Several factors aiding successful moves have already been identified (Scott et al. (2013)): Landlord outreach, pre-search counseling, housing search assistance, post-move support, and voucher values tied to rents in small areas.[2] Several additional factors, however, are not as well understood. For example, how important is it that vouchers needed to be ported across Public Housing Authority (PHA) jurisdictions in some previous HMPs but not in others? We know that there is a low supply of units in high-rent areas and that landlords increasingly avoid voucher tenants as rents increase (Phillips (2017)). How binding is this constraint, and might we be able to relax supply constraints by targeting lower-ranked tracts? Likewise, we know that higher rent areas have less access to public transportation. How important is this constraint, and might we be able to relax it by assisting HMP participants in accessing cars or ride shares?

[1] We show that our qualitative conclusions are unchanged when considering HMPs with a tract-level constraint that is one- or two-thirds the size of our reference HMP. Moreover, the number of movers in the reference HMP is consistent with evidence in the literature finding incumbent non-response (Davis et al. (2019); Rosenbaum (1995)) and is well below the numbers found to induce incumbent response (Diamond and McQuade (2019a); Davis et al. (2019)) or to change neighborhood externalities (Agostinelli et al. (2020)). Following the scale and timeline of existing HMPs, if the reference HMP were implemented gradually over the course of two decades, receiving tracts would add one or two new voucher families per year.

[2] For example, see for landlord outreach (Cossyleon et al. (2020)), pre-search counseling (Darrah and DeLuca (2014); DeLuca and Rosenblatt (2017)), housing search assistance (Bergman et al. (2020a), Bergman et al. (2020b), Schwartz et al. (2017)), post-move support (Cunningham et al. (2010); DeLuca and Rosenblatt (2017)), and Small Area Fair Market Rents (Collinson and Ganong (2018); Aliprantis et al. (2022); Dastrup et al. (2019); Reina et al. (2019)).

Our simulation results can be summarized as follows: When aggregated over an entire HMP, the precise measure of neighborhood effects used in HMP design is not highly consequential. We find that when voucher moves are restricted to stay within PHA jurisdictions, HMP success is reduced by 36 percent relative to our reference HMP that spans each metropolitan division. We find that if participants in our reference HMP were unable to access a car, and so were restricted to moving to tracts with access to public transportation, success would only be 46 percent of the success of the reference HMP. We find that eliminating the supply constraints in highly-ranked tracts would increase program success by 54 percent while respecting the upper bound of 30 families moving into any given tract. While there are several approaches HMPs currently take to increase access to units in high-opportunity areas, we explore an alternative approach to increasing the supply of units. We find that this alternative approach of targeting the middle third of tracts improves racial equality by the same amount as would completely eliminating rental supply constraints when targeting the top third of tracts.

2 Identifying Opportunity Neighborhoods

2.1 Data

While the objective of exposing participants to positive neighborhood effects is straightforward, the question of how to identify those effects is not. There are many ways to rank neighborhoods, and here we consider three rankings of neighborhood-level outcomes, where we define neighborhoods as Census tracts.[3] Each ranking of neighborhoods is in terms of the national distribution of individuals, although we note the cases when we use metro-level rankings. As we discuss later, there are statistical challenges specific to these rank measures (Mogstad et al. (2021)).

The first ranking, "neighborhood quality," is an index used in Aliprantis and Richter (2020), which is the ranking of the first principal component of a tract's national rankings on six socioeconomic characteristics. The six characteristics used to calculate neighborhood quality are the poverty rate, the share of adults 25+ with a high school diploma, the share of adults 25+ with a BA, the Employment to Population Ration for adults 16+, the labor force participation rate for adults 16+, and the share of families with children under 18 with only a mother or father present. These variables are available in the 1990 decennial Census and 2014-2018 American Community Survey (ACS), which we download from the National Historical Geographic Information System (NHGIS, Manson et al. (2020)).[4] The second ranking is the Childhood Opportunity Index 2.0 (COI). Developed at Brandeis University (Noelke et al. (2020)), the COI aggregates information from 29 items, many of which come from data sources beyond the Census, like the National Center for Education Statistics (NCES) and the Environmental Protection Agency (EPA).

[3]Assuming that Census tracts are the unit over which neighborhood externalities operate is a strong assumption, typically made due to data limitations. See Durlauf (2004) and Galster (2019) for broad discussions.

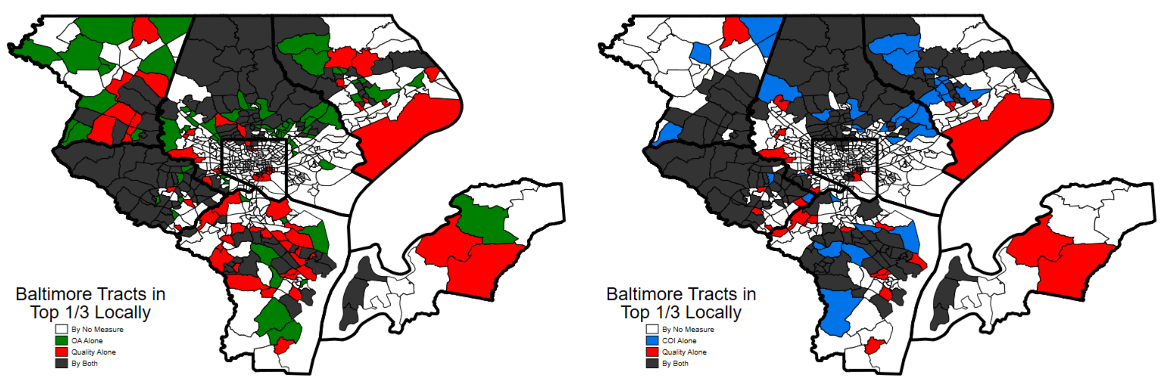
[4]For decennial Census data before 2010, when appropriate we impute count estimates into 2010 tract boundaries using the Longitudinal Tract Data Base (LTDB) described in Logan et al. (2014), Logan et al. (2016), and Logan et al. (2021).

The third ranking comes from the Opportunity Atlas (OA), which estimates the average outcomes for individuals born between 1978 and 1983 who spent time residing in a given neighborhood (Chetty et al. (2020a)). This birth cohort corresponds to children aged 6-11 in the 1990 Census. Unless otherwise stated, our analysis focuses on the OA ranking of neighborhoods based on the estimated average family income between ages 31-37 for children who had parents at the 25th percentile of income. We sometimes also refer to the OA rankings for high-income kids and low-income kids to denote children with, respectively, 75th and 25th percentile income parents.

Appendix A describes these measures in greater detail.

2.2 The OA Has Many Large Disagreements with Other Rankings

Many HMPs encourage participants to move to the top third of local tracts according to some ranking of neighborhoods. Different rankings often disagree about where such a program should encourage participants to move. Figure 2 shows the disagreement between the top third of tracts in Baltimore as identified by each ranking we consider in our analysis. While these rankings agree about the top-third status of many tracts, there are many tracts over which they disagree. The disagreement between OA and quality is considerably higher than is the disagreement between COI and quality. OA and quality disagree on the top-third ranking of 140 tracts, while COI and quality only generate this disagreement for 71 tracts, out of 671 tracts total. Which ranking should a PHA use to define the opportunity areas to which they encourage moves?[5]



(a) OA and Quality

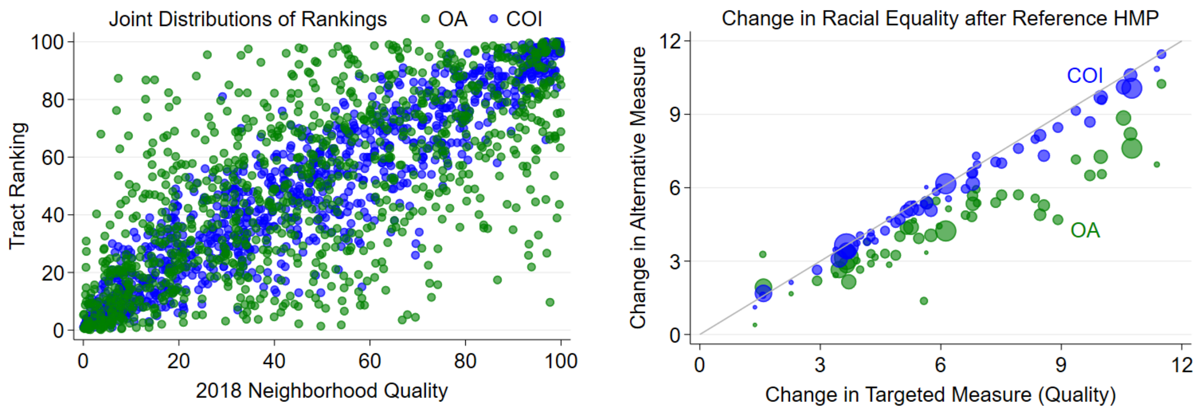
(b) COI and Quality

Figure 2: Overlap in Opportunity Maps
Note: These maps show the overlap in tracts ranked in the top third of the Baltimore metro by alternative rankings of neighborhoods. The left panel shows rankings based on Opportunity Atlas (OA) income estimates for poor children and neighborhood quality in the 2014-2018 ACS. The right panel shows the Childhood Opportunity Index (COI) 2.0 and neighborhood quality in the 2014-2018 ACS. Tracts where different measures agree about ranking in the top third are shaded in black, and tracts where measures agree about ranking in the bottom third are left white. Tracts where measures disagree, so that only one of the displayed measure ranks the tract in the top third, are colored in either green, red, or blue.

While we began looking at Baltimore due to the prominence of the Baltimore HMP, it remains true beyond Baltimore that OA and quality disagree more on the ranking of tracts than do COI and quality. Figure 3a plots 1,000 randomly chosen Census tracts to illustrate broad features of the joint distributions of measures. The joint distribution of COI and quality is shown with the blue

[5]Appendix D shows that opportunity mapping is a worthwhile pursuit: An HMP targeting the highest ranked tracts in a metro improves racial equality considerably more than an HMP that simply targets any tract in a suburb.

dots. While there is variation in one measure conditional on the other, the measures broadly agree, and tracts ranking very high in one measure do not rank very low in the other. In contrast, the joint distribution of OA and quality, shown with the green dots, exhibits much more disagreement on the ranking of tracts. There are tracts that rank high according to quality that rank low according to OA, and vice versa.



(a) Joint Distributions

(b) Baseline HMPs Designed around Quality

Figure 3: Additional Variation in the OA

Note: The left panel displays a scatterplot of 1,000 randomly-selected Census tracts. Green dots show the joint distribution of the OA and 2018 neighborhood quality rankings of neighborhoods, and blue dots show the joint distribution of the COI and 2018 neighborhood quality rankings of neighborhoods. The right panel shows the success of the Reference HMP in the metros in our sample where the x-axis measures success in terms of 2018 neighborhood quality, the targeted ranking of the reference HMP, and the y-axis measures success in terms of either the COI (in blue) or the OA (in green).

How much does this statistical disagreement matter for the design of HMPs? Figure 3b shows the changes in racial equality that would result for the baseline HMP designed around quality, where both the measure of racial inequality and the baseline HMP are discussed in Section 3. The x-axis shows the resulting change in racial equality as measured in quality, and the y-axis shows the change as measured in either COI or OA. The fact that the blue dots representing the COI hug the 45 degree line indicates that an HMP targeting quality will also tend to improve COI; the improvement in COI would on average be 95 percent of the improvement in quality. The fact that the green dots representing the OA tend to fall below the 45 degree line indicates that an HMP targeting quality will improve OA less in a quantitatively important way; the improvement in OA would on average be 75 percent of the improvement in quality.

Since targeting quality will improve the COI, and vice versa, the question becomes: How should one interpret the disagreement between OA and contemporaneous measures? Chetty et al. (2020a) interpret this additional variation as evidence that the OA ranking better measures neighborhood externalities than other rankings like the COI or quality. We find evidence that suggests caution when giving this interpretation to the disagreement between the outcomes of a neighborhood's previous residents and the outcomes of its current residents. We also find that a key strength of the OA – the ability to rank neighborhoods by demographic groups – does not appear operational for the design of HMPs.

In the ensuing analysis we will focus on the 1990 decennial Census because the OA sample is for individuals born between 1978 and 1983, and this birth cohort's age range of 6-11 in the 1990 decennial Census is likely when neighborhoods most influence children's outcomes relative to the alternative age ranges for decennial Censuses of 0-1 or 16-21.

2.3 Large Disagreements Are Often Due to Small Sample Sizes in the OA

Neighborhood sorting leads to both statistical and conceptual uncertainty in the case of measuring income-specific outcomes. Here we focus on statistical uncertainty.[6]

The 1990 Decennial Census directly measures the number of children aged 6-11 in each tract, as well as the number of Black or white boys aged 6-11. Figure 4 shows that the disagreement between OA and quality is the largest in tracts with very few children. The green dots in Figure 4 plot the R^2 of a regression of the OA ranking of a tract on its 1990 neighborhood quality ranking conditional on being within a given percentile in the distribution of children in the 1990 Census. We see that the R^2 can rise above 0.7 for tracts with many children, but that the R^2 starts below 0.1 in tracts with the fewest children.

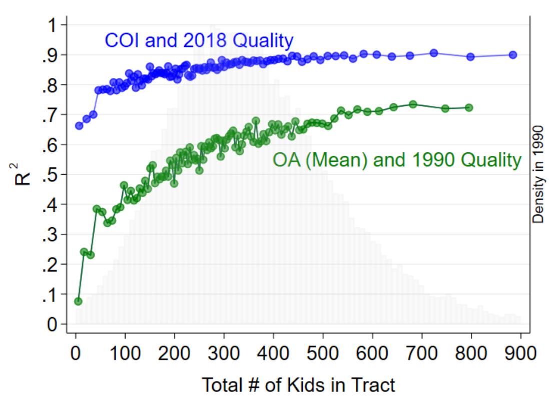


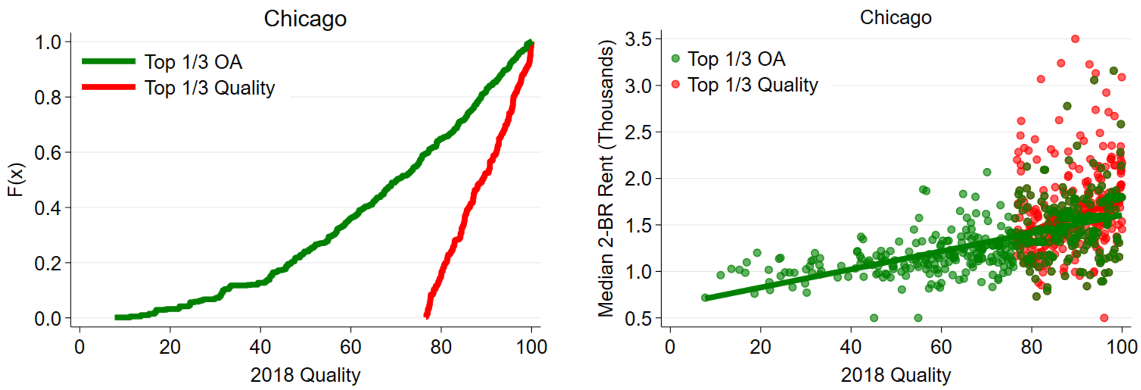
Figure 4: R^2 by Sample Size
Note: This panel reports the R^2 from population-weighted regressions within single percentiles of the total number of children aged 6-11 in the tract in the 1990 Census. The green dots show the R^2 for regressions of OA (mean) ranking on 1990 neighborhood quality and the blue dots show the R^2 for regressions of COI ranking on 2018 neighborhood quality.

2.4 Large Disagreements Are Often Due to Sorting over Time: The Case of Opportunity Bargains

Opportunity bargains are neighborhoods with strong, positive effects on residents that also have low rents. How should we think about using alternative rankings to identify such neighborhoods? Chetty et al. (2020a) argue that the OA is the best measure to target opportunity bargains when implementing HMPs. Below we find evidence that suggests caution when using the OA to target opportunity bargains: The bias creating low-rent, highly-ranked tracts in the OA is likely in the ranking, not the rent.

[6]See Manski (2015) for a definition of statistical and conceptual uncertainty.

Low-rent tracts that are ranked highly according to the OA tend to be ranked much lower by neighborhood quality. Figure 5 shows data from Chicago to illustrate this point. Figure 5a shows the distribution of rental units over 2018 neighborhood quality for tracts in the top third of Chicago when ranked by either the OA or 2018 quality. Because Chicago has many highly-ranked tracts relative to the national distribution, the top third of tracts in Chicago as ranked by quality are nearly all in the top quintile nationally. In contrast, the OA has a long left tail, with about a quarter of tracts in the top third of the OA being below the median in terms of quality.



(a) Local Top Third

(b) Rent in Local Top Third

Figure 5: The Top Third of Tracts in Chicago
Note: The left panel plots the Cumulative Distribution Functions (CDFs) of the 2 bedroom and larger rental units in the top third of tracts in Chicago as ranked by either the OA or 2018 neighborhood quality. The right panel plots the joint distribution of median 2 bedroom rent and 2018 neighborhood quality for tracts in the top third in Chicago as ranked by either the OA or 2018 neighborhood quality, as well as lines fitted by Ordinary Least Squares (OLS).

While targeting the top third of tracts as ranked by the OA will allow for tracts that are low-ranked in terms of quality, additionally targeting low-rent tracts will select for these low-ranked tracts. Figure 5b shows that there is a positive relationship between rent and quality in the top third of tracts in Chicago as ranked by the OA. The left tail of quality is over-represented in the low-rent group of OA top third tracts. Appendix H shows that this same pattern is found across metros.

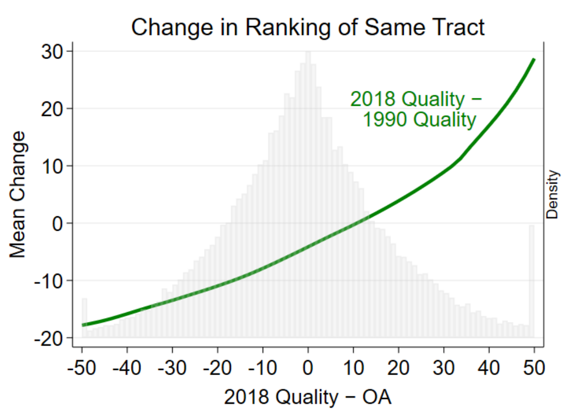
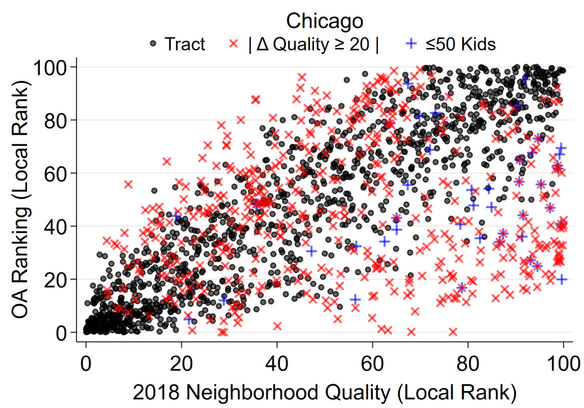


Figure 6: Change in Quality by Disagreement
Note: This figure shows the change in the characteristics of tracts' residents over time. The figure shows the expected change in residents' characteristics, or 2018 Quality minus 1990 Quality, as a function of the disagreement between the 2018 Quality and the Opportunity Atlas (OA) rankings of tracts.

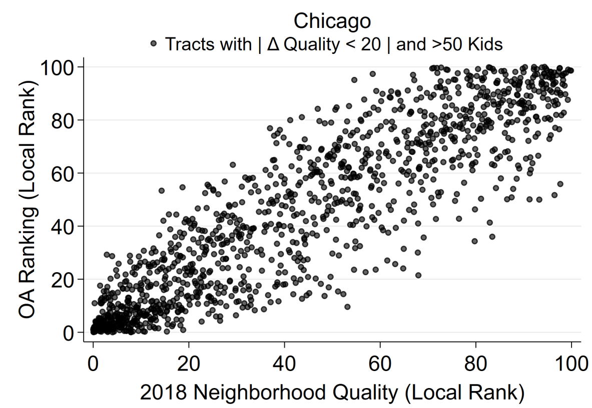
Figure 6 shows that the low-rent opportunity bargains identified by the OA are likely to have dropped considerably in quality between 1990 and 2018.[7] Recall that Figure 5 just showed that the low-rent opportunity bargains identified by the OA are likely to have a low ranking according to 2018 quality. When we look at such tracts, where the 2018 quality ranking minus the OA ranking is very negative, say –30 or less, we see in Figure 6 that these tracts also experienced large declines in quality between 1990 and 2018. Thus, low rents in the "opportunity bargain" tracts whose residents' outcomes have dropped considerably since the time they were occupied by OA residents likely convey information about the effects of living in such neighborhoods.

2.5 Large Disagreements Can Be Interpreted as Bias or Noise in the OA

When looking at the local ranking of tracts by the OA and neighborhood quality, large disagreements become rare when we plot rankings that do not include tracts with large changes in quality between 1990 and 2018 or small sample sizes. Figure 7 shows the implications of sorting over time in Chicago for interpreting disagreements between the outcomes of a tract's current and previous residents. Appendix G.1 shows that a similar pattern holds in other cities, with the joint distribution of local quality and OA rankings looking more like the joint distribution of quality and COI when these outliers are removed.



(a) All Tracts in Chicago



(b) "Unbiased" Tracts in Chicago

Figure 7: Disagreement in Rankings in Chicago
Note: These figures show the joint distribution of the local ranks of tracts in terms of 2018 neighborhood quality and mean family income pooled over race/ethnicity and gender as estimated in the Opportunity Atlas (OA). The left panel flags tracts that either experienced a change in quality (in the local distribution) between 1990 and 2018 of at least 20 percentile points, or else that had less than 50 children in the OA sample age range in the 1990 Census. The right panel shows only those tracts that are not subject to these two sources of uncertainty in OA estimates. Appendix G.1 shows similar figures for other metros.

In practice, PHAs are likely to make discretionary changes to move rankings toward those implied by current outcomes when drawing an opportunity map (See Chapter 3 of Scott et al. (2013), Appendix A of Bergman et al. (2020a), or Weismann et al. (2020)). The evidence on uncertainty and bias just presented suggest that such adjustments are important for the neighborhood effects

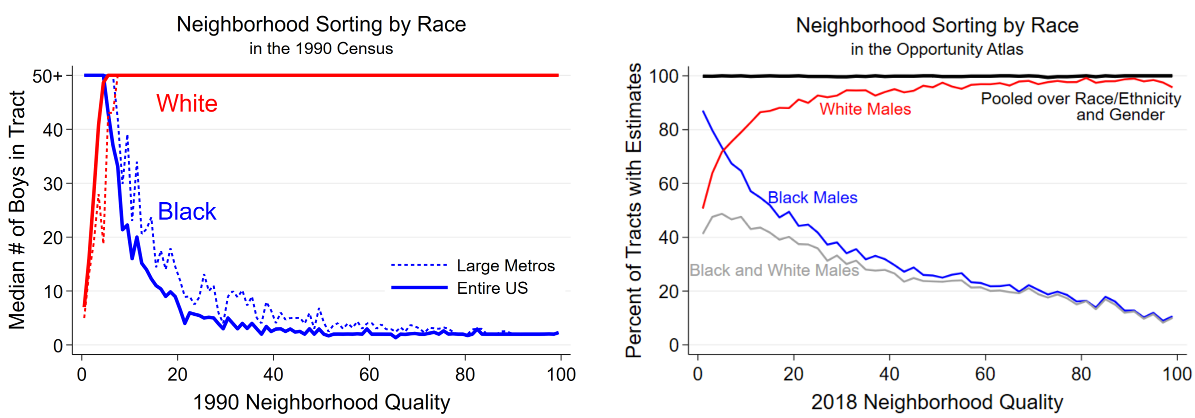
[7] Appendix Figures 23 and 24 show similar results in terms of population growth.

experienced by HMP participants.

2.6 We Cannot Rank Neighborhoods by Race-Specific Outcomes

Targeting outcomes specific to demographic groups could be especially important in the case of race, where the experience of being "Black in white space" could generate different experiences for Black and white individuals occupying the same physical space (Anderson (2020), Harriot (2019)), a mechanism that has been noted by HMP participants (Lott (2021)) and that could be perpetuating residential segregation at all levels of income and wealth (Aliprantis et al. (2022)).

Unfortunately, race-specific outcome estimates are simply not available for the most relevant tracts when designing an HMP. Residential sorting by race is so strong in the US that we have not observed enough Black children growing up in most high-opportunity neighborhoods to estimate race-specific outcomes. Consider Black boys: In the 1990 Census, the median tract in the top half of neighborhood quality had 2 Black boys in the OA sample age range (6-11).



(a) Number of Boys by Quality

(b) Overlap of Estimates

Figure 8: Sample Sizes and Common Support by Race
Note: The left panel shows the median number of black and whites boys in a tract conditional on being in a given percentile of 1990 neighborhood quality. The dashed lines show the medians when calculated only for tracts in the 54 largest metros in the 2017 American Community Survey, with each metro having at least 1 million inhabitants. The right panel shows the percent of tracts with OA estimates of conditional outcomes for Black males and white males at each percentile of neighborhood quality.

Figure 8a shows how quickly the median number of Black boys in 1990 Census tracts falls as 1990 neighborhood quality increases. At the lowest levels of quality, most tracts have 50 Black boys or more with which to estimate outcomes. But once quality gets out of the bottom decile, the number of Black boys is already too low to reliably estimate outcomes in many neighborhoods. Outside the bottom third of tracts, most neighborhoods simply do not have enough observations to reliably estimate how a sample of Black boys – even a selected sample – performed in adult outcomes after residing there. The dashed lines in the figure show that this sample selection is not reflective of Black boys being concentrated in urban areas; the same pattern holds in metros with populations of at least 1 million inhabitants.

Figure 8b shows how this neighborhood sorting by race in the 1990 Census passes through to the Opportunity Atlas. The share of tracts with publicly-reported outcome estimates for Black males drops rapidly as 2018 neighborhood quality rises. In the top half of tracts, 19 percent of tracts have estimates for Black males.[8]

The strength of neighborhood sorting by race has implications for how we interpret potential outcomes estimated via regressions of Black boys' outcomes on parental income and tract- or block-fixed effects (Chetty et al. (2020b)). We interpret the documented patterns of sorting by race as evidence that using administrative data to study neighborhood effects faces the problem of "bias in, bias out" common to the use of administrative data sets in other settings (Mayson (2019)).[9]

3 Encouraging Moves to Opportunity Neighborhoods

3.1 Overview of Previous Housing Mobility Programs

The four most-studied HMPs are the Gautreaux HMP (Gautreaux), the Moving to Opportunity for Fair Housing (MTO) experiment, the Baltimore HMP (BHMP), and the Creating Moves to Opportunity (CMTO) experiment. Figure 9 shows how residential outcomes for movers vary across different existing HMPs. Changes in neighborhood poverty rates between baseline and initial lease-up locations were largest in Gautreaux and the BHMP, both of which are regional programs. The gap between initial placement and subsequent locations is the smallest in the BHMP. The long-term success of BHMP participants' residential outcomes is likely a function of the BHMP's focus on landlord outreach, tenant counseling, search assistance, and post-move support. These features serve to overcome resistance to subsidized tenants among landlords and increase the effectiveness of search among those tenants, thereby increasing the reachable housing supply.

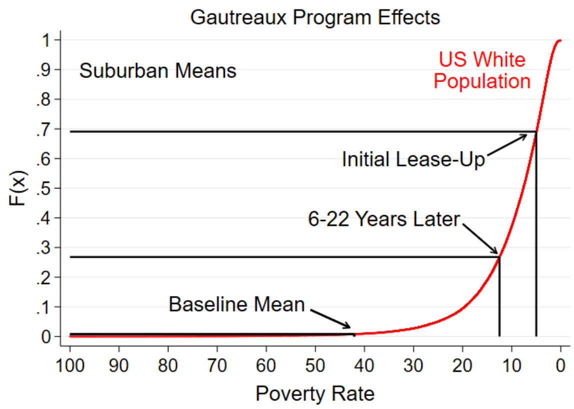
Gautreax and the BHMP have been implemented as regional partnerships, encouraging residents to move beyond a single PHA's jurisdiction and throughout their respective metropolitan areas. While MTO technically encouraged participants to move across jurisdictions, the program's Section 8 certificates and vouchers were allocated to the central city PHAs at each site (Feins et al. (1996), p 1-4), and it is unclear how much the obstacles to portability across PHA jurisdictions constrained participants' choices (Feins et al. (1996), pp 13-4 to 13-9).[10] And while CMTO was implemented by two PHAs, the Seattle and King County PHAs, it does not appear that moves across these PHAs' jurisdictions were encouraged (Bergman et al. (2020a)).

Gautreaux is the only HMP to explicitly use an individual's race as an eligibility criterion

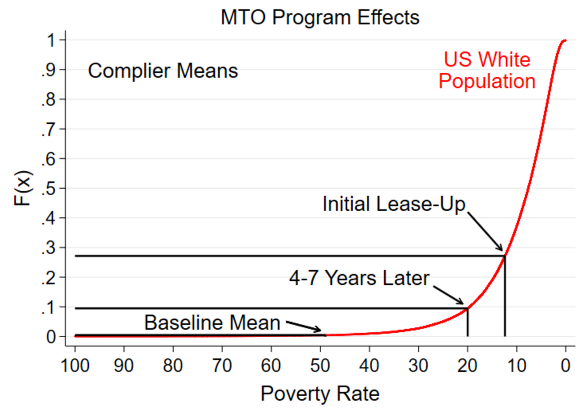
[8]Chetty et al. (2020a) report a sample size cutoff of 20 observations for publicly releasing a tract's estimate, and the distributions of within-tract gaps shown in Chetty et al. (2020b) Online Appendix Figure XIVa excludes tracts with fewer than 50 Black or white boys.

[9]Some of the other contexts in which this problem presents itself is occupational sorting by gender when predicting job performance (Ajunwa (2019)); access to care when predicting illness (Obermeyer et al. (2019), Noor (2020)); judicial decisions when predicting recidivism (Kleinberg et al. (2017)); or police decisions to interact with civilians when predicting police bias (Fryer (2019), Durlauf and Heckman (2020), Knox et al. (2020)).

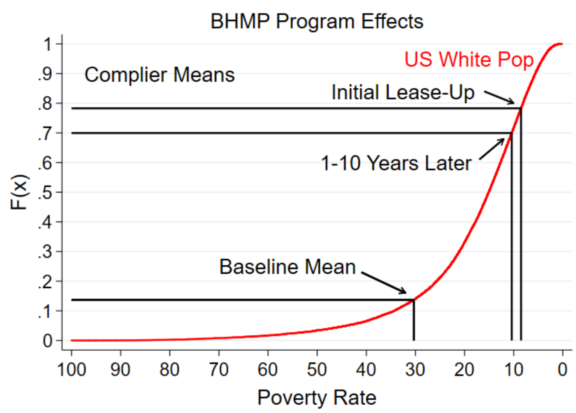
[10]Two thirds of MTO experimental compliers' initial lease ups were within their site's central city (de Souza Briggs et al. (2010)) and 70 percent of this group stayed within the same school district (de Souza Briggs et al. (2008)).



(a) Gautreax



(b) Moving to Opportunity



(c) Baltimore Housing Mobility Program

Figure 9: Residential Outcomes of Movers in Housing Mobility Programs
Note: Panel a shows mean neighborhood poverty rates in Table 1 of Keels et al. (2005) in terms of the 2000 Census distribution of the US non-Hispanic white population. Panel b shows mean tract poverty rates in the 2000 Census from Orr et al. (2003), with baseline poverty rates taken from Exhibit 2.7, complier mean in initial lease-up location taken from Exhibit 2.3, and complier mean 4-7 years after randomization taken from Exhibit 2.5. Panel c shows mean neighborhood poverty rates in the 2005-2009 American Community Survey from DeLuca and Rosenblatt (2017), with complier locations at baseline, after initial lease-up, and 1-10 years after program locations taken from Table 2 and suburban mean 1-10 years later taken from Table 4.

for program participation. Gautreaux targeted low-income African Americans in Chicago public housing (Rosenbaum and DeLuca (2008)). The BHMP does not select tenants based on their individual race or ethnicity. Although the BHMP is based on the same legal precedent as Gautreaux – that HUD has the obligation to remedy segregation by doing more than simply refraining from discriminating (PRRAC (2005)) – court rulings have disallowed race-based individual eligibility criteria.[11] MTO targeted residents of public housing in the lowest ranked neighborhoods in the country, and the participating population ended up being about two thirds African American (Orr et al. (2003)). The eligible population in CMTO was any household with a newly-awarded Housing Choice Voucher (HCV); this made the target population of CMTO effectively the poor residents of

[11]See Scott et al. (2013) and Tegeler (2009) for related discussions.

King County, Washington.

Participants in Gautreaux were eligible to move to neighborhoods defined in terms of racial composition; eligible tracts were those with no more than 30 percent Black residents (Rosenbaum (1995)). In the BHMP neighborhood eligibility has changed over time. From 2002 until 2015, eligible neighborhoods were those with no more than 30 percent Black residents, no more than 10 percent poverty, and no more than 5 percent of residents receiving housing assistance. From 2015 until today, the BHMP has been administered by the Baltimore Regional Housing Partnership (BRHP), which uses a combination of 21 variables to determine tract eligibility. The eligible neighborhoods in MTO were defined in terms of poverty rates; eligible tracts were those with less than 10 percent poverty. In CMTO, eligible tracts were determined by combining the Opportunity Atlas data with several additional variables in an estimation procedure that shrinks the OA ranking toward contemporaneous variables like 2010 poverty rates and 4th grade test scores (Bergman et al. (2020a), Appendix A).

Tenant counseling pre- and post-move have been a part of each HMP; what has varied considerably across HMPs has been the precise form of counseling provided, financial support to tenants, and outreach to landlords. For example, the BHMP makes its workshops mandatory for program participants. The BHMP and CMTO provide financial assistance toward moving costs, while Gautreaux and MTO did not. And while the BHMP actively recruits landlords in opportunity areas, contacts landlords on behalf of searching clients, and provides mediation between tenants and landlords, these services varied across sites in MTO. See Table 2 in Schwartz et al. (2017) or Cunningham et al. (2010) for further details.

The objective of an HMP that aims to dismantle racial segregation is not simply to expose Black participants to more white neighbors, as there is nothing special about living next to white neighbors per se. Instead, the goal of an HMP that aims to dismantle racial segregation is to expose Black participants to neighborhood effects that will improve their economic outcomes and life-satisfaction. For example, adults' mental health improved in MTO as a result of movers' decreased exposure to toxic stress in their neighborhoods (Kling et al. (2007a); Popkin et al. (2002); Han and Madaleno (2019)). Children in Gautreaux and the BHMP had higher academic achievement after attending higher-performing schools (Rubinowitz and Rosenbaum (2000); DeLuca et al. (2016)). Children in MTO did not experience higher academic achievement, but they also did not attend higher-performing schools (Sanbonmatsu et al. (2006)). There were long-term effects on the educational attainment and labor market outcomes of children and adolescents who moved through MTO (Chetty et al. (2016)). And while labor market outcomes did not improve for all adults who moved through MTO (Kling et al. (2007a)), labor market outcomes did improve for adults who moved to higher SES neighborhoods due to MTO (Aliprantis and Richter (2020), Pinto (2019)), with the same being true for adults who moved to higher SES, less-segregated neighborhoods in Gautreaux (Mendenhall et al. (2006)) and mixed evidence for the entire group of adults in Gautreaux (Chyn et al. (2023)).

The residential outcomes in Figure 9 are helpful for understanding how the literature interprets evidence from HMPs in terms of neighborhood effects. Much of the literature assumes that changes in observable *characteristics* uniformly imply a proportionate change in neighborhood effects, but this is not necessarily so. Movement through the *distribution* of neighborhood ranks may better reflect proportionate changes in their effects. The literature provides examples of both interpretations. For instance, looking at the large changes along the x-axis in Figure 9b, one could interpret the lack of effects from MTO on adult labor market outcomes as evidence against neighborhood effects (Ludwig et al. (2008)); while adults experienced large declines in exposure to poverty rates, their labor market outcomes did not appreciably improve. The small changes in neighborhood *ranking* (on the y-axis), however, suggest that adults may not have moved sufficiently through the distribution to experience substantially different neighborhood effects. Looking at the small changes along the y-axis in Figure 9b, one could interpret the results from MTO as providing limited evidence about neighborhood effects (Aliprantis (2017), Clampet-Lundquist and Massey (2008)). Likewise, focusing on the similar changes along the x-axes in Figures 9a and 9b, one could interpret the differences in effects from Gautreaux and MTO as arising from differential exposure to white neighbors (Chyn et al. (2023)). But focusing on the very different changes along the y-axes in Figures 9a and 9b, one could interpret the differences in effects from Gautreaux and MTO as arising from differential exposure to higher income neighbors and the resulting mechanisms described in Wilson (1987).

3.2 Simulating a Reference Housing Mobility Program

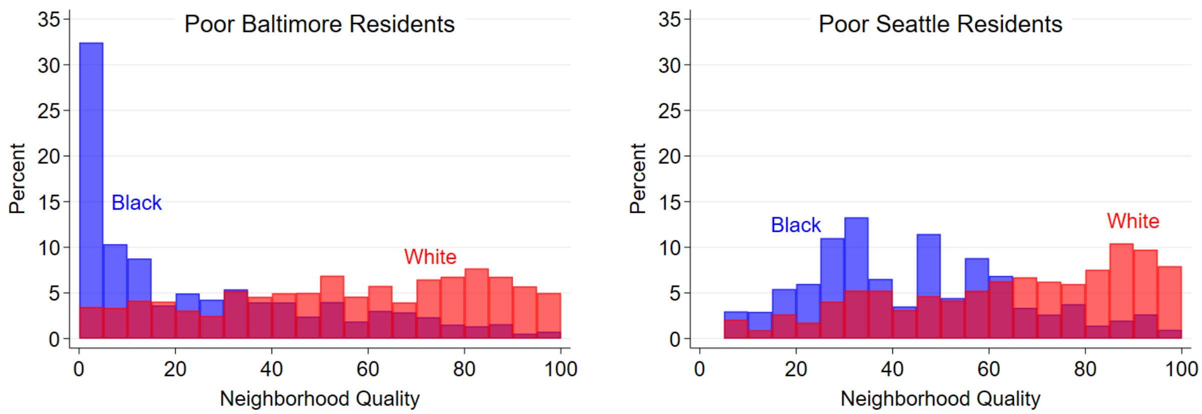
We begin our analysis by simulating a reference Housing Mobility Program (HMP). Simulating this reference HMP will allow us to highlight data details and modeling assumptions that will be made across simulations. Results from this HMP will serve as a reference point when alternative assumptions are adopted.

3.2.1 Measuring Success

As described above, the differences in previous HMP's residential outcomes illustrate the importance of selecting features of an HMP in accordance with the program's goals. Many PHAs today focus on economic integration by deconcentrating poverty. In the cases of Gautreaux and the BHMP, the primary goal has been to reduce racial segregation for Black residents.

Without minimizing the disparities faced by other groups, we focus this analysis on the residential segregation of Blacks and whites. Black neighborhoods have struggled to gain upward mobility in a way ethnic enclaves have not because of specific exclusionary policies, coupled with durable systemic racism and violence that have left many Black communities disinvested of the institutions that support upward mobility. While HMPs are not the only approach to addressing racial segregation, they are a means of addressing the areas of concentrated economic disadvantage that are still with us today. Figure 10a shows the remarkable clustering of poor Black residents in Baltimore in the lowest quality neighborhoods. A third of Baltimore's poor Black residents live in tracts below the 5th percentile of the national distribution of quality.

Not all cities in the US have this type of residential segregation. Figure 10b shows that in Seattle there are no tracts in the bottom 5 percent of quality. While poor Black residents are over-represented in low-ranked tracts, poor Black residents are not clustered in the city's lowest ranked tracts.



(a) Baltimore

(b) Seattle

Figure 10: Racial Segregation of Neighborhood Quality
Note: These figures show the distributions of Black and white poor residents of Baltimore and Seattle using data from the 2014-2018 ACS/NHGIS. The panels display the distributions in terms of their Probability Mass Functions (PMFs). The construction of neighborhood quality is described in Section 2.1 of the text.

We measure success in terms of the racial equality of poor Black and white residents' neighborhood characteristics. In the case of neighborhood quality q, we define the racial equality in metro m after HMP h as a function of the area between Black and white CDFs,

$$RE_m(h) = 100 \left\{ 1 - 2 \left[\int_0^{100} \left(F_{B,m,h}(q) - F_{W,m,h}(q) \right) dq \right] \right\}.$$

This measure of racial equality is equal to 100 if poor Black and white residents are equally exposed to neighborhood characteristics in metro m under HMP h (ie, if $F_{B,m,h} = F_{W,m,h}$). The measure is equal to zero if all poor Black residents live in the lowest quality neighborhood and poor white residents are uniformly distributed (ie, if $F_{B,m,h}(0) = 1$ and $F_{W,m,h} \sim U[0, 100]$). Figure 12a displays the empirical CDFs for Baltimore, for which our measure of racial equality is 38.

3.2.2 Description of Simulations and Assumptions

Simulating an HMP requires making assumptions along several dimensions. To organize our analysis, we make a group of assumptions about program design and behavioral responses that we will collectively refer to as our reference HMP. We will then run simulations after changing program design features one by one to look at the relative change in HMP success.

A simple description of the computational approach is that based on the housing supply in targeted destination tracts, we first determine the number of movers that can move to a new tract in an HMP of a given size. We then select that number of movers from origin tracts and move them to destination tracts. That is, we simply subtract program participants from the population counts in origin tracts and add them to the population counts in destination tracts. Our simulations allow us to quantify how residential segregation would change under various definitions of origin and destination tracts that represent various program design features. More details are provided about each of these steps in the Computational Appendix F.

Housing Supply and Participant Mobility to Destination Tracts: Our first assumption for the reference HMP is that residents move to destination tracts located throughout their entire metropolitan division.[12] We also assume that rental housing supply, the number of available and affordable units in a tract, is equal to 7.5 percent of the 2 bedroom and larger rental units in the tract.[13] We assume that if rental housing supply is greater than or equal to 30 units, then 30 families move into a given opportunity tract. If rental housing supply is $r < 30$ units, then we assume that r families move into the opportunity tract.[14]

Figure 11 shows the joint distribution of rental housing supply and neighborhood quality for tracts in Baltimore. We see that the rental supply constraint is binding for tracts at all levels of quality, and that the constraint is strongest for the highest quality tracts. In many of the highest-ranked tracts less than 10 families will be able to move in under our reference simulation.

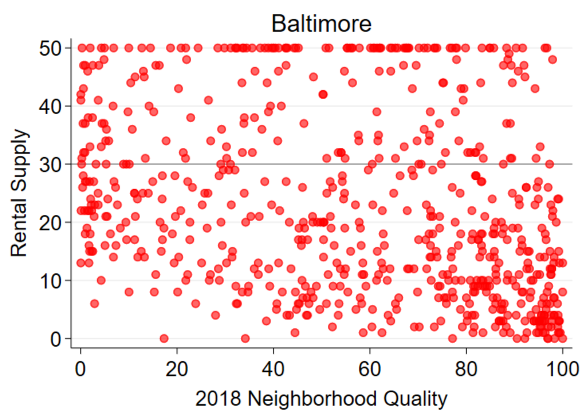


Figure 11: Supply of Rental Housing Units in Baltimore
Note: This figure shows the joint distribution of rental housing supply and neighborhood quality for tracts in Baltimore. As described in the text, we define "Rental Supply" as 0.075 times the number of 2 bedroom or larger rental units in the tract in the 2014-2018 ACS/NHGIS.

We also assume that participants move uniformly into available units in eligible tracts. This is a strong assumption about counseling and participant preferences. In the BHMP participants often initially held preferences against eligible neighborhoods (Darrah and DeLuca (2014)), and

[12]We measure metros as Core-Based Statistical Areas (CBSAs), and when possible, as the metropolitan divisions within those CBSAs.

[13]The number 7.5 is selected based on a conversation with BRHP staff estimating that 5-10 percent of rental units in opportunity tracts are available and affordable to their program participants. Scott et al. (2013) cite 5 percent as a typical market vacancy rate when designing an HMP.

[14]We assume 30 families is $4 \times 30 = 120$ individuals and r families is $4 \times r$ individuals. We examine some relaxations of these assumptions in our simulations.

in MTO participants did not move uniformly to eligible neighborhoods (Aliprantis and Kolliner (2015); Davis et al. (2021); Chetty et al. (2020a)).[15]

Incumbent Non-Response in Destination Tracts: While the number of families allowed to move to a destination tract is an important assumption, we show that this choice is not critical for our main findings. We consider a "fully developed" HMP with the overall number of participants chosen (i) to approximately match the size of the BHMP after 20 years and (ii) to avoid sorting responses of incumbents so as to maintain current levels of neighborhood effects.

The assumption in our baseline HMP of 30 families moving per destination tract makes it reasonable to assume that no incumbents in receiving neighborhoods move in response to the HMP participants' arrival. Since we interpret the moves in our HMP as occurring over two decades or more, this assumes that every year one or two units in a tract changes to voucher holders. The evidence in the literature is that a one-time placement of 10 units per high-opportunity tract is not likely to generate a sorting response from incumbents (Davis et al. (2019); Rosenbaum (1995)). The possibility for welfare losses and sorting responses have been estimated to result from much larger one-time changes, such as building of 82 units or placing 100 housing vouchers in the same high-opportunity tract (Diamond and McQuade (2019b); Davis et al. (2019)).[16] Nevertheless, if one believed that it was necessary to limit the size of our reference HMP to 10 or 20 families moving per tract to mute incumbents' sorting responses and/or to maintain the neighborhood externalities in destination tracts (Agostinelli et al. (2020, 2021)), we show in Appendix K that our main findings are unchanged for HMPs of these smaller sizes.

Program Participants in Origin Tracts: Finally, we make assumptions about how movers select into the program. To find our population of movers, we randomly select poor residents in tracts with poverty rates greater than 30 percent. While a variety of alternative criteria have been used, this is the criterion used in HUD's current HCV Mobility Demonstration (HUD (2020)). We assume that 25 percent of eligible poor residents take up the program and move, an assumption about target population outreach and selection (Scott et al. (2013); Rosenbaum (1995)) roughly guided by the rate of selection into the MTO experiment (Orr et al. (2003)) and considerations of moving costs (Ross (2011)). In a few cases, to fill the eligible housing units available in destination tracts, we move on from tracts with greater than 30 percent poverty and randomly select poor residents from the bottom third of tracts.[17]

3.2.3 Reference HMP Simulation Results

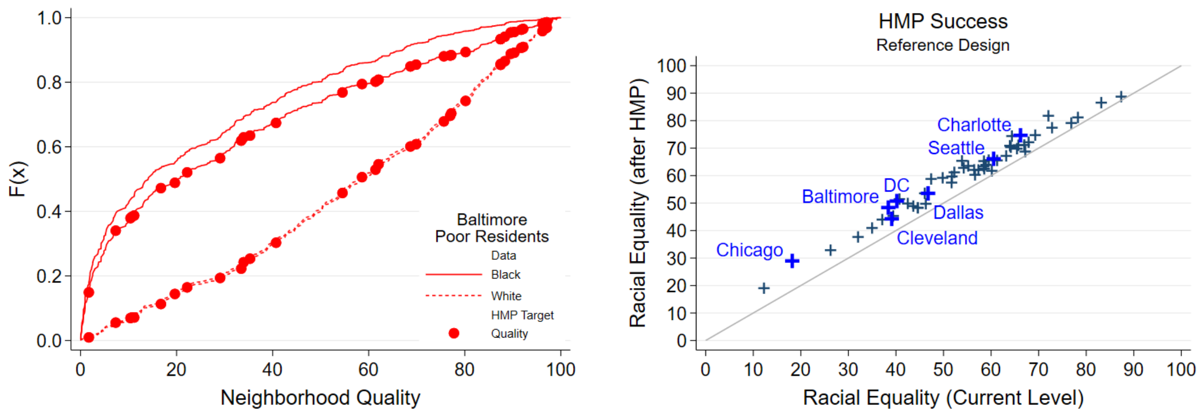
Figure 12a shows the result of the reference HMP in Baltimore. The CDF of poor Black residents shifts to the right much more than does the CDF of poor white residents, so that our

[15]The evidence from MTO suggests that counseling must have very strong effects on location decisions to offset poverty restrictions (Galiani et al. (2015); Shroder (2002)).

[16]It is also important to consider, if difficult to model, the types of equilibrium dynamics that could result in neighborhoods (Davis et al. (2019); Aliprantis and Carroll (2018); Chyn and Daruich (2021); Caetano and Maheshri (2021)) and schools (Caetano and Maheshri (2017); Agostinelli et al. (2020); Angrist and Lang (2004)).

[17]In the reference HMP this happened in 10 cities and represented 52.2 percent of movers in those cities.

measure of racial equality increases from 38 to 48. As suggested by Figure 10, Table 1 confirms that this greater shift for Black poor residents is due to the over-representation of poor Black residents in areas of concentrated poverty. Also suggested by Figure 10 and confirmed in Table 1 is that different racial and ethnic groups will be affected depending on the metro.



(a) Baltimore

(b) In All Large metros

Figure 12: Results of the Reference Housing Mobility Program
Note: The left panel shows the distribution of Baltimore's Black and white poor residents in the 2014-2018 ACS/NHGIS, indicated, respectively, with a solid and dashed line. The left panel also shows the distribution of these groups before and after the reference HMP, indicated by the dotted solid and dashed lines. The right panel shows the racial equality measure for each metro as defined in Section 3.2.1. On the x-axis is the racial equality measure from the data, the 2014-2018 ACS/NHGIS. On the y-axis is the racial equality measure after the reference HMP is simulated in each metro.

Table 1: Black Movers by Metro (Percentage of Total Movers)

	Baltimore	Chicago	DC	Dallas	Charlotte	Seattle
Percent Black	86	70	64	40	58	20

Note: This table reports the percentage of movers who were Black in the reference HMP. The highlighted metros are chosen for their prominent HMPs or early adoption of Small Area Fair Market Rents.

Figure 12b shows the result of the reference HMP in all of the 54 large metros in our sample. The x-axis in the figure shows racial equality as measured in the current data, and the y-axis shows racial equality in the metro after implementation of the baseline HMP. All metros are above the 45 degree line, meaning there were increases in racial equality. A few cities are highlighted due to their prominent HMPs or early adoption of SAFMRs.

Figure 12b makes an important point about the magnitude of effects from HMPs. If HMPs are designed at a small scale to avoid endogenous sorting responses by incumbents so as to maintain current neighborhood effects (Agostinelli et al. (2020, 2021)), they will not by themselves entirely create racial equality in the neighborhoods of poor Black and white residents. HMPs are a powerful tool for generating racial equality of opportunity through neighborhood effects, but HMPs are one part of the larger changes in our society that would be required to achieve racial equality.

3.3 Regional Partnerships for Porting Vouchers across Jurisdictions

A central difference between Gautreaux or the BHMP as opposed to MTO or CMTO is that Gautreax and the BHMP have been implemented as regional partnerships, encouraging residents to move beyond a single PHA's jurisdiction and throughout their respective metropolitan areas. Because voucher holders rarely port their vouchers across PHA jurisdictions (Garboden (2021)), it is likely that obstacles to portability across PHA jurisdictions could have constrained participants' choices in MTO in ways that were not experienced in Gautreaux or the BHMP. Consistent with PHA jurisdictions constraining mobility, residential moves in MTO were shorter distances and more likely to be within city and school district boundaries than those experienced in Gautreaux or the BHMP. For MTO experimental compliers, two-thirds of initial lease ups were within their site's central city (de Souza Briggs et al. (2010), p 150) and 70 percent of initial lease ups were within the same school district (de Souza Briggs et al. (2008), p 61), with less than 5 percent of the experimental group moving more than 10 miles from their baseline address due to MTO (Kling et al. (2007b)). Nearly all suburban movers in Gautreaux changed school districts (Rubinowitz and Rosenbaum (2000)), and the mean suburban mover was in a location 18 miles from their original address 6-20 years after initial lease-up (Keels et al. (2005)). Only twelve percent of BHMP participants stayed within the city (DeLuca and Rosenblatt (2017)), with three quarters of suburban movers leaving city schools (DeLuca et al. (2016)) and average initial moves of 11 miles (DeLuca and Rosenblatt (2017)).

Given the potential importance of regional partnerships allowing for voucher holders to easily port their vouchers across PHA boundaries, we simulate a version of the baseline HMP with no porting across PHAs. Measuring PHA jurisdictions is difficult, as the HCV program is administered by about 2,200 state and local PHAs (HUD (2021b)). Additionally, it is not clear how many small PHAs would fit into an HMP. This issue is especially pronounced in the central counties of metros, which often have separate PHAs for cities or incorporated areas.

Appendix Figure 37a shows this issue for several metros, including the metropolitan division of Chicago, using HUD data on the boundaries of PHA jurisdictions (HUD (2021a)). In light blue is the city of Chicago, in dark blue is the remainder of Cook County, Illinois, and in white inside Cook County are small cities with their own PHAs: Park Forest, Cicero, Oak Park, and Maywood. In many metros it is not clear from the data alone how jurisdictions overlap.

We resolve the issues of measurement and realism of HMP implementation by making the following assumptions. First, we assume that each county has its own PHA. Second, within the central county of each metro, we check whether there is a separate PHA serving a central city within that county. If so, then we use boundaries on Census Designated Places (CDPs) to delineate the boundaries of the central city, and we assume that the central city PHA serves the central city CDP and the central county PHA serves the remainder of the central county outside the central city. Figure 37b shows how these assumptions create our assumed PHA boundaries in a few metros. Appendix I lists the information we used about PHAs in central counties.

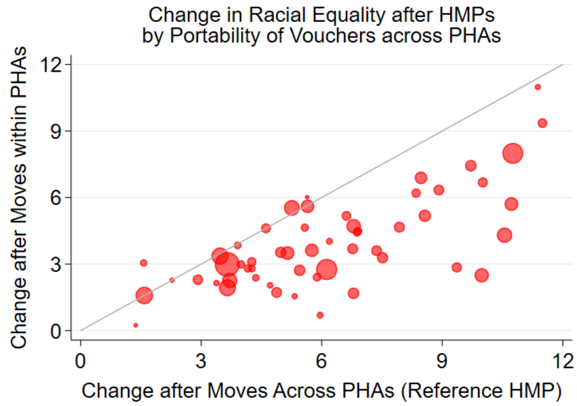


Figure 13: No Porting HMPs
Note: This figure shows the results of the reference HMP on the x-axis along with a "No Porting" HMP on the y-axis. In the reference HMP moves are allowed across PHA jurisdictions, and in the "No Porting" HMP moves are only allowed within PHA jurisdictions.

We consider a "No Porting" HMP that changes the baseline HMP by targeting neighborhoods with greater than 30 percent poverty and those in the bottom third of tracts, in that order, but now only within each PHA's jurisdiction. Likewise, the "No Porting" HMP only moves participants to the top third of tracts within each PHA's jurisdiction. Figure 13 shows the results of the "No Porting" HMP. We see that in many metros the effectiveness of the HMP falls considerably. These results quantify the benefits of forming regional partnerships (Scott et al. (2013)).

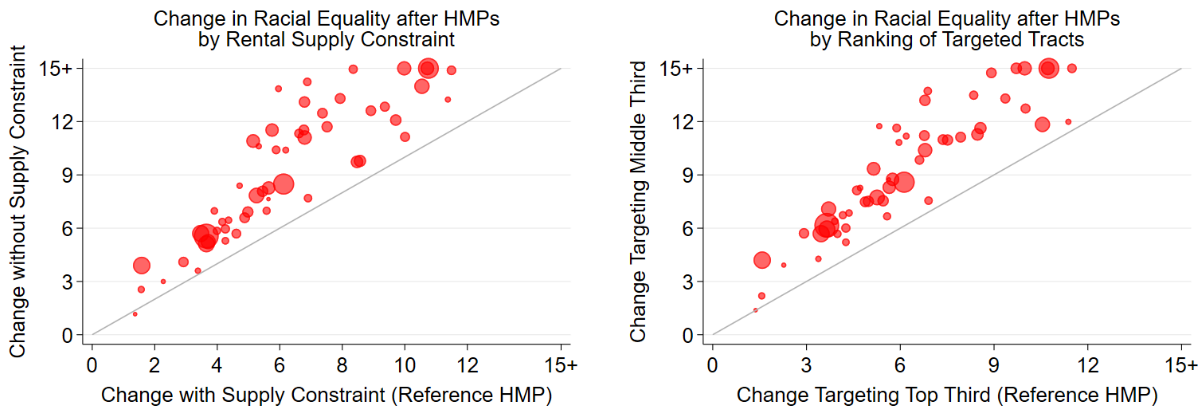
3.4 Rental Housing Supply

The supply of rental housing is one of the most important constraints HMP practitioners face. Polikoff (2006) describes how supply constraints emerged early on in the 1970s as a major issue for the implementation of Gautreaux (Chapter 5.3). Today the supply of rental units in high-opportunity areas is an eligibility criterion facing PHAs applying for HUD's HCV Mobility Demonstration (HUD (2020)).

Supply constraints can be especially binding for voucher holders due to barriers that limit supply like search costs, information frictions (Bergman et al. (2020b)), and landlord avoidance of voucher holders (Phillips (2017); Aliprantis et al. (2022)). Some PHA-provided services can therefore relax supply constraints, with housing search assistance and landlord outreach being two key services provided by the BHMP (Cossyleon et al. (2020)). But such services are not always given priority when implementing housing programs (Popkin et al. (2003)). Should they be? And are there any other strategies for expanding the supply of rental housing available to HMP participants?

Figure 14a shows the results of the reference HMP altered so that families move uniformly to all targeted neighborhoods, regardless of each neighborhood's supply of rental housing. The metros all being located well above the 45 degree line indicates that relaxing the supply constraint has a major effect on the success of the HMPs.

Figure 14b shows an approach to relaxing supply constraints; targeting lower-ranked tracts with a greater supply of rental units.[18] We find that targeting the middle third of tracts as opposed to the top third of tracts actually reduces racial inequality much more than the baseline HMP; generating as much improvement as eliminating the supply constraint. Table 2 helps explain the results of this HMP. In most cities, the share of supply-constrained tracts is much higher in the top third of tracts than it is in the bottom third of tracts. The resulting supply of units in the middle third of tracts is higher than in the top third of tracts.



(a) Results by Rental Supply Contraint

(b) Results by Targeted Third of Tracts

Figure 14: Relaxing Housing Supply Constraints
Note: The left panel compares the Reference HMP, which constrains the number of families moving to a targeted tract based on the supply of rental housing in the tract, with an HMP that moves 30 families to targeted tracts, regardless of their rental housing supply. The right panel compares the Reference HMP, which targets the top third of tracts in each metro, with an HMP that targets the middle third of tracts in each metro.

Table 2: Rental Housing Supply

	Share Supply-Constrained by Third		Avg. Rental Supply by Third	
MSA	Middle	Top	Middle	Top
Baltimore	63	84	28	16
Chicago	67	78	26	19
DC	65	79	25	20
Dallas	47	67	36	26
Charlotte	58	65	32	27
Seattle	55	59	32	31

Note: This table reports statistics on the rental housing supply in select metros. The rental supply in a tract is 7.5 percent of its rental units that are 2 bedrooms or larger, and a tract is supply constrained if this number is less than 30; Section 3.2.2 provides relevant discussion.

The results from HMPs targeting the middle third of tracts raises a host of questions that appear unresolved since the time of Gautreaux (Rosenbaum (1995)). Are original residents in middle third tracts more likely to move out in response to program participants moving into the tract (Caetano and Maheshri (2021))? What is the marginal improvement in the externalities in top third of

[18] Recall that in each of these HMPs, the size of the program is being constrained not by the number of vouchers, but by the ability of receiving tracts to absorb no more than 30 vouchers per tract.

tracts versus the middle third (Weinberg et al. (2004))? And might program participants be more successful in finding stable housing or social integration in middle third neighborhoods?

3.5 Access to Transportation

In general, geographic mobility may be a less important spatial friction than information and referral networks (Schmutz and Sidibé (2019); Heise and Porzio (2021); Miller and Schmutte (2021)). However, in the context of low-income Americans residing in neighborhoods of concentrated poverty, access to transportation, especially an automobile, could play a relatively large role in accessing economic opportunity (Gobillon et al. (2007)). Jobs in American cities have suburbanized (Miller (2021)); transit mode is a key determinant of the commute times that low-wage employers consider in hiring decisions (bunton et al. (2022); Phillips (2020)), and access to a car improves labor market outcomes (Gurley and Bruce (2005), Baum (2009), Ong (2002)).[19]

Car ownership has represented a central barrier to suburban moves in previous HMPs and consent decree programs (Polikoff (2006), Popkin et al. (2003)). In MTO, less than 40 percent of program participants had access to a running vehicle (Kling et al. (2007b), Table F12). Residential outcomes in MTO could be explained by the lack of access to a car, much as the need for access to public transportation can explain the urbanization of the poor in the US (Glaeser et al. (2008)). The neighborhood effects on adult labor market outcomes observed in MTO could also be explained by access to a car (Blumenberg and Pierce (2014); Pendall et al. (2016); Aliprantis and Richter (2020); Pinto (2019)).

We assess the importance of access to a car by conducting an HMP that modifies the reference HMP to only target tracts with access to public transportation. We use data from The National Transit Map, which contains GTFS data collected by the Bureau of Transportation Statistics (BTS (2021)), augmented by additional GTFS data downoaded from Open Mobility Data. We define a tract as having access to public transit if its centroid is within half a mile of a transit stop.[20] Figure 15a shows that access to public transportation tends to be negatively correlated with neighborhood quality, and that there is considerable variation across metros in the strength and levels of this relationship.

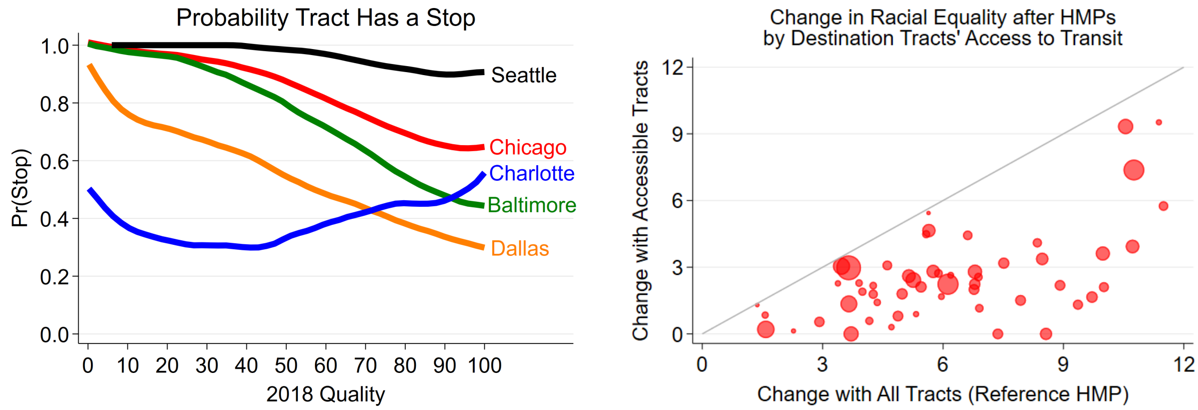
We measure access to public transportation using General Transit Feed Specification (GTFS) data on stops that are a compilation of local transit agencies' data, either compiled by the Bureau of Transportation Statistics' National Transit Map (BTS (2021)) or Open Mobility Data (MobilityData IO Volunteers (2021)).

Figure 15b shows that the effect on racial equality plummets when HMP participants only move to transit-accessible tracts. Given the massive decline when only moving to accessible tracts, along with the fact that it is not clear that access to public transportation is sufficient for access to employment (Sanchez et al. (2004), Smart and Klein (2020)), suggests that supplementing program

[19]The finding that positive income shocks are often spent on cars (Aaronson et al. (2012); Imbens et al. (2001); West et al. (2021)) could therefore represent access to economic opportunity for low-income households.

[20]Appendix J describes the construction of our transportation data set and provides some descriptive statistics.

design with access to cars could improve the success of HMPs (Pendall et al. (2016)).



(a) Neighborhood Accessibility and Quality

(b) Results Restricted to Accessible Neighborhoods

Figure 15: Access to Public Transportation
Note: The left panel shows local linear regression estimates of metro-level linear probability models summarizing the probability that a tract's centroid is within half a mile of a public transit stop as a function of neighborhood quality. The right panel shows the results of the Reference HMP plotted against the results of an HMP in which participants only move to tracts with access to public transportation. Access to transit is defined as a tract's centroid being within half a mile of a transit stop as measured in the National Transportation Map.

3.6 Constraints on Program Design

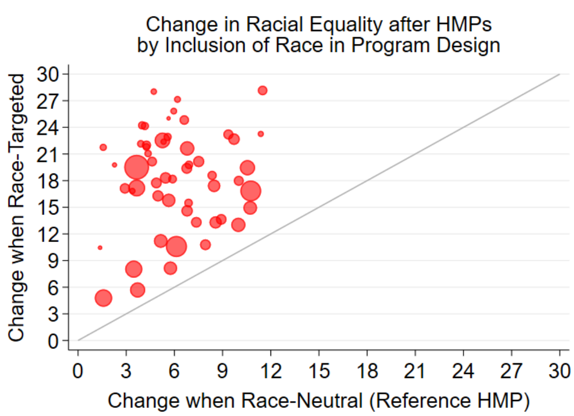


Figure 16: Race-Targeted Program Design
Note: This figure shows the results of the reference HMP plotted against the results of an HMP in which the only participants are poor residents who are Black.

Table 3: Black Movers by HMP (Percentage of Total Movers)

	HMP	
MSA	Reference	Race-Targeted
Baltimore	86	100
Chicago	70	100
DC	64	100
Dallas	40	100
Charlotte	58	100
Seattle	20	100

Note: This table reports the percentage of movers who were Black in the reference HMP and in an HMP targeting Black poor residents. The highlighted metros are chosen for their prominent HMPs or early adoption of Small Area Fair Market Rents.

The US Supreme Court's interpretation of the US Constitution is constantly evolving, and the history of interpretation with respect to race is full of major changes. Thus, while the current legal precedent would indicate that designing an HMP that targeted only Black participants would be unconstitutional, one could imagine a change in interpretation that would render such a policy legal. What would be the implications of an HMP designed explicitly around race and Black participants?

Figure 16 shows that an HMP targeting only Black participants would have a substantially larger impact on racial equality than the race-neutral reference HMP. Table 3 characterizes this HMP's additional success as being a function of its more directed focus on Black residents.

3.7 Summarizing Results

We discuss here the differences in results for the alternative HMP designs explored above. To summarize our results across metros, we compute the change in racial equality resulting from reference HMP h relative to the racial equality found in the data in each metro m. Then we sum across metros weighting by π_m, the share of the Black poor in all 54 metros that resides in metro m. We then use this change to normalize the analogous population-weighted average change in racial equality resulting from alternative HMP h' relative to the racial equality found in the data. This allows us to report results in terms of the average improvement from an HMP as a percentage of the reference HMP:

$$\text{Average Improvement (\% of Reference HMP)} = 100 \times \frac{\sum_{m=1}^{54} \left[RE_m(h') - RE_m(\text{data})\right] \times \pi_m}{\sum_{m=1}^{54} \left[RE_m(h) - RE_m(\text{data})\right] \times \pi_m}.$$

Recall that the reference HMP is one in which poor residents living in neighborhoods of concentrated poverty are encouraged to move to tracts in the top third of their metro area as ranked by "neighborhood quality," and a supply constraint binds in receiving neighborhoods.

Figure 17 plots the results for the reference HMP along with several HMPs examined earlier that differ in one design feature relative to the reference HMP. Many receiving neighborhoods have little access to public transportation; if transit is important to movers, this may seriously impact the effectiveness of an HMP. An HMP where participants only move to tracts with access to public transportation is just 46 percent as successful as the reference HMP at improving racial equality. Access to a car, implicitly assumed in the reference HMP, appears to be a major factor in HMP success.

HMPs administered by regional partnerships are likely to be more successful at combating racial segregation than are HMPs administered by individual PHAs. An HMP administered by individual PHAs in which participants cannot port their vouchers across PHA jurisdictions is 64 percent as successful as the reference HMP.

Across our simulations, an HMP does not move more than 30 families to a single census tract. Most models also impose a constraint that caps neighborhoods to receive no more families than would occupy 7.5 percent of rental units that are at least two bedrooms in size. An HMP that permits up to 30 movers to occupy as many as 100 percent of available rental units in receiving neighborhoods would generate 154 percent of the success of the reference HMP. An HMP might broaden access to existing units through landlord outreach and tenant counseling during search.

We also test the impact of targeting more marginal moves in neighborhood quality by targeting the middle third of tracts rather than the upper third. On the one hand, such moves do less to improve racial equality than more dramatic moves to high-opportunity neighborhoods by definition. On the other hand, the rental housing supply may be larger in such neighborhoods, enabling more moves in the aggregate. In our simulations, the increase in housing supply from targeting this set of receiving neighborhoods outweighs the effect of mechanically smaller changes in quality. Such an HMP would result in similar improvements in racial equality to that which relaxes the supply constraint in high quality neighborhoods. And an HMP targeting the middle third of tracts in a metro, rather than the top third, would generate 153 percent of the success of the reference HMP.

Figure 18a highlights the change in racial equality that would result from designing an HMP around the alternative rankings of neighborhoods considered in our analysis, the OA and the COI. For HMPs that reach all eligible receiving neighborhoods, the difference due to changes in the chosen ranking are considerably smaller than the differences due to changing other design features. An HMP targeting the OA or COI would generate, respectively, 86 and 92 percent of the success of the reference HMP targeting quality, as measured by quality. As discussed in Section 2, it is unclear that disagreements between these measures capture differences in neighborhood externalities rather than simply bias or statistical noise.

The targeted ranking matters quite a bit, though, when targeting opportunity bargains, which are the least expensive among the top third of tracts according to a given ranking. We show this by shrinking the scale of the HMP and preferentially filling the least expensive opportunity neighborhoods first. While targeting opportunity bargains identified by quality has little impact on HMP success, at 96 percent of the reference HMP, targeting opportunity bargains as identified by the OA has a large impact on HMP success. The strong negative selection of low ranked tracts among OA-identified opportunity bargains results in an HMP generating only 67 percent of the success of the reference HMP. This suggests that opportunity bargains as identified by the OA are neighborhoods which disagree particularly with the quality measure, and highlights the need to understand what drives differences in these rankings when selecting one for housing mobility programs.

Finally, 18b shows that, were HMPs able to specifically target Black residents, the resulting programs would generate more than two and a half times the success as the reference HMP, which is race-blind.

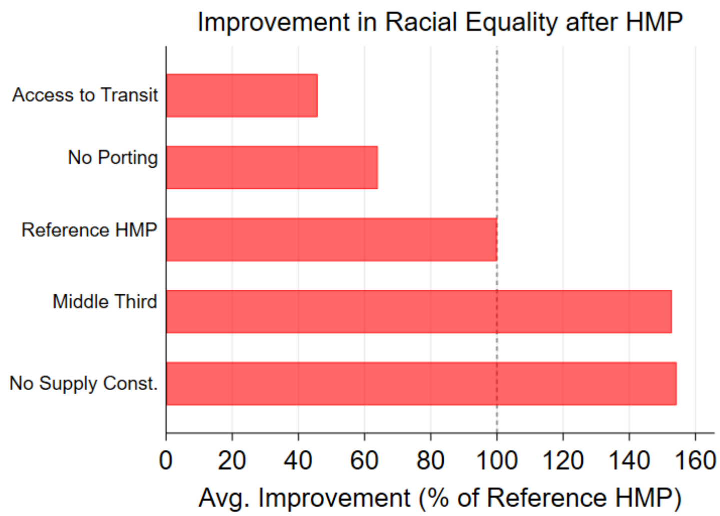
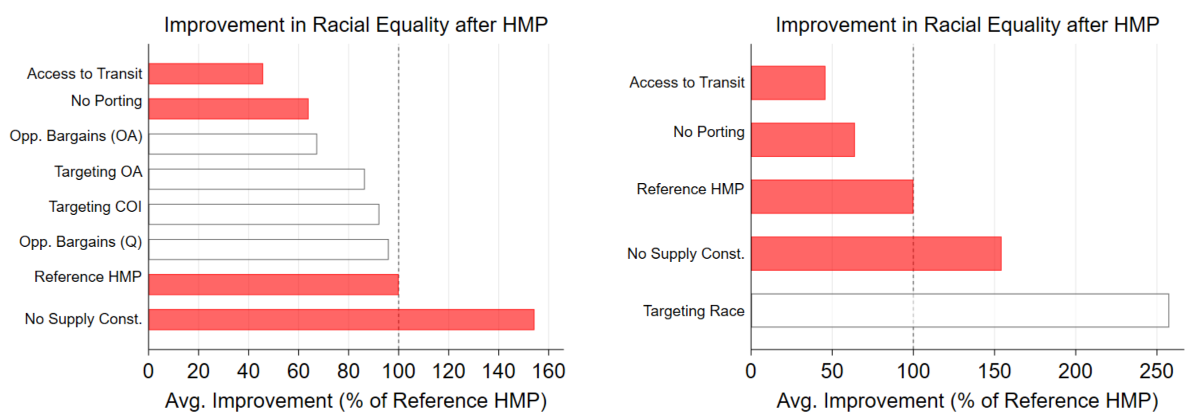


Figure 17: Average Improvement in Racial Equality across All Metros
Note: This figure shows the average improvement in racial quality across all metros for the reference HMP along with several HMPs that change one design feature. Each of the HMPs is described in detail in the main text, as is the measure of racial equality and associated measure of average improvement.



(a) By Targeted Ranking

(b) Targeting Race

Figure 18: Average Improvement in Racial Equality across All Metros
Note: The left panel shows the average improvement in racial quality across all metros for the reference HMP along with several HMPs that change one or two design features, highlighting HMPs that change the targeted ranking or the rent in targeted tracts. The opportunity bargain HMPs are 1/4 the size of the reference HMP, and their average improvement is scaled relative to a 1/4-sized version of the reference HMP. The right panel shows the average improvement in racial quality across all metros for the reference HMP along with several HMPs that change one design features, highlighting an HMP targeting race. Each of the HMPs is described in detail in the main text, as is the measure of racial equality and associated measure of average improvement.

4 Conclusion

Residential segregation by race limits social interactions across racial groups, creating unequal provision of public safety, segregating schools, and separating job referral networks (Pew Research

Center (2019); Meyer (2000); Miller and Schmutte (2021)). Such mechanisms are the reason many social scientists hold the "perspective that racism and segregation are really just two sides of the same coin" (Bayer (2019)). Unfortunately, public policy in the United States has often acted as a force increasing residential segregation by race (Rothstein (2017)). Housing Mobility Programs (HMPs) are a rare example of a public policy that has been employed to reduce racial segregation in the US (Polikoff (2006)).

This paper studied how design features lead to residential outcomes in Housing Mobility Programs (HMPs). We first assess the suitability of a prominent new measure, the Opportunity Atlas (OA), which uses observed neighborhood outcomes as an indicator of neighborhood effects. We compare neighborhood rankings based on the OA to those based on contemporaneous observed neighborhood characteristics that are more traditionally used in HMP designs. We find that the OA introduces bias in neighborhood rankings along at least two dimensions: small sample size and changes in neighborhoods over time. These biases have real consequences for the selection of neighborhoods to target in an HMP. For example, while we might want to target neighborhoods based on the outcomes of a tracts' previous Black residents, we simply have not observed enough Black children grow up in most high-SES tracts to estimate race-specific effects. Similarly, HMPs would also find it advantageous to target opportunity bargains, or tracts that are both highly-ranked and low-rent, to maximize returns to program participants while limiting program costs. However, we show that using tracts' previous residents to identify opportunity bargains tends to select tracts that are low-ranked in terms of today's neighborhood characteristics, suggesting caution when using previous residents' outcomes for this purpose.

Beyond the selection of target neighborhoods, we investigated other design features with major implications for HMP success. There are several ways that HMPs might expand the set of neighborhoods available to HMP participants. Consistent with the residential outcomes observed in previous HMPs like Gautreaux, the Baltimore Housing Mobility Program (BHMP), Moving to Opportunity (MTO), and Creating Moves to Opportunity (CMTO), regional partnerships facilitating the porting of vouchers across PHA jurisdictions appear central to HMP success. Ensuring HMP participants have access to cars would make a range of neighborhoods available that do not have access to public transportation. And targeting neighborhoods that are in the middle of the distribution, rather than at the top, would increase the supply of rental housing available. Although such a design raises questions about implementation, if the goal of HMPs is to address the issue of poor Black residents' hyper-concentration in the lowest ranked neighborhoods, then this design could prove effective.

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Appendix to
"What Determines the Success of Housing Mobility Programs?"

Dionissi Aliprantis Hal Martin Kristen Tauber

September 2, 2023

A Strengths and Weaknesses of Each Ranking

As a measure of neighborhood externalities, the strength of each ranking we consider tends to be a weakness of the other rankings. Table 5 summarizes the strengths and weakness of each measure.

The strength of neighborhood quality as a ranking of neighborhood externalities is that (Q-i) it can be easily calculated from timely Census data that is made publicly-available by the NHGIS. (Q-ii) While only negligibly more difficult to calculate than neighborhood poverty, neighborhood quality captures many of the additional variables thought to determine how a neighborhood affects its residents above and beyond poverty alone. Weaknesses of quality are that (Q-a) it may not capture all relevant neighborhood characteristics; and (Q-b) the characteristics included may not affect outcomes in a linear way or in a way that is homogeneous across individuals of different demographic groups.

Two strengths of the COI as a ranking of neighborhood externalities are that (COI-i) it can be calculated from timely data; and (COI-ii) it incorporates even more neighborhood characteristics thought to affect residents' outcomes, like school district outcomes and pollution, from disparate datasets that contain information not available in the Census. Strength COI-ii helps to address weakness Q-a of quality by doing more to capture all relevant neighborhood characteristics, but this comes with the tradeoff of (COI-a), that the COI is more difficult to calculate, requiring the assembly of multiple datasets. Another weakness is a holdover from quality: (COI-b) the characteristics included may not affect outcomes in a linear way or in a way that is homogeneous across individuals of different demographic groups.

Two strengths of the OA as a ranking of neighborhood externalities are that it allows us to (OA-i) measure outcomes conditional on individual characteristics like race/ethnicity and gender; and (OA-ii) measure a wide variety of outcomes like incarceration, teenage pregnancy, and marriage. Three weaknesses of the OA as a measure of neighborhood effects are (OA-a) neighborhood sorting by individual-level demographic characteristics X_i resulting in small sample sizes; (OA-b) neighborhood sorting on unobservables resulting in bias; and (OA-c) neighborhood sorting over time resulting in bias. Weakness OA-a is an issue because OA rankings are estimated. Thus, to capture strength OA-i, we may be concerned for cases where sample sizes are small enough to make estimates noisy. Strength OA-i is particularly exciting because it could allow us to address weaknesses Q-b and COI-b. However, weaknesses OA-b and OA-c makes strength OA-i difficult to gauge. Measuring outcomes does not overcome the fundamental issue in neighborhood effects research, neighborhood sorting. We do not know if realized outcomes reflect neighborhood effects or neighborhood sorting.

Table 4: Rankings of Neighborhoods

Neighborhood Quality: Aliprantis and Richter (2020)'s tract-level neighborhood quality index

Years: 2014-2018, 2013-2017, . . . , 2005-2009, 2000, 1990, 1980, 1970

Area: All census tracts

Sources: American Community Survey (ACS) from 2005–; Decennial censuses from 1970-2000; Longitudinal Tract Database (LTDB)

Construction: Created by using principal components analysis to combine tract-level ranks of six neighborhood characteristics into a single tract-level ranking of neighborhoods. Those six characteristics are the poverty rate, the share of adults 25+ with a high school diploma, the share of adults 25+ with a BA, the Employment to Population Ration for adults 16+, the labor force participation rate for adults 16+, and the share of families with children under 18 with only a mother or father present. LTDB is used to interpolate earlier years into 2010 census tract boundaries.

COI: Brandeis University's tract-level Child Opportunity Index 2.0

Years: 2013-2017 and 2008-2012

Area: All census tracts

Sources: 29 indicators from numerous sources including the American Community Survey (ACS), National Center for Education Statistics (NCES), Stanford Education Data Archive (SEDA), GreatSchools (GS) proprietary data, US Department of Education EDFacts, US Department of Education Office for Civil Rights Data Collection (CRDC), Environmental Protection Agency Risk-Screening Environmental Indicators (EPA RSEI), Centers for Disease Control and Prevention (CDC), Opportunity Atlas, RW Johnson Foundation 500 Cities Project

Construction: Created by combining tract-level measures of many neighborhood characteristics into a single tract-level ranking of neighborhoods.

OA: Opportunity Atlas tract-level income estimates

Years: 1978-83 birth cohorts

Area: Census tracts with sufficient observations

Sources: Census 2000 and 2010; Federal income tax returns in 1989, 1994, 1995, and 1998-2015

Construction: Estimate child's expected income conditional on their parents' household income; parameterize income distribution within a tract using a functional form estimated on the national income distribution.

Table 5: Strengths and Weaknesses of Neighborhood Rankings

Neighborhood Quality Strengths

Q-i: Measure can be easily calculated from timely census data that is made publicly-available by the NHGIS

Q-ii: Measure captures 6 key variables thought to determine neighborhood effects

Neighborhood Quality Weaknesses

Q-a: Measure may not capture all relevant neighborhood characteristics

Q-b: Linear effects of variables/homogeneous by X's?

Q-c: Linear preferences over variables?

COI Strengths

COI-i: Measure can be calculated from timely data

COI-ii: Measure captures many measurable variables thought to determine neighborhood effects

COI Weaknesses

COI-a: Measure is more difficult to calculate than poverty or quality

COI-b: Linear effects of variables/homogeneous by X's?

COI-c: Linear preferences over variables?

OA Strengths

OA-i: Measure can be made conditional on individual characteristics like race/ethnicity, parental income, and gender

OA-ii: Measure can be made for a wide variety of outcomes beyond income, like incarceration, teenage pregnancy, and marriage

OA Weaknesses

OA-a: Neighborhood sorting by individual characteristics resulting in small sample sizes

OA-b: Neighborhood sorting on unobservables resulting in bias

OA-c: Neighborhood sorting over time resulting in bias

B Variation in Neighborhood Rankings

Table 6: Variation Explained

Neighborhood Ranking	Independent Variable	R^2
2018 Quality	2018 Poverty	0.74
COI	2018 Poverty	0.70
OA	2018 Poverty	0.35
OA	1990 Poverty	0.33
OA	1990 Quality	0.39
2018 Quality	1990 Quality	0.67
2018 Quality	COI	0.86

Note: The top three rows are the relationships shown in the figure on the right. All regressions are weighted by the population at the time of measurement for the independent variable. The OA rank is in terms of the income estimates pooled over race/ethnicity for children from parents with 25th percentile incomes.

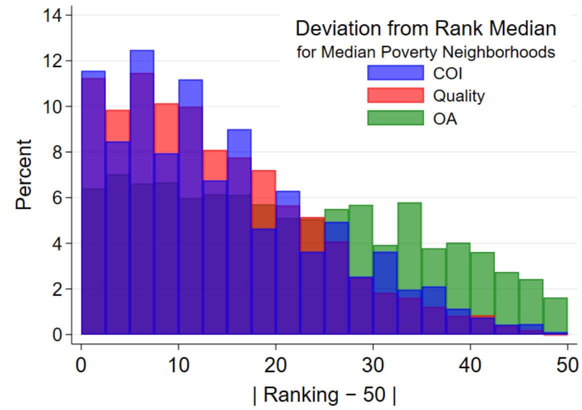
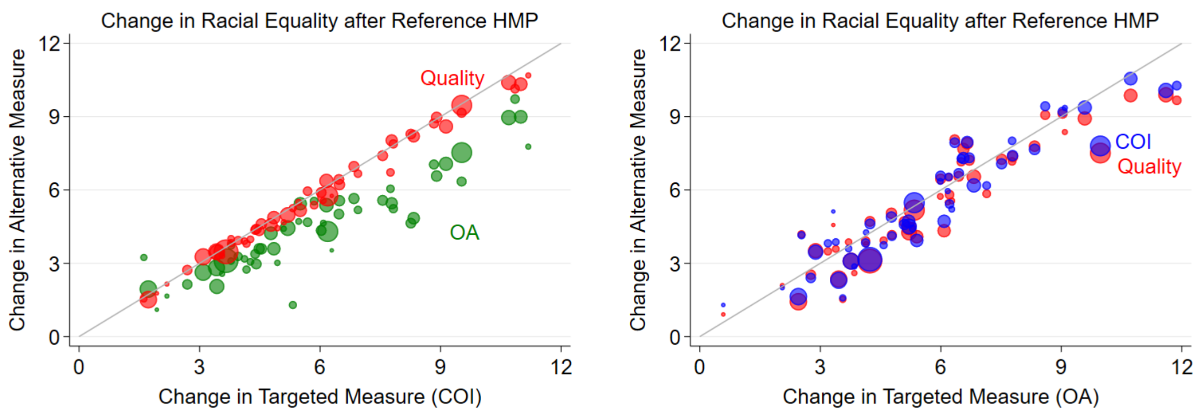


Figure 19: Variation in Other Rankings for Median Poverty Tracts
Note: The figure shows tracts that are between the 47.5th and 52.5th percentiles of the individual-level distribution of tract-level poverty rates in 2014-2018.

C More Details on HMP Design Choices

C.1 Choice of Neighborhood Effects Ranking

Figure 20 shows the change in HMP success for alternative measures of neighborhood effects when the reference HMP is targeted to a given measure of neighborhood effects. The left panel shows the improvement in racial equality, as measured in terms of quality or the OA, when the reference HMP targets the COI. The right panel shows the improvement in racial equality, as measured in terms of quality or the COI, when the reference HMP targets the OA. In the main text Figure 3b shows the improvement in racial inequality, as measured in terms of the COI or the OA, when the reference HMP targets the quality.



(a) Targeting COI

(b) Targeting OA

Figure 20: HMP Success by Measure of Neighborhood Effects
Note: The left panel shows the success of the Reference HMP in the metros in our sample where the x-axis measures success in terms of the Childhood Opportunity Index (COI) when the COI is the targeted ranking of the reference HMP, and the y-axis measures success in terms of either quality (in red) or the Opportunity Atlas (OA, in green). The right panel shows the success of the Reference HMP in the metros in our sample where the x-axis measures success in terms of the Opportunity Atlas (OA) when the OA is the targeted ranking of the reference HMP, and the y-axis measures success in terms of either the COI (in blue) or quality (in red).

C.2 Opportunity Bargains

Figure 21 explores the consequences for the success of HMPs of selection by rent. Each color represents an HMP targeting a different set of tracts, where the overall number of vouchers is 1/4 the size of the reference HMP. By hugging the 45 degree line, the red dots show that targeting low-rent tracts in the top third of quality has little impact on success relative to the reference HMP randomly targeting top third tracts. Targeting low-rents while sticking with quality as the criterion for being top third only decreases HMP success to 96 percent of the 1/4-sized reference HMP.

We consider an HMP that has 1/4 the number of vouchers as the reference HMP, and while moving residents to the top third of a given metro's tracts, begins by moving participants to the lowest cost tracts. We find that targeting low-rent tracts would have a much more detrimental effect on HMPs targeting outcomes of tracts' previous residents (ie, the OA) than doing so would have on HMPs targeting outcomes of tracts' current residents (ie, quality).

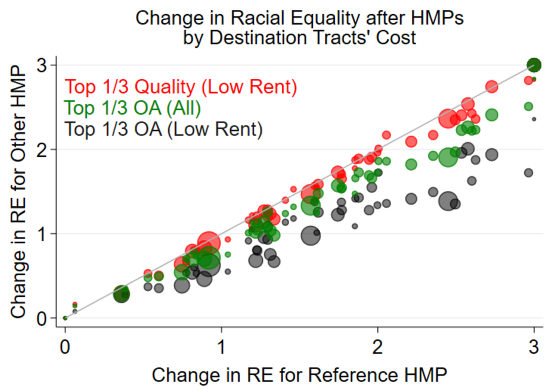


Figure 21: HMP Success by Targeted Measure and Rent

Note: This figure shows the success of HMPs that all have 1/4 the number of vouchers as the reference HMP. The x-axis shows the quarter-sized reference HMP, while the y-axis shows HMPs with some change. The red dots show an HMP targeting the lowest rent tracts in the top third of quality. The green dots show an HMP targeting the top third of OA tracts, but where success is measured in terms of quality. And the black dots show an HMP targeting the lowest rent tracts in the top third of OA, where success is measured in terms of quality.

Ignoring rents, and instead targeting the top third of OA tracts would have a larger negative impact on the success of HMPs than targeting low-rent top-third quality tracts. This fact is shown by the green dots being slightly below the red dots. Now, the success of HMPs would on average be 84 percent of the 1/4-sized reference HMP.

Designing an HMP around not just the top third of OA, but also the lowest-rent tracts within that group, would have an even larger effect on the racial equality resulting from the HMP. The black dots show that the increase in racial equality resulting from this HMP would fall considerably, to 67 percent of the 1/4-sized reference HMP. These simulation results confirm the intuition gathered by looking at the distributions in Figure 5: Targeting low-rent tracts in the top third of OA rankings selects tracts that disagree considerably with quality rankings. Section **??** describes reasons to suspect these large disagreements reflect bias from sorting over time.

D Does Ranking Neighborhoods Improve HMP Success?

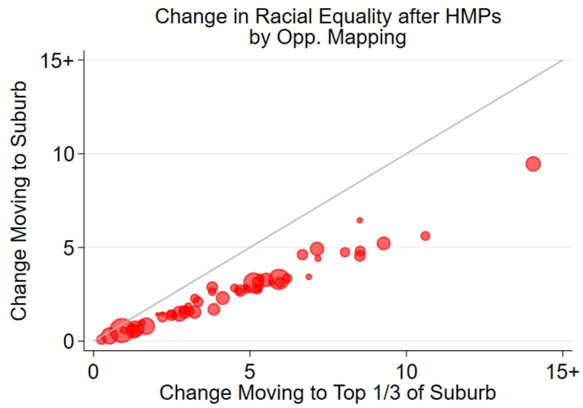
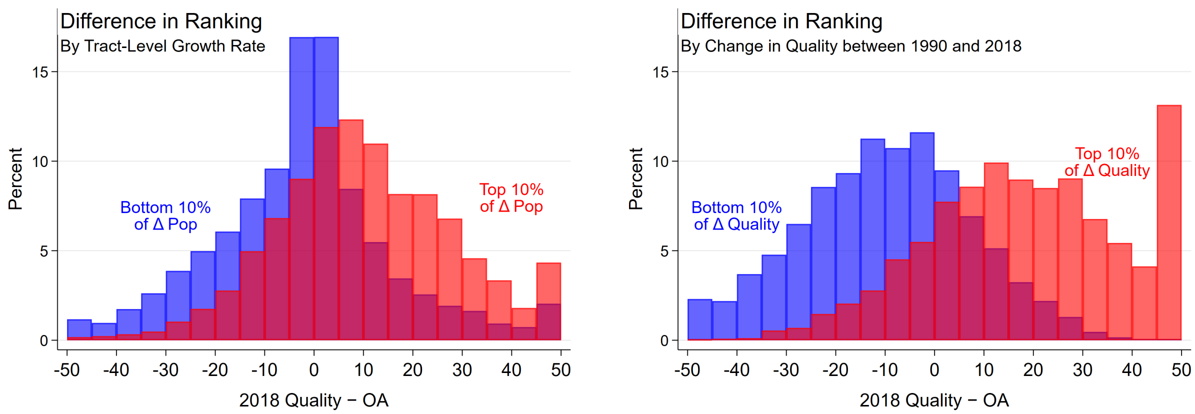


Figure 22: Anywhere in the Suburbs Versus the Top Third of Suburbs
Note: This figure shows a comparison between HMPs targeting any suburb (on the y-axis) versus HMPs targeting the top third of tracts in a metro's suburbs (on the x-axis). We define suburban tracts as any tract outside the metro's central county.)

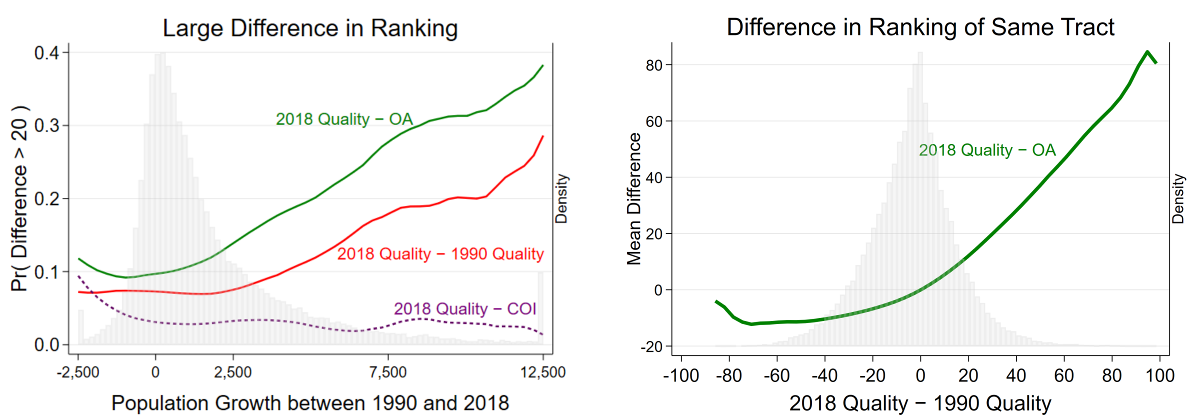
E Changes over Time



(a) Change in Population

(b) Change in Quality

Figure 23: Predicting Disagreement in 2018 Quality and OA Rankings
Note: The left panel shows the distributions of disagreement between the 2018 quality and OA rankings of tracts for those tracts in the top and bottom 10 percent of population growth between 1990 and 2018. The right panel shows the distributions of disagreement between the 2018 quality and OA rankings of tracts for those tracts in the top and bottom 10 percent of the change in quality between 1990 and 2018.



(a) Large Disagreements by Population Growth

(b) Expected Disagreement by Change in Quality

Figure 24: Predicting Large Disagreements in 2018 Quality and OA Rankings
Note: The left panel shows local linear regressions of the probability that 2018 quality ranks a tract at least 20 percentile points higher than another measure as a function of population growth in the tract between 1990 and 2018. The other rankings shown are OA in green, 1990 quality in red, and the Childhood Opportunity Index 2.0 (COI, Noelke et al. (2020)) in purple. The right panel shows the mean difference in 2018 quality and OA rankings of a tract as a function of the change in quality between 1990 and 2018.

F Computational Appendix

F.1 Reference HMP

Step 1: Determine M_m, the total number of movers M in each metro m given f, the maximum number of families that can move to a new tract.

Step 1.1: Determine the total number of movers per tract in receiving tracts, or those in the top third of the metro's tracts as ranked by quality:

a. If a tract has housing supply equal to or greater than f, then assign $f \times 4$ as the number of movers to the tract.

b. If a tract has housing supply $h < f$, then assign $h \times 4$ as the number of movers to the tract.

Step 2: In origin neighborhoods, select individuals to move from original tracts.

Step 2.1: Identify tracts that have poverty rates greater than 30 percent or are otherwise in the bottom 1/3 of the metro's distribution of quality.

Step 2.2: Identify the number of poor persons in these tracts that are compliers and will move (25 percent of the total number of poor persons in the tract). Let hp_j represent the number of compliers in high-poverty tract j and bt_k represent the number of compliers in bottom third tract k. Then define the sums in metro m as $HP_m = \sum_{j \in \{1,2,\ldots,J_m\}} hp_j$ and $BT_m = \sum_{k \in \{1,2,\ldots,K_m\}} bt_k$. $HP_m + BT_m = C_m$, the total number of compliers in metro m.

a. If $HP_m \geq M_m$, we will only move from high-poverty tracts.

b. If $HP_m < M_m$, HP_m people are moved from high-poverty tracts and $M_m - HP_m$ people are moved from tracts that are in the bottom third of their neighborhood measure and not high-poverty tracts. This will still be M_m total movers.

c. If $C_m < M_m$, we will move C_m people.

Step 2.3: Create a vector or vectors of the eligible moving tracts. Let php_j represent the number of compliers in high-poverty tract j and pbt_k represent the number of compliers in bottom third tract k. Then define the sums in metro m as $PHP_m = \sum_{j \in \{1,2,\ldots,J_m\}} php_j$ and $PBT_m = \sum_{k \in \{1,2,\ldots,K_m\}} pbt_k$. $PHP_m + PBT_m = P_m$, the total number of compliers in metro m. Let p_j represent the number of poor persons in tract j.

a. If $HP_m \geq M_m$, the vector will have the tract number of high-poverty tract j repeated php_j times, where the vector is a stacked vector of length PHP_m.

b and c. If $HP_m < M_m$ or $C_m < M_m$, there will be two vectors. One will have the tract number of each high-poverty tract j repeated php_j times. The other vector will have the tract number of each bottom third tract k that is NOT a high-poverty tract repeated pbt_k times. Both vectors are again stacked vectors of length PHP_m and PBT_m respectively.

Step 2.4: Randomly select tract numbers to represent the number of people who are going to move from each tract.

a. If $HP_m \geq M_m$, we randomly draw M_m tract numbers from our one vector.
b. If $HP_m < M_m$, we randomly draw HP_m tract numbers from our first set of vectors and $M_m - HP_m$ tract numbers from our second set of vectors.
c. If $C_m < M_m$, we randomly draw HP_m tract numbers from our first vector and BT_m tracts from our second vector.
Note: Let the number of times tract j is chosen be denoted by n_j such that in cases (a) and (b) above $\sum_{j\in\{1,2,...,J_m\}} n_j = M_m$ and in case (c) above $\sum_{j\in\{1,2,...,J_m\}} n_j = C^m$.

Step 2.5: Randomly select n_j poor individuals from each tract j to move.

a. For each tract j, create a matrix ip_j that is $p_j x4$, that will contain indicator variables representing the number of poor persons of each race in tract j. The first vector will be all ones, representing all poor persons, regardless of race, in tract j. There will then be three race vectors with ones indicating whether the poor person is of race black, white, or other.The race vectors will be created in a way so that the first column is a linear combination of the other three, so in each row there will be exactly two columns with ones in them.
b. Randomly draw n_j persons from matrix ip_j. This allows to keep track of how many poor persons of each race are moving from tract j. A poor person is "moved out" of a tract by changing the ones to zeros in that row.

F.2 HMP Focused on Access to Public Transportation

<u>Change Step 1</u>: Determine M_m, the total number of movers M in each metro m given f, the maximum number of families that can move to a new tract.

Step 1.1: Determine the total number of movers per tract in receiving tracts, or those in the top third of the metro's tracts as ranked by quality:
a. If a tract has housing supply equal to or greater than f, then assign $f \times 4$ as the number of movers to the tract.
b. If a tract has housing supply $h < f$, then assign $h \times 4$ as the number of movers to the tract.
c. <u>If a tract does not have access to public transportation, then assign 0 as the number of movers to the tract.</u>

F.3 HMP with No Porting Across PHA Jurisdictions

<u>Change Steps 1 and 2</u>: Instead of indexing the HMP to metro m, conduct Steps 1 and 2 at the level of each PHA p, and then sum across PHAs in metro m to obtain metro-level outcomes.

F.4 HMP Targeting the Middle Third of Tracts

Change Step 1: Determine M_m, the total number of movers M in each metro m given f, the maximum number of families that can move to a new tract.

Step 1.1: Determine the total number of movers per tract in receiving tracts, or those in the middle third of the metro's tracts as ranked by quality:

a. If a tract has housing supply equal to or greater than f, then assign $f \times 4$ as the number of movers to the tract.

b. If a tract has housing supply $h < f$, then assign $h \times 4$ as the number of movers to the tract.

F.5 HMP without Housing Supply Constraints

Change Step 1: Determine M_m, the total number of movers M in each metro m given f, the maximum number of families that can move to a new tract.

Step 1: Set the total number of movers per tract in receiving tracts, or those in the top third of the metro's tracts as ranked by quality, to $f \times 4$, regardless of the rental housing supply in the tract.

F.6 HMP Targeting Another Ranking of Tracts

Change Step 1: Determine M_m, the total number of movers M in each metro m given f, the maximum number of families that can move to a new tract.

Step 1.1: Determine the total number of movers per tract in receiving tracts, or those in the top third of the metro's tracts as ranked by either COI or OA:

a. If a tract has housing supply equal to or greater than f, then assign $f \times 4$ as the number of movers to the tract.

b. If a tract has housing supply $h < f$, then assign $h \times 4$ as the number of movers to the tract.

Change Step 2: In origin neighborhoods, select individuals to move from original tracts.

Step 2.1: Identify tracts that have poverty rates greater than 30 percent or are otherwise in the bottom 1/3 of the metro's distribution of either COI or OA.

G Uncertainty in Measuring Neighborhood Effects

G.1 Two Sources of Disagreement

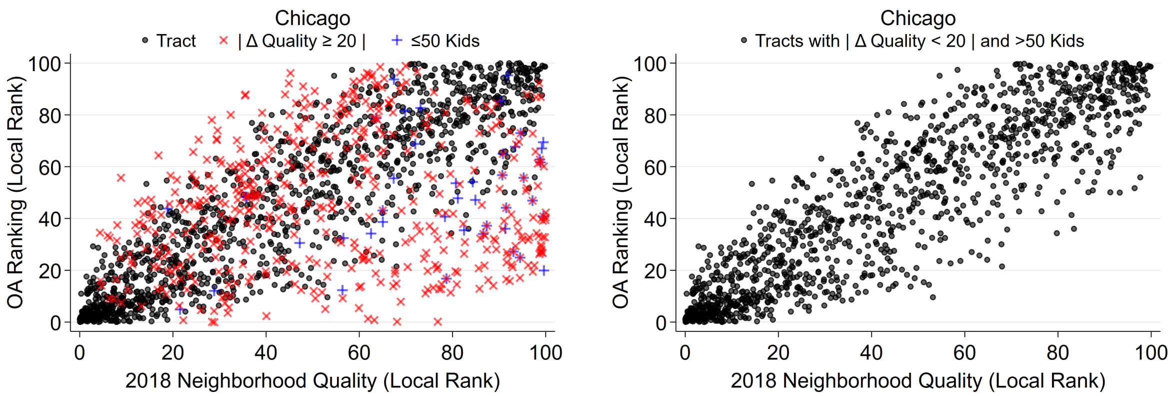


Figure 25: Chicago
Note: See note to Figure 30.

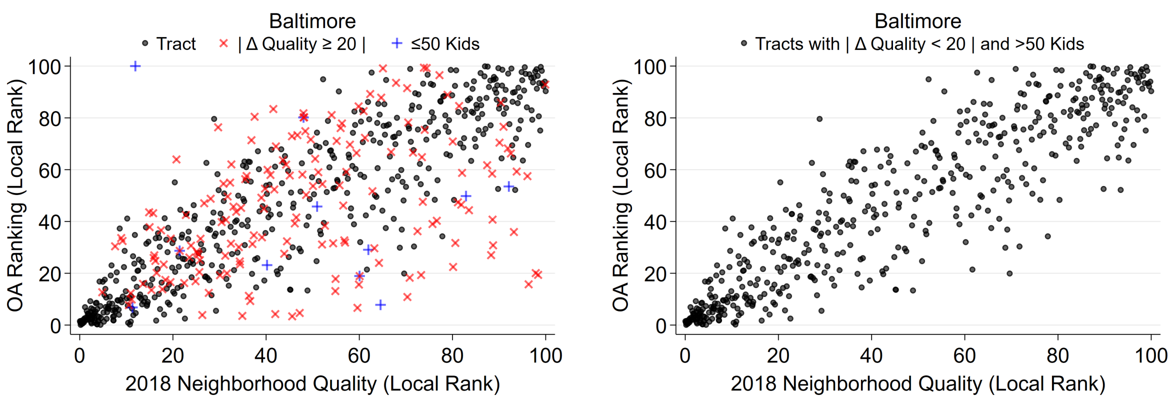


Figure 26: Baltimore
Note: See note to Figure 30.

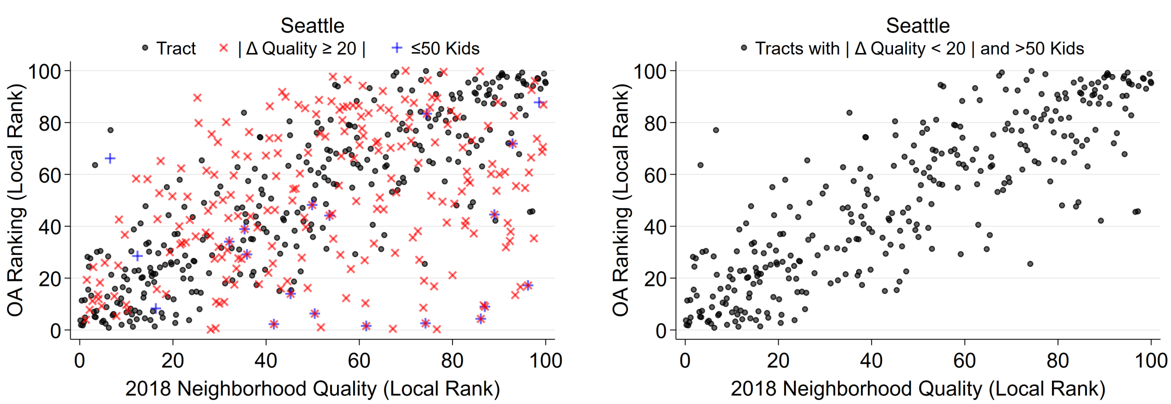


Figure 27: Seattle
Note: See note to Figure 30.

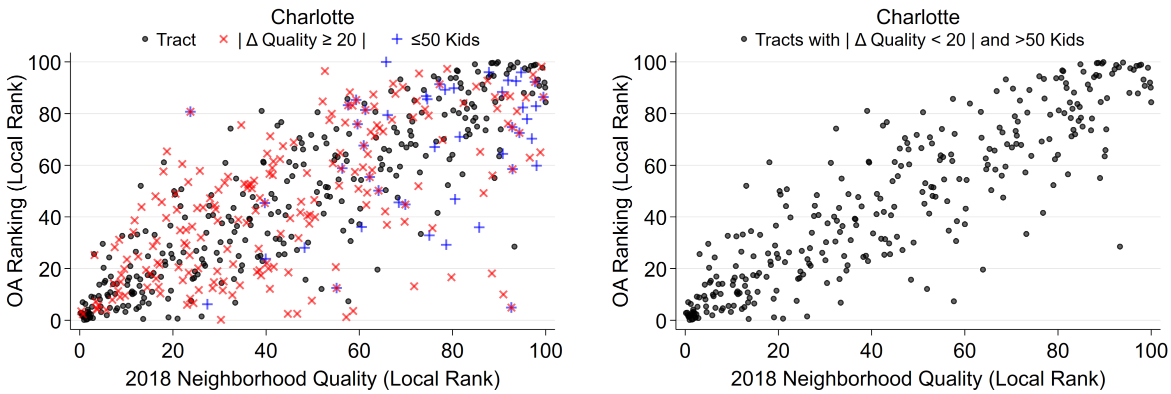


Figure 28: Charlotte
Note: See note to Figure 30.

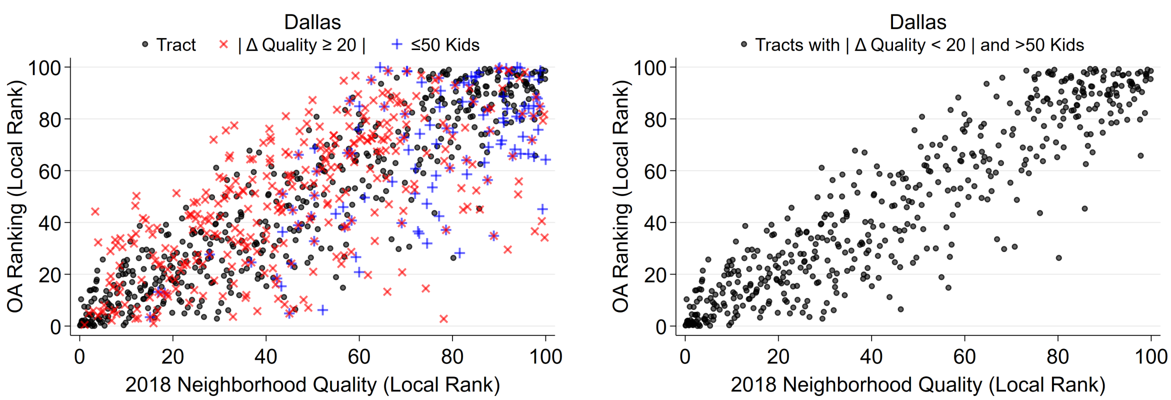


Figure 29: Dallas
Note: See note to Figure 30.

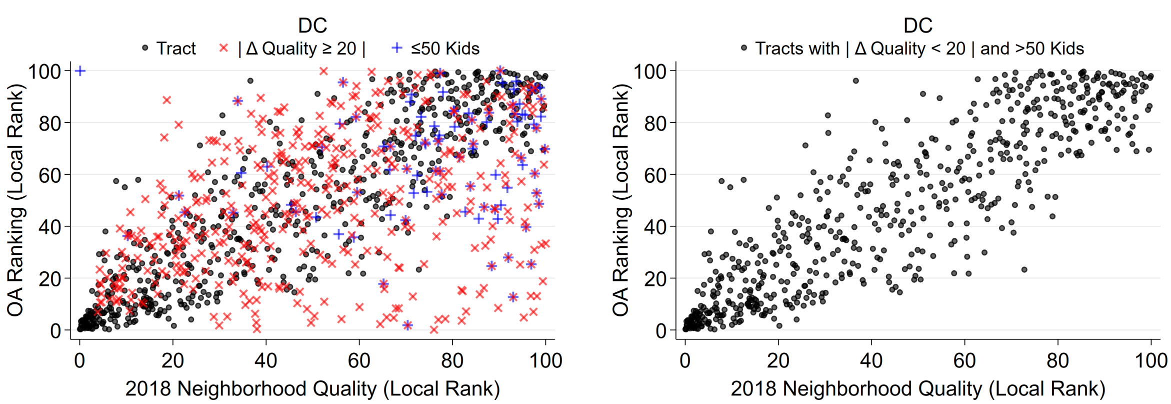
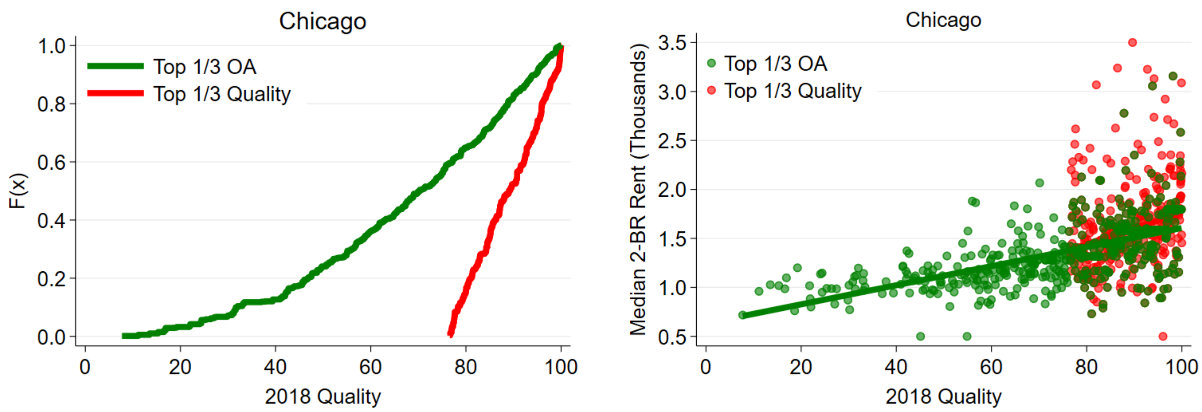


Figure 30: DC
Note: These figures show the joint distribution of the local ranks of tracts in terms of 2018 neighborhood quality and mean family income pooled over race/ethnicity and gender as estimated in the Opportunity Atlas (OA). The left panel flags tracts that either experienced a change in quality (in the local distribution) between 1990 and 2018 of at least 20 percentile points, or else that had less than 50 children in the OA sample age range in the 1990 Census. The right panel shows only those tracts that are not subject to these two sources of uncertainty in OA estimates.

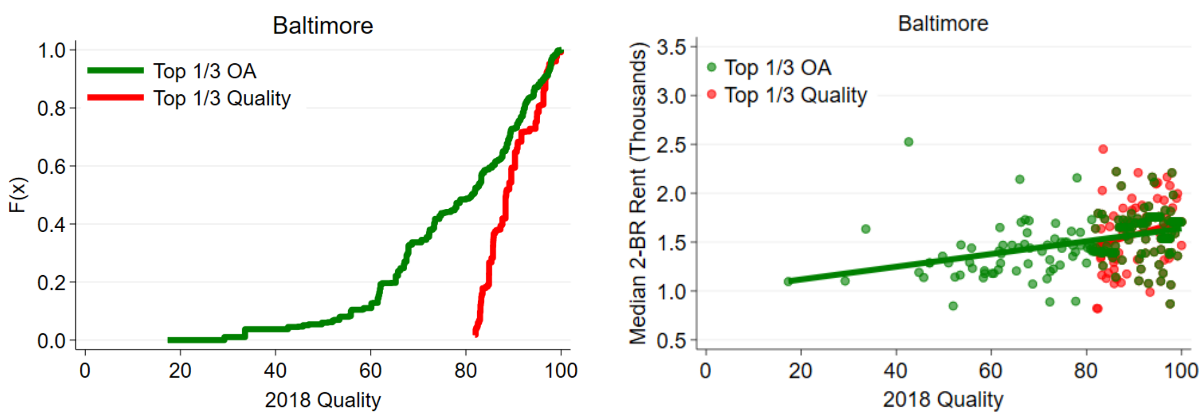
H Opportunity Bargains and Cost



(a) Local Top Third

(b) Rent in Local Top Third

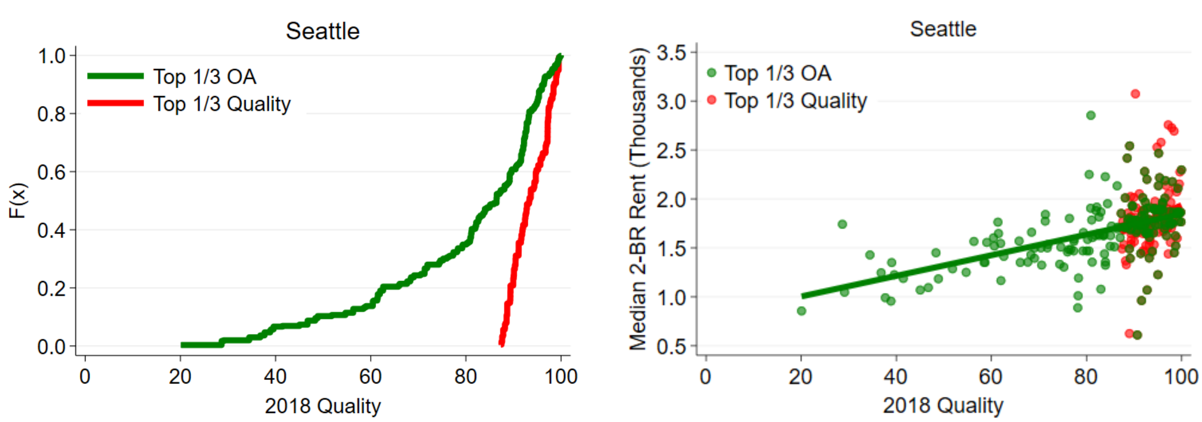
Figure 31: The Top Third of Tracts in Chicago
Note: The left panel plots the Cumulative Distribution Functions (CDFs) of the 2 bedroom and larger rental units in the top third of tracts in the metro as ranked by either the OA or 2018 neighborhood quality. The right panel plots the joint distribution of median 2 bedroom rent and 2018 neighborhood quality for tracts in the top third in the metro as ranked by either the OA or 2018 neighborhood quality, as well as lines fitted by Ordinary Least Squares (OLS).



(a) Local Top Third

(b) Rent in Local Top Third

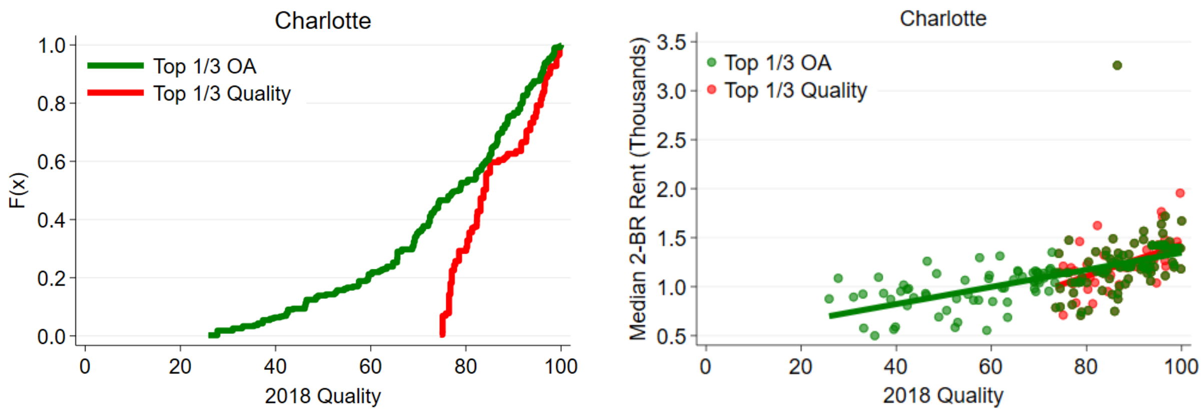
Figure 32: The Top Third of Tracts in Baltimore
Note: See note to Figure 31.



(a) Local Top Third

(b) Rent in Local Top Third

Figure 33: The Top Third of Tracts in Seattle
Note: See note to Figure 31.

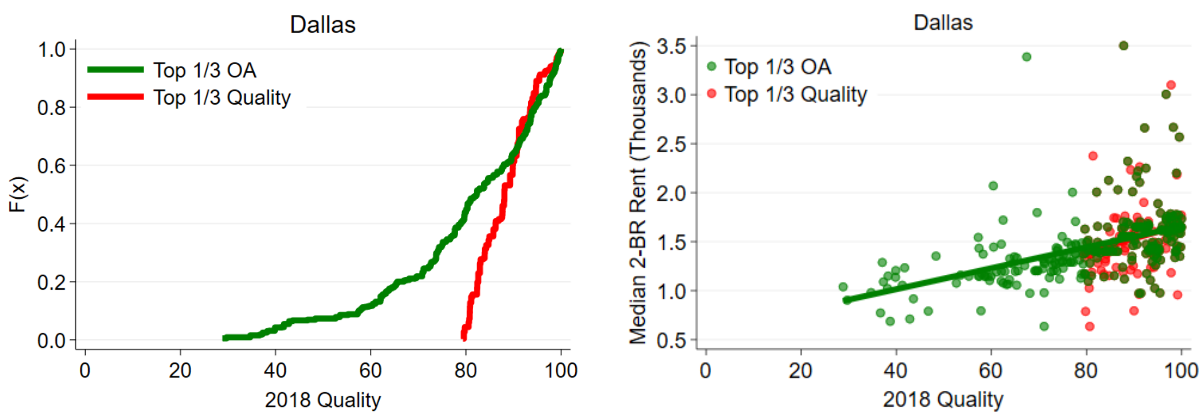


(a) Local Top Third

(b) Rent in Local Top Third

Figure 34: The Top Third of Tracts in Charlotte

Note: See note to Figure 31.

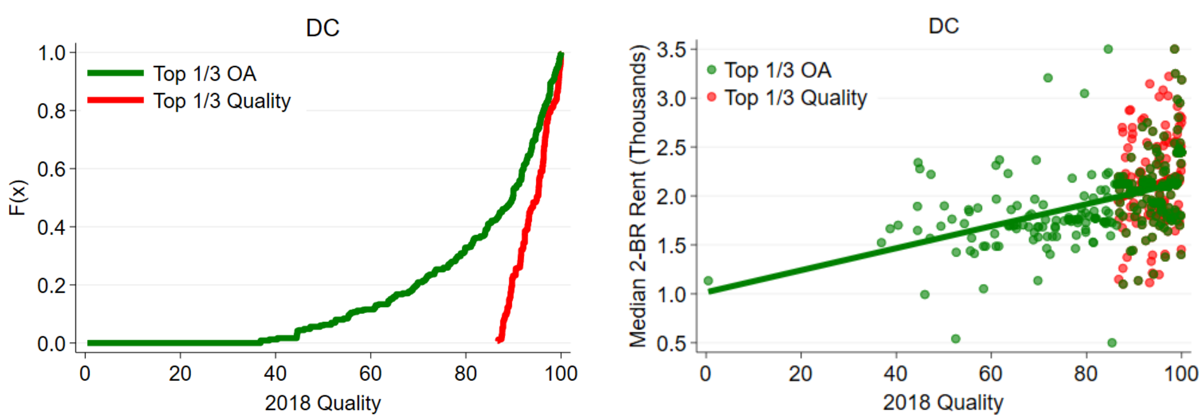


(a) Local Top Third

(b) Rent in Local Top Third

Figure 35: The Top Third of Tracts in Dallas

Note: See note to Figure 31.



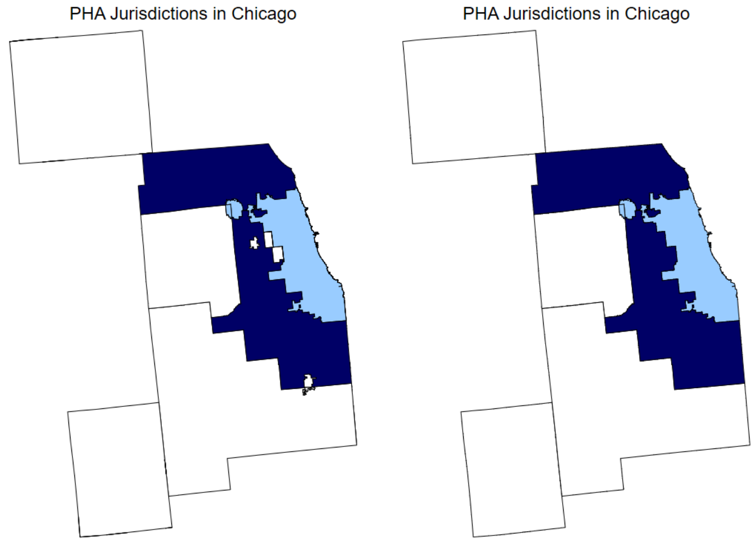
(a) Local Top Third

(b) Rent in Local Top Third

Figure 36: The Top Third of Tracts in DC

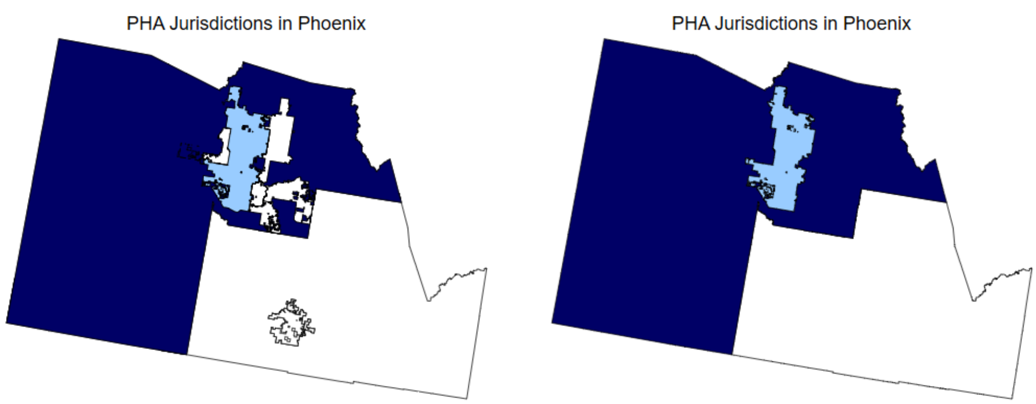
Note: See note to Figure 31.

I Measuring PHA Jurisdictions



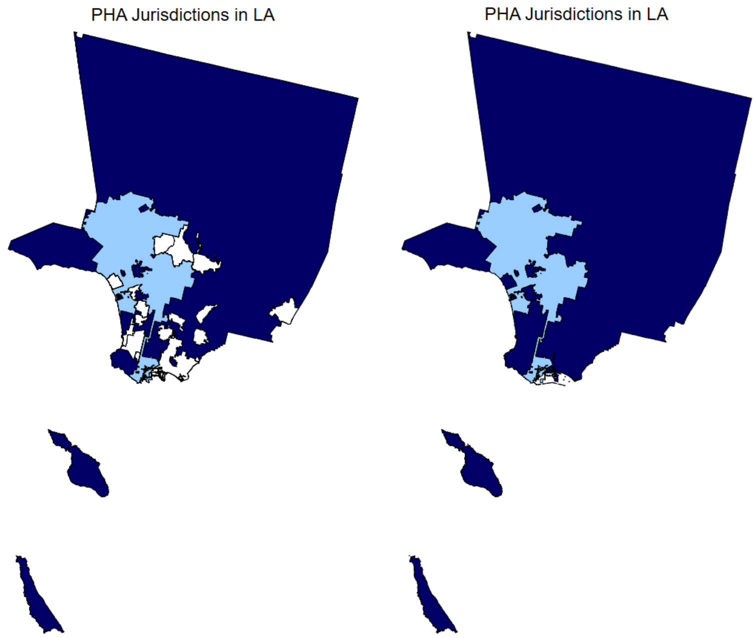
(a) HUD Data (b) Census Data

Figure 37: PHA Jurisdictions in Chicago
Note: This figure shows PHA jurisdictions in Chicago, with the central county highlighted in blue. In light blue is largest city in the central county, and in dark blue is the remainder of the central county. In the left panel, small areas of white indicate where the HUD data report the jurisdictions of small PHAs within the central county. In the right panel, the dark blue filling in the white areas from the left panel indicates how the assumptions we make about the boundaries of PHA jurisdictions maps into the Census data used to determine jurisdiction boundaries.



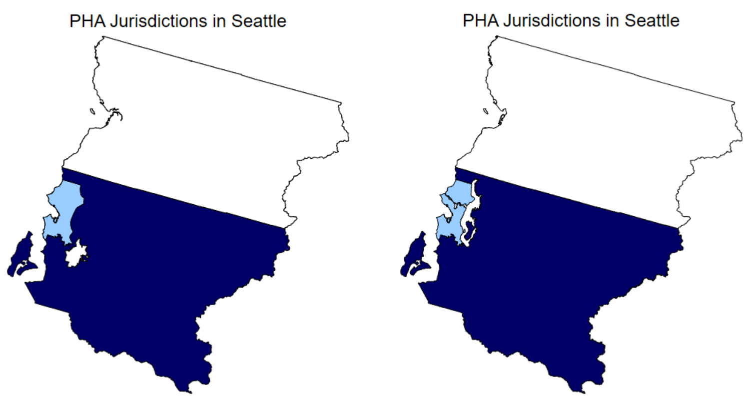
(a) HUD Data (b) Census Data

Figure 38: PHA Jurisdictions in Phoenix
Note: See note to Figure 37.



(a) HUD Data (b) Census Data

Figure 39: PHA Jurisdictions in Los Angeles
Note: See note to Figure 37.



(a) HUD Data (b) Census Data

Figure 40: PHA Jurisdictions in Seattle
Note: See note to Figure 37.

Table 7: Central City and County PHA Jurisdictions

	Central City is Central County	Separate Central City and Central County PHAs	Exclusionary Central County PHA Jurisdiction
New York	Yes	No	No
Los Angeles	No	Yes	Yes
Chicago	No	Yes	Yes
Dallas	No	No	No
Houston	No	Yes	Yes
DC	Yes	No	No
Miami	No	Yes	No
Philadelphia	Yes	No	No
Atlanta	No	Yes	Yes
Boston	No	No	No
Phoenix	No	Yes	Yes
San Francisco	No	No	No
Riverside	No	No	No
Detroit	No	No	No
Seattle	No	Yes	Yes
Minneapolis	No	Yes	Yes
San Diego	No	Yes	Yes
Tampa	No	No	No
Denver	No	No	No
Baltimore	Yes	No	No
St. Louis	Yes	No	No
Charlotte	No	No	No
Orlando	No	Yes	No
San Antonio	No	Yes	No
Portland	No	No	No
Pittsburgh	No	Yes	No
Sacramento	No	Yes	No
Las Vegas	No	No	No
Cincinnati	No	No	No
Kansas City	No	Yes	Yes
Austin	No	Yes	No
Columbus	No	No	No
Cleveland	No	No	No
Indianapolis	No	No	No
San Jose	No	Yes	No
Nashville	No	No	No
Virginia Beach	No	No	No
Providence	No	Yes*	Yes*
Milwaukee	No	Yes	No
Jacksonville	No	No	No
Oklahoma City	No	No	No
Memphis	No	No	No
Raleigh	No	Yes	Yes
Richmond	No	No	No
Louisville	No	No	No
New Orleans	Yes	No	No
Hartford	No	Yes*	Yes*
Salt Lake City	No	Yes	No
Birmingham	No	Yes	No
Buffalo	No	Yes	No
Rochester	No	No	No
Grand Rapids	No	Yes	No
Tucson	No	No	No
Tulsa	No	No	No

* There is no county PHA, all cities have separate PHA jurisdictions
Exclusionary PHA jurisdiction means the central county explicitly states it does not serve the central city.

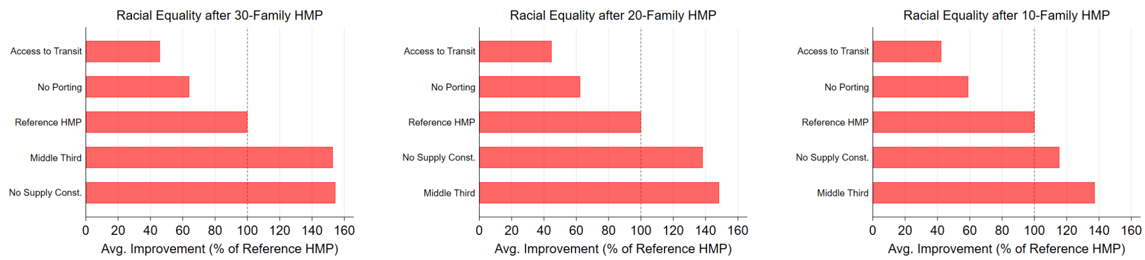
J Access to Public Transportation

We have the latitude and longitudes of transit stops from the General Transit Feed Specification (GTFS) data, taken from the National Transit Map (NTM) of the Bureau of Transportation Statistics, or Open Mobility Data if the NTM had missing or insufficient data. Table J shows the source of transit access data by metro.

Table 8: Data Source on Transit Stops, by Metro

Metro	Data Source	Metro	Data Source
New York	National Transit Map	Philadelphia	Open Mobility Data
Los Angeles	National Transit Map	Atlanta	Open Mobility Data
Chicago	National Transit Map	Phoenix	Open Mobility Data
Dallas	National Transit Map	Tampa Bay	Open Mobility Data
Houston	National Transit Map	Charlotte	Open Mobility Data
DC	National Transit Map	Orlando	Open Mobility Data
Miami	National Transit Map	San Antonio	Open Mobility Data
Boston	National Transit Map	Sacramento	Open Mobility Data
San Francisco	National Transit Map	Las Vegas	Open Mobility Data
Riverside	National Transit Map	Cincinnati	Open Mobility Data
Detroit	National Transit Map	Indianapolis	Open Mobility Data
Seattle	National Transit Map	Louisville	Open Mobility Data
Minneapolis	National Transit Map	New Orleans	Open Mobility Data
San Diego	National Transit Map	Rochester	Open Mobility Data
Denver	National Transit Map	Grand Rapids	Open Mobility Data
Baltimore	National Transit Map	Virginia Beach	Not Found
St. Louis	National Transit Map	Memphis	Not Found
Portland	National Transit Map	Richmond	Not Found
Pittsburgh	National Transit Map		
Kansas City	National Transit Map		
Austin	National Transit Map		
Columbus	National Transit Map		
Cleveland	National Transit Map		
San Jose	National Transit Map		
Nashville	National Transit Map		
Providence	National Transit Map		
Milwaukee	National Transit Map		
Jacksonville	National Transit Map		
Oklahoma City	National Transit Map		
Raleigh	National Transit Map		
Hartford	National Transit Map		
Salt Lake City	National Transit Map		
Birmingham	National Transit Map		
Buffalo	National Transit Map		
Tucson	National Transit Map		
Tulsa	National Transit Map		

K HMPs by Program Size



(a) 30 Families (b) 20 Families (c) 10 Families

Figure 41: HMP Results by the Maximum Number of Families per Destination Tract
Note: This figure shows how changes in HMP design affects the overall improvement in racial equality due to the HMP, depending on the maximum number of families eligible to move to destination tracts.

Appendix References

Aliprantis, D. and F. G.-C. Richter (2020). Evidence of neighborhood effects from Moving to Opportunity: LATEs of neighborhood quality. *The Review of Economics and Statistics 102*(4), 633–647. DOI: 10.1162/rest_a_00933.