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Abstract

This paper presents research on the distribution of economic benefits from brownfield cleanup and land development. There is growing concern that cleaning up blighted areas, including brownfields, can entrench inequality by disproportionately benefiting some demographic groups more than others. We look for evidence of disproportionate benefits by relating changes in move decisions to land use activity in Chicago using a heterogeneous sorting model. Our research produces two key insights: first, Black and Hispanic households benefit less than White households from brownfield cleanup and vacant land development. Second, owners appear to benefit more than renters from cleanup and development. Overall, these results provide evidence of differences associated with race and housing tenure in who benefits from local land use actions.

Keywords

Sorting, housing market, environmental justice, segregation

JEL Codes

Q53, Q58, R21, R23

1. Introduction

Although communities often want to clean up and develop brownfield properties, cleanup actions can be controversial with residents because of concerns that the benefits of redevelopment tend to be one-sided (Bryson 2013, Anguelovski 2016). When officials or developers remove environmental contamination or blight from a property, housing in the surrounding area can become more expensive as developers and landlords market local redevelopment projects to attract tenants (Ali et al. 2020). Competition with new households who want to move in pushes prices up and existing residents out—particularly the most vulnerable and those with the lowest ability or willingness to pay (Pearsall 2010, Bryson 2012). Consequently, the primary beneficiaries of cleanup will be the households that move in or stay (NEJAC 2006). Furthermore, although existing residents may value neighborhood improvements per se, once the consequences of ensuing gentrification are considered, they may value the improvement very little or not at all (Sieg et al. 2004, Krings and Copic 2020). Income inequality, housing discrimination, racism, and marginalization from civic life can play important and intersecting roles in the outcomes of this "environmental gentrification" process that risks devaluing neighborhood improvements for many households (Sieg et al. 2004).[1]

Scholars have responded to concerns about the impacts of gentrification by studying characteristics associated with neighborhood change, especially neighborhood income and racial composition, two focal points of inequality (Galster and Keeney 1993; Carter et al. 1998, Halloway et al. 1998, Freeman and Rohe 2000, Ding, Hwang and Divringi 2016, Freedman and McGavock 2015, Anguelovski et al. 2018). Many of these studies compare population statistics at two points in time to variation in development or land use activity to learn about the effects of gentrification on demographic and socioeconomic outcomes. Unfortunately, the effects are not so simple, because population statistics can mask changes occurring at the individual level (Depro, Timmins and O'Neil 2015). This can occur, for example, when higher rents increase tenant turnover but the demographics of move-ins match move-outs. This makes research that tracks individuals and households more definitive on the consequences of gentrification (Freeman 2005, Newman and Wyly 2006, Crowder and Downey 2010, Ellen and O'Regan 2011).

This paper extends current research on environmental gentrification by measuring the economic benefits to households of brownfield cleanup and land development. Our research is conducted in two parts: First, we develop a sorting model that simulates the mobility decisions of Chicago households between 2010 and 2019. Second, we use data generated from the sorting model to learn how neighborhood land use actions drive mobility decisions for households in different groups, allowing these decisions to vary by race and tenure characteristics. We focus on brownfield cleanup and the amount of vacant land as potential drivers of mobility decisions. We then measure the tradeoffs households are willing to make between cleanup, vacant land, and housing prices. Our results provide some support for concerns about environmental gentrification: we find household willingness to pay (and ability to pay) for brownfield cleanup is highest when the householder is White, which essentially confirms claims that the economic benefits of land revitalization flow disproportionately to Whites relative to other types of households (i.e. Black and Hispanic).[2] We also find significant race group differences in willingness to pay to avoid neighborhoods with vacant land as well as willingness to pay differences between owners and renters.

Beyond the question of who benefits, our research departs from prior work on environmental contamination and gentrification in two important ways. First, our sorting model avoids the identification problem that has plagued the models that researchers have traditionally used to study nuisance and amenity-driven population flows (Depro, Timmins and O'Neil 2015). Sorting models are well-suited to examining questions related to neighborhood change, household mobility and economic disparities (Bayer, Ferreira and McMillan 2007, Bruch and Mare 2012, Kuminoff, Smith and Timmins 2013, Melstrom and Mohammadi 2021), and using a sorting model likely makes our results more definitive on the consequences of gentrification than prior research that compares population statistics at points in time. Second, we find evidence of heterogeneous sorting over neighbor characteristics. This type of sorting can strengthen gentrification and segregation patterns, which often intersect with residents' concerns about neighborhood change. For example, with heterogeneous sorting over neighborhood amenities that correlate with race, cleanup in minority neighborhoods can have a secondary effect: move-in of higher-income, predominately White persons that subsequently attracts new amenities and move-in of more White persons (Sidon 2005).

The remainder of our paper is organized as follows. Section 2 describes the setting in Chicago. Sections 3 and 4 describe the heterogeneous sorting model and data, respectively. Section 5 presents the results and section 6 provides a discussion. Section 7 concludes.

2. Setting

Community advocates have raised concerns that neighborhood change and gentrification disproportionately harm low-income individuals and people of color (Anderson and Sternberg 2013, Betancur 2011, Boyd 2008, Nyden, Edlynn and Davis 2006, Thurber et al. 2021). In Chicago, advocates are increasingly aware of the paradox this concern implies for removing environmental hazards: low income and communities of color endure disproportionate exposure but removing hazards can contribute to a higher cost of living or displace the intended beneficiaries

(Copic, Schusler, & Krings, 2020). However, while these concerns may be real, the disparities associated with environmental gentrification have not been solidly confirmed in empirical research (Banzhaf and McCormick 2012). One of the challenges of measuring these disparities is that one needs information about individual move and stay decisions, alternative residential locations, and the timing of the siting or removal of hazards (Depro, Timmins and O'Neil 2015).

Consider a descriptive analysis of brownfield cleanups and demographic change in Chicago that compares White, Black and Hispanic households, as well as households that own and rent their home.[3] We collected the cleanup data from the Illinois Site Remediation Program (SRP) and the demographic data from Chicago's community data website.[4] We focus on these demographics because (1) Chicago is a racially segregated city and land use and cleanup decisions could partially contribute to racial segregation; and (2) owners and renters could view the consequences of cleanup differently, for example if renters dislike changes that contribute to the conversion of housing in their neighborhood.[5] Table 1 summarizes the number of brownfield cleanups and demographic changes between 2010 and 2017 in the city's 77 community areas. Since 1980 the city has disaggregated its population statistics into community areas to allow for longitudinal comparisons between areas with constant boundaries (Keating 2008). Stakeholders often use these city-defined neighborhoods to describe change and highlight inequalities (for example, see Great Cities Institute (2019)). Panel A of Table 1 shows that average (i.e. city-wide) changes can mask extreme changes in particular neighborhood demographics. The community area (Logan Square) that accounts for the largest decrease in Hispanic residents and one of the largest increases in White residents has been a focal area of the struggle for residents to stay in their neighborhood because of gentrification.

Community area statistics show strong associations between brownfield cleanup and racial change. Panel B of Table 1 presents a correlation matrix of cleanups and group demographic change. Most of the correlations are predictable but they are nevertheless informative. The first row shows a correlation between cleanup and White population change of 0.525, which is substantially higher than the correlations between cleanup and Black and Hispanic population change, which are both close to zero, implying that areas with more cleanup tend to become more White. In contrast, the correlation between cleanup and the change in owner population is about the same as between cleanup and the change in renter population—0.143 vs 0.181—which implies that owners (of any race) occupy neighborhoods with cleanup in about the same numbers as renters. The panel also shows negative correlations between changes in White and Hispanic populations as well as between owning and renting households, which suggests Hispanic residents tend to move out of neighborhoods that White residents are moving into, with a similar displacement pattern between owners and renters. These statistics suggest that the benefits of cleanup are not equitably distributed based on race. Rather, neighborhoods with more cleanups shift toward White people, i.e. the group with greater income and wealth (Melstrom and Redding 2020).

3. Methods

In this section, we describe the sorting model we use to measure group-level differences in mobility and willingness to pay for cleanup. We adopt the two-stage approach developed by Depro, Timmins and O'Neil (2015) to estimate these differences. In the first stage, we simulate the move and stay patterns of households living in Chicago. We segment households by race and tenure into six groups: White owners, White renters, Black owners, Black renters, Hispanic owners and

Hispanic renters. For each group we set up and solve a system of equations that simulates how likely a household is to move or stay in their neighborhood. The solution to each system of equations, which is calculated using a mathematical procedure, yields a set of parameters measuring each neighborhood's relative economic value. In the second stage, we estimate willingness to pay by applying regression analysis to the group-level neighborhood values and data on neighborhood characteristics, including brownfield cleanup and the share of vacant land. Note that the willingness to pay we estimate is the outcome of both ability to pay and preferences—conditions that hinge on each groups' constraints and experiences.

3.1. Moves and neighborhood utilities

We model the move patterns of Chicago households between 2010 and 2019 as a discrete choice problem. Households choose to live in one of the city's 77 community areas, which we denote by j, which are composed of community characteristics X_j and housing price p_j. There are also unobservable characteristics ξ_j. We write the average value or utility δ_j from living in community area j as a function of X_j, p_j and ξ_j as

(1) $$\delta_j = f(X_j, p_j, \xi_j; \alpha)$$

where α is a vector of preference parameters. The actual utility a household i receives from community area j is

(2) $$U_{i,j} = \delta_j + \eta_{i,j}.$$

where $\eta_{i,j}$ is an idiosyncratic variable specific to the household. Now, consider how moving affects utility. Let b refer to the neighborhood a household lived in before the decision to move (or to stay) and a the neighborhood after the decision. The change in utility is

(3) $$U_{i,a} - U_{i,b} = (\delta_a - \delta_b) - \alpha_{MC} MC_{a,b} + (\eta_{i,a} - \eta_{i,b})$$

where $MC_{a,b}$ is the cost of moving from b to a and α_{MC} measures the effect of moving cost on household utility. If $b = a$, $MC_{a,b} = 0$ and $U_{i,a} - U_{i,b} = 0$ because the change in utility must be zero if a household chooses not move, conditional on the year of the move.

Neighborhood dynamics depend on the mean utility from living in location b, δ_b, relative to all other locations a. Denote the share living in b who move to a as $s_{a,b}$. Assuming that $\eta_{i,j}$ is i.i.d. Type I extreme value, then the probability that a household living in b moves to a is

(4) $$s_{a,b} = \frac{e^{\left(\delta_a - \delta_b - \alpha_{MC} MC_{a,b}\right)}}{\sum_{j=1}^{N+1} e^{\left(\delta_j - \delta_b - \alpha_{MC} MC_{j,b}\right)}}$$

where N is the number of Chicago community areas, and $N + 1$ is the number of community areas plus an outside "catch-all" alternative. The population of the catch-all alternative in our model equals the net change in group population between 2010 and 2019 in Chicago. In theory, the population of the catch-all includes all other locations households would consider moving to, however in practice the results are largely insensitive to the population assigned to the catch-all (Depro, Timmins and O'Neil 2015).[6]

For each group in our study, we estimate the mean utilities δ_j and moving cost parameter α_{MC} by solving an exactly identified system of equations that calculates the probability of moving $s_{a,b}$. We construct the system of equations by first noting that for any given group we can write the population living in location a in 2019 as:

(5) $$gpop_a^{2019} = \sum_{b=1}^{N+1} s_{a,b} \, gpop_b^{2010}.$$

Then divide both sides of equation (5) by the total population of the group $GPOP = \sum_{b=1}^{N+1} gpop_b^{2010} = \sum_{b=1}^{N+1} gpop_b^{2019}$ to get:

(6) $$\sigma_a^{2019} = \sum_{b=1}^{N+1} \left[\frac{e^{\left(\delta_a - \delta_b - \alpha_{MC} MC_{a,b}\right)}}{\sum_{j=1}^{N+1} e^{\left(\delta_j - \delta_b - \alpha_{MC} MC_{j,b}\right)}} \right] \sigma_b^{2010}$$

where $\sigma_j^t = \frac{gpop_j^t}{GPOP}$. In essence, equation (6) says that the share of the group population living in location a in 2019 is the sum of move shares from $b \neq a$ plus those who stayed $b = a$.

Equation (6) presents a system of $N + 1$ equations, which is not enough to uniquely solve for the unknowns, which includes $N + 1$ mean utilities δ_j and the moving cost parameter α_{MC}. We need one more equation to solve this problem. One piece of information that we have not used is the share who stayed in their neighborhood from 2010 to 2019. For each group it must be true that

(7) $$\%Stay = \frac{\sum_{b=1}^{N} s_{b,b} gpop_b^{2010}}{\sum_{b=1}^{N} gpop_b^{2019}}$$

where $\%Stay$ is the percent of the city-wide population that did not move.

Solving the system of equations (6) and (7) means finding the δ_j and α_{MC} that equate the predicted population shares ($\hat{\sigma}_j^{2019}$ and $\widehat{\%Stay}$) with the actual population shares ($\bar{\sigma}_j^{2019}$ and $\overline{\%Stay}$). We do this using the generalized reduced gradient method in Excel Solver to minimize the sum of squared residuals, starting with an initial guess of δ_j and α_{MC} as well as data on moving costs, and then use the right-hand sides of equations (5) and (6) to generate the predictions $\hat{\sigma}_j^{2019}$ and $\widehat{\%Stay}$.[7] Because there is no scale associated with utility, for each run of the model we set the mean utility of one location to zero; our conclusions are robust to this choice because it is the relative rather than the absolute levels of the mean utilities that affect move decisions.

We should note that the sorting model described above is not the only way to calculate δ_j and measure willingness to pay. Typically, analysts estimate δ_j in a discrete choice framework using cross-section data on individual neighborhood choices (Bayer et al. 2007, Klaiber and Phaneuf 2010, Bakkensen and Ma 2020). This approach uses the effect of housing cost on utility to determine the marginal utility of income, which is crucial for converting the mean utilities into measures of willingness to pay. However, estimating the effect of housing cost in this manner raises well-known endogeneity concerns. The solution is to perform instrumental variable regression on the mean utilities using instruments for housing price (Bruch and Mare 2012). Our sorting model conveniently circumvents this endogeneity problem by using the moving cost parameter as the marginal utility of income, which the first stage estimates conditional on both observed and unobserved characteristics. Nevertheless, omitted neighborhood characteristics could still bias the preference parameters when we decompose the mean utilities in the second stage. We use a fixed effects design to control for these omitted variables, as described in the next section.

3.2. Estimating willingness to pay

This section describes the second stage of the model, which decomposes δ_j^g using regression analysis to measure willingness to pay for neighborhood attributes. First, note that we drop the δ_j^g of the catch-all alternative from this stage because the population we assumed for that location determines its value. Next, let δ_j^g and α_{MC}^g represent the mean utilities of the other locations and the marginal utility of income for group g, respectively. Then for each group, we specify mean utility as the linear function

(7) $$\delta_j^g = \alpha_X^g X_j - \alpha_p^g p_j + \xi_j^g.$$

Next, we convert the mean utilities into comparable dollar values and the parameters into measures of willingness to pay by dividing δ_j^g by α_{MC}^g. Let $\tilde{\delta}_j^g = \delta_j^g / \alpha_{MC}^g$, $\beta_X^g = \alpha_X^g / \alpha_{MC}^g$, $\beta_p^g = \alpha_p^g / \alpha_{MC}^g$ and $\tilde{\xi}_j^g = \xi_j^g / \alpha_{MC}^g$. β_X^g measures the marginal willingness to pay for neighborhood characteristics and β_p^g measures the effect of housing price. Because we have converted utility into dollar values, utility must decrease by one dollar when the price of housing increases by one dollar, so $\beta_p^g = 1$. We can therefore re-write equation (7) into

$$p_j + \tilde{\delta}_j^g = \beta_X^g X_j + \tilde{\xi}_j^g. \tag{8}$$

We estimate equation (8) using the following functional form for β_X^g:

$$\beta_X^g = \beta_{X,0} + \sum \beta_{X,k} z_k \tag{9}$$

where $\beta_{X,0}$ measures the effect on White owners (the base group) and $\beta_{X,k} z_k$ measures the effect in group k relative to the base group, where z_k is an indicator for k = Black, Hispanic, renter. If households benefit from cleanup regardless of their demographic characteristics, then $\beta_{X,0} + \sum \beta_{X,k} z_k > 0$ for any k. However, $\beta_{X,0} + \sum \beta_{X,k} z_k$ and willingness to pay could vary by group because of structural constraints, for example, differences in income or discriminatory practices that steer Black and Hispanic households away from clean neighborhoods.

We estimate two versions of equation (8) to control for the influence of omitted variables in different ways. First, note that we can write $\tilde{\xi}_j^g = \psi^g + \varphi_j + \epsilon_j^g$, where ψ^g is group-specific willingness to pay unexplained by location characteristics, φ_j is the willingness to pay for location characteristics that households in all groups value equally, and ϵ_j^g measures group idiosyncratic willingness to pay. Correlation between any of these terms and the observed location characteristics will lead to bias. The first specification addresses this bias by including group fixed effects ψ^g and a set of district fixed effects that correspond to 16 city planning districts. Chicago's community areas naturally group into districts based on physical boundaries and barriers such as rivers and railroad embankments (Chicago Community Trust 2015). The assumption here is that community areas in the same district share the unobserved location characteristics that cause X_j and $\tilde{\xi}_j^g$ to be correlated, and that within districts X_j is as good as random. This means that differences in the utilities of community areas in the same district reflect differences in observable characteristics, including brownfield cleanup and the amounts of vacant land.

The second specification includes community area fixed effects, i.e. a full set of location-specific constants. This absorbs any unobserved community area effects that could, through correlation with X_j, bias $\beta_{X,k}$. One potentially important unobserved variable is the number of brownfields that could have been cleaned up, which could correlate with the number of cleanups; ignoring the number of brownfields could induce a downward bias in estimated willingness to pay for cleanup if there tends to be few brownfields with potential cleanup in high amenity neighborhoods. Including community area fixed effects solves the correlated unobservables problem by controlling for all possible location-specific characteristics. It is not possible to identify willingness to pay in the base group in this specification, $\beta_{X,0}$, but we can still estimate the difference in preferences for cleanup, $\beta_{X,k}$, between the groups.

We estimate both specifications in Stata with standard errors clustered on community areas. We perform each regression after combining the mean utilities from the first stage with community area characteristics, stacked across all six groups. In these regressions, X_j includes the number of cleanups in 2010-2015, the amount of vacant land, median household income, the fraction of college degree holders, crime rate, the percent of Black and Hispanic residents in 2010, as well as price and demographic pre-trends from 2000-2010. We also include a variable controlling for the conversion of an abandoned rail corridor to a greenway in 2015. The modeling assumption is that residents adjusted their 2010 locations based on the characteristics they saw in 2010-2015, resulting in their 2019 locations. We discuss these characteristics in more detail in the next section.

4. Data

The first stage of the sorting model uses neighborhood population data, citywide moving statistics, and moving cost estimates. The population data come from the U.S. Census Bureau's tract-level cross tabulations from the 2010 census and the 2019 American Community Survey 5-year sample. We use these data to construct $gpop_j^{2010}$ and $gpop_j^{2019}$ for the demographic groups in our study. The citywide stay percentages come from the 2019 American Community Survey 1-year sample microdata published by IPUMS USA, which reports the year subjects moved into their current residence. We used these statistics to construct $\%Stay$ for each group, based on the population living in Chicago that moved into their house before 2010. Table 2 presents these stay percentages for the six groups in our study.

The first stage of our analysis also uses moving cost estimates, which we separate into physical, financial and search costs. Physical costs include hiring a moving company and the value of residents' time spent moving. Financial costs include closing costs and non-refundable deposits. Search costs include the cost of learning about and securing a new residence. We further separate these costs between owners and renters because owners tend to have larger and more expensive moves.

To calculate physical costs, note that the typical owner-occupied home and rental unit have three and two bedrooms, respectively (Zillow 2016). We therefore use a physical cost of $2,194 for owners, which is the mid-point of the range provided by moving.com for a Chicago move with partial packing services for a three-bedroom household, and a physical cost of $1,416 for renters, which is the mid-point of the range provided by moving.com for a Chicago move with partial packing services for a two-bedroom household. To these costs we add the value of the moving household's time, using an hourly wage of $28, assuming two adults in the household and 8 moving hours, plus the time driving to the new community area assuming a speed of 20 miles per hour.

For moves to and from the catch-all, we assume a flat move cost of \$5,000 for owners and \$4,000 for renters, based on the estimate for intercity moves in Bieri, Kuminoff and Pope (2019).[8]

For financial costs, we assume owners pay 3.75% and 3.3% of the 2010 median housing value in the old and new community areas, respectively, which includes evenly splitting a 6% realtor commission between buyer and seller and Chicago transfer taxes. For renters, we use a financial cost equal to half monthly rent, i.e. a non-refundable deposit.[9] Finally, we assume both owners and renters have a search cost of \$20/mile based on the distance between their old and new community area, to account for the cost of learning about and securing a new residence.

We sum up the physical, financial, and search costs of moving separately for owners and renters, and then annualize these costs using a discount rate of 5% and the formula:

$$\text{Annual moving cost} = \frac{\text{Moving cost}}{(1-1/1.05^{t})/0.05}$$

where *t* is the time horizon. We use a time horizon of eight and two years for owners and renters, respectively, which are the median lengths of time these groups spend in their homes before moving.

The second stage of the sorting model uses data on the price of housing, neighborhood demographics, crime, amount of vacant land, and brownfield cleanups. We use the demographic profiles published by the City of Chicago's Department of Planning and Development to measure the percent of Black residents, Hispanic residents, residents with a college degree, and median household income. We next include the number of index crimes in 2010, including homicide, rape, robbery, assault and battery, human trafficking, burglary, theft and arson, based on Chicago Police Department annual reports. We considered including measures of school quality but found they did not significantly improve the fit of the model. Table 3 presents summary statistics of these neighborhood characteristics.

We measure the price of housing separately for owners and renters. For owners, p_j is the user cost of owner-occupied housing, or 4.46% of the median housing value in 2010, assuming an equity rate of return of 6%, based on U.S. Department of Housing and Urban Development estimates (HUD 2000). For renters, p_j is median rent in 2010.

We measure the number of brownfield cleanups based on participation in the Site Remediation Program (SRP) managed by the Illinois Environmental Protection Agency (EPA). The SRP aims at redeveloping abandoning properties by helping property owners document contamination, develop a remediation plan and certify that cleanup has occurred. Participation in the program is voluntary, and property owners have an incentive to participate because the No Further Remediation (NFR) letters the Illinois EPA provides after remediation are often necessary to sell, resolve litigation, obtain insurance or obtain financing for brownfield properties (Illinois Environmental Protection Agency 2001). Prior research on SRP participation has found that cleanup increases local property values (Linn 2013). In each community area, we count the number of brownfields cleaned up between 2010 and 2015 based on the date of NFR letters. It should be noted that because SRP participation is voluntary the number of cleanups is not strictly exogenous. Our identification assumption is that cleanup is exogenous or as good as random conditional on the covariates and fixed effects. To control for the potentially confounding effect of historic neighborhood change, the regressions in the second stage include variables measuring the percent change in housing values and demographic shares (e.g. White households, owners) in 2000-2010.[10]

We measure the amount of vacant land in community areas using the Chicago Metropolitan Agency for Planning's (CMAP) 2010 land use inventory. CMAP's vacant land category includes undeveloped properties not used for agriculture nor protected as open space, as well as properties with razed structures. In urban areas, vacant land tends to attract trash, crime and poor landscaping, and residents often view these properties as a nuisance (Garvin et al. 2013). Vacant land that includes brownfields can also function as a health risk. Development or redevelopment of vacant land is typically a priority of cities, however, the conversion of vacant land can also be associated with gentrification (Rigolon et al. 2020).

Finally, we include a control for a particularly extensive land use action that took place in Chicago during the study period. In 2010, the Trust for Public Land (TPL) signed a contract with the Chicago Park District to transform a vacated rail line into a three-mile greenway known as The 606. Between 2013 and 2015, the TPB and City of Chicago spent $95 million on this pedestrian project (Rigolon and Németh 2018). The 606 has proved controversial because of perceptions that it gentrified the three surrounding community areas (Humboldt Park, Logan Square, and West Town) to the particular detriment of Hispanic residents (Harris et al. 2020). We include an indicator variable for these three community areas because the timing of The 606 construction could have influenced location decisions after 2010.

5. Results

The first stage of our analysis calculates the mean utilities and moving cost parameters in each group. For the sake of brevity, we do not report the mean utilities.[11] Table 2 presents the moving cost parameters from these calculations. The estimates indicate that moving cost affects White households less than Black and Hispanic households and affects owners less than renters.[12] These differences are consistent with diminishing marginal household utility, in which a dollar of spending is worth less to the households that tend to have higher incomes (Whites, owners).

The second stage estimates in Table 4 reveal important group differences in willingness to pay for neighborhood characteristics. Column (1) presents the coefficients in the specification that includes district fixed effects. These estimates indicate that, among owners, White willingness to pay for a brownfield cleanup is $220 per year, which is $53 and $45 more than Black and Hispanic willingness to pay for cleanup, respectively. Renter willingness to pay is $81 less than owner willingness to pay (and the combination of race and tenure is cumulative, so Black and Hispanic renter willingness to pay is $134 and $125 less than White owner willingness to pay), although this difference is imprecisely measured and not significantly different from zero. The estimates also indicate, among owners, White willingness to pay of $121 per year to live in a community area with one-percentage point less vacant land, which is significantly more than Black and Hispanic willingness to pay for the same change. And between owners and renters, the difference in willingness to pay for less vacant land is a statistically significant $104. The estimates reveal disparities of even greater magnitude to live in the community areas with access to The 606, with White owner willingness to pay exceeding $1900 per year for these areas, which is many hundreds of dollars more than other groups' willingness to pay.

Table 5 presents the average level of willingness to pay in each group for selected characteristics, including brownfield cleanup and the share of vacant land, based on the estimates in column (1) of Table 4. These results show that Black and Hispanic owner willingness to pay is significantly positive for cleanup, although White owner willingness to pay is larger. White renter willingness to pay for cleanup is also positive, but Black and Hispanic renter willingness to pay have confidence intervals that overlap with zero. The results also show that White and Black owner willingness to pay to live in areas with less vacant land is significantly positive, but given standard confidence levels we cannot reject the possibility that renter willingness to pay, for any race group, could be zero. Thus, owners, particularly White owners, benefit most clearly from cleanup and land development. Other groups can benefit from these changes but, relative to White owners, the benefits tend to be smaller and, in some cases, can be close to zero.

What about willingness to pay for other neighborhood characteristics? The results in Tables 4 and 5 reveal several differences in the importance of neighborhood characteristics to these groups. First, the estimates imply that Black and Hispanic willingness to pay exceeds White willingness to pay for neighborhoods with higher median incomes—which suggests that move-in by higher-income households per se is not associated with devaluing a neighborhood for people of color (often a concern about gentrification). Second, among owners, White willingness to pay is significantly more than Black and Hispanic willingness to pay to live in neighborhoods with more college-educated neighbors. There is also a disparity between owner and renter willingness to pay for college-educated neighbors. These values suggest that an increase in the share of college graduates is associated with more Whites and owners in a neighborhood. Third, White and Hispanic willingness to pay to live in neighborhoods with more Black residents is significantly negative, which is consistent with households in these groups locating away from predominantly Black neighborhoods.

Next, consider the estimates in column (2) of Table 4, when the specification replaces the district fixed effects with community area fixed effects. These estimates indicate that White willingness to pay is \$45-\$53 more than Black and Hispanic willingness to pay for cleanup, and \$22-\$46 more than Black and Hispanic willingness to pay for a percentage point reduction in vacant land. The estimates also indicate that owner willingness to pay is \$107 more than renter willingness to pay for a reduction in vacant land (the owner-renter difference for cleanup is not statistically significant). Overall, the estimates in columns (1) and (2) are similar, which means that controlling for omitted neighborhood variables does not change the scale or significance of race and tenure disparities in willingness to pay.

In addition to omitted variables, another potential source of bias is aggregated location alternatives. Most Chicago community areas are considerably larger than the census tracts prior research has used as location alternatives. One-third of community areas include at least one dozen tracts based on 2010 boundaries. This could be a problem if the level of development was quite variable in large community areas, where valuable tracts are assigned cleanups that occurred in less developed tracts. Unfortunately, due to high levels of segregation in Chicago, we cannot estimate tract-level mean utilities for a large percentage of these tracts.[13] However, we can control for aggregation in the community area-level mean utilities by including the term $\alpha_M \ln(M_i)/\alpha_p^g$ in the regression, where M_i is the number of locations (tracts) in each alternative (community area) (Parsons and Needelman 1992). We do this first fixing α_M equal across groups in one specification, and then allowing this coefficient to vary across groups (i.e. α_M^g) in a second specification. The results, presented in Table 6, provide evidence of modest aggregation bias.[14] White owner willingness to pay for cleanup is \$132 (in the first specification) and \$143 (in the second specification), which is less than \$220 reported above (in Table 4). Race group differences are also smaller: compared with White, Black willingness to pay for cleanup is \$26 less (in the first specification) and \$40 less (in the second specification), instead of \$53 less (in Table 4). We see a similar, if smaller, decline in the estimates associated with vacant land and even The 606 relative to earlier values. However, the willingness to pay differences between owners and renters for cleanup and reductions in vacant land are little changed (in the first specification) or even larger (in the second specification) compared with Table 4, although these differences should be interpreted with caution because they are imprecisely estimated.

6. Discussion

Our key finding is that brownfield cleanup disproportionately benefits White households. Although we find households in most groups value cleanup, White willingness to pay exceeds Black and Hispanic willingness to pay by $20-$50 per cleanup, depending on model specification. Given large racial differences in household incomes and wealth in Chicago, this result could be partly attributable to affordability.[15] It could also be due to experiences that keep Black and Hispanic households away from cleanups by, for example, restricting access to homes in cleaner neighborhoods (Christensen, Sarmiento-Barbieri and Timmins 2020). Regardless of cause, these findings corroborate two of the outcomes of environmental gentrification claimed by community advocates: that the benefits of cleanup flow mainly to White households, and that neighborhoods with cleanup tend to experience move-in by White households more than other race groups (consistent with greater willingness to pay), shifting neighborhood demographics. We find a similar disparity in values for reductions in vacant land, with willingness to pay larger for White than for Black and Hispanic households.

Our results largely affirm prior research on differences in willingness to pay between race groups. Depro, Timmins and O'Neil (2015) use a similar heterogeneous sorting model in a study of air quality in Los Angeles and find that, relative to White households, Hispanics have a lower willingness to pay to reduce air pollution. Melstrom and Mohammadi (2021) use the same model to examine the effect of brownfield cleanups on sorting in Chicago, and they find a significant difference in White and Black willingness to pay for cleanup. Our study builds on this research by showing evidence of disparities across three race groups for several different land use actions, including brownfield cleanup and vacant land development. Our results are also consistent with prior research that shows significant heterogeneity in the consequences of environmental policies across households (e.g. Bishop and Timmins 2018, Bakkensen and Ma 2020).

We also find evidence that owners benefit more than renters do from cleanup and reductions in vacant land, although there is more uncertainty associated with these differences. Owner willingness to pay exceeds renter willingness to pay by $71-$112 for a cleanup and $99-$122 for a one-percentage-point reduction in vacant land, depending on the specification. In fact, although owner willingness to pay is significantly positive for both changes, renter willingness to pay is statistically indistinguishable from zero. We also find a large difference in owner and renter willingness to pay associated with The 606 rail trail, which suggests that the benefits of the trail flowed mainly to owners. Both results suggest that owners disproportionately move into neighborhoods with these land-use changes, as most renters have little willingness or ability to pay and developers convert rental units to owner-occupied housing.[16]

Finally, we find evidence of heterogeneous values for neighbor characteristics. For a one-percentage-point increase in the share of college graduates, White exceeds Black and Hispanic willingness to pay by $19-$39 and owner exceeds renter willingness to pay by $73-$78, depending on the specification. Presence of college graduates could therefore be interpreted as a sign of impending gentrification, as White households and owners are disproportionately drawn to these neighborhoods. We also find that, relative to Black households, White and Hispanic willingness to pay is lower to live in predominantly Black neighborhoods and that, relative to Black and Hispanic households, White households have lower willingness to live in predominantly Hispanic neighborhoods. These patterns align with prior research that shows evidence of racial preferences in housing decisions (Lewis et al. 2011, Hwang and Sampson 2014, Bader and Krysan 2015). This kind of preference heterogeneity implies that move-in by one race group (e.g. driven by brownfield cleanup) could have a multiplier effect that attracts even more households of the same race group, potentially strengthening gentrification and segregation patterns. However, willingness to pay for neighbors' race may not necessarily reflect racial preferences. Neighbors' race can be correlated with local unobservables, so the effect may be driven by preferences for amenities strongly associated with race—i.e. a correlated unobservables problem—rather than race per se.[17]

7. Conclusion

Our key discovery is that people value brownfield cleanup but that these valuations differ with respect to race and tenure status. Where a household moves depends on its ability to compete in the housing market, so heterogeneity in ability and willingness to pay for housing leads to sorting behavior that concentrates environmental improvements among certain groups. Our results imply that cleaning up brownfields benefits mainly White households and homeowners over Black and Hispanic households and renters. This result helps explain concerns that removing environmental hazards, such as brownfields, changes more than simply the environmental quality of a neighborhood.

Our research also shows that how much households benefit from vacant land development can vary with race and tenure status. White household willingness to pay (and ability to pay) is larger than Black and Hispanic household willingness to pay (and ability to pay), and owners have a larger willingness to pay than renters, to avoid neighborhoods with large amounts of vacant land. Similar to the effect of brownfield cleanups, this result implies that developing vacant land benefits mainly White households and homeowners. These differences can explain the perception that land-use decisions have spillover effects on neighborhood demographics and amenities, by becoming associated with move-in of White households more than other race groups as well as the conversion of rental to owner-occupied housing. This type of sorting is important because it can exacerbate existing inequalities; for example, the conversion of rental housing can increase competition among renters and contribute to displacement. Taken as a whole, these results show why urban redevelopment and gentrification can put race, ethnic and housing occupancy groups at odds: the effects are unequal, out of their control, and yet systematically associated with their characteristics. Urban policy that fails to address these differences—i.e. by focusing on property rather than on people—may therefore create more injustice than it solves.

Notes

[1] Research shows that brownfield development is a potentially important contributor to gentrification. In particular, in 2006, the National Environmental Justice Advisory Council (NEJAC) of the U.S. Environmental Protection Agency published a report concluding that redevelopment can cause "gentrification, displacement and equity loss" in poor and minority communities, an unintended and undesirable side effect of cleanup policies. This conclusion aligns with academic research that finds brownfield cleanup can be an important catalyst for environmental gentrification (Essoka 2012, Bryson 2012, Lee and Mohai 2012, Rigolon and Németh 2018), although redevelopment, as with other neighborhood improvements, does not always cause gentrification (Rigolon and Németh 2020). Cleanup and redevelop can also follow rather than catalyze the early stages of gentrification (Rigolon et al. 2020).

[2] Throughout the paper, we will use the phrases economic benefit and willingness to pay interchangeably, because to a person or household the economic value of any benefit from a good is their maximum willingness to pay for the good. It is important to recognize that this value results from internal and external factors, including factors intrinsic to the individual, such as their personal tastes, as well as factors that determine their ability to pay, including but not limited to income, wealth, access to markets and information, discriminatory practices and the prices of other goods.

[3] The term Hispanic includes all race groups. In Chicago, 96% of Hispanic residents identify as white or "some other race alone," with the next largest share (2%) identifying as two or more races. By origin, Hispanic residents are predominantly Mexican American, with Puerto Rican the next largest heritage share.

[4] The community data is available at https://www.cmap.illinois.gov/data/community-snapshots.

[5] Indeed, opinion research finds that homeowners are more likely than renters to approve of neighborhood changes, which suggests that homeowners have larger willingness to pay for improvements (Sullivan 2007).

[6] This is because the size of the catch-all does not affect the value of the mean utilities relative to each other.

[77] Depro et al. (2015) use contraction mapping and normalize the utilities in their model to be mean zero when solving the system of equations. Our Solver-based method is practical because our application involves considerably fewer location alternatives, i.e. less than 100 instead of hundreds.

[8] This flat rate is near the lower bound of the cost range in Bieri, Kuminoff and Pope (2019) because we expect most locations in the catch-all are adjacent municipalities.

[9] For moves to and from the catch-all alternative, we use a housing value of $191,800 and rent of $709, which were the median values in Cook County.

[10] One might be concerned that cleanups could occur more frequently in neighborhoods experiencing negative trends, where values have moved low enough that redevelopment becomes worthwhile. The pre-trends we include should correlate with these historic trends, strengthening the conditional independence assumption and reducing the confounding effect on cleanups. We also considered allowing the effect of the demographic pre-trends to vary by group, in case 2010-2019 move decisions just continued previous demographic trends. In an appendix available upon request, we show that results are qualitatively similar across versions of the model with and without demographic pre-trends, including group-specific demographic pre-trends.

[11] We estimated 451 out of 468 possible mean utilities. We could not estimate the remaining 17 mean utilities because for these groups the community area had a population of zero.

[12] Because at this stage the model is exactly identified, there are no standard errors associated with these estimates.

[13] We cannot estimate a mean utility in a tract where a group has no population. There are many such tracts in our application. For example, in 2019, 26% and 17% of Chicago tracts contained no Black and Hispanic owners, respectively. This level of segregation is actually an improvement since 2010, when 34% and 26% of tracts contained no Black and Hispanic owners, respectively.

[14] In theory, α_M should equal one (Parsons and Needelman 1992). This is the approximately the case in first specification in Table 6, in which α_M = 0.701 (s.e. = 0.271), but not the case in the second specification, where several α_M^g are significantly different from each other. This suggests that the unobserved heterogeneity in tracts may matter more to some groups than to others.

[15] In 2016, Black, Hispanic and white median household incomes in Chicago were $37,258, $52,730 and $79,865, respectively.

[16] Renter willingness to pay for vacant land reductions is roughly zero and their willingness to pay for The 606 is negative. This does not mean renters do not care about redevelopment (or dislike the rail trail, for that matter), but that the eventual equilibrium outcome is associated with renters disproportionately moving out of the area. As pointed out by a reviewer, renters may have little choice if the development involves or is associated with the conversion of rental properties to owned units (although conversion of housing could be interpreted as an equilibrium response by developers).

[17] As pointed out by reviewers, racial demographics at the neighborhood level could be proxying for local unobservables that vary with race. For example, this could occur in Chicago if historic churches (Black, Lithuanian, etc.) were valued highly by some race groups and not others.

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Table 1. Chicago community area demographic change

	Cleanup	White residents	Black residents	Hispanic residents	Owning households	Renting households
A. Change 2010-2017						
Mean	5	460	-684	141	-39	54
Median	4	159	-211	281	98	6
St. Dev.	5	1383	1581	1492	460	748
Min	0	-2109	-6874	-5502	-1391	-1521
Max	35	5474	1861	4333	1244	3953
B. Correlations of change 2010-2017						
White households	0.525					
Black households	0.049	0.056				
Hispanic households	-0.088	-0.415	-0.155			
Owning households	0.143	0.079	0.304	-0.187		
Renting households	0.181	0.252	0.227	0.250	-0.229	

Table 2. Stay percentages and moving cost parameters

Group	% Stay	α_{MC}
White - owners	51%	0.00078
White - renters	11%	0.00088
Black - owners	70%	0.00143
Black - renters	22%	0.00196
Hispanic - owners	59%	0.00123
Hispanic - renters	22%	0.00209

Table 3. Neighborhood characteristics in the residential sorting model

Name	Description	Mean	St. Dev.
Cleanup	Number of brownfields cleaned up under SRP between 2010 and 2015	5.09	4.76
Vacant	Percent of land classified as vacant	4.70	5.92
Rail trail	=1 for community areas adjacent to rail trail conversion (The 606)	0.04	0.19
Income	Median income in $1,000s	55.01	22.65
College	Percent of residents age >25 with college degree	28.10	20.50
Crime	Number of index crimes per 10000 persons	569.91	326.50
Black	Percent of Black residents	39.18	40.04
Hispanic	Percent of Hispanic residents	25.54	27.95

Table 4. Sorting model regression estimates

	(1)		(2)	
Characteristic	Coefficient	St. Error	Coefficient	St. Error
Cleanup	220.207**	61.952		
×Black	-52.906**	15.474	-52.594**	14.753
×Hispanic	-44.531**	14.646	-44.776**	14.274
×Renter	-80.834	63.480	-80.947	61.307
Vacant	-121.206**	48.718		
×Black	21.278**	9.374	22.160**	9.408
×Hispanic	44.278**	8.651	46.385**	9.064
×Renter	104.631**	52.289	106.623**	50.263
Rail trail (The 606)	1901.910**	818.664		
×Black	-676.322**	211.592	-701.294**	198.941
×Hispanic	-863.161**	216.981	-859.017**	204.565
×Renter	-2212.467**	635.648	-2207.621**	610.501
Income	32.135	26.398		
×Black	12.107**	5.928	9.676*	5.803
×Hispanic	14.711**	4.974	12.244**	4.877
×Renter	8.040	30.839	6.453	29.788
College	128.366**	40.763		
×Black	-22.184**	7.223	-21.041**	6.965
×Hispanic	-38.717**	5.431	-38.741**	5.123
×Renter	-74.516*	38.620	-74.068*	37.347
Crime	-1.968	1.408		
×Black	0.991**	0.439	1.036**	0.417
×Hispanic	1.263**	0.327	1.299**	0.322
×Renter	5.654**	1.562	5.675**	1.515
Black	-55.000**	16.882		
×Black	60.124**	5.736	60.156**	5.362
×Hispanic	26.207**	4.455	24.720**	4.132
×Renter	8.463	20.303	8.282	19.663
Hispanic	-10.147	15.901		
×Black	18.534**	6.596	18.946**	6.344
×Hispanic	25.848**	4.757	24.640**	4.441
×Renter	9.773	19.837	9.428	19.284
Group pre-trends		Yes		Yes
District fixed effects		Yes		No
Community area fixed effects		No		Yes
Observations		451		451

Standard errors clustered on community areas. * and ** indicate significance at the 10% and 5% levels, respectively.

Table 5. Heterogeneity in marginal willingness to pay for neighborhood change

Group	+1 cleanup	-1% vacant land	+10k income	+10% Black
White owners	220.2	121.2	321.4	-550.0
	(62.0)	(48.7)	(264.0)	(168.8)
White renters	139.4	16.6	401.8	-465.4
	(60.0)	(38.76)	(205.4)	(181.2)
Black owners	167.3	99.9	442.4	51.2
	(56.9)	(46.9)	(263.2)	(174.3)
Black renters	86.5	-4.7	522.8	135.9
	(58.4)	36.7	(202.9)	(168.2)
Hispanic owners	175.7	76.9	468.5	-287.9
	(56.3)	(47.2)	(268.2)	(173.8)
Hispanic renters	94.8	-27.7	548.9	-203.3
	(58.8)	(36.2)	(191.9)	(170.5)

Standard errors in parentheses below willingness to pay.

Table 6. Sorting model regression with ln(*M*) adjustment for site aggregation

	Common ln(*M*) coefficient		Group-specific ln(*M*) coefficient	
Characteristic	Coefficient	St. Error	Coefficient	St. Error
Cleanup	131.772**	52.601	143.106**	57.392
×Black	-25.853	17.235	-40.280**	13.289
×Hispanic	-19.507	15.166	-31.776**	14.012
×Renter	-71.184	61.400	-112.185	76.349
Vacant	-99.600**	46.941	-114.938**	51.177
×Black	6.548	11.831	15.930*	9.463
×Hispanic	30.789**	10.424	38.013**	8.473
×Renter	98.836*	52.460	122.682**	58.368
Rail trail (The 606)	1482.694*	866.290	1708.872*	882.638
×Black	-423.002**	206.276	-550.325**	209.580
×Hispanic	-623.749**	188.004	-747.617**	206.516
×Renter	-2131.364**	621.602	-2500.140**	795.825
Income	38.092	25.433	32.816	24.673
×Black	6.661	5.929	9.671	5.824
×Hispanic	9.049*	5.067	11.692**	4.677
×Renter	5.877	30.881	12.716	29.925
College	125.859**	39.774	128.564**	38.894
×Black	-19.439**	7.347	-20.651**	7.326
×Hispanic	-36.151**	5.701	-37.233**	5.478
×Renter	-73.428*	38.898	-77.516**	38.247
Crime	-2.209*	1.316	-2.316*	1.315
×Black	0.938*	0.487	0.899**	0.438
×Hispanic	1.203**	0.368	1.200**	0.350
×Renter	5.659**	1.551	5.744**	1.590
Black	-55.784**	16.173	-54.660**	15.490
×Black	60.735**	5.388	60.820**	5.513
×Hispanic	26.309**	3.875	25.842**	4.181
×Renter	8.698	20.608	7.369	19.977
Hispanic	-11.203	15.814	-11.503	15.380
×Black	18.158**	5.924	18.459**	6.281
×Hispanic	25.281**	4.179	25.585**	4.458
×Renter	9.829	20.132	9.656	19.528
Group pre-trends		Yes		Yes
District fixed effects		Yes		Yes
Observations		451		451

Standard errors clustered on community areas. * and ** indicate significance at the 10% and 5% levels, respectively.

Appendix

Table A1 presents the sorting model without any pre-trends and Table A2 presents the model with group-specific demographic pre-trends. The group-specific pre-trends are formed by multiplying an indicator for each group in the model by its own demographic pre-trend; this means that the pre-trend appears only in the utility function for individuals in that particular demographic group. In contrast, the sorting model presented in the paper includes demographic pre-trends (that are not group-specific) that appear in all utility functions. In both tables, column (1) presents the coefficients in the specification that includes district fixed effects and column (2) when the specification includes community area fixed effects. Note that community area fixed effects absorb demographic pre-trends (that are not group-specific), so the results in column (2) of Table 4 and Table A1 are identical. Otherwise, the inclusion of pre-trends appears to play little role in the results, as the coefficients are qualitatively similarly across Tables 4, A1 and A2.

Table A1. Sorting model regression estimates without demographic pre-trends

	(1)		(2)	
Characteristic	Coefficient	St. Error	Coefficient	St. Error
Cleanup	228.326***	63.658		
×Black	-50.332***	15.165	-52.594***	14.753
×Hispanic	-42.212***	14.462	-44.776***	14.274
×Renter	-79.890	63.418	-80.947	61.307
Vacant	-137.211***	46.022		
×Black	20.424**	9.545	22.160**	9.408
×Hispanic	44.419***	8.591	46.385***	9.064
×Renter	106.684**	51.569	106.623**	50.263
Rail trail (The 606)	1544.049**	695.874		
×Black	-682.444***	215.866	-701.294***	198.941
×Hispanic	-848.492***	215.024	-859.017***	204.565
×Renter	-2179.493***	633.456	-2207.621***	610.501
Income	34.010	26.299		
×Black	12.395**	5.890	9.676*	5.803
×Hispanic	14.684***	4.899	12.244**	4.877
×Renter	8.000	30.594	6.453	29.788
College	109.924**	44.247		
×Black	-21.621***	7.109	-21.041***	6.965
×Hispanic	-38.191***	5.411	-38.741***	5.123
×Renter	-74.256*	38.349	-74.068*	37.347
Crime	-2.051	1.313		
×Black	0.919**	0.449	1.036**	0.417
×Hispanic	1.134***	0.347	1.299***	0.322
×Renter	5.505***	1.614	5.675***	1.515
Black	-66.256***	16.926		
×Black	60.376***	5.742	60.156***	5.362
×Hispanic	26.764***	4.423	24.720***	4.132
×Renter	9.362	20.300	8.282	19.663
Hispanic	-17.071	16.468		
×Black	19.150***	6.636	18.946***	6.344
×Hispanic	26.112***	4.783	24.640***	4.441
×Renter	9.653	19.661	9.428	19.284
District fixed effects		Yes		No
Community area fixed effects		No		Yes
Observations		451		451

Standard errors clustered on community areas. * and ** indicate significance at the 10% and 5% levels, respectively.

Table A2. Sorting model regression estimates with group-specific demographic pre-trends

	(1)		(2)	
Characteristic	Coefficient	St. Error	Coefficient	St. Error
Cleanup	231.660***	68.696		
×Black	-64.482***	16.453	-50.722***	15.535
×Hispanic	-52.763***	15.172	-41.922***	15.177
×Renter	-43.058	73.919	-9.312	77.641
Vacant	-166.067***	49.020		
×Black	26.406**	11.058	23.985**	10.764
×Hispanic	43.129***	9.722	47.267***	10.254
×Renter	118.190**	46.994	114.099**	43.427
Rail trail (The 606)	1209.928*	702.887		
×Black	-781.648***	212.528	-717.023***	206.074
×Hispanic	-1024.958***	262.588	-841.735***	214.495
×Renter	-2269.435***	664.330	-2062.727***	623.616
Income	38.201	26.043		
×Black	14.428**	5.884	9.079	5.627
×Hispanic	19.149***	5.933	11.830**	4.974
×Renter	-2.684	32.371	-28.876	32.228
College	100.942**	45.279		
×Black	-28.101***	9.925	-19.560**	7.428
×Hispanic	-46.188***	8.986	-37.071***	5.381
×Renter	-49.408	38.246	-25.168	37.766
Crime	-0.984	1.483		
×Black	0.834*	0.470	1.098**	0.442
×Hispanic	1.154***	0.350	1.261***	0.336
×Renter	5.019***	1.514	4.105***	1.278
Black	-75.055***	15.599		
×Black	57.579***	6.505	59.399***	5.681
×Hispanic	25.546***	4.512	25.996***	4.177
×Renter	13.055	16.729	15.644	15.049
Hispanic	-16.199	16.595		
×Black	19.908***	6.588	18.639***	6.111
×Hispanic	24.589***	4.980	23.693***	4.290
×Renter	9.710	19.115	4.558	19.316
House value pre-trend	-2.851	7.013		
White population pre-trend				
×White	-3.066	2.725	1.874	1.514
Black population pre-trend				
×Black	-2.507	1.914	-0.971	1.131

Hispanic population pre-trend ×Hispanic	-3.170	2.180	-0.570	0.642
Owning population pre-trend ×Owner	19.237*	9.995	33.960***	9.824
Renting population pre-trend ×Renter	6.120	16.842	36.522**	17.908
District fixed effects		Yes		No
Community area fixed effects		No		Yes
Observations		451		451

Standard errors clustered on community areas. * and ** indicate significance at the 10% and 5% levels, respectively.