Disparities in Pollution Capitalization Rates: The Role of Direct & Systemic Discrimination

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Abstract

We examine how exogenous changes in exposure to air pollution over the past two decades have altered the disparities in home values between Black and White homeowners. We find that air quality capitalization rates are significantly lower for Black homeowners. In fact, they are so much lower that, despite secular reductions in the Black-White pollution exposure gap, disparities in housing values have increased during this period. An exploration of mechanisms suggests that roughly two-thirds of this difference is the result of direct discrimination while the remaining one-third can be attributed to systemic discrimination.

Keywords: house prices, environmental justice, air pollution, race, discrimination
JEL codes: Q51, R30, J15

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I. Introduction

While racial segregation in the United States formally ended more than half a century ago, the existence of predominantly Black and White neighborhoods persists, and they continue to differ on a wide range of dimensions. One important dimension is pollution, where Black communities are disproportionately exposed to poor air quality relative to their White counterparts (Jbaily et al. 2022). Since the harms from air pollution, which include health as well as other human capital impairments (Graff Zivin & Neidell 2012), have been shown to capitalize into housing values[1] (e.g. Chay & Greenstone 2005) it may also contribute to the well-documented racial disparities in housing values across and within neighborhoods (Myers 2004, Faber & Ellen 2016, Bayer et al. 2017, Perry et al. 2018, Kermani & Wong 2021, Kahn 2021, Higgins 2023, Diamond & Diamond 2024). In this paper, we examine this relationship directly by examining how changes in exposure to air pollution over the past two decades have altered the disparities in home values between Black and White homeowners, the single biggest factor in household wealth.

We begin by noting that there are good reasons to be optimistic. The Clean Air Act Amendments and other secular trends have led to significant air quality improvements (Colmer et al. 2020), and those improvements were larger in Black communities thereby reducing the Black-White exposure gap (Currie et al. 2023, Sager & Singer 2023). Whether this also reduced disparities in housing values, however, depends not only on relative exposure, but also on whether this amenity capitalizes similarly across homeowners of different race. To analyze this relationship, we combine three types of administrative data, including address-level housing characteristics and transaction information from Zillow, homeowner characteristics including race from HMDA (2022), and neighborhood characteristics from the Census, with fine particulate matter pollution exposure (PM2.5) in the US at a fine level of spatial resolution. Our main sample includes around 9 million transactions where we observe seller race in the contiguous US to estimate the relationship between air quality and house prices by seller race.

Our estimation strategy relies on a hedonic design that controls for observed house and neighborhood characteristics, as well as unobserved time-invariant property characteristics or amenities that differ across communities and race at the most granular administrative level of Census blocks (around 53 individuals on average).[2] We allow for unobserved flexible trends at the state or county

[1]Capitalization could be driven by the buyer or seller side. Note that even if air quality were not a salient feature on the buyer side, capitalization could be driven by the seller side, where air quality may be more easily inferred, e.g. some residents detecting dark smoke plumes or experiencing breathing difficulties and moving out as in Tiebout sorting (Banzhaf & Walsh 2008). It has been shown that air pollution capitalizes in house prices at least since Ridker & Henning (1967), with mounting evidence over the past two decades (e.g. Bayer et al. 2009, Grainger 2012, Bajari et al. 2012, Currie et al. 2015, Bento et al. 2015, Bayer et al. 2016, Sager & Singer 2023).

[2]In this context, a related approach to the widely used hedonic design (e.g. Chay & Greenstone 2005, Bajari et al.

level and by degree of urbanicity. A main challenge is that changes in pollution are likely to be correlated with changes in other amenities that affect house prices, such as economic activity. We overcome this challenge using a well-established instrumental variable strategy that exploits Clean Air Act rules that led to plausibly exogenous differential changes in air quality across counties (Chay & Greenstone 2005). We follow Sager & Singer (2023) to account for the bias in the first stage arising from confounding trends between treated and control units due to differences in pre-sample pollution, and allow for heterogeneous effects within nonattainment areas based on pre-sample pollution levels (Auffhammer et al. 2009, Bishop et al. 2023). To address concerns about endogenous sorting during our sample, we fix neighborhood characteristics at the beginning of our sample, show that changes in air quality do not affect sorting into neighborhoods based on race,[3] and show robustness to using a sub-sample that focuses on areas with little change in racial composition during our study period.

Our first set of results show that a one-unit decrease in $PM_{2.5}$ increases house prices by 6.3%, a figure consistent with previous estimates (Bento et al. 2015, Sager & Singer 2023), but this average figure masks considerable heterogeneity across racial groups. While the Non-Hispanic White (NHW) pollution capitalization rate is 7.5%, the Black capitalization rate is only 5.3%, a difference of 42% in relative terms, and over 100% in absolute terms since price levels are higher for NHW homeowners.[4] Importantly, the results are almost unchanged when conditioning on property size or seller income fully interacted with air quality. This implies that the disparity by race persists irrespective of the stance one takes on whether these characteristics should be viewed as the result of some form of discrimination or that discrimination should be defined after conditioning on them.[5] Despite the larger decrease in $PM_{2.5}$ for Black homeowners (6.6 units) relative to NHW homeowners (4.9 units) from 2000-2019, the much lower Black capitalization rate per unit of cleaner air means that the Black-White housing-value gap actually *increased* as a result of those pollution reductions. To be clear, both groups still experience gains from cleaner air, but at differential rates. Indeed, if Black homeowners had the same capitalization rate as their NHW counterparts, their home values

2012) are structural equilibrium sorting models (e.g. Bayer et al. 2009, Depro et al. 2015, Bayer et al. 2016). Cassidy et al. (2024) find no differential sorting along socio-economic dimensions as a response to waste cleanup across the US and similar estimates as with a hedonic approach.

[3] We acknowledge that the ideal test for sorting in response to changes in air quality requires not only data on changes in population shares, but also knowledge of source-destination movement matrices (Depro et al. 2015).

[4] Capitalization rates can vary because property characteristics, including amenities and the identity of the seller, are valued as a bundle rather than independently (Rosen 1974); that is, complementarities usually exist among characteristics within the bundle.

[5] We show that this is in part driven by our identification strategy that exploits shocks to air quality. As one might expect, if we conduct an unconditional analysis of house price disparities, controlling for income or property size affects the measured disparity significantly. Focusing on exposure itself, Colmer et al. (2024) find that equalizing the Black-White income gap would only reduce the pollution exposure gap by 10%.

would have been 16% higher by the end of 2019.

Since our results with observed seller race are based on a sample that is restricted to properties or transactions that involved a mortgage or loan, we also show results using seller race predicted by a neural network algorithm based on first and surnames. Using this sample that encompasses five times the observations, we find that our results are externally valid and, based on an analysis of measurement error due to prediction, conclude that the difference in capitalization rates may, if anything, be even larger. We also show that our results by seller race are not driven by homophily in transactions. Simultaneously including observed or predicted buyer race does not explain the difference in capitalization rates by seller, and if anything, Black buyers pay a premium on air quality improvements, consistent with the literature focused on buyer race (Bayer et al. 2017, Higgins 2023). This asymmetry between the discount received by Black sellers and the premium paid by Black buyers for air quality improvements reveals a potential double jeopardy in terms of the welfare of Black homeowners.

We probe the mechanisms underlying our results by distinguishing between direct and systemic discrimination, inspired by Bohren et al. (2023).[6] While the lines between the two can be blurry, systemic discrimination generally refers to discrimination that occurs at a societal level as a result of institutional, cultural, or persistent historical practices that unfairly privilege one group over another. Since disadvantages can accumulate over time, these effects are pernicious and difficult to precisely measure (Schell et al. 2020). For example, historical practices of "redlining" that limited finance based on the racial composition of neighborhoods led to underinvestment in these communities that persists today (Aaronson et al. 2021). Direct discrimination are disparities by race in a transaction conditional on relevant characteristics, as, for example in correspondence studies. Defining systemic discrimination is more nuanced and requires a "point of reference" (Bohren et al. 2023). At one extreme, the reference point could be defined as the moment of the transaction, in which case one would condition on every characteristic that differs between racial groups. This is tantamount to assuming that the only form of discrimination is direct. At the other extreme, one could fix the reference point going back for centuries. This implies that observed differences in characteristics across racial groups that are due to historic discrimination, unfair social or economic treatment, or biased political practices whose impacts persist (e.g. slavery, segregation etc.) represent a form of systemic discrimination.[7]

[6]For example, employers that are formally race-blind in their criteria (direct discrimination) may still implicitly discriminate against certain racial groups if those racial groups have on average less access to e.g. signaling devices or networks due to historically persistent effects of discrimination (systemic discrimination).

[7]For example, experimental evidence shows that average preference differences across gender for salient dimensions such as for risk may not be innate, but shaped by societies (Gneezy et al. 2009).

In this paper, we take a more intermediate position, defining systemic discrimination as one that arises due to the racial composition of neighborhoods, conditional on seller race, and affects the capitalization rate of air quality. Racial neighborhood composition can, for example, be correlated with differences in access to complementary amenities that impact the capitalized value of clean air across communities (e.g. green outdoor spaces), but could also capture hard-to-measure objective or subjective factors that could affect the value of clean air (e.g. opportunities). While home sellers of all races can live in all types of neighborhood compositions, Black sellers tend to be, on average, in neighborhoods with a larger share of Black residents, in part due to historical and persistent practices that constrain options for Black homeowners as well as investments in those communities (Ahmed & Hammarstedt 2008, Ewens et al. 2014, Akbar et al. 2022, Christensen et al. 2022).

We define direct discrimination as the differences in capitalization that are driven by seller race directly, conditional on racial neighborhood composition. As described above, we obtain almost identical results when conditioning on interacted seller income. Here, direct discrimination can but does not need to be of a taste-based nature (e.g. racial animus), it could also be statistical (Phelps 1972) or paternalistic (Buchmann et al. 2024). It could come from buyers who are the counterpart in transactions, but importantly, as the housing market is highly intermediated, it can also be driven by real estate agents (Christensen et al. 2022, Christensen & Timmins 2022). There is also evidence of discriminatory mortgage lending practices and home valuations (Munnell et al. 1996, Charles & Hurst 2002).[8]

By simultaneously interacting air quality with neighborhood racial composition and seller race, we decompose the capitalization rate disparity into a systemic and direct discrimination component. Our decomposition suggest that approximately 40% of the difference in capitalization rates is driven by systemic discrimination via neighborhood racial composition, and 60% by direct discrimination via seller race. We also show robustness to alternative conceptions of systemic discrimination by controlling for other neighborhood characteristics (captured, for example, by baseline median neighborhood house value), instrumented and fully interacted with pollution. Including these controls is tantamount to assuming those characteristics are not the result of systemic discrimination and in the terminology of Bohren et al. (2023) constitute an alternative reference point. Controlling for a rich set of neighborhood observables decreases measured systemic and therefore also total discrimination by at most 20% and 9% respectively, yielding a similar split of 35% to 65% between systemic and direct discrimination.[9]

[8] As an illustrative recent example, a Black couple filed a lawsuit after they received substantially higher valuations from an appraiser when a White colleague posed as the homeowner (US District Court 2022).

[9] It is noteworthy that even in the extreme case, where one completely disavows the notion of systemic discrimination, a sizable 60% of the capitalization rate differences remain due to direct discrimination.

In the language of Bohren et al. (2023), systemic discrimination can stem from technological differences (other tangible amenities from neighborhood composition) or informational distortions (biased and subjective perceptions or distorted signals). The fact that controlling for other interacted neighborhood characteristics (including greenness, neighborhood income or housing supply elasticities) has little impact on measured systemic discrimination due to neighborhood racial composition is consistent with the channel of informational distortions rather than technological differences, although we cannot conclusively rule out technological differences as there might be tangible differences that are hard to measure.

Finally, if our results are indeed driven by discrimination, we would expect areas with more racial residential segregation to show large disparities in capitalization rates, as discrimination is typically higher in such areas (Enos & Celaya 2018, Ananat 2011). We construct an index of racial residential segregation within Census tracts, and based on quartile of segregation sample splits, show that capitalization rate disparities are indeed much larger in more segregated areas, driven by both direct and systemic discrimination, but predominately by the former.

This paper contributes to the growing literature on environmental justice (Banzhaf et al. 2019), and connects the literature on housing prices and racial groups (Aaronson et al. 2021, Kahn 2021, Kermani & Wong 2021, Akbar et al. 2022, Higgins 2023, Diamond & Diamond 2024) with that on housing prices and pollution (Chay & Greenstone 2005, Bayer et al. 2009, Bajari et al. 2012, Grainger 2012, Currie et al. 2015, Bento et al. 2015, Bayer et al. 2016, Sager & Singer 2023). Our findings that the pollution capitalization rate differs by race provides novel insights into how the marginal effects of pollution exposure differ across the population, which is critical for understanding the distributional effects of air quality policies (Hsiang et al. 2019). Furthermore, our analysis of mechanisms is, to our knowledge, the first to unpack the relative roles of direct discrimination and systemic racial discrimination vis-a-vis neighborhood amenities. Our findings are consistent with recent evidence on discriminatory pathways, such as racial steering in the housing market Christensen & Timmins (2022, 2023), Christensen et al. (2022), racial disparities in mortgage lending and refinancing practices (Munnell et al. 1996, Charles & Hurst 2002, Ambrose et al. 2021, Bhutta et al. 2022), and lower offers for Black sellers in other marketplaces (List 2004, Doleac & Stein 2013, Barnes & Stein 2024).

The paper proceeds with a description of the data in Section II. We then discuss our empirical strategy in Section III. We show all of our results and discuss mechanisms in Section IV before we conclude in Section V.

II. Data and Descriptives

A. Transaction-Level House Price Data

We use two databases from Zillow (2020) that allow us to obtain house prices and basic hedonic characteristics at the transaction level from 2000-2019 for the contiguous US. The first database are transactions (ZTransaction) sourced from county recorder's offices with information including transaction price (deflated to 2012 US$), type of deed and date of sale. The second database contains hedonic information (ZAssessment), sourced from county assessor's offices, including square footage (SQFT) and geolocation.[10] For counties that report details such as transaction price, this should capture the universe of transactions, but not all counties report prices, e.g. few do in Texas (see spatial coverage below).[11] Importantly, we only use arm's length transactions and residential properties, dropping transactions such as refinancing or foreclosures, and use historic assessment data to reduce missing values of hedonic information (for details on data cleaning see Appendix A.4). Since we use log prices and state-by-year or county-by-year fixed effects for our analysis, our data are effectively deflated with state or county deflators. We map the geolocation of each transacted property to US Census blocks using the 2010 US Census boundaries.

B. Observed and Predicted Race and Income at Transaction Level

The Zillow data contains no information on buyer or seller race. We use two separate approaches to obtain observed and predicted race respectively for each transaction.

First, for observed race we use administrative data from HMDA (2022) that contains information on the universe of mortgage applications from all banks, savings associations, and credit unions with assets above a threshold ($39 million in 2010).[12] Importantly, HMDA data contains information on race/ethnicity and income of mortgage applicants. We use three racial groups, Black and Non-Hispanic White ("NHW") Americans (as in Currie et al. (2023)), and a third group for Other Americans ("Other"). We match Zillow with HMDA data based on common variables including Census tract, year of transaction, loan amount rounded to the nearest thousand and name of lending institution.[13] For joint sellers or buyers, we assign the race as Black or NHW if at least one of the joint sellers/buyers is Black or NHW, and the other is not of the other race (i.e. no mixed race Black-NHW joint applicants, but one is allowed to be of other ethnicity).

[10]We only use property location and size, as other hedonic information is often missing.

[11]Much of our analysis relies on within county variation.

[12]In 2017, 92% of originated mortgage loans nationwide were covered in HMDA (Consumer Financial Protection Bureau 2018).

[13]In the rare occasion that there are multiple matches between Zillow and HMDA, we use the lender name with the best fuzzy string match within each Census tract, year, loan amount correspondence.

We are primarily interested in seller race. To obtain seller race for a particular transaction we actually don't require a HMDA entry for the corresponding transaction. Instead, we need to match the seller of this specific transaction to a previous transaction on the same property where that seller was a buyer or borrower and thus recorded in HMDA. We accomplish this using the first and surnames of sellers and previous buyers/borrowers of the same property and fuzzy string matching where at least two of three state-of-the art algorithms agree.[14] We dramatically improve our success rate of finding a previous transaction from a specific seller by also including all previous non-sales transactions for this step, such as refinancing, home improvements, or HELOCs, as these transactions are contained in both Zillow and HMDA data.[15] With the identified previous transaction of a specific seller, we can match these previous transactions to HMDA to obtain seller race. For obtaining buyer race, we can match the transaction to HMDA and use recorded buyer race directly, provided that the transaction involved a qualified mortgage.

We further restrict our sample by requiring a minimum match quality on lender name between Zillow and HMDA. Our baseline version uses a cutoff of 60% bi-gram match resulting in 9.2 million observations with observed seller race, and we show robustness to stricter cutoffs at 75% and 90%, which reduces observations to 8.1 and 5.2 million, respectively.[16] The number of observations where we observe both seller and buyer race is 2.6 million.[17]

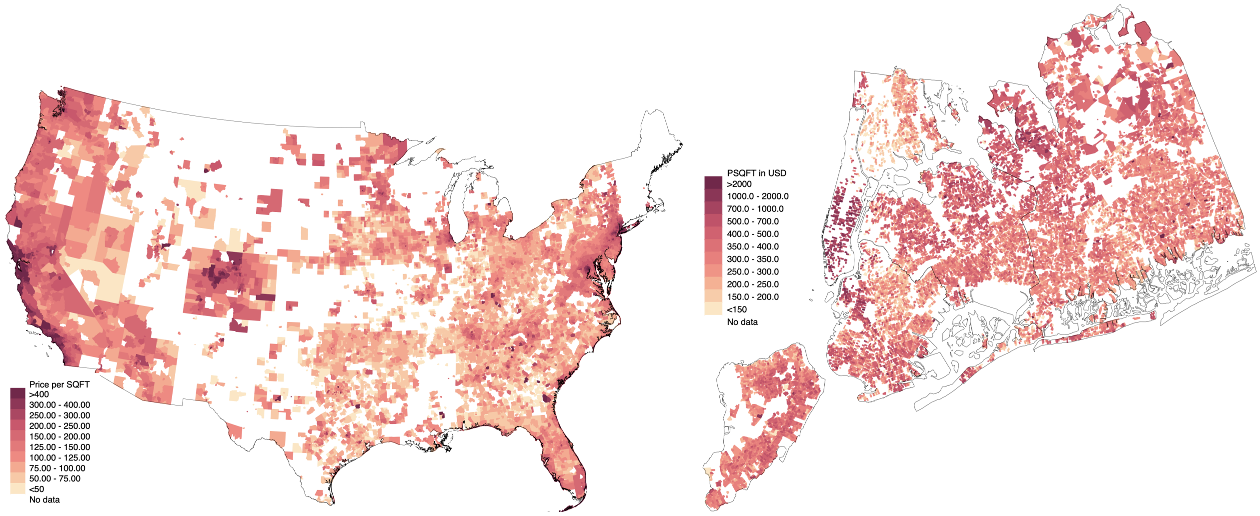
Second, as an alternative to observed race, we use predicted buyer and seller race. One shortcoming of using observed race from HMDA data is that we can only include transactions on properties that involved a mortgage from a reporting lender (for sellers: previously involved financing on same property). Therefore we also construct predicted race of buyers and sellers for each transaction based on full names of buyers and sellers. In particular, we use a neural network algorithm trained by Xie (2022) who uses Florida voter registration data with a focus on minority groups. The algorithm calculates probabilities for belonging to different racial groups for each first and surname pair of each buyer and seller. We classify a buyer or seller as belonging to a racial group when

[14]We use the Jaro-Winkler, the Jaccard and the Damerau-Levenshtein distances from van der Loo (2014) for fuzzy string matching. For joint buyers or sellers we allow for swaps in who is listed as primary or secondary buyer/seller.

[15]We use all transactions from 1992 to identify sellers that are previous buyers/borrowers. In case we have multiple matched previous transactions per seller, we use an iterative procedure that prioritizes those matches for which we have non-missing reported race and income on previous transactions and are closer to the date of the eventual sales transaction. We deflate recorded seller income to 2012.

[16]Note that observations reported in regression tables may be slightly lower as fully partialed out observations through fixed effects are not counted.

[17]The number of observations where we have observed buyer race irrespective of observing seller race is 12.3 million. As a point of comparison: Of the 64.7 million transactions in the Zillow data in the continental US with non-missing transaction price and square footage, 48% involve a mortgage with information on loan amount. Of these transactions we match 49% to the HMDA data based on Census tract, year and loan amount to obtain buyer race (i.e. for 24% of all observations). This is a similar ratio as for San Francisco (Bayer et al. 2016) or Florida alone (Graff Zivin, Liao & Panassie 2023). Applying our match quality thresholds regarding lender name and thresholds for defining race including no mixed race applicants reduces this to 19% of total observations for buyer race.



(a) Price/SQFT aggregated up to Census tracts: USA (b) Price/SQFT aggregated up to Census blocks: NYC

Figure 1: Spatial distribution of price per SQFT

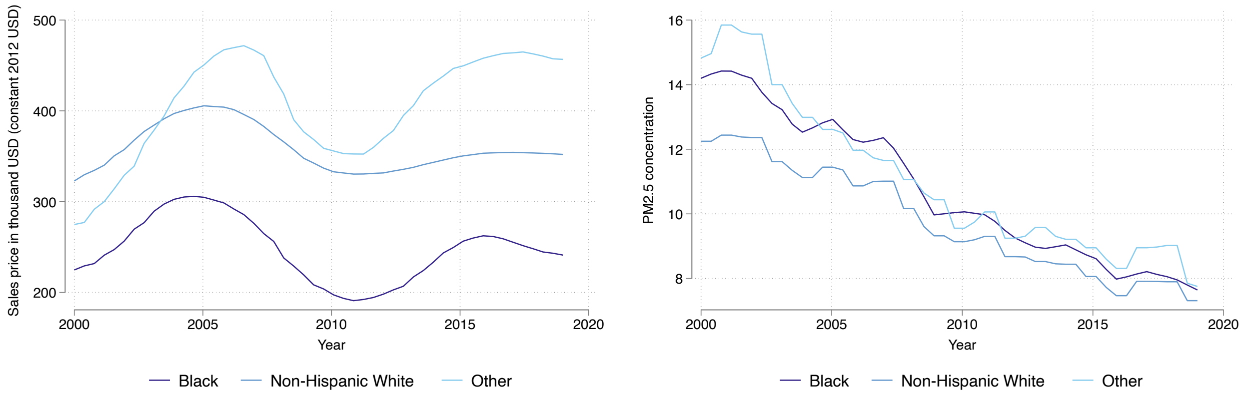
Notes: Panel (a) and (b) show the spatial distribution of price per SQFT in our sample pooled across time. Panel (a) aggregates up to Census tract averages. Panel (b) shows the variation around New York City aggregated to the more granular Census block level. All monetary values are deflated to 2012 US$.

the probability of belonging to a single racial group is at least 70% (and show robustness to different thresholds), allowing us to identify predicted seller race for 40.1 million transactions, and both predicted seller and buyer race for 23.7 million transactions. Overall the accuracy of the prediction (share of correct predictions in observations) is 78%, with 94%, 79%, 84% accuracy for Black, NHW, and Other respectively, measured in the sample where we have both predicted and observed race. The accuracy conditional on observed race (true positives divided by all positives) is 75%, 74%, 96% respectively. To provide additional reassurance about the quality of our prediction, we test how well the prediction performs by comparing our main estimates based on predicted race for the observations where we also observe race, before showing estimates using the larger sample with predicted race only.

The advantage of using observed seller race is that we have no measurement error, and the advantage of using predicted race is that we can include transactions which are not linked to a mortgage resulting in a much larger sample.

C. Pollution Data and Clean Air Act Nonattainment Areas

We use annual data on fine particulate matter concentrations ($PM_{2.5}$) at the 1km-by-1km resolution from van Donkelaar et al. (2021), which is constructed by combining ground-based measurements, satellite images and chemical transport models. We map the $PM_{2.5}$ data into Census blocks using



(a) Sales price by racial group

(b) PM2.5 concentration by racial group

Figure 2: Evolution of prices and PM2.5 by seller racial groups

Notes: Panel (a) shows the evolution of average sales price (real 2012 US$) by racial group. Panel (b) shows the evolution of average PM2.5 concentrations of home sellers by racial group. All monetary values are deflated to 2012 US$.

the closest pollution grid point to the Census block centroid. To identify the effect of pollution on house prices, we make use of the 2005 Clean Air Act rules for $PM_{2.5}$, following Sager & Singer (2023) who provide a detailed account of this regulation. We use the 208 counties from the EPA (2005) that became regulated in 2005, because they did not meet the necessary threshold of 15 $\mu g/m^3$ for the three-year average of annual mean $PM_{2.5}$ concentrations. These counties were assigned into nonattainment, and were subject to stricter action to reach air pollution standards from the Environmental Protection Agency.

D. Neighborhood Racial Composition and Additional Place-Based Data

We combine our transaction information with data from the 2000 Census on population counts by race (Manson et al. 2022). We calculate the share of Black, NHW and Other at the Census block level in 2000 and the share of that block that is urban/rural. Census blocks are the most granular administrative unit, and in 2000 there were 5.3 million non-empty Census blocks in the contiguous US with an average population of 53 individuals and 77% of housing units owner-occupied. We use the first year of the sample for neighborhood characteristics throughout to exclude variation coming from spatial sorting during our sample.

We use additional information on characteristics of neighborhoods. At the Census block level this includes vegetation indices in 2000 (NDVI and EVI) derived from satellite imagery at the 1km-by-1km resolution based on Didan (2021), which provide a proxy measure for local green spaces like parks. At the Census block group level (1315 individuals per block group on average) this includes the share of the population in poverty, median household income, median personal income,

Table 1: Summary statistics in sample: averages of selected variables by racial groups

Group	PM2.5	Price (th.)	SQFT	HH income	Med income	Poverty	Spop B	Spop NHW	Spop OTH	Spop URB
Black	10.10	251.2	1798	98.6	48.06	0.12	0.35	0.47	0.18	0.92
NHW	9.07	357.0	1918	122.5	56.16	0.07	0.05	0.81	0.14	0.85
Other	10.95	418.4	1781	116.9	56.12	0.10	0.07	0.53	0.40	0.94
Total	9.28	357.9	1900	121.0	55.81	0.08	0.06	0.77	0.17	0.86

Notes: The table show averages of the indicated variables by racial group based on the sample used in estimation. PM2.5 is in $\mu g/m^3$, "Price" is in thousand US$, "HH income" stands for seller income at the transaction level in thousand US$, "Med income" stands for median income of the Census block group in 2000 in thousand US$, and all monetary values deflated to 2012 US$. "Poverty" stands for poverty rate at the Census block group in 2000, and Spop B, Spop NHW, Spop OTH, and Spop URB stand for share of population in Census block in 2000 that is Black, NHW, Other, and urban. Appendix Table A.1 provides further summary statistics.

median rent and median house values from the 2000 Census, all deflated to 2012 US$. At the Census tract level (4319 individuals per tract on average), we use the proportion of land that is developed with high intensity ("BuiltHigh") from NHGIS (Manson et al. 2022), that is with at least 80% share of impervious surfaces (e.g. asphalt and concrete), derived from the National Land Cover Database in 2001. Based on Chetty et al. (2018), we construct economic opportunities at the tract level using the average percentile in the 2014-2015 income distribution for children born between 1978-1983. We use housing supply elasticities at the tract level from Baum-Snow & Han (2024). We calculate an index of racial residential segregation within tracts based on the 2000 Census that measures how uniformly residents of different races are mixing across Census blocks within Census tracts (e.g. high index if racial groups are living in separate blocks), following Reardon & Firebaugh (2002). At the county level (89,927 individuals per county), we measure arrest rates from the FBI (2006) in 2000 (results are similar with crime rates).

E. Descriptive Statistics on Housing and Pollution Disparities

Figure 1a provides an overview of the spatial coverage of our data where we observe seller race, showing price-per-sqft (PSQFT) aggregated to the Census tract averages for better visualization across the entire US. This masks a large degree of spatial granularity within Census tracts. Figure 1b show the variation in a few counties around New York City, aggregated to the Census block level instead. This illustrates that, even across a few city blocks, house prices can vary substantially due to differences in amenities among other things.

Figure 2a shows the house price gaps and how real house prices evolved differently by observed seller race. The housing crisis hit Black and Other sellers particularly hard, consistent with Faber & Ellen (2016). While prices recovered for Other relative to NHW homeowners, the recovery for Black homeowners was more modest, resulting in a persistent gap of house prices between Black and NHW homeowners.

Figure 2b shows falling PM2.5 concentrations by observed seller race. Black homeowners faced higher pollution levels on average, but the gap between Black and NHW homeowners narrowed over time. This is consistent with some recent empirical work focused on environmental justice (Jbaily et al. 2022, Currie et al. 2023), and shows that this relationship also holds for the subset of the general population who own a home that is sold during our study period.

Table 1 shows summary statistics by observed seller race. Black homeowners sell slightly smaller houses and have a lower income. They also live in neighborhoods (block groups) that are lower income, have a higher poverty rate, and are characterized by a significantly larger share of Black population relative to NHW. Appendix Table A.1 shows more detailed summary statistics for all variables used in the analysis.

III. Empirical Strategy

To formally explore how pollution reductions affect home sales prices P_i across racial groups, we run regressions at the transaction level i in year t, Census block b, county c, state s, and racial group j:

$$\begin{aligned}\log(\mathrm{P}_i) =& \alpha \mathrm{PM}_{bt} + \sum_j \left(\beta_j S_i^j \mathrm{PM}_{bt}\right) + \sum_j \left(\gamma_j Spop_b^j \mathrm{PM}_{bt}\right) \\ &+ \boldsymbol{\delta}_1 \boldsymbol{X}_i + \boldsymbol{\delta}_2 \boldsymbol{X}_i \mathrm{PM}_{bt} + \delta_3 \boldsymbol{W}_b \mathrm{PM}_{bt} + \boldsymbol{\xi}_{jb} + \boldsymbol{\lambda}_{(s \text{ or } c)t} + \sum_t \left(\tau_t Urb_b t\right) + \varepsilon_i\end{aligned} \tag{1}$$

where PM_{bt} denotes pollution concentrations of PM2.5 in $\mu g/m^3$, S_i^j race of seller in a transaction, and $Spop_b^j$ the racial composition of the block (shares). We later also enrich this specification to include buyer race. $\boldsymbol{X}_i$ is a vector of property characteristics (including property fixed effects for part of the analysis) and $\boldsymbol{W}_b$ a vector of neighborhood characteristics, interacted with PM_{bt}, which we discuss later.[18]

We use seller-race-by-block fixed effects $\boldsymbol{\xi}_{jb}$ that net out time-invariant differences in average house prices by seller race. We allow these absorbed differences in levels to differ by block, as different neighborhoods could have differential average house quality across racial groups, which may otherwise introduce spurious correlation with air quality averages. That is, we only rely on variation in the housing *returns* of air quality in our analysis, using our shock to air quality to identify differences in pollution capitalization rates. These fixed effects also capture all other time-invariant amenities and other block characteristics.

State-by-year or county-by-year fixed effects $\boldsymbol{\lambda}_{(s \text{ or } c)t}$ allow for flexible confounding trends dif-

[18]Note that uninteracted $\boldsymbol{W}_b$ would be absorbed by the $\boldsymbol{\xi}_{jb}$ fixed effect.

ferentiated by state or county, including unobserved changes in local labor markets. Bayer et al. (2009) argue that the larger the unobserved moving costs are, the more attenuated the estimated hedonic willingness-to-pay for air quality. Our county-by-year fixed effects also help to reduce the impacts of moving cost differences as moving costs within county are lower than outside of the county (or state). Note that differences in moving costs across race that could affect our coefficients of interest are likely negligible compared to the level of moving costs that would primarily affect α. Finally, heterogeneous slopes of the urban share of block by year $\sum_t (\tau_t Urb_b t)$ allow for confounding trends based on the urbanicity of neighborhoods.

We fix all of our neighborhood characteristics, including racial composition of the block, at the start of our sample period in 2000 to isolate the source of temporal variation that comes from pollution. Changes in racial population shares over time as well as changes in house prices are at least partially driven by sorting. This concern may be partially addressed as racial compositions of neighborhoods are relatively persistent (Bayer et al. 2016). As in Greenstone & Gallagher (2008), benefits from improvements in amenities affect the benefits to incumbent property owners, irrespective of subsequent sorting by marginal willingness to pay for air quality.[19] Note that sorting in response to air quality changes is less problematic due to our instrument for air quality described below. Moreover, Table A.2 shows that changes in pollution overt time (relative or absolute) are not significantly correlated with changes in the share of the block population that is Black, with a ten percent increase in pollution increasing the share of Black population by 0.001. Finally, to test the robustness of our approach, we use the 2020 Census and calculate the change in population shares for each racial group at the block level to focus only on those blocks where racial composition changed little.

A. Instrumenting Air Pollution with Regulatory Nonattainment

Despite the use of fixed effects, changes in air pollution are likely to be correlated with changes in unobserved amenities that also impact house prices. For example, changes in economic activity or infrastructure are likely to drive both, pollution and house prices. We therefore use the 2005 $PM_{2.5}$ Clean Air Act regulation that induced changes in pollution in nonattainment counties as an instrument. The identifying assumption is that, conditional on our fixed effects and controls, the regulation only shifted pollution, and no other unobservables correlated with house prices. We follow Sager & Singer (2023) to address bias from underlying trends that differ by baseline pollution and attainment status by including pre-period pollution levels from 1998-99 (PMpre_b) interacted

[19]Individuals with a higher marginal willingness to pay for air quality may want to move to areas with relatively improved air quality, but also drive up house prices as a result.

with year dummies as part of our controls $\boldsymbol{X}_i$.[20]

As Auffhammer et al. (2009) show, nonattainment effects are often stronger in those parts of nonattainment areas that are initially more polluted. To allow for such heterogeneous effects, we additionally interact nonattainment status with pre-period pollution concentrations PMpre_b (see also Bishop et al. (2023)). We include instruments for each term that contains PM_{bt} in Equation 1. The first stage, for example, for PM_{bt} itself, is:

$$\begin{aligned} \text{PM}_{bt} = & \theta_0 \text{NA}_{bt} + \theta_1 \text{NA}_{bt} \text{PMpre}_b \\ & + \sum_j \left(\eta_j S_i^j \text{NA}_{bt} + \rho_j S_i^j \text{NA}_{bt} PMpre_b \right) + \sum_j \left(\phi_j A_b^j \text{NA}_{bt} + \kappa_j A_b^j \text{NA}_{bt} PMpre_b \right) \\ & + \boldsymbol{\omega}_1 \boldsymbol{X}_i + \boldsymbol{\omega}_2 \boldsymbol{X}_i \text{PM}_{bt} + \omega_3 \boldsymbol{W}_b \text{PM}_{bt} + \boldsymbol{\psi}_{jb} + \varsigma_{(s \text{ or } c)t} + \sum_t (\sigma_t Urb_b t) + \mu_i \end{aligned} \tag{2}$$

Our set of instruments vary at the block level, but we allow for spatial correlation by clustering standard errors at the tract level, which contains an average of 151 blocks.[21] Appendix Table A.4 shows the first stages for the three endogenous variables in our initial specification using only seller race without neighborhood composition. Reassuringly, the exogenous interaction between nonattainment and racial groups affect the corresponding endogenous interactions between change in $\text{PM}_{2.5}$ and racial groups. The Kleibergen-Paap F statistic is high (≥ 100) for the vast majority of our results and reported in our main tables.

IV. Results

A. Disparities in Pollution Capitalization Rates

We begin by showing results from estimating versions of Equation 1 that omit neighborhood racial composition in Table 2. Column 1 also omits seller race interactions, and shows that air quality capitalizes into house prices. The omitted variable bias is sizable and positive in the OLS estimates in Panel (a) when comparing with the results in Panel (b) that use our regulatory instruments. This is consistent with the notion that economic activity is accompanied by beneficial amenities that push up house prices, while simultaneously increasing pollution. A one-unit decrease in $\text{PM}_{2.5}$ increases house prices by 6.3%.[22] This corresponds to an overall elasticity of -0.58, broadly in line with Sager

[20]Note that this also helps to address concerns over shifting hedonic price functions that can conflate willingness to pay with such shifts in price functions (Kuminoff & Pope 2014), as this effectively controls for the changing value of baseline air quality, similar to Banzhaf (2021).

[21]This is more conservative than clustering at the block group level in Bishop et al. (2023), who use a similar instrument by interacting nonattainment with historic pollution levels to examine the impacts of pollution on dementia.

[22]Since the outcome is in logs, the semi-elasticity is calculated as $\exp(0.061) - 1$, and the elasticity is calculated as $(\exp(0.061) - 1) * 9.23$ using the overall endline period mean of $\text{PM}_{2.5}$.

Table 2: Capitalization rates with observed race of seller

	Transaction Price (log)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel (a) OLS results:								
PM2.5	-0.018***	-0.018***	-0.014***	-0.014***	-0.011***	0.026***	0.002*	0.015***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.007)	(0.001)	(0.002)
PM2.5 * Black seller		0.036***	0.038***	0.038***	0.042***	0.038***	0.034***	0.036***
		(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
PM2.5 * Other seller		0.000	0.007***	0.008***	0.006***	0.007***	-0.000	0.003***
		(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
log(SQFT)	0.519***	0.519***	0.520***	0.498***		0.569***	0.496***	0.519***
	(0.005)	(0.005)	(0.005)	(0.005)		(0.012)	(0.005)	(0.005)
log(HH income)				0.060***			0.099***	
				(0.001)			(0.001)	
PM2.5 * log(SQFT)						-0.005***		
						(0.001)		
PM2.5 * log(HH income)							-0.004***	
							(0.000)	
PM2.5 * PM2.5								-0.001***
								(0.000)
Panel (b) IV results:								
PM2.5	-0.061***	-0.061***	-0.070***	-0.071***	-0.060***	-0.239***	-0.093***	-0.019***
	(0.003)	(0.003)	(0.005)	(0.005)	(0.006)	(0.022)	(0.004)	(0.007)
PM2.5 * Black seller		0.021***	0.024***	0.025***	0.021***	0.025***	0.025***	0.023***
		(0.002)	(0.002)	(0.002)	(0.005)	(0.002)	(0.002)	(0.002)
PM2.5 * Other seller		0.001**	0.004***	0.004***	0.003***	0.005***	0.004***	0.003***
		(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
log(SQFT)	0.520***	0.520***	0.520***	0.498***		0.329***	0.497***	0.520***
	(0.005)	(0.005)	(0.005)	(0.005)		(0.028)	(0.005)	(0.005)
log(HH income)				0.060***			-0.001	
				(0.001)			(0.006)	
PM2.5 * log(SQFT)						0.021***		
						(0.003)		
PM2.5 * log(HH income)							0.007***	
							(0.001)	
PM2.5 * PM2.5								-0.001***
								(0.000)
Census block by Black seller FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census block by Other seller FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Property FE					Yes			
State by year FE	Yes	Yes					Yes	Yes
County by year FE			Yes	Yes	Yes	Yes		
Urban by year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,745,962	7,745,962	7,743,104	7,376,157	2,297,704	7,743,104	7,379,025	7,745,962
First-stage F (KP)	680.555	279.610	249.262	248.774	200.619	276.349	19.529	10.218

Notes: The table shows regression estimates using OLS in Panel (a) and IV in Panel (b) with log transaction price as the dependent variable. The columns show results with varying controls and fixed effects as indicated. "HH income" means seller income at the transaction level, and SQFT stands for square footage of the property. Standard errors are clustered at the Census tract level. *** Significant at the 1 percent level, ** significant at the 5 percent level, * significant at the 10 percent level.

& Singer (2023) in 2001-13 and Bento et al. (2015) in the 1990s.

Column 2 adds interactions with seller race. Panel (b) shows that the capitalization rate for Black homeowners is lower by one third, which is robust throughout our analysis (we turn to visualizations in Figure 3 later). This implies that racial house price disparities not only exist in levels, but also in house price changes resulting from plausibly exogenous changes in amenities, here air quality. The capitalization rate for Other homeowners is similar to that of NHW homeowners throughout, so we will focus on the Black-NHW gap in the remainder.

In Column 3 we include county-by-year instead of state-by-year fixed effects. One concern may be that our instrument also affects local industry or labor markets (Greenstone 2002, Walker 2013), potentially violating the exclusion restriction. As labor markets are usually defined at the county or MSA level, using county-by-year fixed effects provides reassurance on the validity of our instruments, as we are only exploiting the heterogeneous policy effects within nonattainment counties, rather than the policy effect across attainment and nonattainment counties. Another concern is that unobserved moving costs attenuate the willingness-to-pay for air quality (Bayer et al. 2009). Both concerns affect primarily our estimate of the uninteracted $PM_{2.5}$ and would bias it upward. Indeed, when controlling for county-by-year fixed effects, this estimate becomes slightly more negative, but our estimated disparity in pollution capitalization rates remains nearly unchanged at one third. For the remainder, we continue to use county-by-year fixed effects.

B. Conditioning on Further Seller or Property Characteristics and Nonlinearities

So far, the only property control included is log(SQFT). While homeowners are generally drawn from higher SES groups than non-homeowners, we also see income differences among homeowners along racial lines. In particular, Table 1 shows that Black sellers have a lower income on average than NHW sellers, and this could also affect house prices. In Column 4 of Table 2 we include seller income from HMDA data, which hardly affects our estimates. There may, however, still be several confounding property characteristics that are unobserved, such as the configuration of rooms or quality of the house. To address this concern, we include property fixed effects in Column 5 that accounts for average price and characteristics of each home, but requires repeat sales in the data. This reduces our sample size by two thirds, but the results are highly robust. It is also worth noting that since we estimate capitalization rate differences in relative terms with log prices as the dependent variable, we should, at least partially, address differences in level effects from baseline home values.

While this may control for differential property characteristics across racial groups, a remaining concern is that these property characteristics may themselves be driving different capitalization rates from air quality and confound our main estimate, i.e. we know that Black homeowners have smaller homes, on average, so it could be that SQFT is driving the difference in capitalization rates. In Columns 6 and 7 we interact log(SQFT) and log seller income respectively with $PM_{2.5}$. While these characteristics indeed affect capitalization rates themselves (to a small degree), they do not confound the estimated capitalization rate differences between Black and NHW sellers. While there may be other seller characteristics that we cannot observe, income is likely one of the most relevant, if not the most relevant, characteristic one may want to condition on to disentangle whether it is race itself or correlated characteristics driving the difference in capitalization rates. Similarly, size of the property is likely the most important property characteristic. Since we obtain almost identical results on the racial disparity, irrespective of whether we condition on the most salient characteristics (income or property size) interacted with $PM_{2.5}$, these results point towards some form of discrimination, which we will unpack later. While the fact that controlling for income or property size does not affect our estimates may seem surprising, it is worth noting that our identification strategy relies on shocks to home values based on instrumented air quality improvements conditional on fixed effects, which helps to address potential bias in the racial disparity arising from correlated characteristics. In Appendix Table A.5, we show that in a simple analysis of the racial disparity in housing prices per se, the estimated disparity due to seller race drops significantly once we condition on seller income.

Finally, since Black homeowners experience higher pollution reductions (see Figure 2b), there could be confounding nonlinearities in $PM_{2.5}$, so we include a quadratic $PM_{2.5}$ term in Column 8. Our estimates remain robust which rules out that our racial differences in capitalization rates are driven by non-linear effects of air quality improvements across racial groups. In Appendix Table A.6, Columns 6-7, we show similar robustness to including the interaction of $PM_{2.5}$ with baseline pollution, as a related concern for nonlinearity may be that Black homeowners live in more polluted areas at baseline and experience different effects for the same unit reductions as a result. Appendix Table A.6 Columns 1-3 also shows the robustness of Columns 6-8 to including property fixed effects.[23] Table A.7 Columns 1-3 shows robustness to different thresholds for the match quality of lender names between Zillow and HMDA data (60% vs 75% vs 90% threshold).

[23]Note that for Columns 7-8 in Table 2, we only include state by year fixed effects. Appendix Table A.6 Columns 4-5 shows these results with county by year fixed effects instead, with almost identical coefficients, but a lower first stage F-stat. For some specifications, the F-stat is lower as we need instruments for each interaction with $PM_{2.5}$, and in some first stages the interaction of specific control variables with nonattainment has relatively lower t-stats, resulting in lower F-stats.

Table 3: Capitalization rates: Observed vs. predicted race and seller vs. buyer race

	Transaction Price (log)					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel (a) OLS results:						
PM2.5	-0.014***	-0.021***	-0.023***	-0.015***	-0.022***	-0.033***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
PM2.5 * Black seller	0.038***	0.025***	0.029***	0.022***	0.026***	0.029***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
PM2.5 * Other seller	0.007***	0.011***	0.012***	0.005***	0.010***	0.023***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
PM2.5 * Black buyer				0.003***	0.009***	0.010***
				(0.000)	(0.000)	(0.001)
PM2.5 * Other buyer				-0.000*	0.003***	0.003***
				(0.000)	(0.000)	(0.001)
log(SQFT)	0.520***	0.513***		0.518***	0.535***	
	(0.005)	(0.004)		(0.006)	(0.003)	
Panel (b) IV results:						
PM2.5	-0.070***	-0.118***	-0.142***	-0.060***	-0.136***	-0.177***
	(0.005)	(0.008)	(0.010)	(0.006)	(0.009)	(0.011)
PM2.5 * Black seller	0.024***	0.027***	0.031***	0.007***	0.034***	0.041***
	(0.002)	(0.001)	(0.002)	(0.003)	(0.002)	(0.004)
PM2.5 * Other seller	0.004***	0.016***	0.018***	0.003***	0.016***	0.023***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)
PM2.5 * Black buyer				-0.007***	-0.020***	-0.026***
				(0.001)	(0.003)	(0.005)
PM2.5 * Other buyer				-0.004***	-0.004	0.015***
				(0.001)	(0.003)	(0.005)
log(SQFT)	0.520***	0.513***		0.518***	0.535***	
	(0.005)	(0.004)		(0.006)	(0.003)	
Census block by Black seller FE	Yes	Yes	Yes	Yes	Yes	Yes
Census block by Other seller FE	Yes	Yes	Yes	Yes	Yes	Yes
Property FE			Yes			Yes
County by year FE	Yes	Yes	Yes	Yes	Yes	Yes
Black buyer FE				Yes	Yes	Yes
Other buyer FE				Yes	Yes	Yes
Urban by year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,743,104	34,313,433	19,791,941	1,907,273	20,045,603	10,159,730
First-stage F (KP)	249.262	180.324	130.190	80.710	181.471	267.230

Notes: The table shows regression estimates from our transaction level approach using OLS in Panel (a) and IV in Panel (b). Column 1 reproduces Column 3 from Table 1 using observed seller race. Column 2 uses predicted instead of observed seller race and therefore also includes transactions without links to the mortgage data resulting in a larger sample size. Column 3 adds property fixed effects using predicted race. Column 4-6 add buyer race interacted with $PM_{2.5}$ and buyer race fixed effects. Column 4 is based on observed seller and observed buyer race, with a resulting lower sample size. Columns 5-6 are based on predicted seller and buyer race, with Column 6 adding property fixed effects. Standard errors are clustered at the Census tract level. *** Significant at the 1 percent level, ** significant at the 5 percent level, * significant at the 10 percent level.

C. Observed vs. Predicted Seller Race

We now turn to using predicted seller race instead of observed seller race, which greatly expands our sample size with the advantage of exploring external validity beyond transactions connected to a mortgage. In our case, predictions of race based on names may actually be an advantage when in practice only names are known and discrimination is based on such beliefs derived from names. Column 1 in Table 3 replicates our baseline Column 3 of Table 2 for OLS and IV for convenience.

Column 2 shows a similar estimate for the difference in capitalization rates across race when using predicted race, with a sample that is more than 400% larger. Column 3 shows robustness to adding property fixed effects in a repeat sales analysis. Since we know that there is measurement error in *predicted* seller race by construction, the true difference in capitalization rates is likely larger if the measurement error is classical. Indeed, in Table A.7, we vary the prediction threshold from 70% required probability of race classification in Column 4 to 60% in Column 5 where attenuation is larger yielding a smaller estimate, and 80% in Column 6, where attenuation is lower yielding a larger estimate. In Table A.8, we use the same sample of Column 1 of Table 2 but use predicted race in Column 2, resulting in an attenuated coefficient compared to using observed seller race. Taken together, these results demonstrate the external validity of our estimated disparity in capitalization rates beyond transactions connected to mortgages, and if anything, implies that the true disparities may be even larger outside of our sample with observed race.

D. Seller vs. Buyer Race

While the disparity in capitalization rates across races in concerning, it is a priori unclear whether it is driven by seller race or buyer race. If Black homeowners only sell to Black buyers, then these buyers would effectively be purchasing air quality at a discount, limiting the welfare implications only to those holding properties at the time of the air quality shock. Alternatively, if Black buyers do not receive a discount, the welfare implications from the capitalization rate differences would be magnified along the chain of sales. We begin by showing the degree of homophily in transactions in Appendix Table A.3. While the share of Black sellers selling to Black buyers is much higher than for other sellers selling to Black buyers, it is still only 40% with 60% selling to non-Black buyers, using the observations where we observe both seller and buyer race. To formally test how much seller vs. buyer race drives our result, we include buyer race interacted with $PM_{2.5}$ fully instrumented in Columns 4-6 of Table 3. Column 4 is based on observed seller and buyer race, while Column 5 is based on predicted seller and buyer race with Column 6 adding property fixed effects. In all three columns, the coefficient on Black seller remains positive and statistically significant, while the interaction coefficient with Black buyer is negative. Note that the coefficients in Column 4 for

Table 4: Capitalization rate differences: seller by buyer race

Seller/Buyer	Black Buyer	NHW Buyer	Other Buyer	Weighted average for seller
Black Seller	-0.014	-0.033	-0.029	-0.025
NHW Seller	0.020	0.000	0.004	0.001
Other Seller	0.004	-0.016	-0.011	-0.013
Weighted average for buyer	0.008	-0.002	-0.003	0.000

Notes: The table is based on Column 7 of Table 3 and shows the impact of a one-unit decrease in $PM_{2.5}$ on capitalization rate differences in percentage points (appropriately exponentiated coefficients), all compared to a NHW seller with a NHW buyer. For example, a Black seller with NHW buyer has a 3.3 percentage point lower capitalization rate. The last column shows the weighted average across rows with shares based on sales going to respective buyer groups, applied before exponentiating to get percentage points.

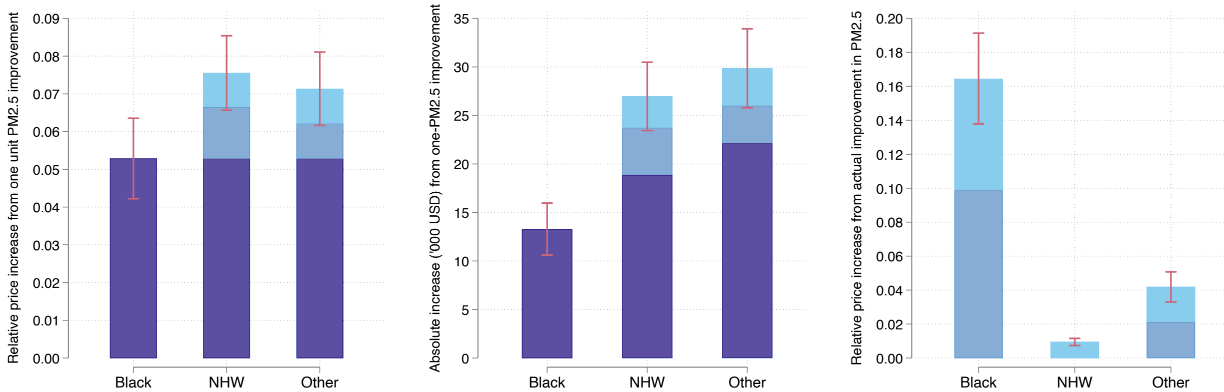
seller race interactions are somewhat smaller than in the rest of the table, but are also based on a much smaller subsample. They are in line with a version without buyer race interactions run on the same smaller subsample where we observe both races.[24] Importantly, we highlight that the OLS estimates are highly robust throughout the table for either observed or predicted seller race and with or without including buyers. This is reassuring as there is no a-priori reason why the OLS bias in the interaction of $PM_{2.5}$ with seller race should vary significantly *across* these specifications.

These results demonstrate that the disparity in capitalization rates is indeed driven by seller race. In fact, Black buyers pay a premium for air quality capitalizations, ceteris paribus, echoing results from other papers focused on buyers (Bayer et al. 2017, Higgins 2023). Resulting arbitrage opportunities may remain in part because of discriminatory bias itself, and in part because of high transaction costs in this market (Christensen & Timmins 2023). Based on Column 7 of Table 3 the capitalization rate for a Black seller is around one-third lower compared with a NHW seller who both sell to the same buyer race (e.g. a Black buyer). For a Black seller selling to a Black buyer compared to a NHW seller selling to a NHW buyer the capitalization rate is only 10% lower. Table 4 shows a three-by-three table for all combinations of seller and buyer race indicating the difference in capitalization rates in percentage points. Our main results capture the disparities across sellers averaged by the respective buyer shares in the data as shown in the last column of Table 4.

E. Direct & Systemic Discrimination: People vs. places

We now turn to decomposing the disparity into direct and systemic parts. Black homeowners tend to live in blocks with different racial compositions than NHW homeowners as shown in Table 1. As defined in our introduction, we consider disparities arising from baseline neighborhood racial com-

[24] Appendix Table A.8 Column 3 shows that when running a specification without buyer race interactions, but on the same smaller sample where we observe both seller and buyer race, the coefficient on seller race interactions is smaller as well. Columns 4 and 5 of Table A.8 show results without using seller race at all, based on observed or predicted buyer race respectively. Due to (partial) homophily and omitting seller race, these estimates are positive, capturing some of the seller race effect.



(a) Relative effect of one-PM2.5 decrease (b) Absolute effect of (a) (c) Counterfactual with actual ΔPM2.5

Figure 3: Visualization of main effects and counterfactual

Notes: Panel (a) visualizes the main effect from Table 5 Column 1 showing relative price increases by race, where the violet bars represent the price increase common to all racial groups, the dark blue represents additional price increases from direct and the light blue from systemic discrimination using the average Census block composition for a seller from the respective group in our sample. Panel (b) shows corresponding absolute price increases using the average home values by group. Panel (c) shows the relative price increases by racial groups in the absence of direct and systemic discrimination setting the interaction coefficients to zero and using the actual PM2.5 changes over the sample period by racial group. Red bars indicate 95% confidence intervals based on clustered Standard Errors at the Census tract level.

position as systemic discrimination, and disparities arising from seller race itself, holding neighborhood racial composition constant, as direct discrimination. Note that we have already shown that the disparity is unchanged when controlling for interacted seller income or other property characteristics in Table 2. Therefore, our measurement of direct discrimination is robust to fully controlling for what are likely the most relevant seller or property characteristics, again in part due to our identification strategy from air quality shocks, as disparities in levels certainly change when conditioning on income.[25] To formally unpack these discriminatory channels, we include both observed seller race and neighborhood racial shares interacted with $PM_{2.5}$ as in Equation 1.[26] We first show our baseline results and then analyze the discrimination channels in more depth.

Column 1 in Table 5 shows that our estimate for the interaction with Black seller drops by almost a half, and that the interaction with the share of Black residents in the Census block is highly significant, so at least part of the disparity is driven by the area where sellers live rather than the race of seller. Average racial neighborhood shares vary on the continuum between zero and one for different seller races, so we cannot directly read off the average split between direct and systemic

[25]See above for details. While interacted individual income does not change our estimate, had we found that it did, there would be two potential interpretations. One could either interpret results driven by individual income difference as reflective of historic practices that systemically discriminated against Black Americans, or alternatively view systemic discrimination after conditioning on individual income.

[26]While we defined neighborhoods here as blocks, our results are robust to defining them as block groups or tracts instead.

Table 5: Direct & Systemic Discrimination: Seller race and neighborhood composition

	Transaction Price (log)										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Panel (a) OLS results:											
PM2.5	-0.018***	0.022***	0.068***	-0.007***	-0.021***	-0.018***	-0.013***	-0.017***	0.021***	-0.018***	-0.042***
	(0.001)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.003)
PM2.5 * Black seller	0.024***	0.024***	0.023***	0.024***	0.024***	0.024***	0.024***	0.024***	0.021***	0.023***	0.024***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
PM2.5 * Other seller	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
PM2.5 * Black share	0.038***	0.036***	0.033***	0.038***	0.038***	0.036***	0.037***	0.039***	0.022***	0.039***	0.036***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
PM2.5 * Other share	0.012***	0.010***	0.007***	0.011***	0.011***	0.010***	0.011***	0.013***	0.005***	0.012***	0.012***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
PM2.5 * log(Med. HH income)		-0.004***									
		(0.000)									
PM2.5 * log(Med. Hval)			-0.007***								
			(0.000)								
PM2.5 * log(Med. Rent)				-0.002***							
				(0.000)							
PM2.5 * Urban share					0.004***						
					(0.001)						
PM2.5 * Pov. rate						0.013***					
						(0.002)					
PM2.5 * NDVI							-0.010***				
							(0.002)				
PM2.5 * Built highmed								-0.000***			
								(0.000)			
PM2.5 * Opportunity									-0.063***		
									(0.003)		
PM2.5 * Supply Ela.										0.001	
										(0.001)	
PM2.5 * Arrest rate											0.534***
											(0.057)
log(SQFT)	0.520***	0.520***	0.520***	0.521***	0.520***	0.520***	0.519***	0.520***	0.521***	0.522***	0.520***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Panel (b) IV results:											
PM2.5	-0.075***	-0.055***	0.009	-0.068***	-0.073***	-0.075***	-0.083***	-0.071***	-0.051***	-0.062***	-0.071***
	(0.005)	(0.008)	(0.009)	(0.005)	(0.005)	(0.005)	(0.006)	(0.004)	(0.006)	(0.004)	(0.010)
PM2.5 * Black seller	0.013***	0.013***	0.013***	0.012***	0.013***	0.013***	0.013***	0.013***	0.015***	0.013***	0.013***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
PM2.5 * Other seller	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
PM2.5 * Black share	0.027***	0.026***	0.022***	0.026***	0.028***	0.030***	0.030***	0.030***	0.025***	0.028***	0.026***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
PM2.5 * Other share	0.005***	0.004***	-0.000	0.005***	0.005***	0.007***	0.007***	0.008***	0.002	0.005***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
PM2.5 * log(Med. HH income)		-0.002***									
		(0.000)									
PM2.5 * log(Med. Hval)			-0.006***								
			(0.000)								
PM2.5 * log(Med. Rent)				-0.001**							
				(0.000)							
PM2.5 * Urban share					0.005*						
					(0.003)						
PM2.5 * Pov. rate						-0.019***					
						(0.003)					
PM2.5 * NDVI							0.022***				
							(0.004)				
PM2.5 * Built highmed								-0.000***			
								(0.000)			
PM2.5 * Opportunity									-0.031***		
									(0.005)		
PM2.5 * Supply Ela.										-0.004*	
										(0.002)	
PM2.5 * Arrest rate											-0.013
											(0.323)
log(SQFT)	0.520***	0.520***	0.520***	0.521***	0.520***	0.520***	0.519***	0.520***	0.521***	0.522***	0.520***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Census block by Black seller FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census block by Other seller FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County by year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Urban by year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,743,104	7,736,534	7,708,698	7,546,254	7,743,104	7,736,545	7,727,118	7,741,938	7,658,970	7,302,613	6,747,729
First-stage F (KP)	147.191	101.076	92.543	99.917	58.897	35.107	60.498	23.712	37.036	47.719	12.516

Notes: The table shows regression estimates from our transaction level approach using OLS in Panel (a) and IV in Panel (b). Seller race is observed and additional interactions with neighborhood racial composition are included throughout. Columns 2-11 add various neighborhood interactions with $PM_{2.5}$, as described in the text, and are fully instrumented in Panel (b). The non-interacted characteristics are absorbed by the fixed effects as they are time invariant. Standard errors are clustered at the Census tract level. *** Significant at the 1 percent level, ** significant at the 5 percent level, * significant at the 10 percent level.

discrimination from the table. Instead, we visualize our results from Column 1 in Figure 3a for a one-unit reduction in $PM_{2.5}$ and using average Census block compositions by respective seller race in our sample. The violet bars represent the price increase common to all racial groups, the dark blue bars represent additional price increases from direct discrimination and the light blue bars reflect price increases due to systemic discrimination, with confidence intervals calculated from the covariance matrix of our estimates. The first thing to note is that the total capitalization rate by seller race is almost identical to that from Column 3 of Table 2, which omits neighborhood racial composition, and is also lower by around one-third for Black sellers compared with NHW sellers.[27] Second, the component of the Black-NHW capitalization rate disparity that is driven by direct discrimination (seller race) is around 60%, with the remaining 40% driven by systemic discrimination. This, of course is the average, and varies depending on the racial composition of a specific block. At the extreme, when comparing a Black seller in an entirely Black community with a NHW seller in an entirely NHW community, the capitalization rate for the NHW seller would be 120% larger (7.8 vs 3.5 percent per μg),[28] and the split would reverse to be 32% direct discrimination and 68% driven by systemic discrimination. As previously, the capitalization rates between NHW and Other sellers are similar, and the components in the visualization for Other sellers are with respect to Black sellers.

We next turn to potential mechanisms underlying our measure of systemic discrimination. In particular, we ask whether neighborhood racial composition is likely to capture other amenities that drive systemic discrimination. Differences in amenities may change the value of clean air by being complements (or substitutes), such as green outdoor spaces, playgrounds, sports facilities, crime rates, walkability, or school quality. For example, Black Americans tend to live in areas with fewer green spaces, i.e. more impervious surfaces, and tend to be lower income (Table A.1), in part due to persistent historic formal discrimination (Aaronson et al. 2021). They also live in neighborhoods with fewer economic opportunities (Table A.1 and Chetty et al. (2018)). Housing supply elasticities may also vary with neighborhood composition, and areas with higher supply elasticities may see muted price effects as housing stock expands more in response to air quality improvements (Chakma & Krause 2024).[29]

To formally test these, we begin by including median household income or median home value at the block group level at the beginning of our sample fully interacted with $PM_{2.5}$ and instrumented

[27] More precisely, it is lower by 30% here and by 35% based on Table 2.

[28] Recall that the difference is 42% between Black and NHW homeowners based on average neighborhood compositions.

[29] Note, however, that this is unlikely to explain disparities in our setting since housing supply elasticities are, if anything, slightly *lower* in Black neighborhoods (see Table A.1).

in Columns 2 and 3 of Table 3. While median income and home value themselves increase the value of air quality improvements, including them hardly changes our main estimates based on race, both for the direct and the systemic component (similar to including seller income in Table 2). While median home value arguably captures a summary value of amenities, we examine the role of several other neighborhood characteristics at the beginning of our sample in the remainder of Table 3 and visualize differences in capitalization rates stemming from direct and systemic components in Figure 4, where the labels indicate the relevant controls. The table and figure show that our results are largely unchanged when including interactions with median rent, urban share, poverty, median income, median home value, local vegetation index (NDVI), measures of imperviousness (BuiltHigh), economic opportunities, housing supply elasticities, or arrest rates.[30]

Bohren et al. (2023) define two main channels for systemic discrimination, technological and informational, and we interpret our results along these lines to shed light on the nature of systemic discrimination at play. In our setting, technological differences from systemic discrimination would manifest as tangible amenities that are driven by neighborhood racial composition and a result of discrimination (e.g. underinvestment in public goods), which in turn may affect capitalization rates. Taking our results at face value leaves two possibilities. First, racial neighborhood composition could be correlated with amenities that are hard to accurately measure at the required level of granularity, and if one could measure them, we could find evidence for the technological channel from tangible amenities. The fact that our results are so robust to including amenities suggest this may be unlikely, although we cannot conclusively rule it out. Second, the primary channel for systemic discrimination in our setting may be informational. Rather than tangible amenities being driven by bias and discrimination, the informational channel operates via signal bias and noise. Neighborhoods may subjectively be evaluated based on racial composition, stigmatized from outdated perceptions that were driven by direct discrimination itself, or from distorted and noisy signals.[31] As with direct discrimination, the bias may come from the buyer side but could also arise in the market through intermediation, e.g. through steering and restricted choice sets via discrimination (Christensen & Timmins 2023).

While our contention is that the aforementioned differences due to neighborhood composition are the result of systemic discrimination without conditioning on additional variables, one could also condition on any of our neighborhood control interactions to define an alternative reference point. If, for example, one wished to define systemic discrimination due to neighborhood composition as one that arises holding neighborhood income constant, systemic discrimination would

[30] All of our results are also robust to using Census tract level racial composition instead of block level composition.

[31] See also Fogli et al. (2024) for subjective biases from historical correlations driven by discrimination.

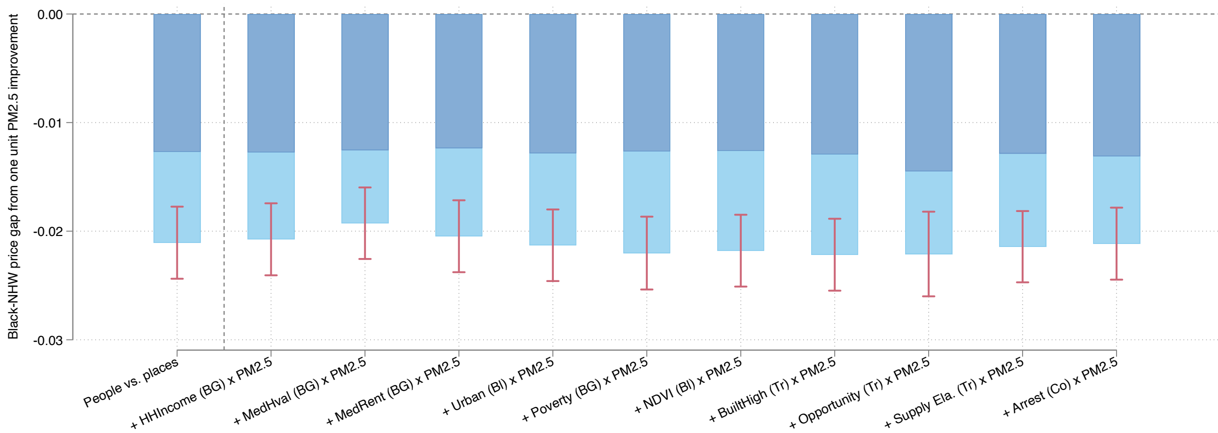


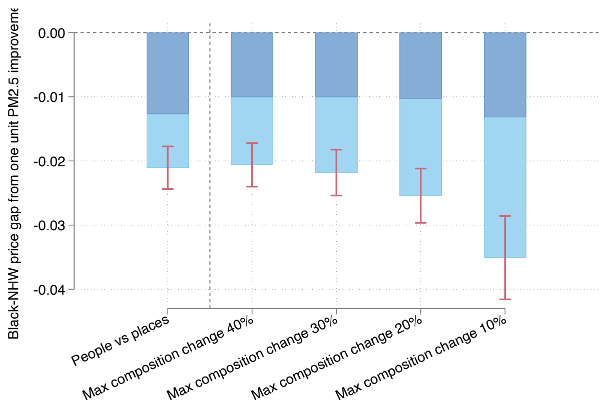
Figure 4: Visualizing difference in capitalization rates: Controlling for neighborhood characteristics

Notes: The figure visualizes the difference in capitalization rates between Black and NHW by direct (blue) and systemic (light blue) discrimination from Table 5, varying the included controls that are interacted with PM2.5 as indicated and analogously to Table 5. BL, BG, Tr, and Co indicate controls measured at Census block, block group, tract, or county level. Red bars indicate 95% confidence intervals based on clustered Standard Errors at the Census tract level.

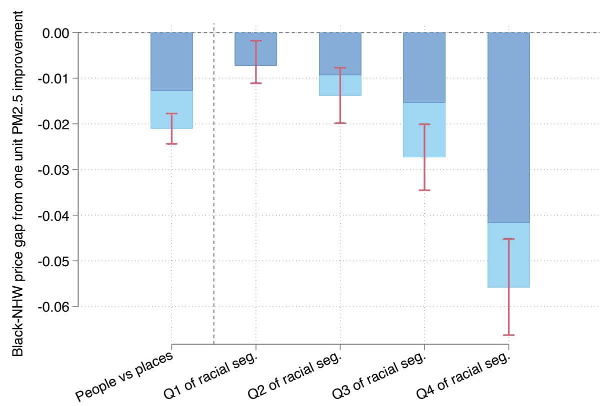
fall by 1.5% (0.03 percentage points). A focus on baseline median house values, the most impactful measure in our analysis, suggests that the systemic discrimination component would shrink by 20% and measured total discrimination (direct plus systemic) in the capitalization rate disparity would only shrink by 9%, resulting in a split of 65% to 35% between direct and systemic discrimination. It is also worth noting that if one were to argue that neighborhood composition and all of the associated benefits and disadvantages of neighborhoods arise purely through choice uninfluenced by external constraints, bias or persistent discriminatory legacies, our measure of direct discrimination still implies a sizable 25% difference in capitalization rates between Black and NHW homeowners.[32]

Finally, as a robustness check, we restrict our sample to blocks that see little change in racial composition (e.g. little gentrification) over time from 2000-2020 in Figure 5a, with a maximum 10 percentage point racial share difference in the right column (corresponding to Table A.9). The difference in capitalization rate becomes slightly larger in our restricted samples, with a roughly unchanged split between direct and systemic discrimination, implying that, if anything, our results may be too conservative and underestimate the disparity in pollution capitalization rates.

[32]To be clear, we offer this extreme position to facilitate the interpretation of our results, but it appears inconsistent with a range of empirical evidence (Akbar et al. 2022, Ewens et al. 2014, Christensen & Timmins 2023, Trounstine 2016, Alesina et al. 1999).



(a) Blocks with little compositional change over time



(b) Effect by quartile of residential segregation

Figure 5: Restricting to neighborhoods with little change, and results by residential segregation

Notes: The figure visualizes the difference in capitalization rates between Black and NHW by direct (blue) and systemic (light blue) discrimination. The leftmost baseline in both panels corresponds to Column 1 of Table 5. Panel (a) restricts the sample to blocks with a maximum compositional change in racial shares by the indicated percentage points (see Table A.9). Panel (b) shows results for sample splits by quartile of residential racial segregation within tracts (see Table 6). Red bars indicate 95% confidence intervals based on clustered Standard Errors at the Census tract level.

F. *Size of Effect and Counterfactual Analysis*

Our relative effects in Figure 3a, based on Column 1 of Table 5, imply that while a one-unit reduction in $PM_{2.5}$ increases house prices by 5.3% for Black homeowners, it increases them by 7.5% for NHW homeowners, a pollution capitalization rate that is 42% larger. We provide estimates in absolute terms in Figure 3b using average house prices by racial groups from Table 1. A one-unit improvement in $PM_{2.5}$ (around 10%) increases house prices by US$ 13,000 for average Black sellers, while the figure for average NHW sellers is roughly double that at US$ 27,000. This is larger than the difference in relative estimates, as baseline house prices are higher for NHW sellers.

On average, the NHW-Black house price gap in levels is 42% (see Table 1). While air quality improvements helped to improve home values for all groups, our striking result is that air quality improvements have actually widened the gap of home values between Black and NHW homeowners by 2 percentage points despite the shrinking pollution exposure gap, entirely due to the sizable differences in pollution capitalization rates.[33] This can easily be seen as the reduction in pollution is only 35% greater for Black homeowners (6.6 vs 4.9 $\mu g/m^3$), but the capitalization rate is 42% greater for NHW homeowners.

We next ask what counterfactual prices would have prevailed if Black and Other homeowners had the same measured pollution reductions during our sample period, but experienced a capital-

[33] This is calculated by combining the realized pollution improvements by racial groups with the capitalization rate and house price levels by group.

Table 6: Capitalization rates by quartile of residential racial segregation

	Transaction Price (log)							
	Panel (a) OLS results:				*Panel (b) IV results:*			
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PM2.5	-0.023***	-0.017***	-0.013***	-0.006**	-0.095***	-0.053***	-0.071***	-0.064***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.007)	(0.007)	(0.012)	(0.019)
PM2.5 * Black seller	0.012***	0.019***	0.028***	0.048***	0.007***	0.009***	0.016***	0.043***
	(0.001)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.004)	(0.007)
PM2.5 * Other seller	0.002***	0.005***	0.007***	0.008***	0.002***	0.002**	0.003**	0.005*
	(0.000)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.003)
PM2.5 * Black share	0.039***	0.035***	0.040***	0.026***	-0.003	0.015***	0.038***	0.045***
	(0.003)	(0.003)	(0.004)	(0.003)	(0.005)	(0.004)	(0.006)	(0.007)
PM2.5 * Other share	0.014***	0.012***	0.010***	0.011***	-0.002	0.000	0.016***	0.020***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.005)
log(SQFT)	0.527***	0.520***	0.519***	0.515***	0.527***	0.520***	0.519***	0.515***
	(0.008)	(0.007)	(0.012)	(0.013)	(0.008)	(0.007)	(0.012)	(0.013)
Census block by Black seller FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census block by Other seller FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County by year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Urban by year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Estimator	OLS	OLS	OLS	OLS	IV	IV	IV	IV
Observations	2,100,872	2,064,784	1,945,040	1,622,392	2,100,872	2,064,784	1,945,040	1,622,392
First-stage F (KP)					67.875	68.701	16.930	6.888

Notes: The table shows regression estimates from our transaction level approach using OLS in Panel (a) and IV in Panel (b). The specification is the same as in Column 1 of Table 5. We split the sample by quartile of within-tract segregation, and report estimates by quartile, indicated by Q1-Q4. Standard errors are clustered at the Census tract level. *** Significant at the 1 percent level, ** significant at the 5 percent level, * significant at the 10 percent level.

ization rate at the level of NHW homeowners, i.e. setting β_j and γ_j to zero in Equation 1. Figure 3c shows that in this case house prices would be 16% higher for Black homeowners (equivalent to $40,000 per homeowner) and 4% higher for Other homeowners, and higher by 1% for NHW homeowners (through neighborhood shares). This would have implied that the Black-NHW house price gap would have reduced by 14 percentage points from the air quality improvements over two decades, instead of the 2 percentage point increase.

G. Residential Segregation

We know from the literature that racial bias and discrimination are generally higher in areas with more residential racial segregation (Enos & Celaya 2018, Ananat & Washington 2009, Ananat 2011), i.e. in Census tracts where different racial groups mainly live in separate blocks.[34] If our mechanism are forms of discrimination, we would expect that the disparities in capitalization rates are larger in areas that are more residentially segregated. We test this formally by splitting our sample into quar-

[34]There is also a literature showing that underinvestment is higher and complementary amenities are lower in such areas (Trounstine 2016, Alesina et al. 1999).

tiles based on our index of residential segregation by race (Figure A.1 maps our tract level index). Indeed, as the ascending Columns in Table 6 show, and as visualized in Figure 5b, the disparity in pollution capitalization rates is much larger in tracts with more residential segregation.[35]

V. Conclusion

The environmental justice movement has its roots in the Civil Rights Movement of the 1960s, but its prominence in national priority setting and policy making is much more recent. Indeed, in an effort to address "...the disproportionate health, environmental, and economic impacts that have been borne primarily by communities of color..." President Biden issued Executive Order 14008 aimed at providing 40 percent of the benefits from Federal investments in the environment to marginalized communities, a commitment that was reinforced with Executive Order 14096 in 2023. Our analysis underscores the complexity of this effort. Despite improvements in the pollution exposure gap, Black homeowners in the US benefited substantially less from pollution reductions than NHW homeowners. Indeed, had Black homeowners experienced the same capitalization rates as NHW homeowners, each would have gained $40 thousand over our study period, equivalent to $223 billion when extrapolating to all Black homeowners in the US.[36] These differential impacts have their roots in both direct and systemic sources of discrimination and highlight the need for research that moves beyond exposure analysis to better understand the marginal damages and benefits from that exposure.[37] They also underscore the inextricable link between various forms of inequality across communities such that environmental justice policies designed to overcome environmental disparities must also address social justice questions including forms of discrimination and unequal access to complementary amenities that help define the impacts of those disparities.

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[35]We find a similar result when using segregation within counties instead of segregation within tracts.

[36]Calculated using the coefficients of our main result in Table 5 Column 1, as explained in our section on counterfactual analyses. We multiply the relative 16% gain that Black homeowners would have gained with the average level of home values for Black homeowners to arrive at the per homeowner gain. The national figure comes from applying this to the total number of Black homeowners in the 2000 Census.

[37]While we study the distribution of housing capitalization changes resulting from pollution reductions, this insight is likely important for other realms of public policy such as health or education. Graff Zivin, Neidell, Sanders & Singer (2023), for example, find heterogeneous marginal pollution damages on health by vaccination status.

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APPENDIX FOR ONLINE PUBLICATION

Disparities in Pollution Capitalization Rates: The Role of Direct & Systemic Discrimination

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A.1 Additional Descriptive Statistics

Table A.1: Summary statistics

	Mean	SD		Mean	
	Overall		Black	Non-Hisp. White	Other
Count	9186277	-	393483	7972109	820685
Shares	1	-	0.04	0.87	0.09
Transaction level					
Price in thousands (constant 2012 USD)	357.9	1731.3	251.2	357	418.4
SQFT	1900.3	42797.9	1797.8	1917.6	1781.2
Price per SQFT (constant 2012 USD)	201.4	1091.3	150.8	198.9	250.4
Predicted seller race: Black	0.09	0.28	0.75	0.07	0.01
Predicted seller race: Non-Hispanic White	0.59	0.49	0.11	0.74	0.03
Predicted seller race: Other	0.32	0.47	0.14	0.19	0.96
Income of seller in thousands (constant 2012 USD)	121	169.9	98.6	122.5	116.9
Observed buyer race: Black	0.05	0.21	0.4	0.03	0.05
Observed buyer race: Non-Hispanic White	0.84	0.37	0.47	0.89	0.49
Observed buyer race: Other	0.12	0.32	0.12	0.08	0.46
Income of buyer in thousands (constant 2012 USD)	121.4	160.6	96.2	122.4	122.4
Census block level					
Black population share of Census block (2000)	0.06	0.15	0.35	0.05	0.07
NHW population share of Census block (2000)	0.77	0.25	0.47	0.81	0.53
Other population share of Census block (2000)	0.17	0.2	0.18	0.14	0.4
Urban population share of Census block (2000)	0.86	0.35	0.92	0.85	0.94
PM2.5 concentration of Census block	9.3	3	10.1	9.1	11
Normalized Difference Vegetation Index of Census block	0.5	0.18	0.5	0.51	0.4
Census block group level					
Med. HH income in block group (2000, const. th. 2012 USD)	55.8	32.6	48.1	56.2	56.1
Share in poverty in Census block group (2000)	0.08	0.08	0.12	0.07	0.1
Med. home value in block group (2000, const. th. 2012 USD)	181.3	151.8	132.5	181	207.4
Med monthly rent in block group (2000, const. th. 2012 USD)	0.74	0.47	0.7	0.73	0.86
Census tract level					
Share high intensity built-up env. of Census tract (2001)	24.9	25.8	31.4	22.8	42.3
Opportunities in Census tract (1978-1983)	0.56	0.08	0.49	0.56	0.54
Housing supply elasticity of Census tract (2001)	0.37	0.26	0.33	0.38	0.26
Racial segregation within Census tract (2000)	0.28	0.1	0.28	0.28	0.24
Black population share of Census tract (2000)	0.07	0.13	0.33	0.05	0.07
NHW population share of Census tract (2000)	0.75	0.22	0.48	0.79	0.53
Other population share of Census tract (2000)	0.18	0.18	0.19	0.15	0.4
Urban population share of Census tract (2000)	0.86	0.29	0.93	0.85	0.94
County level					
Racial segregation within county (2000)	0.45	0.09	0.5	0.45	0.46
Arrest rate within county (2000)	0.05	0.02	0.05	0.05	0.05
PM2.5 Nonattainment county	0.3	0.46	0.45	0.29	0.34

Notes: The table shows the mean and standard deviation of indicated variables in the overall sample, and the mean by seller group.

Table A.2: Change in neighborhood composition and pollution changes

	(1)	(2)	(3)	(4)
Change in PM2.5	.00056	.001		
	(.00065)	(.00073)		
Log change in PM2.5			.0095	.012
			(.0073)	(.0096)
Observations	5904673	2979638	5904673	2979638
State FE	No	Yes	No	Yes

Notes: The table shows regressions where the dependent variable is the change in the share of Black people in a given Census block between 2000 and 2020. All regressions include state fixed effects. The independent variable is based on the change from 2000 to 2020 of block level pollution concentrations. Column (2) and (4) exclude Census blocks with zero change in the dependent variable. Standard errors in parentheses are clustered at the county level.

Table A.3: Homophily: Percent of transactions going to specific buyer race, by seller race

Seller:	Black	NHW	Other
Black	40%	47%	12%
NHW	3%	89%	8%
Other	5%	49%	46%

Notes: The table shows the percent of transactions per seller racial group that go to specific buyer racial groups in our sample. This is based on observed seller and buyer race. See also Table A.1.

A.2 Additional Results, and Results in Table Form – Main Analysis

Table A.4: First Stage for Column 2 of Table 2

	PM2.5	PM2.5 * Black seller	PM2.5 * Other seller
	(1)	(2)	(3)
Nonattainment	0.021	-0.091***	-0.077***
	(0.143)	(0.007)	(0.027)
Nonattainment * Base PM2.5	-0.075***	0.009***	0.025***
	(0.010)	(0.001)	(0.002)
Nonattainment * Black seller	1.533***	3.262***	-0.078*
	(0.149)	(0.249)	(0.044)
Nonattainment * Black seller * Base PM2.5	-0.100***	-0.426***	-0.003
	(0.010)	(0.016)	(0.003)
Nonattainment * Other seller	1.938***	-0.020***	3.529***
	(0.135)	(0.006)	(0.185)
Nonattainment * Other seller * Base PM2.5	-0.141***	0.001*	-0.497***
	(0.009)	(0.000)	(0.011)
log(SQFT)	0.001	0.001*	-0.001**
	(0.001)	(0.000)	(0.001)
Census block by Black seller FE	Yes	Yes	Yes
Census block by Other seller FE	Yes	Yes	Yes
State by year FE	Yes	Yes	Yes
Urban by year FE	Yes	Yes	Yes
Observations	7,745,962	7,745,962	7,745,962

Notes: The table shows first stage regression estimates of our three endogenous variables in Column 2 of Table 2, using our instruments. The combined Kleibergen-Paap F-stat of 279.6 is indicated in Table 2. Standard errors are clustered at the Census tract level. *** Significant at the 1 percent level, ** significant at the 5 percent level, * significant at the 10 percent level.

Table A.5: Controlling for individual income or property size in a simple analysis

	Transaction Price (log)		
	(1)	(2)	(3)
Black seller	-0.378***	-0.279***	-0.330***
	(0.004)	(0.003)	(0.003)
Other seller	-0.072***	-0.019***	-0.041***
	(0.004)	(0.003)	(0.003)
log(HH income)		0.504***	
		(0.002)	
log(SQFT)			0.792***
			(0.008)
State by year FE	Yes	Yes	Yes
Observations	9,186,262	8,779,922	9,186,262

Notes: The table shows regression estimates from a simple analysis of how transaction price is correlated with seller race, and how this estimated relationship changes by including seller income or property size. Standard errors are clustered at the Census tract level. *** Significant at the 1 percent level, ** significant at the 5 percent level, * significant at the 10 percent level.

Table A.6: Additional robustness for Table 2: fixed effects and baseline pollution

	Transaction Price (log)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel (a) OLS results:							
PM2.5	0.068***	-0.006***	0.014***	0.002	0.006***	-0.005**	-0.006**
	(0.004)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
PM2.5 * Black seller	0.042***	0.035***	0.038***	0.037***	0.039***	0.036***	0.037***
	(0.002)	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
PM2.5 * Other seller	0.006***	-0.003***	0.000	0.007***	0.008***	0.001**	-0.002**
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
log(SQFT)				0.498***	0.520***	0.519***	
				(0.005)	(0.005)	(0.005)	
log(HH income)		0.029***		0.090***			
		(0.002)		(0.001)			
PM2.5 * log(SQFT)	-0.011***						
	(0.001)						
PM2.5 * log(HH income)		-0.002***		-0.003***			
		(0.000)		(0.000)			
PM2.5 * PM2.5			-0.001***		-0.001***		
			(0.000)		(0.000)		
PM2.5 * Basline PM2.5						-0.001***	-0.001***
						(0.000)	(0.000)
Panel (b) IV results:							
PM2.5	0.020*	-0.118***	-0.005	-0.086***	0.091*	-0.027***	-0.013*
	(0.011)	(0.007)	(0.009)	(0.005)	(0.050)	(0.006)	(0.008)
PM2.5 * Black seller	0.021***	0.021***	0.018***	0.026***	0.027***	0.023***	0.017***
	(0.005)	(0.005)	(0.005)	(0.002)	(0.002)	(0.002)	(0.005)
PM2.5 * Other seller	0.002**	0.003**	-0.000	0.005***	0.006***	0.002***	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
log(SQFT)				0.498***	0.521***	0.520***	
				(0.005)	(0.005)	(0.005)	
log(HH income)		-0.140***		0.032***			
		(0.014)		(0.004)			
PM2.5 * log(SQFT)	-0.010***						
	(0.001)						
PM2.5 * log(HH income)		0.016***		0.003***			
		(0.001)		(0.000)			
PM2.5 * PM2.5			-0.001***		-0.003***		
			(0.000)		(0.001)		
PM2.5 * Basline PM2.5						-0.002***	-0.002***
						(0.000)	(0.000)
Census block by Black seller FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census block by Other seller FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Property FE	Yes	Yes	Yes				Yes
State by year FE		Yes	Yes			Yes	Yes
County by year FE	Yes			Yes	Yes		
Urban by year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,130,549	2,133,403	2,303,046	7,376,157	7,743,104	7,745,962	2,303,046
First-stage F (KP)	4.880	200.683	20.153	0.199	0.004	2.101	6.589

Notes: The table shows regression estimates from our transaction level approach using OLS in Panel (a) and IV in Panel (b). Columns 1-3 show the robustness of Columns 6-8 of Table 2 to including property fixed effects. Columns 4-5 show results with county by year fixed effects instead of state by year fixed effects corresponding to Columns 7-8 in Table 2. Columns 6-7 show robustness to including the interaction of $PM_{2.5}$ with baseline pollution instead of pollution squared. Standard errors are clustered at the Census tract level. *** Significant at the 1 percent level, ** significant at the 5 percent level, * significant at the 10 percent level.

Table A.7: Robustness to data matching thresholds between HMDA and Zillow for observed race, and prediction thresholds for predicted race

	Transaction Price (log)					
	Lender match HMDA-Zillow			Race prediction threshold		
	60%	75%	90%	70%	60%	80%
	(1)	(2)	(3)	(4)	(5)	(6)
Panel (a) OLS results:						
PM2.5	-0.014***	-0.014***	-0.014***	-0.118***	-0.108***	-0.127***
	(0.001)	(0.001)	(0.001)	(0.008)	(0.008)	(0.008)
PM2.5 * Black seller	0.038***	0.040***	0.041***	0.027***	0.020***	0.035***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
PM2.5 * Other seller	0.007***	0.007***	0.007***	0.016***	0.016***	0.016***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
log(SQFT)	0.520***	0.521***	0.527***	0.513***	0.507***	0.519***
	(0.005)	(0.005)	(0.006)	(0.004)	(0.004)	(0.004)
Panel (b) IV results:						
PM2.5	-0.070***	-0.071***	-0.069***	-0.118***	-0.108***	-0.127***
	(0.005)	(0.005)	(0.006)	(0.008)	(0.008)	(0.008)
PM2.5 * Black seller	0.024***	0.025***	0.025***	0.027***	0.020***	0.035***
	(0.002)	(0.002)	(0.003)	(0.001)	(0.001)	(0.002)
PM2.5 * Other seller	0.004***	0.004***	0.003***	0.016***	0.016***	0.016***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
log(SQFT)	0.520***	0.521***	0.527***	0.513***	0.507***	0.519***
	(0.005)	(0.005)	(0.006)	(0.004)	(0.004)	(0.004)
Census block by Black seller FE	Yes	Yes	Yes	Yes	Yes	Yes
Census block by Other seller FE	Yes	Yes	Yes	Yes	Yes	Yes
County by year FE	Yes	Yes	Yes	Yes	Yes	Yes
Urban by year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,743,104	6,755,258	4,142,871	34,313,433	41,571,561	28,217,750
First-stage F (KP)	249.262	241.896	199.987	180.324	193.575	164.017

Notes: The table shows regression estimates from our transaction level approach using OLS in Panel (a) and IV in Panel (b). Columns 1-3 show robustness to different thresholds for the match quality of lender names between Zillow and HMDA data, using a 60% vs 75% vs 90% threshold as indicated. Columns 4-6 rely on predicted rather than observed race, where Column 4 replicates Column 2 of Table 3 with a 70% prediction threshold of a name belonging to a race. Columns 5 and 6 use a threshold of 60% and 80% respectively. Standard errors are clustered at the Census tract level. *** Significant at the 1 percent level, ** significant at the 5 percent level, * significant at the 10 percent level.

Table A.8: Additional robustness for Table 3: Observed or predicted race of seller and buyer

	Transaction Price (log)				
	(1)	(2)	(3)	(4)	(5)
Panel (a) OLS results:					
PM2.5	-0.014***	-0.019***	-0.016***	-0.013***	-0.018***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
PM2.5 * Black seller	0.038***	0.023***	0.023***		
	(0.001)	(0.001)	(0.001)		
PM2.5 * Other seller	0.007***	0.006***	0.005***		
	(0.000)	(0.000)	(0.001)		
PM2.5 * Black buyer				0.019***	0.015***
				(0.001)	(0.001)
PM2.5 * Other buyer				0.003***	0.005***
				(0.000)	(0.000)
log(SQFT)	0.520***	0.523***	0.518***	0.506***	0.512***
	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)
Panel (b) IV results:					
PM2.5	-0.070***	-0.090***	-0.063***	-0.072***	-0.091***
	(0.005)	(0.006)	(0.006)	(0.005)	(0.005)
PM2.5 * Black seller	0.024***	0.017***	0.004		
	(0.002)	(0.002)	(0.003)		
PM2.5 * Other seller	0.004***	0.004***	0.001		
	(0.000)	(0.001)	(0.001)		
PM2.5 * Black buyer				0.015***	0.011***
				(0.001)	(0.001)
PM2.5 * Other buyer				0.002***	0.004***
				(0.000)	(0.000)
log(SQFT)	0.520***	0.523***	0.518***	0.506***	0.512***
	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)
Census block by Black seller FE	Yes	Yes	Yes		
Census block by Other seller FE	Yes	Yes	Yes		
County by year FE	Yes	Yes	Yes	Yes	Yes
Census block by Black buyer FE				Yes	Yes
Census block by Other buyer FE				Yes	Yes
Urban by year FE	Yes	Yes	Yes	Yes	Yes
Observations	7,743,104	3,107,203	1,907,273	10,564,102	4,962,901
First-stage F (KP)	249.262	219.635	190.436	284.281	242.845

Notes: The table shows regression estimates from our transaction level approach using OLS in Panel (a) and IV in Panel (b). Column 1 repeats Column 1 of Table 3 using observed seller race, and Column shows results when using predicted seller race but on the sample where we also observe seller race. Column 3 shows results with observed seller race but on the sample where we also observe buyer race. Column 4 uses observed buyer race, and Column 5 uses predicted buyer race, but on the sample where we also observe buyer race. Standard errors are clustered at the Census tract level. *** Significant at the 1 percent level, ** significant at the 5 percent level, * significant at the 10 percent level.

Table A.9: Capitalization rates when restricting the sample to neighborhoods with little compositional change over time

	Transaction Price (log)				
	All	≤ 40 pp	≤ 30 pp	≤ 20 pp	≤ 10 pp
	(1)	(2)	(3)	(4)	(5)
Panel (a) OLS results:					
PM2.5	-0.018***	-0.018***	-0.018***	-0.016***	-0.015***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
PM2.5 * Black seller	0.024***	0.019***	0.019***	0.019***	0.021***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
PM2.5 * Other seller	0.004***	0.004***	0.004***	0.004***	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
PM2.5 * Black share	0.038***	0.052***	0.057***	0.065***	0.080***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
PM2.5 * Other share	0.012***	0.014***	0.014***	0.015***	0.015***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
log(SQFT)	0.520***	0.523***	0.528***	0.537***	0.545***
	(0.005)	(0.005)	(0.005)	(0.006)	(0.007)
Panel (b) IV results:					
PM2.5	-0.075***	-0.073***	-0.070***	-0.067***	-0.064***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
PM2.5 * Black seller	0.013***	0.010***	0.010***	0.010***	0.013***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)
PM2.5 * Other seller	0.002***	0.002***	0.002***	0.002***	0.002**
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
PM2.5 * Black share	0.027***	0.034***	0.038***	0.049***	0.072***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.006)
PM2.5 * Other share	0.005***	0.006***	0.007***	0.008***	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
log(SQFT)	0.520***	0.523***	0.528***	0.537***	0.545***
	(0.005)	(0.005)	(0.005)	(0.006)	(0.007)
Census block by Black seller FE	Yes	Yes	Yes	Yes	Yes
Census block by Other seller FE	Yes	Yes	Yes	Yes	Yes
County by year FE	Yes	Yes	Yes	Yes	Yes
Urban by year FE	Yes	Yes	Yes	Yes	Yes
Observations	7,743,104	6,781,568	5,988,388	4,573,743	2,400,413
First-stage F (KP)	147.191	130.109	109.310	86.013	83.382

Notes: The table shows regression estimates from our transaction level approach using OLS in Panel (a) and IV in Panel (b). Column 1 reproduces our baseline result from Column 1 of Table 5. Columns 2-5 restrict our sample to blocks that experienced a maximum 40 (30, 20, 10) percentage point change in racial shares respectively. Standard errors are clustered at the Census tract level. *** Significant at the 1 percent level, ** significant at the 5 percent level, * significant at the 10 percent level.

A.3 Additional Descriptives – Residential Segregation

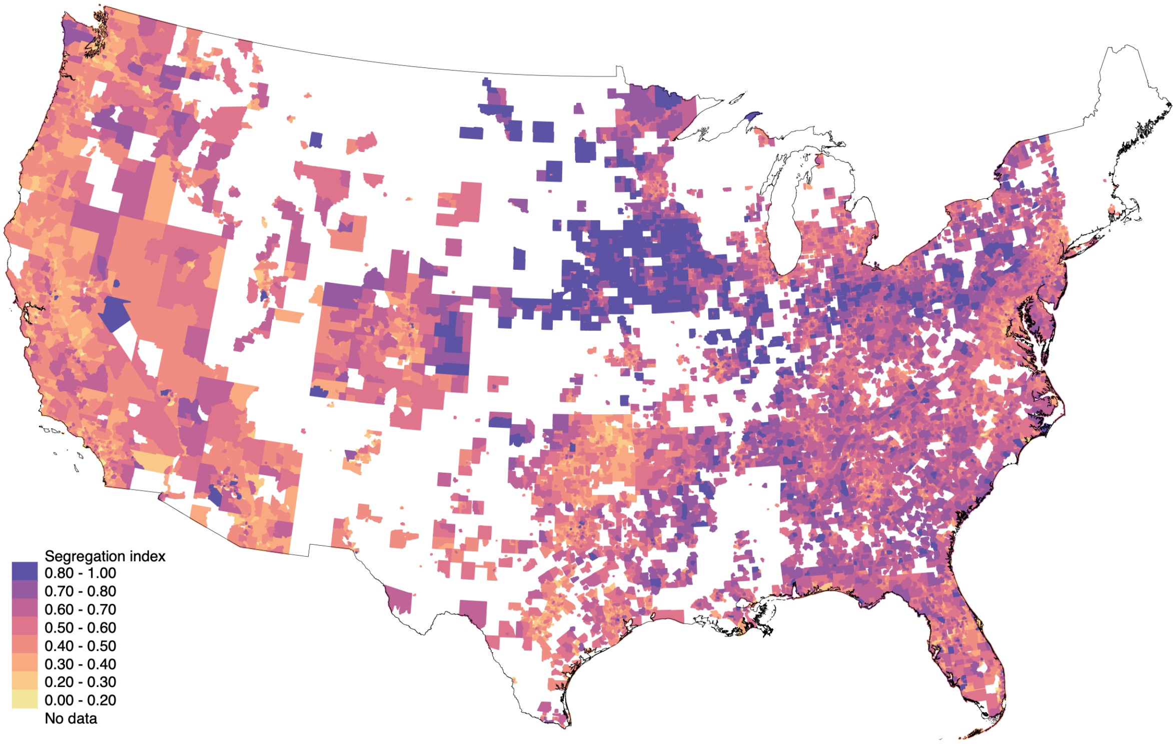


Figure A.1: Spatial distribution of within Census tract segregation in 2000

Notes: The map shows the spatial distribution of segregation within Census tracts across the contiguous US in 2000. We only use Census tracts which are in our final sample of transactions.

A.4 Details of Price, Location and Square Foot Data from Zillow

This section documents the transaction level data from Zillow. This has three building blocks which we discuss in turn: (A) identifying arm's length transactions for residential properties from the raw data, (B) identifying a property's location, and (C) identifying the property's area in square footage. Overall, we have both square footage and coordinates for 44,799,731 (84.3%) of our arm's length properties and for 80,544,782 (86.9%) of our arm's length transactions. Restricting this to the years used for analysis 2000-2019 and the contiguous US results in 64,737,270 (69.9%) transactions. The main text lists the number of observations of the subset used for anlysis where we can observe or predict race.

A. Identification of residential arm's length transactions

The Zillow data contains a large number of transactions which are not arm's length housing transactions for residential property. These often have missing or zero prices, are foreclosures, intra-family transfers, pure loans, or refinancing transactions. This section documents how we identify arm's length transactions for residential properties. The raw transaction data contains 460.8 million observations which we reduce to 92.6 million transactions that are defined as arm's length, which are in turn based on 53.2 million properties.[38] The following sections document how we identify our set of residential arm's length transactions

1. Missing or low sales price (71.3% of total)

As a first step, we remove transactions with a missing or low sales price. This amounts to removing 328.7 transaction bringing the count down to 132.1 million. This helps to address several other issues as well (as e.g. refinancing transactions are likely to have a missing sales price). We choose a threshold for low sales price of ≤ 1000 as there is a drop-off in density after 1000US$ and 5000US$. Out of all transactions (incl. Texas where prices are typically not recorded), 70% have a missing sales price, and 1.3% of transactions have a sales price of zero or ≤ 1000US$. Of the 1.3% of the last category (≤ 1000US$), most prices are near zero. We drop all transactions with a sales price of ≤ 1000 or missing.

[38] This is the data downloaded from Zillow on April 7th 2020. This excludes observations with a transaction date before 1990. Since one transaction can contain multiple housing units, the number of units transacted in the raw data is slightly higher at 485 million.

2. Foreclosures and distress sales (2.0% of total)

As a second step, all remaining identified foreclosures are removed. This includes all *data* types "Foreclosure". Since all of these observations have a missing or low sales prices, no additional observations are removed. We classify and remove additional *document* types associated with distressed sales and foreclosures. Some of them are not foreclosures in a strict legal sense, but practically very close to it (Receiver's Deed, for example). The Bargain and Sale Deed (BSDE) is one of the main deed types in Nevada and is therefore retained. BSDE deeds make up 69% of transactions with a sales price >US$1000 in Nevada, compared to 1.3% in all states. This removes an additional 9.3 million transactions bringing the count down to 122.8 million.

3. Intra-family and gift transfers (0.7% of total)

The third step is to remove intra-family and gift transactions. There is an intra-family flag coded by the Zillow team, which predominately corresponds to the INTR document type. We identify and remove additional intra-family or gift document types, such as Gift Deeds or Affidavit - Surviving Spouse.[39] In total, 3.4 million intra-family and gift transfer transactions are removed, bringing the count down to 119.5 million transactions.[40]

4. Credit lines, refinancing and pure mortgages (1.4% of total)

While Zillow defaults deed transfer documents to DEED, pure loan documents default to MTGE. All document types MTGE are removed (only 9 at this stage). The default value for loan types is empty. There are 6.5 million observations with recorded loan types, mainly commercial loans and seller take back loans. All transactions with a recorded loan type are removed, which includes refinancing transactions and new credit lines (e.g. HELOCs). In total this brings the observations down to 113.0 million transactions.[41]

5. Non-residential property types (1.2% of total)

We next remove non-residential property types. Table A.10 lists the retained and removed property types. Transactions with missing property types (45% of the remaining transactions) are also

[39] There is an additional code in the data types (GT: No Consideration - Gift), which does not remove any additional observations, however.

[40] Quitclaim deeds are around 3 million transactions. Some may be used for intra-family transfer, but not necessarily, so they are retained in the data.

[41] It is possible that some of these loan types are actual transactions, although it is unlikely. One way to further refine this could be to use the information on buyers and sellers.

Table A.10: Retained and removed property types

Retained property types	Removed property types
AP – Apartment Building	AG – Agricultural
CD – Condominium	CI – Commercial & Industrial
MF – Multi-Family Dwelling (2-4 Units)	CM – Commercial
MH – Manufactured Home	CP – Cooperative
MX – Mixed Use	EX – Exempt
NW – New Construction	GV – Government
PD – Planned Unit Development	IM – Improved Land
RR – Residential	IN – Industrial
SR – Single Family Residence	MB – Mobile Home
	RC – Recreational
	UL – Unimproved Land/Lot
	VL – Vacant Land/Lot

Notes: The table lists the retained and removed property types. Missing property types are also retained.

retained. Most of the non-missing property types are single family residences. This step removes 5.4 million transactions bringing the count to 107.6 million transactions.

6. Multiple properties per transaction and missing panel ids (2.3% of total)

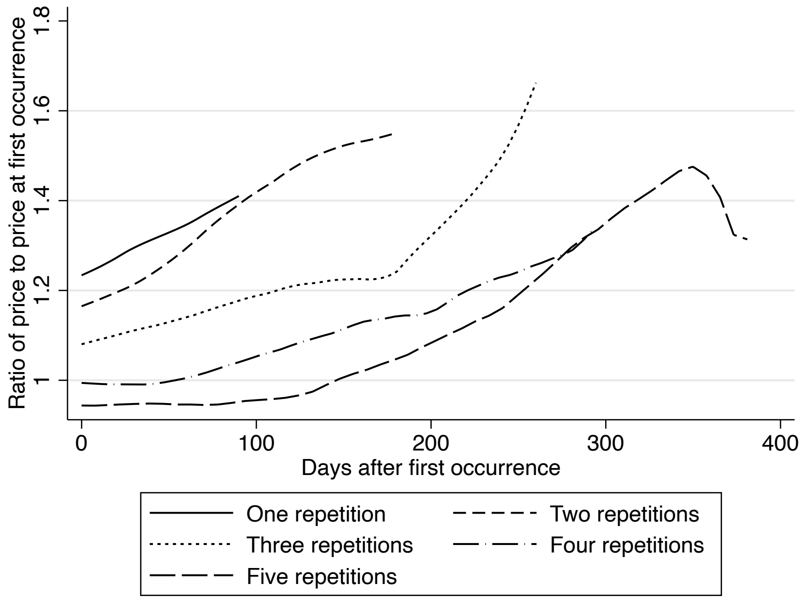
A particular transaction can contain multiple units. All transactions with multiple units are dropped as the sales price cannot be assigned to a particular property. This first step removes 2.3 million transactions (0.5% of total). We also remove the transactions with missing property (panel) ids, which constitutes 8.4 million transactions (1.8% of the total). For a handful of small states, missing property ids are more than or near 50%, but in most states it is missing less than 20% of cases. In total, this step removes 10.7 million observations bringing the count to 96.8 transactions.

7. Repeated sales (0.7% of total)

Next, a subset of transactions within a short period of time are removed. Specifically, if there are multiple transactions of the same property within a 90 day rolling window, only the last of these transactions is retained.[42] The last transaction of a spell of repeated sales is typically higher than the removed previous sales as Figure A.2 shows. Overall the last transaction in a spell is larger than the first in around 80% of spells. This step removes 3.4 million transactions bringing the total count to 93.5 million transactions.

[42]Since the window is rolling, if there are multiple repeated sales a spell of repeated sales can extend beyond 90 days, and the last observation of the entire spell is retained. A property can have multiple spells through time.

Figure A.2: Repeated sales within a 90 days rolling window and sales price



Notes: The figure plots the smoothed average ratio of the sales price to the sales price at the first occurrence of a spell of repeated sales. The average ratio is the exponentiated average of the log ratios to account for the non-linear scale of ratios. One particular property can have multiple spells of repeated sales. A transaction belongs to a spell of repeated sales if the previous transaction was up to 90 days ago. It is a rolling window, so a spell can extend beyond 90 days from the first transaction if there are multiple transactions in a spell. The figure plots five separate graphs by the number of repeated sales in a spell, e.g. "one repetition" indicates a spell of two transactions, and can therefore only be up to 90 days. Plotted is a kernel smoother with a triangular kernel and a bandwidth of 30 days. The graphs show that the later transactions in a spell of transactions are on average higher than the previous transactions. The graphs for more than five repetitions look similar and become more noisy due to fewer spells with highly repetitive sales.

8. Multiple unit properties (0.2% of total)

Finally, after merging the properties to the assessment data, there are a few properties with multiple units per unique property ID. These are for example two individual apartments treated as one. Since it is not clear how to aggregate hedonic variables across these, they are dropped. This removes 0.8 million transactions bringing the total count to 92.6 million.

B. Identifying Property Locations

We next describe how we define property locations. The 92,639,072 transactions that are defined as arm's length above are based on 53,164,562 properties.

The property geolocation and address is provided in the transaction, assessment and historical assessment tables. To evaluate the quality of the provided latitudes/longitudes and addresses, we have drawn a sample of 10,000 properties and geocoded the provided addresses with ESRI based on the provided address. For 95%, the newly geocoded location is less than 160 meters away from the original lats/lons, and for 99% it is less than 1400 meters away. One discrepancy, for example, arises in rural areas, where the geocoded ESRI coordinates are at the street entrance of the property, while the Zillow coordinates are sometimes on the property itself. In the few cases with a large distance between original lats/lons and the geocoded ones, the original lats/lons are closer to a third set of coordinates derived from Google Maps. The ESRI coordinates are slightly closer to the lats/lons from the transaction tables than to those in the assessment tables for the 3.1% when they do not match exactly. Furthermore, in the cases where the zip code from the transaction and assessment tables disagrees (0.8% of times), the transaction zip code matches the Google Maps zip code much more frequently (85%).[43]

We construct the set of lats/lons, zip codes and street addresses in five steps. First we take the lats/lons from the transaction tables, which are available in 97.5% of the cases (we do the same steps for zip codes and addresses).[44] Second, we complement missing ones from the assessment tables which adds 0.4 percentage points to the lats/lons. As a third step, we complement the missing values with the historic information, preferring the most recent non-missing values which adds another 0.7 percentage points to the lats/lons. Of the 53,164,562 properties with arm's length transactions, there are non-missing coordinates for 98.6% (52,443,223), non-missing zip codes for 99.8% (53,066,792), non-missing addresses for 97.3% (51,737,628).

As a fourth step, we ensure the quality of the existing lats/lons by calculating the distance to the official TIGER county boundaries. If the counties in the Zillow data match the TIGER counties (distance is zero) they pass our quality test. The existing lats/lons also pass the quality test if the distance to the matching counties is less than 1km. Manual inspection shows that the shape files at the county boundaries can be imprecise (i.e. in the case of a winding road at the border), and that the lats/lons are actually in the correct county. For the lats/lons that do not pass our quality test, we set them to missing and pass them to the next geocoding step. This adds 47,720 properties to the 721,339 properites with missing coordinates. In total, for the 769,059 properties with missing coordinates, we have 51.8% (398,378) with non-missing address and zip code, 3.9% and 38.5% with only address and zip respectively, and 5.8% without address or zip code.

To ensure a high quality of geocoding, we only geocode the properties with existing addresses and zip codes in the fifth step using ESRI Streetmap Premium.[45] A few of the geocoded properties have non-matching geocoded counties and original Zillow counties. We only use the geocoded

[43]The disagreement between assessment and transaction coordinates and zips is scattered across all states and years.

[44]For multiple addresses per property for different transactions, we keep the longer street addresses, after cleaning upper/lower cases and spaces.

[45]We feed in the addresses and county names as the county identification should be the most reliable data because the raw data is obtained from the individual counties.

coordinates for matching counties and where the ESRI score is high ($\geq$80%), which is 91.2% of the 398,378 proprieties. With reverse geocoding, we retrieve missing addresses and zip codes from existing coordinates. We set the location of 912 properties to missing where the reverse geocoded counties do not match existing Zillow counties.

The final share of properties with non-missing coordinates is 99.0% (52,612,606), corresponding to 92,006,045 transactions. The share of properties with non-missing addresses is 98.7%, and the share with non-missing zip codes is 99.8%.

C. *Identifying Square Footage of the Property*

We next identify the size of the property in square footage and link it to our 92,006,045 transactions based on our 52,612,606 properties for that we also have coordinates from the previous section.[46] Due to the last step of identifying the arm's length transactions, all properties are single unit properties.[47]

There are several different types of building areas that define the size of the property. Some refer to total areas such as "Living Building Area" (BAL), "Gross Building Area" (BAG) or "Total Building Area" (BAT), and others refer to parts, such as "Balcony/Overhang", "Basement", "Porch". The coverage on the total areas is much better than on the individual parts. Each property can have multiple building area types, referring e.g. to the balcony area and the total area. According to Zillow, the "Living Building Area" is usually taken as the property area. While it has the lowest number of missing observations of all types of areas, it is still only available for 66.2% of arm's length properties in the assessment tables.

Before proceeding, we ask whether the missing data comes from particular counties or states. We calculate the share of properties with non-missing "Living Building Area" (BAL) information both within counties or within states. There are many counties that do not report the BAL for any property, so there seems to be little selection within counties. This is the main driver for the

[46] Around 0.1% of these cannot be matched to the assessment tables. These missing properties are missing across states and years, and are not just concentrated in recent years. The ca. 50 million properties are a third of the 150 million properties in the raw assessment tables. For the other 100 million properties, there are no arm's length transactions recorded.

[47] There are sales prices available in the assessment tables as well, but it is recommended to avoid them, as Zillow notes: "Generally, you can think of the data in ZAssessment tables as data sourced ultimately from county's assessor's offices and ZTransaction tables as data ultimately sourced from legal recordings processed by each county recorder's offices. These are usually two separate agencies in the county administration. The Assessor's office tracks many things, like property attributes, completely independently from the County Recorder's office. However, when the County Assessor reports sale prices on homes (the SalesPriceAmount variable in the ZAssessment tables), this is data that the county assessor's office has taken from the recorder's office and blended into their data set before they sent it to us. Some counties will do this to use the most recent sales prices in their assessment amount models. That being said, we've found that the transaction data we get through assessors tends to be marginal and not always up to date, so when available, use the transaction data reported in the ZTransaction tables."

missing information. There are some states (e.g. Illinois) in which less than 40% of properties have information on the BAL.

We next supplement the 66.2% of nonmissing observations of BAL. As a first step we complement this data with information from historical versions of the assessment tables. This increases the share of non-missing "Living Building Area" to 73.6%.[48]

As a second step, we further impute the missing values of BAL by taking the other total area types into account – Total, Base, Finished, and Gross Building Area. Importantly, for 84.4% of properties, we have at least one area type reported. We impute the missing BALs, by taking one of the other codes adjusted by the median ratio between BAL and the other code.[49] We therefore recover square footage for 84.4% of the properties, corresponding to 80,618,103 of our arm's length transactions. Overall, we have both square footage and coordinates for 44,799,731 (84.3%) of our arm's length properties and 80,544,782 (86.9%) of our arm's length transactions.

[48]The most recent available historical information is used for each individual property and area type to replace missing values.

[49]We use the other codes sequentially in the following order: BAT, BAG, BAF, BAB. The median and interquartile ranges of the ratios are unity except for BAG, where the median is 1.2.