Race, Rental Yields, and Housing Decay in Manhattan*

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Abstract

We develop a new dataset on real estate transactions in Manhattan (1912–1939), linked to federal Census records (1930 and 1940) and property images used for tax assessment purposes (around 1940 and 1980). We analyze investor returns and incentives to maintain properties as key drivers of racial housing inequality over the long run. We show that, on average, capital returns were low and rental yields were high in the pre-WWII period. Properties housing Black residents transacted at lower values than those housing White tenants while generating disproportionately high rents, consistent with high demand by Black households in a segregated housing market. The high profits realized by landlords lowered the economic incentives to maintain properties with Black tenants—a pattern we identify through an analysis of renovation data and by comparing property images over time using visual machine learning techniques. Property owners neglected Black neighborhoods, perpetuating disinvestment and inequality.

Keywords: housing markets; rental yields; urban decay; race; Manhattan

JEL classifications: R31, J15, N92

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1 Introduction

Neighborhoods are central to the composition of great American cities, shaping both housing markets and patterns of racial segregation (Glaeser, 2011). Understanding the mechanisms behind the development of neighborhoods is central to research on the intersection of race and real estate (e.g., Cutler, Glaeser and Vigdor, 1999; Logan and Parman, 2017; Akbar et al., 2022), as well as to the design of place-based policies aimed at transforming residential areas. Figure 1 illustrates a crucial aspect of changes in property values in New York over the twentieth century. We show histograms of assessed values for properties transacted between 1912 and 1939 and assessed values as of 2022 for two Manhattan neighborhoods from sources detailed in Section 2. These results reveal that the gap in assessed values between a historically overwhelmingly Black neighborhood—Central Harlem-Morningside Heights—and a more affluent, predominantly White neighborhood—the Upper East Side—has widened substantively over time.

In this paper, we show that the growing disparity illustrated in Figure 1 coincides with visual evidence of exterior property decay over time, and delays in alterations that enhance market value, for properties rented out to Black households in 1940. We also document that segregation in pre-WWII Manhattan led to spatial heterogeneity in rental yields, with landlords earning higher returns on properties occupied by Black households. While prior work has studied racial differences in the cost of housing and households' access to homeownership, our focus thus shifts to the real estate investors' realized returns—and their incentives to maintain or neglect properties—in a setting where demand for housing by Black households was high but their options were limited.

The Great Migration led to an influx of Black residents into concentrated areas in Northern cities, with "White Flight" intensifying residential segregation (Boustan, 2010). Most Black migrants arriving in Manhattan in the decades before WWII could realistically only hope to rent in areas with elevated existing concentrations of Black households. In 1930, more than 80% of the Black population in Manhattan resided in the Central Harlem-Morningside Heights neighborhood, creating focal demand.[1] According to the 1940 Census, this neighborhood had the highest proportion of individuals who had migrated from states not bordering New York. Migration rates from states associated with the Great Migration were nearly 11 times higher in Harlem compared to the affluent Upper East Side. Moreover, turnover was high; the same Census data

[1]The statistics in this paragraph are the authors' own calculations based on the 1930 and 1940 Census records described in detail in Section 2.

show that Harlem had the lowest proportion of residents living in the same house five years earlier. Black households in cities also had fewer opportunities for home ownership compared to suburban or rural areas (Collins and Margo, 2001). The upshot was that downward pressure on rents in Black neighborhoods was limited. As noted in a history of Harlem by Tritter (1998), "the massive migration of Blacks to New York supplied landlords with unprecedented demand for their buildings." A first goal of our paper is thus to test the hypothesis that property investors realized higher net returns—even accounting for differences in capital gains and vacancy rates—when their tenants were Black households.

We then study how the returns to landlords, interacted with persistent segregation-driven demand, affected long-run changes in housing quality. At the start of the twentieth century, when Harlem began transitioning to a Black neighborhood, it offered high-quality housing, and the promise of a thriving Black community—not a "ghetto" (McGruder, 2015). After 1920, the neighborhood started suffering from overcrowding. Moreover, qualitative accounts of the history of the neighborhood argue that landlords—even while charging high rents—were "increasingly unwilling to maintain their properties, and allowed them to deteriorate [...] crucially needed maintenance and up-keep declined" (Rosenbaum and Friedman, 2006). Many landlords did not live in the area, and "were no longer interested in the quality of the neighborhood or even the appearance of their own buildings. Their only concern was profit" (Tritter, 1998). Owners of properties in Black neighborhoods of course faced a clientele of tenants who had no other option but to stay and keep paying their rent, even when their housing conditions deteriorated, meaning that owners had little incentives to maintain their properties. Our second aim with this paper is to complement the existing historical and sociological work by testing empirically whether properties with Black residents were indeed systematically less likely to be renovated—and allowed by their owners to decay more than those rented out to White households in the decades post-WWII.

Our analysis is based on a major data collection exercise with four main components. First, we digitized the corpus of real estate transactions from volumes of the *Real Estate Record and Builders' Guide* (henceforth RERBG) from 1912 to 1939. We observe comprehensive information on the transaction value of properties along with property-level characteristics such as square footage, number of stories, and building style (e.g., dwelling or tenement). Our final dataset includes 23,690 transactions. Second, we access a dataset of over 720,000 images of properties in New York City taken around 1940 by the Works Progress Administration and NYC Tax Department property tax assessment authority. These images, captured as frontal views and accompanied

by descriptive property cards, were used to assess property values during a period of significant debate over taxation and redistribution (Esperdy, 2004). As one NYC assessor at the time noted, "the photograph tells me more about the building than most of the words [on the property cards]," underscoring the unique insights offered by these visual records. Manhattan properties were photographed again for tax purposes by the Department of Finance in the 1980s, allowing us to examine changes in property features and quality over time. Third, we use the 1930 and 1940 federal censuses, which provide household rent data and individual-level demographic characteristics, including race, for Manhattan's population. The Census includes residential addresses, enabling us to match them to geocoded transaction and image data. We aggregate reported rents paid at the property level to estimate the owner's gross rental income. Finally, we link our property transactions, images, and Census data to the Primary Land Use Tax Lot Output (PLUTO) dataset from the NYC Department of City Planning. This dataset provides additional information on properties, including current assessed values, original construction years, and the timing of significant alterations.

The first steps of our analysis on this newly developed data set focus on modeling time-series and cross-sectional variation in property market values. We first estimate a traditional hedonic model on the RERBG data for 1912 to 1939 to understand property price determinants in pre-WWII Manhattan. We then construct real estate price indexes to investigate capital returns to Manhattan property investors over the same time period using a random forest tree-based model that allows for non-linearities and interaction effects when predicting prices. Our primary finding is that capital returns to housing were low, consistent with estimates in Jordà et al. (2019) (henceforth JKKST). Whereas JKKST estimate an annualized gross capital return of 0.41% for this period, we find a similar return of 0.39%. Moreover, our index closely tracks the JKKST index over time. We also estimate indexes by neighborhood and building type. We do not find that tenements (low-income housing) or neighborhoods with large populations of Black residents had below-average price changes over our sample period. This is important because, while under-maintenance of rental properties can be a rational response to deteriorating market conditions (Smith, 1979; Travis, 2019), it is not clear that property owners suffered capital losses or experienced decreasing demand over our time period.[2]

Next, we study whether our property images contain meaningful information about

[2]Neighborhoods like Harlem transitioned from majority White to majority Black relatively early in the twentieth century, and it is thus possible that property values declined substantially around the start of our time frame (Lee, 2022). This would also be consistent with our finding that the higher rental yields for properties rented out to Black households mainly stems from lower relative property values rather than higher rents.

market values. This is important for what follows for two reasons. First, if image features are predictive of property prices, then we can value *all* properties in the Census, and not just those properties for which we have information on characteristics from the RERBG data. Second, if images contain useful information about properties' market values, then having multiple images of the same properties (taken at different points in time) can help us proxy for changes in valuations. We follow the approach in Glaeser, Kincaid and Naik (2018), and use the pre-trained ResNet CNN architecture developed by He et al. (2016) to extract high-level image feature vectors for each property in 1940. We then condense these features into 100 principal components. When we run a linear regression of market prices (for properties transacting between 1912 and 1939) on these principal components, we get an adjusted R-squared of 19.3%. While this compares to 28% for a traditional hedonic model, it is remarkable that we can explain an economically relevant share of the variation in prices even without information on property characteristics.

Building on the previous results, we then predict market values of properties for Census years 1930 and 1940, because it is for those years that we will estimate rental yields. We come up with two types of valuations. A first valuation algorithm is based on a random forest similar to the one we used for constructing our price indexes, and generates valuations for both Census years for those properties in the RERBG (for which we have information on property characteristics). Our second valuation algorithm is also based on a random forest, but now applied to the principal components from the 1940 images, and generates valuations for all properties in the year-1940 Census for which we have images.

We then turn to estimating rental yields, and studying variation therein. To calculate net rental income (the numerator of rental yields), we adjust the aggregated household rent at the property level, computed earlier using the 1930 and 1940 federal Censuses, for estimates of maintenance costs, insurance premiums, and property taxes. We use the random forest-based valuations and image-based valuations just described as our estimate of property values (the denominator of rental yields) for the same years. We find that on average rental yields were high, consistent with Jordà et al. (2019), who present aggregate data on U.S. real estate returns, and Lyons et al. (2024), who document elevated gross rental yields across multiple U.S. cities during the twentieth century.

Next, we find that Black households lived in properties that generated rental yields for their owners that were substantially higher after controlling for property features and tenant demographic characteristics. The difference in (property-level) rental yield between Black and White household heads ranges from 1.3 and 4.4 percentage points across specifications. Decomposing the rental yield results shows that properties housing

Black residents were valued systematically lower; in some specifications, rents are also estimated to have been higher relative to what White households would pay.

In the last part of the paper, we explore the potential long-term housing inequality implications of high demand by Black households combined with persistent segregation by tracking the properties in our dataset over time. We show that properties housing Black residents in 1940 experienced an almost five-year delay in structural alterations that could have enhanced their market value. This delay persists even after controlling for redlining districts, suggesting that any systemic disinvestment associated with redlining does not fully explain the pattern.

To assess long-term changes in property values, we predict 1980 property values by applying the coefficients from a regression of 1940 property values on the principal components of the 1940 image vectors to the 1980 principal components, assuming that the pricing of exterior property attributes does not change too much over time. Properties housing Black residents in 1940 rank significantly lower in value by 1980. We also use our image vectors to analyze property decay over time. We find lower cosine similarity between the 1940 and 1980 principal components of the feature vectors for properties with Black residents in 1940, indicating greater changes in visual characteristics and thus structural decline for these properties.

Our findings of stark racial disparities in property maintenance and visual patterns tied to structural decline highlight how landlords' behavior perpetuated disparities in property conditions and neighborhood segregation.

1.1 Related literature

We make four main contributions. First, a large body of work has studied the rise of segregation in northern cities around the start of twentieth century, and the drivers thereof (e.g., Cutler, Glaeser and Vigdor, 1999; Boustan, 2010; Logan and Parman, 2017; Akbar et al., 2022). Our paper focuses on how segregation shaped investment outcomes and decision-making for property investors, and how these in turn had long-term effects on neighborhoods. A number of papers have recently studied related issues. In particular, Akbar et al. (2022) study how the expansion of segregation led to the destruction of Black wealth as rents in newly Black neighborhoods soared and Black households also overpaid for homes.[3] Lee (2022) describes how urban planning policies amplified segre-

[3]Such work, like ours, also relates to a fast-growing body of work that studies racial differences in the cost of housing and in both access to and the returns to homeownership in more recent time periods (e.g., Bayer et al., 2017; Kermani and Wong, 2021; Box-Couillard and Christensen, 2024; Diamond and Diamond, 2024; Gupta, Hansman and Mabille, 2024).

gation dynamics, and led to substantial property value decreases in neighborhoods that "flipped" to African American majorities. Our perspective differs in that we focus on (multi-family) rental properties' owners' investment returns and incentives, and their implications for urban dynamics.

Second, a number of recent papers have collected historical data to estimate long-term returns to real estate investments (e.g., Jordà et al., 2019; Chambers, Spaenjers and Steiner, 2021; Eichholtz et al., 2021; Lyons et al., 2024). However, it can be challenging to estimate rental yields because often price and rent data are not available for the same properties; also, contractual rents do not always reflect realized income (Chambers, Spaenjers and Steiner, 2021). By linking transaction prices to tenants' reported rent aggregated to the property level, we provide new estimates of realized rental yields in pre-WWII Manhattan. We also study heterogeneity in yields as a function of neighborhood and tenant characteristics. As such, we relate to recent papers arguing that total returns to real estate investments are higher in lower-price neighborhoods (Demers and Eisfeldt, 2022) and that renting to poor households is potentially more risky but also more profitable (Desmond and Wilmers, 2019).

Third, our work speaks to drivers of long-run urban decay, on which less research exists than on the growth and gentrification of cities. Most existing work has studied urban decline through the lens of urban "flight" and population dynamics more generally (e.g., Cullen and Levitt, 1999; Glaeser and Gyourko, 2005; Boustan, 2010), although some sociological accounts focus on the role of discriminatory practices and racial segregation (e.g., references in Travis (2019)). We document how patterns of segregation and the resulting high demand in Black neighborhoods may have decreased landlords' incentives to maintain their properties. Smith, Rosen and Fallis (1988) argue that "when examining the owner/landlord's investment decision, the central issue is to determine the conditions under which a building will be allowed to deteriorate". If the price of housing services is artificially high in Black neighborhoods because of lack of other options for tenants there, then the "optimal maintenance path" may be lowered—even if landlords did not (necessarily) decide on conscious, exploitative "milking" strategies ex ante.[4] Our contribution is to provide new evidence of systematic underinvestment in properties rented out to Black households in the first half of the twentieth century, and also to show that the disinvestment was not driven by lower profitability of those properties.

[4]Segregation may interact with investment structures in explaining maintenance investments. Using contemporary building inspection data for the city of Rochester, New York, Rose and Harris (2022) document lower maintenance in properties where absentee owners outsourced management to professional companies, especially in Black neighborhoods. Travis (2019) shows evidence of lower investment under LLC ownership, which is more common in poor and Black neighborhoods.

Fourth, and finally, our paper makes a number of methodological contributions to the rapidly expanding field of deep learning (Dell, 2025). Image-based machine learning has become a tool to understand price formation in real estate (Glaeser, Kincaid and Naik, 2018; Lindenthal and Johnson, 2021) and art markets (Aubry et al., 2023), and we contribute to this strand of literature through our use of historical data. Recent literature has also used computer vision techniques to further our understanding of the evolution of cultural and societal norms (Adukia et al., 2023; Voth and Yanagizawa-Drott, 2024). By comparing images of buildings taken at different points in time, we illustrate how images can be used to analyze urban change.[5] Linking property images to Census data opens up new possibilities to study economic choices and outcomes at the household level.

2 The Data

2.1 The Real Estate Record and Builders' Guide

Manhattan is the focus of our study because of its importance as a real estate market with 1.9 million residents in 1940, its significance as a metropolitan area segregated by race in the decades before WWII, and the availability of robust transaction data from the RERBG. The RERBG includes transactions where confidential information on the actual sale price was available (Grebler, 1955). Market-based transactions represent the prices buyers are willing to pay for specific property features, location, and amenities at any point in time, thereby also providing a basis for estimating the implicit value of property characteristics in hedonic models.

As we are interested in the pre-WWII period, we used digitized collections of the RERBG from Columbia University's digital archives for the period 1912–1922, and extended the dataset to 1939 through our own efforts. We start in 1912 because from that year onward the layout of the RERBG is more conducive to ORC extraction than before—compare Panel A to Panel B of Figure 2). In total, we OCR 3,864 pages of transactions. Nicholas and Scherbina (2013) hand-entered 30 transactions per month from the same data source, whereas modern digitization methods enable us to capture a significantly larger proportion of transactions (Panel C).

We ensure that the transactions included in our analysis are actual market sales, as

[5] While Glaeser, Kincaid and Naik (2018) find that aesthetic appeal (captured by visual data) plays a more significant role in property price determination in wealthier neighborhoods, we will demonstrate how these features can also highlight structural decay in poorer neighborhoods. This underscores the context-dependent importance of visual data in understanding and predicting property values.

described in the RERBG, excluding those that are non-monetary or between related individuals. From the digitized pages we extracted all the relevant information on property transactions including the transaction value, whether the transaction was a foreclosure, the square footage of the lot, the type of property, the construction material, whether it had a store front, and the number of stories. In Panel B of Figure 2 we see that 1026 Park Avenue, in the Upper East side, is a 20 $\times$ 70 lot with a five-story tenement built from stone that had an assessed value of $31,000-35,000 (land or land plus building) and transacted for $45,000 in August 1920. We know this property transacted at market price, in contrast to 294-96 Bowery in the Lower East Side, which is designated as a "O C & 100" transaction, which the RERBG codifies as "other consideration & 100." 1026 Park Avenue transacted again in March 1936 and again in February 1937, though the vast majority of properties (87%) in our dataset transact only once (Panel D).

We estimate the total gross square footage of a property by the convention used in the PLUTO database by multiplying the lot area by the number of stories. This method is an approximation, since properties can have setbacks, open spaces, or partial coverage.[6] For the 1026 Park Avenue property, the lot dimensions are square, making the calculation of total gross square footage straightforward. For properties with irregularly shaped lots, we approximate the area by squaring off the average of the lot dimensions.

Our dataset contains 23,690 market-based transactions. Figure 3 shows the location of these properties using the modern ArcGIS locator file for geocoding. Despite potential complications from historical address changes, this method has been proven to yield accurate results (Barr and Tassier, 2016; Gray and Bowman, 2021).

Descriptive statistics on our data are shown in Table 1. The most common property type is tenements (47.5%), followed by 'other' dwellings or commercial buildings (22.9%), dwellings (20.6%), and lofts (8.9%). Most properties were constructed with brick (63.1%), while stone and other materials accounted for 13.1% and 23.8%, respectively. 38.9% of properties included a store, which is consistent with Grebler (1955) who shows about 44% of apartment properties contained a store. Building height varied, with 30.7% of properties having six or more stories, indicating the inclusion of particularly large properties in the dataset. Lot sizes averaged 18.73 thousand square feet, while total square footage (lot and building) averaged 81.96 thousand square feet. The average property transaction value is $40,301 (about $700,000 today). Foreclosure transactions account for a substantial share of our data as identified by the text string "FORECLOS"

[6] "New law" residential buildings in New York City constructed after the enactment of the 1901 New York Tenement House Act were required to have courtyards in order to allow for ventilation and natural light in every unit. "Old law" buildings often did not have courtyards and thus occupied a larger fraction of the lot.

in the RERBG listings; given the prevalence of foreclosures, we include them in the construction of our indexes while using an indicator variable to account for their specific value.[7] The distribution of properties covers all neighborhoods, with the largest shares in the Upper East Side (15.1%), Chelsea-Clinton (14.8%), and East Harlem (13.5%). Each property when it transacted was an average of 0.26 miles to the closest subway (cf. subsection 2.4).

2.2 Property Images

We accessed images from a remarkable initiative started during the Great Depression. Photographs of Manhattan properties were taken as part of a large-scale effort initiated by the New York City Department of Taxes and supported by the Works Progress Administration (WPA). Known as the Real Property Tax Card Record System, the project aimed to modernize property assessments by documenting all parcels of real estate with detailed tax cards that included photographs, diagrams, and building data. This was intended to facilitate equitable taxation and administrative efficiency. The project provided employment for about 900 clerical workers and photographers during a period of high unemployment, making it both a practical and relief-driven initiative. Qualified photographers were hired as "skilled non-manual workers" under Class III in the WPA classification system.

The resulting collection of over 720,000 images captures every building across the five boroughs from 1939 to 1941. With the five boroughs containing approximately 815,000 parcels of real estate in 1938, this collection is highly comprehensive (Esperdy, 2004). The photographs are particularly useful for understanding the architectural and urban landscape of the time, as they provide detailed, visual records of building types, materials, and uses. While the angle of the photos was sometimes dictated by the building's size and the street's width, necessitating oblique perspectives in certain cases, the images offer insights into the diversity of urban structures with reasonably standard framing perspectives. Designed to assist tax assessors with valuations they are by construction a visual reflection of underlying property value. Beyond the buildings themselves, the photographs also capture subtle elements of urban life—such as lampposts, signage, vehicles, and street level activities—that can serve as proxies for location attributes and

[7] Panel A of Appendix Figure A1 shows that the share peaks around the time of the First World War and during the foreclosure crisis associated with the Great Depression (Ghent, 2011). Panel B shows an upward trend in foreclosure property values during the Great Depression. We know savings banks purchased properties at foreclosure auctions, primarily in cases where they acted as the plaintiff. In essence, these banks were acquiring properties to protect their mortgage liens. The RERBG also published maps that detail their frequency and location (see Appendix Figure A2).

amenities, which are often difficult to quantify through property characteristic variables alone. Fortuitously, the Department of Finance undertook a project to retake the tax photographs during the 1980s. Thus we have visual features of properties we can compare from both snapshots in time. A limitation of the images is that we do not observe interior conditions.

Figure 4 provides examples of the images in our dataset. 415 West 118th Street in the Morningside Heights neighborhood of Manhattan which transacted for $110,000 in August 1914 in the RERBG is shown in 1940 and 1980 alongside a current image showing its ownership by Columbia University.[8] The 1980 images are of lower quality because the original 35mm photos were converted into a digital format by the Department of Finance and stored on Laser Video Disks, an early optical storage technology. The next set of 1940 images in Figure 4 shows a property with a store front, as well as images of properties with cars or a person walking by. Each 1940 image includes a placard with an identifier code for the building and lot number, which is included in the filename of the images, which we can use to match with the other data sets. Some photos, as shown in the bottom panel of Figure 4, contain defects, or in the case of the 1980 collection, a substitute card was placed where an actual photo was missing. These defects can largely be identified and cleaned through their corresponding feature vectors (subsection 3.3).

2.3 Census Data and Redlining

We use federal Census data as our source of rent information. In the 1930 and 1940 censuses, households indicated whether their home was owned or rented. Renters provided the amount of their monthly rent, while homeowners were asked to estimate the potential sale price of their property.[9] The majority of the properties in our dataset were rentals.

What information do the rents convey? Rent control became widespread during the Second World War. Fetter (2016) estimates that approximately four-fifths of the rental housing stock in 1940 was located in areas subjected to federal rent control measures between 1941 and 1946. Before this, rent control laws existed primarily on an ad hoc basis and, in Manhattan, relied heavily on judicial discretion. Günnewig-Mönert and Lyons (2023) document how judges were empowered to decide whether rent increases were "reasonable" based on a law introduced in 1920, which was subsequently abolished

[8]For simplicity, we refer to the 1939–1941 images as "1940" images and the 1980s images as "1980" ones.

[9]Beyond Census data, comprehensive rent information is available from newspaper listings, as highlighted by the major efforts of Lyons et al. (2024) to collect these data for a multitude of U.S. cities during the twentieth century.

during the late 1920s. Although agitation for rent control continued throughout our period, we assume for the 1930 and 1940 data we have from the Census that rents reflect approximately market prices.

To illustrate the data we obtain and our matching approach, consider our example of 415 West 118th Street in the RERBG shown in Figure 4. In 1940 this property was rented by 20 households containing a total of 60 individuals. 54 of the individuals were White and six were Black all of whom belonged to the same household. Household rents ranged between $45 and $70 per month. Three households did not report rent, including the Black household, but we do not find that missing rental data is systematically a function of race.[10] We impute missing rents based on the average rent of the reporting households for each property. We then aggregate at the property level, with annual rents for 415 West 118th Street totaling $12,732.

The richness of the Census data means we will be able to estimate rental yields at the property level conditional on a range of tenant demographic characteristics. The 1940 Census contains data on wages and education which is particularly useful as we are interested in housing affordability, economic conditions, and social inequality. Louise Kilburn, a White 37-year old waitress with a high school education who earned $1,000 during the prior year, lived at 415 West 118th Street with her 11-year old child and 75-year old aunt. Richard Wildman, a naturalized Black resident with a high school education from the West Indies lived there with his spouse Hazel and four daughters. Wildman appears to have been the superintendent of this, or another, apartment building based on the occupation string in the Census and his stated earnings are $1,200. We focus much of our analysis on the 1940 Census because it provides richer demographic variables. In contrast, the 1930 Census offers more limited data, with literacy serving only as a basic indicator of educational attainment, while wages are not observed at all.

Based on the Census data we can see how segregated Manhattan was. Figure 5 shows that the Black population overwhelmingly resided in the Central Harlem-Morningside Heights neighborhood especially relative to the more dispersed distribution of the White population and other racial groups. We also incorporate spatial data from Home Owners' Loan Corporation (HOLC) maps (1935–1940) from *Mapping Inequality: Redlining in New Deal America* to classify neighborhoods by redlining designations. In 1940 92% of the Black population of Manhattan resided in a redlined area which were designated as "hazardous" according to perceived investment risks, compared to 55% of Whites.[11]

[10] We estimate a linear probability model with an indicator for missing rents as the dependent variable and race indicators as independent variables. The coefficient on Black households heads is -0.012 (s.e. 0.007) and on Other is -0.008 (s.e. 0.010) with White household heads as the baseline.

[11] See Appendix Figure A3 for more details. Appendix Figure A4 plots each geocoded Census obser-

When we geocode the RERBG addresses and the Census addresses we use the same ArcGIS location file, then match all pairwise combinations of properties on their calculated distances. The address strings in the Census are often messy, with numbers frequently spelled out as text (e.g., "One Hundred Eighteenth Street" instead of "118th Street"). This is particularly problematic in Manhattan, where many addresses include numerical components. We first cleaned the addresses using text algorithms. Given the density of properties in Manhattan, we apply a strict matching threshold, requiring a distance of zero meters between properties. Descriptive statistics for the matched RERBG-Census data are shown in Appendix Tables A1 and A2 for 1930 and 1940 respectively.

Our final regression dataset includes only the large majority of residential properties that were fully rented, as we cannot accurately impute the rental value of owned units in mixed-use properties where systematic differences could exist between rented and owned units. For example, rented units may be smaller, less renovated, or located on less desirable floors.[12]

2.4 Subways

In cities like NYC, the subway has historically driven urban expansion.[13] We plot the locations of subways which diffused across Manhattan during the early twentieth century. The inaugural line was built by the Interborough Rapid Transit Company and stretched from City Hall in Lower Manhattan to 145th Street and Broadway in Harlem. We use spatial coordinates for NYC subway stations provided by the Metropolitan Transportation Authority. We supplement this with our own data collected on the opening of each

vation in the data. Shaded areas in the 1940 map are Grade D areas or "redlining" areas on HOLC maps created during the late 1930s and early 1940s.

[12]Panels A and C of Appendix Figure A5 shows the vast majority of properties were fully rented in Manhattan in both 1930 and 1940 due to the city's vertical development. The prevalence of multi-unit buildings and tenements, especially in the late nineteenth and early twentieth centuries, catered to renters rather than individual homeowners. Panels B and D present estimated marginal effects of race on property type based on a multinomial logit model. These marginal effects represent the change in the probability of each property type associated with the household head being Black versus non-Black, controlling for property, individual, and spatial characteristics (latitude and longitude). The results indicate that Black households were significantly more likely to reside in rental properties, equally likely as non-Black households to reside in owner-occupied properties, and less likely to live in buildings with mixed ownership and rental households. Taken together, the figures underscore the predominance of rental housing in Manhattan and racial disparities in access to property types.

[13]The poor tend to live in cities because transportation costs are lower (Glaeser, Kahn and Rappaport, 2008), while property values tend to increase generally with proximity to rail systems due to gentrification (Kahn, 2007) and lower commuting times (Gupta, Van Nieuwerburgh and Kontokosta, 2022). In New York City, Lee (2022) observes a significant increase in segregation through residential sorting by income following the construction of transit infrastructure.

station, from the Broadway–Seventh Avenue Line's opening in 1904 to the opening of the East Broadway station on the Sixth Avenue Line in 1936. For each transaction year (between 1912 and 1939) and Census year (1930 and 1940), we estimate the minimum distance from a property to the network of subways operating in that year. In 1912, 41 subways were in operation, increasing to 130 by 1939.

2.5 PLUTO Database

As a final step in our data collection, we link all our data to the most recent version of the PLUTO (Primary Land Use Tax Lot Output) dataset, using both geocoding or matching by the building block and lot identifiers. PLUTO contains detailed information about every tax lot in New York City, including Manhattan, and is widely used for urban planning and research. An advantage of this dataset is that it contains information on the approximate year that properties were built and the year in which any alterations were made that would enhance market value. Year built is a proxy for unobserved quality, including construction standards, architectural styles as well as ageing and depreciation. Given the inclusion of data on alterations, we can trace out the renovation history of properties in our dataset by race. The PLUTO database also contains contemporary assessed values.

3 Capital Returns and Property Valuation Models

Because properties trade infrequently, their values are typically unobserved. Market transaction prices offer the most reliable basis for valuation (needed to estimate rental yields) and the estimation of capital gains over time, but we need to account for the heterogeneous nature of real estate. In this section, we will first present a simple hedonic model that sheds light on the drivers of cross-sectional price variation in our data set of RERBG transactions (subsection 3.1). This analysis will serve as a stepping board for our construction of price indexes (subsection 3.2), and be a useful benchmark when studying the power of property image features in explaining transaction prices (subsection 3.3). In the final part of this section, we will generate out-of-sample property valuations for Census years (subsection 3.4), which combined with data on rents will allow us to come up with estimates of rental yields in the next section.

3.1 A Simple Hedonic Model

Let $V_{i,t}$ denote the observed market price of property i sold at time t, and let $v_{i,t}$ represent its natural logarithm. Assume that each transaction includes M measurable characteristics that fully describe the property (as outlined in Table 1) and remain constant over some period of time: $\mathbf{z}_i = [z_{i,1}, z_{i,2}, \ldots, z_{i,M}]$.

Using all these characteristics, along with quarter-by-year dummies, we can estimate a standard hedonic regression using our RERBG observations:

$$v_{i,t} = \delta_{q,t} D_{q,t} + \sum_{m=1}^{M} z_{i,m} \gamma_m + \epsilon_{i,t}, \quad (1)$$

where $D_{q,t}$ is a dummy variable for quarter q of year t, and $\delta_{q,t}$ represents the corresponding coefficient for the quarter-by-year effect. These dummies explicitly control for temporal variation in property values at a quarterly level, ensuring that the coefficients on the characteristics reflect within-period differences (rather than picking up broader market trends correlated with changes in the distribution of characteristics over time). This model enables us to estimate the market value of any property at a given time based on its specific attributes and the fitted coefficients.

Table 2 reports the γ_m coefficients corresponding to the property characteristics, neighborhood fixed effects, and location characteristics in $z_{i,m}$. In column 1 we report the coefficients for our full time period 1912-1939 and then we report estimates of subperiod effects for the 1910s, 1920s, and 1930s in columns 2, 3, and 4. The coefficient on the log of square footage is positive and significant though less than unity across all periods suggesting diminishing marginal returns to property size in larger buildings where much of the additional square footage may be allocated to less desirable spaces, such as hallways, storage, or elevator shafts. The coefficients on stories capture the positive aggregate value of taller buildings (the baseline of six stories or over).

Deviations from a standard rectangular shape influence property values. A one-unit increase in the number of dimensions is associated with a 6.1% increase in property value. Irregular lots could be beneficial for commercial or mixed-use developments, for example, driving up prices relative to standard lots. In the full 1912-1939 period having a store is associated with a 14% higher property value ($e^{0.131} - 1 = 0.139$). The effect is largest in the 1930s where properties with a store command a 20.1% higher price compared to those without additional features.

Building type significantly affects property values. Compared to tenements (perhaps due to their association with poor living conditions, lack of amenities, and historical use

as affordable housing), dwellings, lofts, and other building types command substantial transaction premiums, with 'other' building types showing the largest positive effects. Construction material also plays a role; compared to brick (the base category), stone construction adds a small premium, while properties made from other materials are valued less.

Neighborhood fixed effects reveal substantial variation. Affluent neighborhoods like Gramercy Park–Murray Hill and the Upper East Side consistently exhibit significant premiums compared to Union Square–Lower East Side, with the largest premiums observed in the 1930s. Predominantly Black neighborhoods, specifically Central Harlem–Morningside Heights and East Harlem, generally show lower property values, though the disparity does not seem to dramatically change over time. Distance to the nearest subway station negatively impacts property values across all periods, emphasizing the importance of transit accessibility. A 10% increase in the distance to the nearest subway station is associated with a 1.5% to 1.7% decrease in property value across periods.

Finally, the coefficient for foreclosure is negative and significant across all periods, with foreclosed properties being sold at an average discount of about 20.3% from 1912 to 1939 compared to non-foreclosed properties. The discount is largest in the 1920s where foreclosed properties sold for approximately 43.2% less than comparable non-foreclosed properties. Given the preponderance of foreclosures in our data, we include these properties in our estimation of capital returns but account for the lower associated transaction values.

3.2 Aggregate, Property Type, and Neighborhood Returns

We now move to constructing price indexes, comparing them to estimated aggregate capital returns to housing from Jordà et al. (2019), while exploring heterogeneity by property type and neighborhood.

We modify the simple hedonic model introduced in the previous subsection in a number of ways. First, to ensure interpretability and robustness over longer time periods, we replace quarter-by-year effects with year dummies. This allows us to estimate indexes that reflect the relative change in property values across years, with the normalized initial value of $1 as the baseline, thereby measuring the annual capital return on the initial investment. Second, we account for some of the weaknesses of standard hedonic models as a way to estimate price indexes in two different ways. One drawback of a hedonic model estimated on pooled data (i.e., data for the full sample period or pooled over a decade) is that characteristics' shadow prices are constrained to be constant over

relatively long periods of time. In reality, the relative attractiveness and thus pricing of, for example, certain neighborhoods may show faster variation. We therefore switch to using an adjacent-period method, which pools transactions from overlapping two-year time frames to estimate property values relative to adjacent periods. This approach allows for changes in the pricing of characteristics while retaining the ability to estimate annual price changes. In this adjacent-period method, we generate an index by applying the chain rule, linking cumulative relative estimated changes in property values across the overlapping two-year periods. Another weakness of standard hedonic regression models is that they impose a (log-)linear and additive structure, while in reality non-linearities and interaction terms might be important for pricing of real assets (Aubry et al., 2023). We therefore incorporate a random forest approach to capture such complex relationships between features such as location, building type, and square footage—and improve predictive accuracy of the valuation model. Random forest predictions are aggregated across 100 decision trees to produce the final index.

Figure 6 presents our key findings on capital returns, highlighting the close correspondence between our estimates and the nation-wide capital return series for the United States from Jordà et al. (2019).[14] They estimate an annualized gross capital return of 0.41% between 1912 and 1939, whereas we estimate a return of 0.34% using the adjacent-period index or 0.39% using our random forest approach. This correspondence is striking because of the differences in methodologies, granularity, and geographic focus of the data. Our results for Manhattan are highly consistent with their findings, implying that the capital return at the national level also holds true in a major localized urban market, despite potential differences in housing stock composition and market heterogeneity.

Figure 7 explores capital returns further by property type and neighborhood, based on our random forest estimates, revealing some heterogeneity in the real estate market. Different building types appear to cater to distinct buyer or investor groups, leading to variations in price growth. Yet, property investors owning tenements or properties in the neighborhoods with substantial populations of Black households—Central Harlem-Morningside Heights, East Harlem, Washington Heights-Inwood—did not seem to have experienced below-average capital gains over this period.[15]

[14]The U.S. house price index in Jordà et al. (2019) is taken from Knoll, Schularick and Steger (2017), who themselves rely on multi-city single-family house price indexes from Grebler, Blank and Winnick (1956) and Fishback and Kollmann (2014) for the relevant period.

[15]Appendix Figures A6 and A7 show estimated adjacent-period and random forest indexes by property type and neighborhood, respectively.

3.3 Feature Vectors from Property Images

We now turn our database of property images as a novel resource for valuation. We do this for two reasons. First, if the images contain sufficient meaningful information about properties' market values, we can put a valuation on *all* properties for which we have rent information in the Census and not just those properties for which we observe a transaction in the RERBG—allowing us to estimate rental yields on a more exhaustive set of properties. This broader scope mitigates selection bias, as transacted properties may systematically differ from those that did not transact (e.g., by having different rent levels). Second, if images correlate with prices, then changes in image features between 1940 and 1980 can tell us something about disparities in long-term price dynamics.

We analyze what the tax assessor saw to extract a quantitative signal about property value from the images. To do this, we employ a modern convolutional neural network (CNN) architecture to represent the images with pixel-based feature vectors. We follow the approach in Glaeser, Kincaid and Naik (2018) and use the pre-trained ResNet model to extract high-level features and patterns present in the image. The 1940 and 1980 images are preprocessed and fed into ResNet to obtain feature vectors as markers of the visual characteristics and structural attributes of the properties. To address the possibility of multiple properties appearing in a single image due to the positioning and perspective of the photographer, we apply a Gaussian mask to emphasize the central region. The resulting feature vectors are then reduced to 100 principal components, capturing over 80% of the variance of the 1940 and 1980 vectors. Importantly, ResNet is not trained to value properties; rather it is used to extract visual features that our models then link to property value.

Machine learning models like ResNet are often considered a "black box" because, while they effectively extract features from images, the exact nature of these features and their relationship to specific outputs (like property value) can be difficult to interpret (Dell, 2025). We therefore provide visual evidence to illustrate what these feature vectors represent. Figure 8 visualizes the five "nearest neighbors" to each randomly selected 1940 image in the first column using the euclidean distance between the principal components of the feature vectors. Illustratively, proximate properties in vector space also exhibit strong visual similarity.

Moreover, the principal components of the image feature vectors are strongly correlated with property transaction values, as can be illustrated by computing the adjusted R-squared for linear regression models where we use different sets of variables to predict the log of transaction values. If we run a hedonic model with fixed property charac-

teristics and year × quarter fixed effects, we get an adjusted R-squared of 27.9%.[16] A model regressing log transaction prices against fixed attributes extracted from historical images using ResNet (i.e. the 100 principal components described above) achieves a slightly lower but still remarkable adjusted R-squared of 19.3%.[17] This compares favorably to the 11.7% reported by Glaeser, Kincaid and Naik (2018) using Google Street View images and modern transaction data from Boston. The fact that our visual features explain more of the variation in sale prices is intuitive as historical images were designed to aid assessors in property valuation whereas images from Google Street View serve broader purposes and are not tailored for evaluating structural or market-related property features.

3.4 Predicting Property Values for Census Years

So far, this section has explored the correlation of property characteristics with transaction prices (subsection 3.1), estimated price indexes that control for variation in property characteristics (subsection 3.2), and established that images can help predict prices even without information on property characteristics (subsection 3.3).

In Section 4 of this paper, we will present federal Census data on rents in 1930 and 1940. To estimate the rental *yields* realized by landlords, we will need to link property-level aggregate rental income to estimates of properties' market values in those same Census years. Therefore, to end the current section on property pricing, we show how we can use transaction data from 1912 to 1939 and image data from 1940 to predict year-1930 and year-1940 market values,[18] either for those properties in the RERBG (when using information on property characteristics) or for all properties in the Census (when using images).

Since our transaction data includes a temporal component, we train a prediction model and validate it out-of-sample to ensure the model can generalize across different points in time. We start by assessing in general the out-of-sample performance of both a hedonic and a random forest model, with the data split into 80% training and 20%

[16] This number is slightly different from the one reported in Table 2 because here we use the subset of data for which we also have images.

[17] Appendix Figure A8 shows a binscatter plot showing a strong correlation between predicted and realized property values between 1912 and 1939, estimated using only the 100 principal components from the 1940 visual features. Combining hedonic characteristics and visual features in a linear regression model explains 30.7% of the variation in log transaction prices, demonstrating the complementarity of hedonic and visual characteristics, while a placebo test replacing meaningful features with random variables achieves only 3.8% with time period fixed effects and 0% without.

[18] As we have transaction data until 1939, we are proxying for year-1940 market value using the year-1939 price prediction.

testing sets. As predictors we use property characteristics as well as the ratio of assessed-to-market value, year of the transaction, latitude and longitude of the property, and a foreclosure indicator. We find that the random forest model consistently outperforms an OLS hedonic model, demonstrating better predictive accuracy with lower average deviations from actual property values, reduced prediction errors, and improved percentage error metrics.[19] These results suggest that while both models effectively capture key predictors, the random forest model provides more precise and robust predictions, likely due to its ability to account for complex, non-linear relationships.

When specifically predicting the specific property values for Census years 1930 and 1940 to link to rental data, we make two key adjustments to our approach. First, we restrict the training model to use data from only the prior five years, ensuring the training specification reflects more recent market conditions. Second, we exclude foreclosures from the training model, focusing solely on market prices, as these are the values we predict for the cross-section of properties in the RERBG. We then value foreclosed properties using the prediction model as if they transacted at market prices. To minimize missing data, we also drop the assessed-to-market value variable, which is a key predictor in our out-of-sample tests but does not affect accuracy in our in-sample scatter plots. We apply the same approach to images, using image vector data from the 1940 images, along with latitude and longitude, to predict 1940 market values for the full cross-section of properties that transacted between 1912 and 1939.[20]

4 Rental Yields and Race

In this section, we first present our main rental yield estimates (subsection 4.1), which build on our random forest-based property valuations and rent data from the Census. We then introduce our main regression specification used for examining variation in rental yields (subsection 4.2), and discuss the results based on the 1940 Census data (subsection 4.3). We continue with two robustness checks, using 1930 instead of 1940 Census data (subsection 4.4) and using image-based valuations instead of random forest-based ones (subsection 4.5). Finally, we study racial variation in rent burdens (subsection 4.6).

[19] Appendix Table A3 presents key metrics used to evaluate accuracy and predictive performance. Appendix Figure A9 further illustrates the stronger predictive performance and better fit of the random forest model to actual property values.

[20] Appendix Figures A10 and A11 illustrate strong correlations between actual and predicted values for properties transacted in 1930 and 1939, supporting the robustness of our approach.

4.1 Rental Yield Estimates

The (unlevered) total return on a property investment consists of two components: the capital return and the income return. The *capital return* component is captured by our property price indexes, as described in subsection 3.2. We can proxy for the income return component with the *rental yield*, which reflects realized rental income relative to the property's market value. We can now estimate rental yields because we aggregated rents over the households living in any property in subsection 2.3, and estimated in subsection 3.4 property values for Census years where rents are observed. Note that, in our data, vacancies are implicitly accounted for, as vacant apartments would not have been enumerated in the Census, and the method we use to aggregate rents at the property level accounts for this. Our yield estimates thus reflect *effective*—not potential or contractual—rental income.

Next to estimating gross rental yields, we can also estimate *net* rental yields. We first need to subtract maintenance costs and insurance costs from gross rental income to calculate operating profit.[21] Taxes, calculated as a percentage of the assessed value of the property, are then subtracted to arrive at after-tax profit, which we treat as equivalent to net cashflow. This provides a net measure of income generated from each property after accounting for observable expenses and taxes. (To isolate the intrinsic performance of the property as an asset, we abstract from financing decisions, including mortgage and transactions costs.) We measure each of these components using our 1930 and 1940 datasets. In both years, we set maintenance costs at 25% of annual rental income, based on estimates from the *Report of the State Board of Housing of New York*. To estimate assessed values, we use the ratio of assessed value to legal basis (market value), which is 90% in 1930 and 92% in 1940, as reported in the *National Municipal Review*.[22] Insurance costs are estimated at 0.57% of assessed value in 1930 and 0.53% of assessed value in 1940, using data from the *Weekly Underwriter*. Finally, we set the tax rate at \$27.20 per \$1,000 of assessed value in 1930 and \$29.60 per \$1,000 in 1940, also based on data from the *National Municipal Review*.

We present mean and median gross and net rental yield estimates for 1930 and 1940 in Figure 9, using as our denominator the random forest-based property valuations for

[21] We assume that depreciation is accounted for within maintenance costs. An alternative approach would be to model depreciation as an annualized capital expenditure rate based on the property's market value; however, this is problematic for our time period. Grebler (1955) highlights that capital expenditures were often irregular, with deferred maintenance common during periods of financial distress.

[22] RERBG sometimes has information on assessed values but not for every transacted property. We will also want to estimate yields for properties that did not transact.

the same years generated in subsection 3.4.[23] We estimate mean (median) net yields of 6.3% (4.2%) in 1930 and 12.1% (10.8%) in 1940. Our estimated returns in 1940 are higher than those in 1930, largely due to the comparatively lower property prices in 1940, which contributed to higher rental yields. The results indicate that total real estate returns were primarily driven by the rental yield component, consistent with findings by Jordà et al. (2019), who report a national net rental yield of 5.3% in 1930 and 6.3% in 1940, and Lyons et al. (2024), who document gross rental yields of 13.6% in New York City between 1930 and 1945.[24]

4.2 Regression Specification

We can now examine variation in rental yields based on the race of individuals residing in these properties, as identified in federal Census data. Our main regression equation, estimated in the next subsection using 1940 Census data on properties that were fully rented, takes the following form, where i indexes properties and h indexes households:

$$\frac{\text{Net Rent}_i}{\text{Property Value}_i} = \rho_r \text{Race}_{h,r} + \eta_q \text{Wage Quartile}_{h,q} + \tau_e \text{Education}_{h,e} + \kappa \, \text{Subway Distance}_i + \sum_{j=1}^{J} z_{h,j}\zeta_j + \sum_{k=1}^{K} x_{i,k}\lambda_k + \epsilon_i, \quad (2)$$

We examine variation in inverse hyperbolic sine (IHS) transformed rental yields for property i, which can take on negative values, as a function of both household-level and property-level characteristics. Household-level variables are measured using the attributes of the household head and include indicators for race (Black, other, with White as the baseline). We also include income quartiles and education levels (with a baseline of 0 to 2 years of schooling) for which information was included in the 19940 Census. Additional household-level controls (ζ) include individual characteristics from

[23] To minimize the impact of data errors on our means, we trim the returns at the 5th and 95th percentiles, as shown in Appendix Figure A12. Grebler (1955) reports a range of net investment yields (including the capital component) from -4% to 23% for properties between 1930 and 1950, while our trimmed range for 1940 (excluding the capital component) spans from -1.5% to 49.5%, reflecting a longer tail of returns in our dataset.

[24] Grebler (1955) reports that net income on properties accounted for approximately 35% to 37% of gross income in New York City between 1935 and 1945. Our findings are broadly consistent with this range, with net rental yields representing about 33% of gross income in 1930 and somewhat higher in 1940, where net rental yields were approximately 49% of gross income. In the total return series presented by Lyons et al. (2024), New York City ranks third from the bottom in capital returns among 29 cities between 1930 and 1945, but seventh from the top in the ranking of gross rental returns. This underscores the critical role of rents as a primary driver of real estate income in this location.

the Census (age, sex, and employment status).

Property-level variables include the IHS-transformed distance to the nearest subway and a set of additional controls (λ), such as property square footage and type. Because property values are predicted using the same characteristics for the cross-section of RERBG properties, we introduce these variables as controls only in our final specifications. We exclude neighborhood fixed effects from the specifications because race is heavily segregated (cf. supra), so we lack identifying variation. Standard errors are clustered at the property level to account for the hierarchical structure of the specification and potential within-property correlations such as shared characteristics among those households.

4.3 Main Results Based on 1940 Census Data

Panel A of Table 3 presents the results of estimating Eq. (2) on the 1940 Census data. Column 1 shows a baseline racial disparity in net rental yields, with Black household heads living in properties that generate a yield for their owner that is about 1.5% (i.e., 1.5 percentage points) higher compared to White household heads.[25] Adding individual controls from the Census reduces this disparity slightly to 1.3% (column 2). Wage and education controls are not strongly correlated with yields, with the estimated racial disparity stabilizing around 1.4% (columns 3–5). Similarly, adding distance to the nearest subway does not change the yield estimate. While proximity to subways may increase property values through improved accessibility, it may also raise rents proportionally, leaving the rental yield unaffected (column 6).[26]

In the final column of Panel A of Table 3, we incorporate property attributes to account for factors beyond household-level characteristics that may explain differences in rental yields. The coefficient for Black household heads is no longer statistically significant. Note that property characteristics are used to predict property values in the random forest model, which serves as the denominator of rental yields. If these same characteristics also directly influence net rental yields (the dependent variable), this creates a mechanical link between the predictor and the outcome possibly absorbing part of the variation previously attributed to race. Furthermore, race may be more strongly correlated with certain property characteristics—such as tenement housing, for example—potentially attenuating the effect of race in this specification, especially if

[25] Importantly, our results are not driven by adjustments for maintenance, expenses, and taxes. As shown in Appendix Table A4, *gross* rental yields are also similarly higher for Black households.

[26] This is precisely what we observe: the distance to the subway is large but statistically insignificant in the net rent specifications for which the main results are shown in Panel B of Table 3, yet strongly negative in the property value specifications in Panel C.

adding these controls also reduces identifying variation.

In Panels B and C of Table 3, we use the same specifications on the numerator and denominator of net rental yields in order to try to disentangle the factors influencing rents and property values. The net rent specifications in Panel B reflect the rents landlords collect at the property level, revealing patterns that help explain rental yield disparities. We find that properties occupied by Black households generate net rents that are statistically indistinguishable from properties occupied by White households. The regression coefficients shown in Panel C indicate a consistently negative and statistically significant relationship between race and property values across specifications. Black household heads are associated with much lower property values compared to White household heads. This persistent gap in the market value of the household's residence remains significant even as individual controls, as well as education and wages, and property characteristics are added sequentially in columns 3 to 7. In column 7, which includes the full set of controls, we estimate that properties occupied by Black household heads were valued approximately 8.2% lower than those occupied by White household heads.

Overall, we find that a hypothetical real estate investor would earn higher net rental yields from Black households, primarily driven by consistently lower property values. In particular, Black household heads paid about the same rents as White household heads with similar characteristics, but lived in properties of lower value.

For completeness, the coefficients on the wage quartile and education dummies for the specifications in column 5 are shown graphically in Figure 10. Panel A shows the low correlation with net yields. Panel B shows a strong gradient in wages and education for net rents. Properties occupied by household heads in the upper quartile of the wage distribution are associated with 23% higher net rents than those in the bottom quartile, while those occupied by household heads with 15 or more years of education are associated with nearly double the net rents of properties occupied by household heads with only 0–2 years of education. Higher-wage and more educated households are likely to access higher-quality housing, more desirable neighborhoods, and better amenities, which command higher rents. Panel C shows the highest earners and most highly educated individuals resided in the most highly valued properties, suggesting a strong link between socioeconomic status and housing quality.

4.4 Robustness: 1930 Census Data

The main analysis presented in the previous subsection relied on property-level rental income estimated derived from the 1940 Census. We can repeat our estimations using 1930 data, when rental yields were substantially lower on average than in 1940 (cf. Figure 9). In the 1930 Census, we do not observe wages and also have to capture education through an indicator for literacy. The results presented in Table 4 show a significant racial disparity in net rental yields, net rents, and property values. In Panel A, Black household heads are associated with 3.0% to 4.4% higher net rental yields for their landlords, with the coefficient decreasing as additional controls are added, yet remaining significant and of a larger magnitude than the estimates in Table 3. In Panel B, Black household heads are associated with significantly higher net rents, even as controls for literacy, subway distance, and property characteristics are introduced. Notably, the coefficient on literacy is a statistically highly significant 0.707 in column 3 of Panel B, indicating that rents for literate households are approximately double those for non-literate households, consistent with the education gradient observed earlier. Meanwhile, Panel C reveals that properties occupied by Black households have significantly lower property values, with reductions ranging from 10.8% to 14.8% relative to those occupied by White households. The consistent disparities we find highlight systemic differences in property valuation and rent-setting practices.

4.5 Robustness: Image-Based Property Values

We can also replicate our 1940 analysis using the image-based property valuations generated in subsection 3.4 (instead of those based on a random forest) as our denominator in the estimation of rental yields. Our mean net rental yield estimate is now equal to 10.3%, and as such it broadly aligns with our returns estimated off our random forest-based property valuations (cf. Figure 9).

This approach significantly increases our sample size—nearly fivefold—by incorporating all properties matched to the Census, not just those that transacted. However, a limitation is that we cannot control for property characteristics beyond what is captured in the images.

Table 5 shows the results. In column 1 of Panel A, we estimate a racial disparity in net rental yields for Black households of about 2.4%, somewhat higher than the 1.5% reported in Table 3. This increase may reflect the inclusion of non-transacted properties, which adds variation or captures selection effects. In Panel B, however, the larger sample also shows slightly greater racial disparities in net rents, but it may be

driven by improved statistical power rather than a substantive change in the relationship. For example, the coefficient on Black household heads in column 6 is 0.081 compared to 0.067 in the equivalent model in Table 3.

In the property value specifications in Panel C, the point estimates are very similar to before, suggesting Black households resided in properties with 18.5% lower property values in column 6 compared to 15.1% lower in Table 3. While property values likely reflect long-term market conditions that are similar across transacted and non-transacted properties, rents may be more influenced by short-term dynamics, such as tenant turnover, demand fluctuations, and rent-setting practices, which could differ between these groups. In both cases, we find that a hypothetical investor would earn higher returns from Black tenants, who pay higher rents relative to property values compared to their White counterparts.

4.6 Variation in Rent Burdens Across Racial Groups

As a final step in our analysis of rents, we examine rent-to-wage ratios as a measure of affordability. These ratios help disentangle the drivers of rental yield disparities by comparing rent burdens across racial and income groups. Figure 11 presents binscatter plots of the relationships between rent-to-wage ratios, rents, property values, and household wages by race in 1940, controlling for property characteristics and proximity to subways. Panel A shows that rent-to-wage ratios are similar across Black and non-Black households at all income levels, suggesting that rents are proportionally aligned with wages across racial groups. Panel B highlights that household rents increase with wages, with no substantial divergence between Black and non-Black households. Panel C highlights a stark disparity in property values, showing that properties occupied by Black households are consistently valued lower than those occupied by non-Black households, even when income levels are comparable. Finally, Panel D compares the rank of rent-to-wage ratios with the rank of wages, showing broadly similar distributions across races.[27]

The finding that rent-to-wage ratios are largely consistent across racial groups by

[27] Appendix Table A5 presents regression results modeling the rank in the [0,100] rent-to-wage distribution shown in Panel D as a function of the [0,100] household wage rank, race, and their interaction, while sequentially adding controls for individual, property, and location characteristics. This approach builds on prior research that utilizes rank differences to estimate income disparities across racial groups as well as racial segregation in housing markets (Bayer and Charles, 2018; Chetty et al., 2020; Higgins, 2023). Across the specifications we find that higher-wage households spend a smaller proportion of their income on rent (Household Wage Rank), consistent with expectations about affordability. Any observed racial disparity in rent-to-wage rankings is largely explained by the controls (Black=1). The interaction term (Black=1 × Household Wage Rank) indicates that for Black households, the decline in rent-to-wage rank with increasing wages is actually slightly steeper than for non-Black households, with a marginal improvement of 0.063 points per 1-unit increase in wage rank.

income levels is particularly important in our context. It suggests again that higher yields for Black-occupied properties are driven primarily by systemic undervaluation rather than unequal rent burdens. To the extent that landlords maximize profits by balancing rental income against costs, undervaluation would have diminished the perceived long-term benefits of investment. These findings highlight the disincentives landlords and investors may have faced in maintaining these properties.

5 Long-term Property Decay

This section focuses on how the undervaluation of Black-occupied properties and racial disparities may have contributed to property decay. The rental yield reflects the interplay between income generation and asset valuation. When rents can be generated from properties with lower values, owners may lack sufficient incentives to maintain and renovate their properties when necessary.

We first study how the timing of property alterations by landlords varied as a function of tenant race (subsection 5.1). We then study visual evidence of decay based on our 1940 and 1980 images (subsection 5.2). We also examine to what extent property images were predictive of resident race in both 1940 and 1980 (subsection 5.3).

5.1 Variation in Alterations

We study whether properties that housed Black tenants in 1940 were less likely to be maintained by their owners in the decades after. We have information on the renovation/alteration history and construction year of properties in our data set from PLUTO (cf. subsection 2.5). To focus on properties unaffected by urban renewal projects, we limit our dataset to those constructed in 1940 or earlier. Panel A of Figure 12 shows that properties that entirely housed Black residents in 1940 had a higher unconditional probability of being altered in ways that would have improved the assessed value of the structure after 1940. However, Panels B and C show the timing of these changes was crucial with Black properties experiencing a delay relative to properties where less than 100% of the residents were Black.

Table 6 examines the timing of these property alterations by racial composition further using both OLS and Cox proportional hazards models. The OLS results in column 1 indicate that properties occupied entirely by Black residents were altered 4.6 years later compared to properties with less than 100% Black residents, controlling for the original year of construction as well as property characteristics, latitude and longitude,

and a full set of dummy variables for redlining districts. Column 2 examines the share of Black residents, showing that the delay in alterations increases proportionally with the proportion of Black residents, with properties having a higher share experiencing longer delays. In the Cox specifications, properties entirely occupied by Black residents have a hazard ratio of 0.749, meaning they are 25.1% less likely to be altered at any given time compared to properties not entirely occupied by Black residents (column 3). This effect is also proportional to the share of Black residents (column 4). Controlling for redlining is crucial in these specifications as it indicates that the observed delays in property alterations are not being confounded by the historical disinvestment associated with redlined areas. Consistent with Fishback et al. (2024), this finding aligns with evidence that the financial effects of HOLC maps were likely more limited.

5.2 Visual Evidence of Decay

We have property images not just for 1940, but also for 1980 (cf. subsection 2.2). We use them to test for a higher degree of (exterior) decay for properties with Black residents in 1940 in two different ways.

First, we predict 1980 property values based on the 1980 images as follows. We take the coefficients from a regression of 1940 property values on the principal components of the image vectors (cf. subsection 3.3), and apply them to the corresponding 1980 principal components extracted from the feature vectors of properties photographed around 1980. (There is of course an assumption here that the value of these features remains relatively fixed over time.) We can then look at the distribution of changes in estimated property value ranks between 1940 and 1980, both for properties with 100% Black residents in 1940 and other ones. The results are shown in Panel D of Figure 12. We can see that the properties occupied by entirely Black residents in 1940 ranking lower on average in the property value distribution in 1980. A Mann-Whitney U test rejects the null hypothesis, indicating significantly different distributions.

Second, we can compute cosine similarity scores between the principal components of the ResNet-extracted feature vectors for each property's 1940 and 1980 images. Our working assumption is that a lower cosine similarity is likely to be a sign of property decay. Figure 13 provides two visual examples of properties with low cosine similarities between the 1940 and 1980 images. These examples, taken from properties in Central Harlem reveal visible signs of degradation over time, such as broken or boarded-up windows and structural deterioration.[28] Cosine similarity can thus be used as an indicator

[28]More generally, Appendix Figure A13 highlights the ten properties most similar in 1940 and 1980, while Appendix Figure A14 showcases the ten least similar

of property changes over time. Do we see more changes for properties rented out to Black households? Yes. Table 7 shows that properties with 100% Black residents have significantly lower cosine similarity scores, revealing greater changes in visual characteristics, with the effect scaling proportionally with the share of Black residents. These findings underscore the disparities in how properties occupied by Black residents evolved visually between 1940 and 1980.

5.3 Using Property Images to Predict Resident Race

As a final exercise, we test whether visual images alone from 1940 and 1980 can predict which properties in 1940 entirely housed Black residents. The top panel of Figure 14 presents a matrix comparing actual Black property status with predicted Black property status from a logit regression using only the 1940 image feature vector principal components. The bottom panel incorporates both image feature vectors and geographic coordinates (latitude and longitude). Properties with a predicted probability ≥ 0.5 are classified as Black. Using only the images, we correctly predict 36.7% of Black properties, while adding geographic coordinates improves the prediction accuracy to 53.3%. F1 scores, which balance precision and recall as a single measure of predictive performance, equal 0.48 and 0.60, respectively.[29] Similarly, we use 1980 images to predict which properties were housed by Black residents in 1940 in Figure 15. We correctly predict 35% of Black properties with just the images, whereas including geographic coordinates increases the prediction accuracy to 58.4%, with F1 scores of 0.46 and 0.64, respectively. In other words, we can about as well predict whether a property in 1940 had Black residents based on the 1980 images vs. on the 1940 images, which there is something visually distinctive about the 1980 images.

5.4 Discussion

Overall, we find that the delayed alterations and greater visual decay over time of Black-occupied properties in 1940 can be systematically measured using images and complementary data. These patterns reflect racial disparities in property maintenance and investment, likely shaped by landlord incentives and investor expectations of continued segregation, with significant long-term implications for neighborhood stability and economic inequality. Our results help to rationalize the growing gap over time in the assessed values of properties by neighborhoods shown in Figure 1.

[29] Precision measures the proportion of correctly identified positives among all positive predictions, while recall measures the proportion of actual positives that were correctly identified.

6 Conclusion

Real estate markets have long played a pivotal role in shaping economic opportunity and social outcomes, functioning both as a driver of wealth creation and a mechanism for reinforcing inequality. Manhattan's real estate market during the pre- and post-World War II eras offers an important window into the forces that shaped urban housing markets and entrenched racial segregation. While most prior research has focused on the costs borne by households, our approach shifts the perspective to examine landlord and investor returns and their influence on the undervaluation and maintenance of Black-occupied properties. By leveraging a rich dataset of property transactions, federal Census records, and property images, we provide evidence of racial disparities in property values and rental yields earned by landlords. We also find racial disparities in property maintenance over time. Moreover, using modern machine learning methods to estimate image-based property assessments, we find that properties in Black neighborhoods experienced greater visual degradation in the second half of the twentieth century. These findings highlight how segregation perpetuated inequality in urban housing markets, with landlord incentives and behavior playing a central role.

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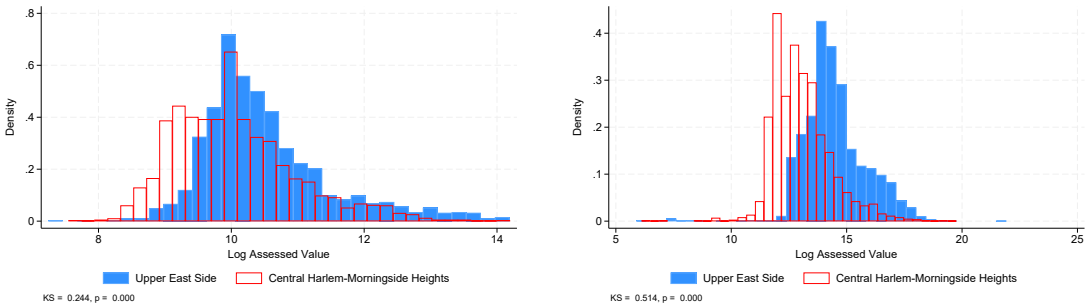
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Figure 1: Changing Distribution of Assessed Values



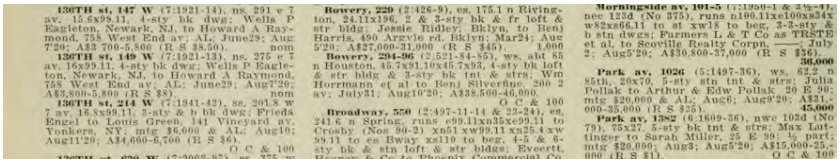
A: RERBG, 1912-1939 B: PLUTO, 2022

Notes: These figures show histograms of assessed values for properties from the *Real Estate Record and Builders' Guide* transacted between 1912 and 1939 and assessed values as of 2022 from the PLUTO (Primary Land Use Tax Lot Output) data. The Kolmogorov-Smirnov (KS) test compares two distributions under the null that they are identical. The KS statistic represents the maximum difference between the cumulative distribution functions of the two distributions. For a KS of 0.244 (left panel), the maximum difference is 24.4%, while for a KS of 0.514 (right panel), the maximum difference is 51.4%.

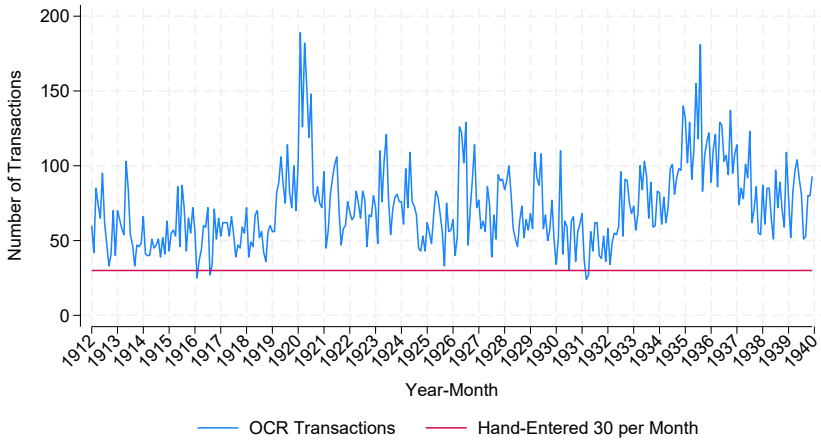
FIGURE 2: REAL ESTATE RECORD AND BUILDERS' GUIDE TRANSACTIONS



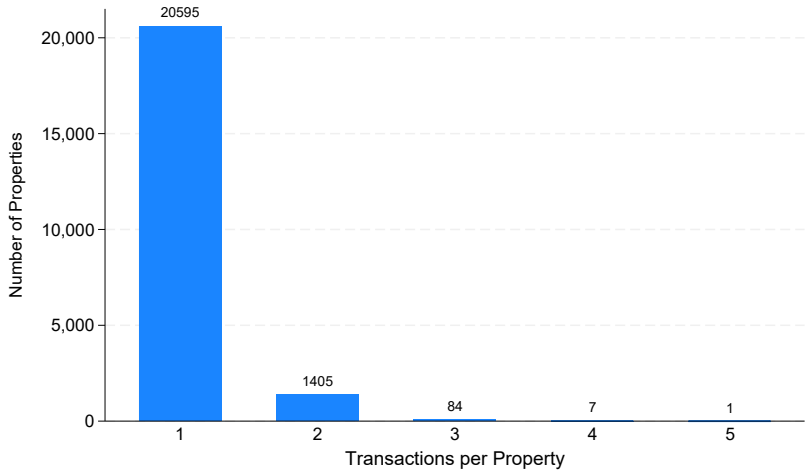
A: LAYOUT (PRE-1912)



B: LAYOUT (1912 ONWARDS)



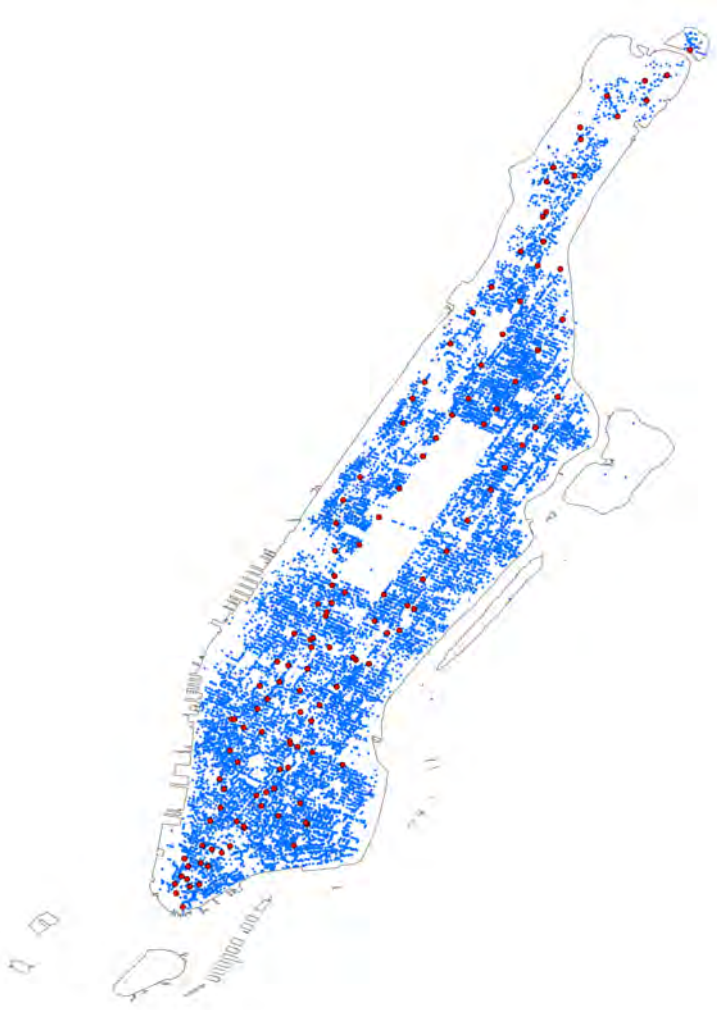
C: NUMBER OF OCR TRANSACTIONS BY YEAR-MONTH



D: TRANSACTION FREQUENCY, 1912-1939

Notes: Transactions data from 1912 to 1939 from the *Real Estate Record and Builders' Guide*.

FIGURE 3: TRANSACTIONS DATA, 1912-1939



Notes: This map shows transactions data from 1912 to 1939 from the *Real Estate Record and Builders' Guide*. Red circles are the location of subway stations that were operational by 1939. Subway coordinates are provided by the Metropolitan Transportation Authority.

Figure 4: Property Images



415 W 118th Street, 1940, 1980 and 2025

The 1940 images were developed for real property tax assessment by the Works Progress Administration in collaboration with the New York City Tax Department between 1939 and 1941 to aid property assessments. A second exercise was conducted by the Department of Finance between 1982 and 1987. 415 West 118th Street is in the Morningside Heights neighborhood of Manhattan and is currently owned by Columbia University and serves as residential housing for students.

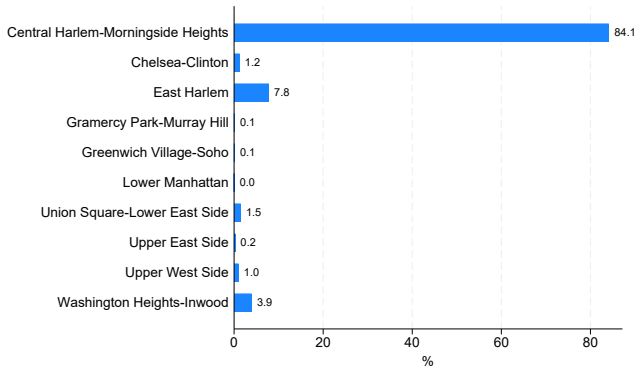


Multiple building types are included, from left to right: 239 East 60th St. (Upper East Side); 432 Lafayette St. (Noho); 366 West 46th St. (Hell's Kitchen); 313 West 88th St. (Upper West Sode).

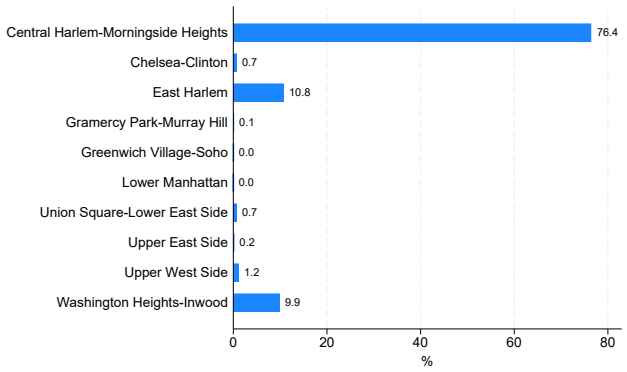


We clean the images where they contain defects (1940 images), or when a substitute card was used instead of a real image (1980 images).

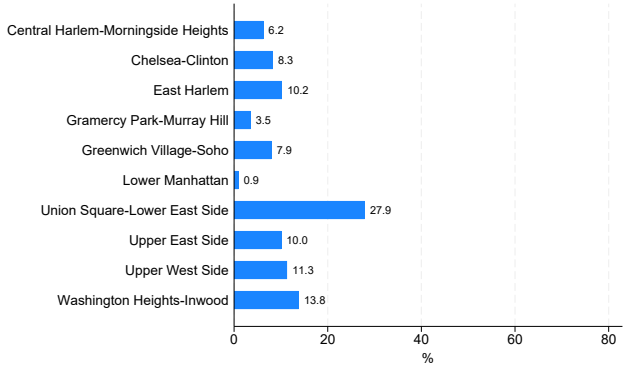
Figure 5: Location of Population by Race, 1930 and 1940



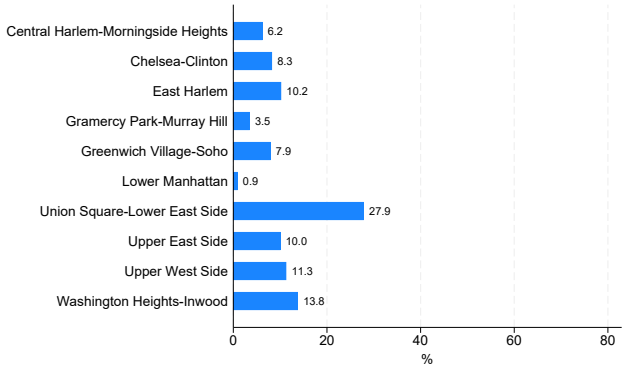
A: Black 1930



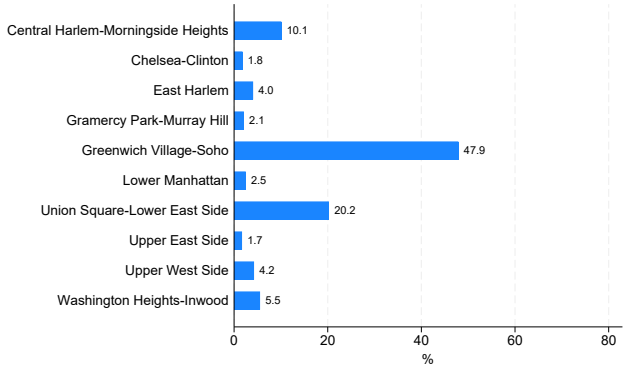
B: Black 1940



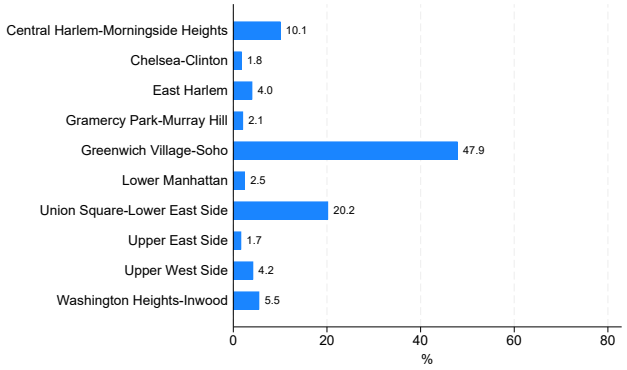
C: White 1930



D: White 1940



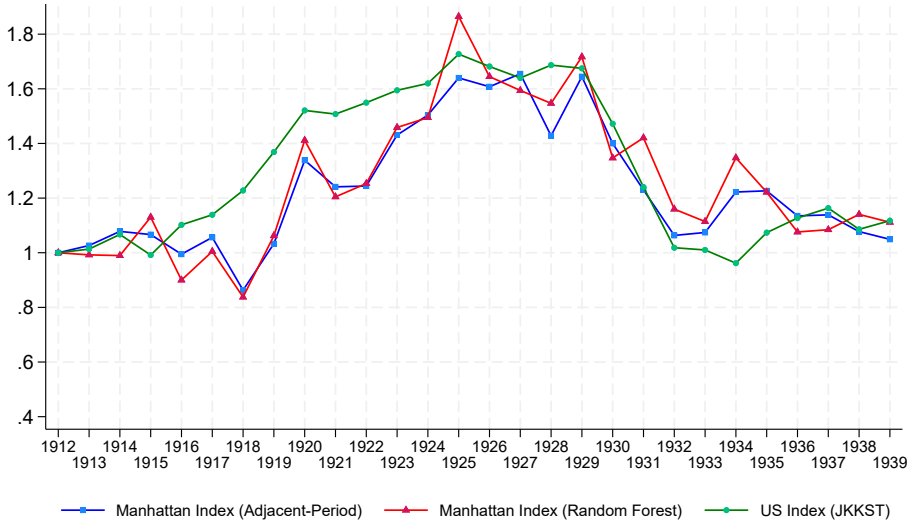
E: Other 1930



F: Other 1940

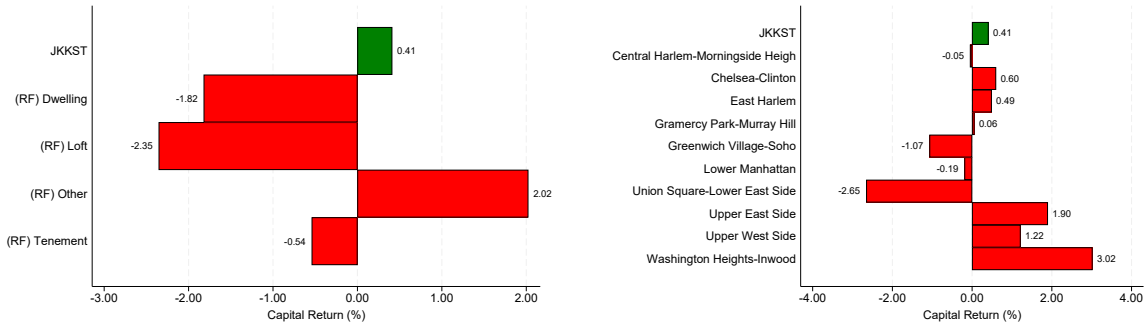
Notes: These figures show the distribution of the population of Manhattan by race based on the 1930 and 1940 Censuses.

FIGURE 6: BENCHMARKING MANHATTAN INDEXES AGAINST U.S. TRENDS



Notes: This figure shows indexes constructed from property transactions between 1912 and 1939 from the *Real Estate Record and Builders' Guide*. The adjacent period model relies on adjacent time periods (e.g., 1912-1913, 1913-1914). The random forest model includes 100 decision trees. The indexes are normalized to $1 at the start of the period. The JKKST series is constructed using the housing capital return series for the USA in Jordà et al. (2019).

Figure 7: Capital Returns by Property Type and Neighborhood



A: Property Type

B: Neighborhood

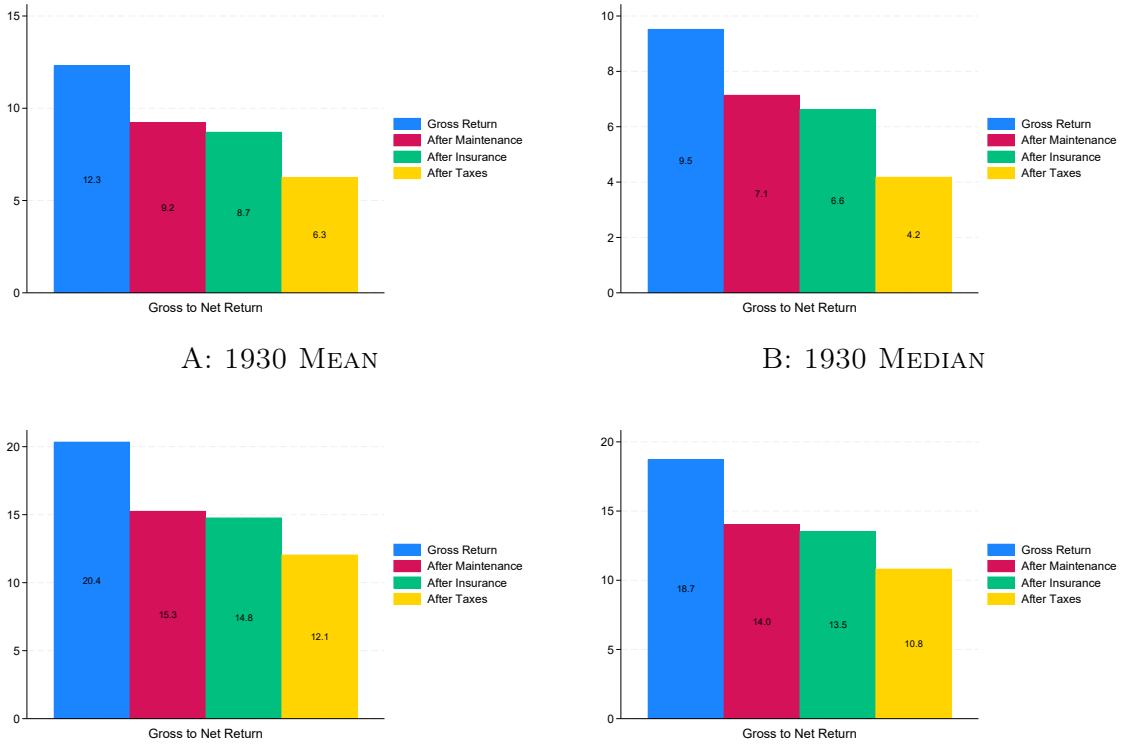
Notes: These figures show capital returns constructed from Random Forest indexes of property transactions between 1912 and 1939. The JKKST series is constructed using the housing capital return series for the USA in Jordà et al. (2019).

Figure 8: Nearest Neighbors using Feature Vectors, 1940



Notes: This figure shows the "nearest neighbors" for 10 randomly selected images developed for real property tax assessment by the Works Progress Administration in collaboration with the New York City Tax Department. Specifically, we calculate the pairwise Euclidean distance between the feature vector of each reference image and those of all other images to identify the five closest matches.

FIGURE 9: ESTIMATING GROSS AND NET RETURNS, 1930 AND 1940



A: 1930 MEAN

B: 1930 MEDIAN

C: 1940 MEAN

D: 1940 MEDIAN

Notes: These figures show gross and net returns for properties. All properties are 100% rented. We use the following assumptions:

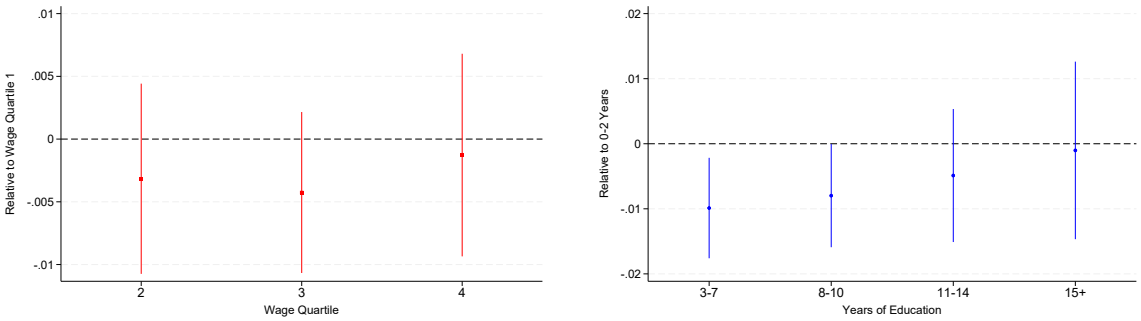
Vacancy Rate: This is already accounted for in our estimates, as vacant apartments within properties would not be enumerated.

Maintenance Rate: In both years, the maintenance cost is assumed to be 25% of annual rental income based on the *Report of the State Board of Housing of New York*. That report shows in newly built lower income properties the maintenance cost was around 24.4% to 24.8%. Grebler (1955) puts maintenance costs as high as 45%.

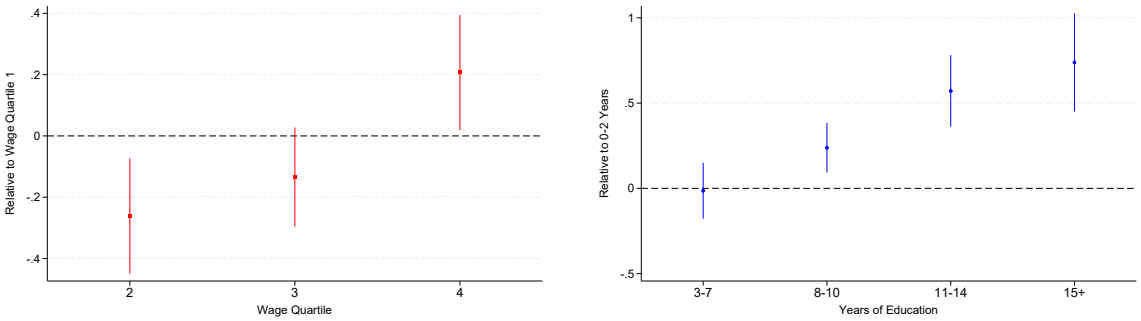
Insurance Cost: Assumed to be 0.57% of assessed value in 1930 and 0.53% of assessed value in 1940, according to the *Weekly Underwriter*.

Tax Rate: Assumed to be $27.20 per $1,000 of assessed value in 1930 and $29.60 per $1,000 of assessed value in 1940, based on the *National Municipal Review*.

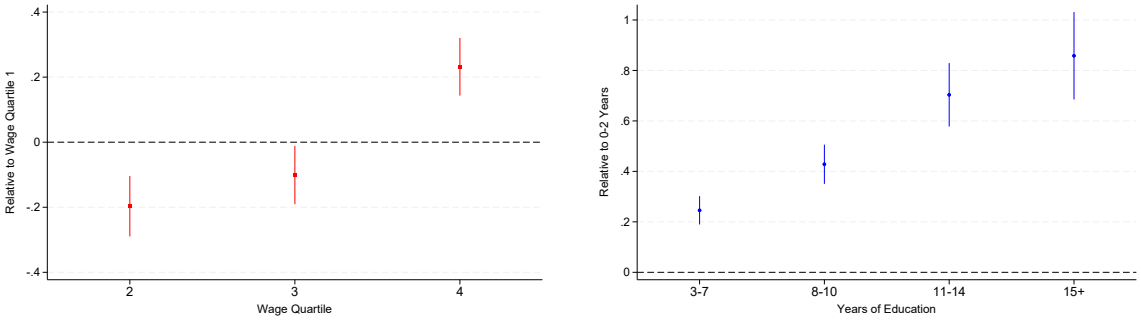
Figure 10: Wage and Education Estimates



A: Net Rental Yields



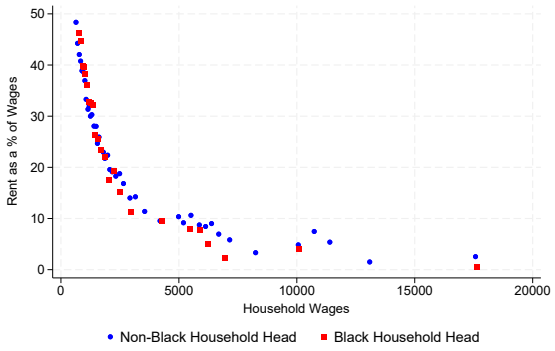
B: Net Rents



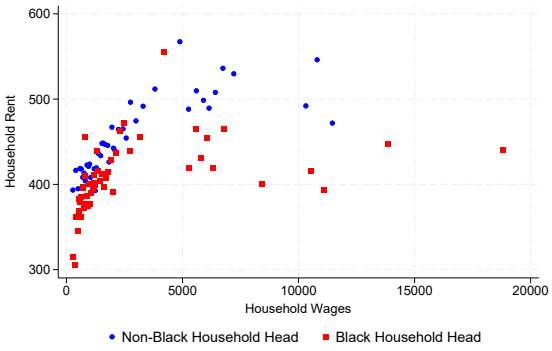
C: Property Value

Notes: These figures show estimates of coefficients on wage quartiles and indicators for years of education from Table 3.

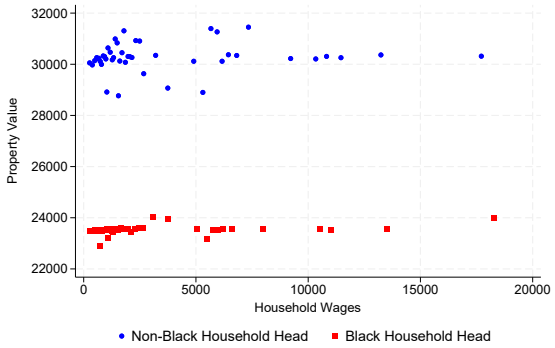
FIGURE 11: RENT-TO-WAGES, RENT, PROPERTY VALUES BY RACE, 1940



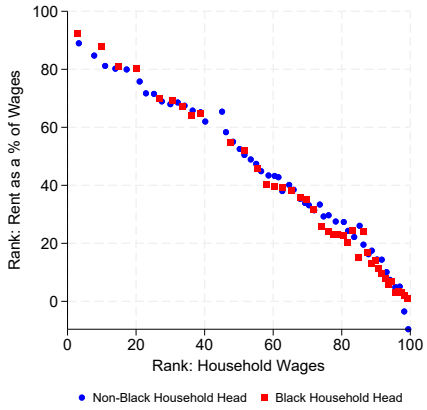
A: RENT-TO-WAGES



B: HOUSEHOLD RENT



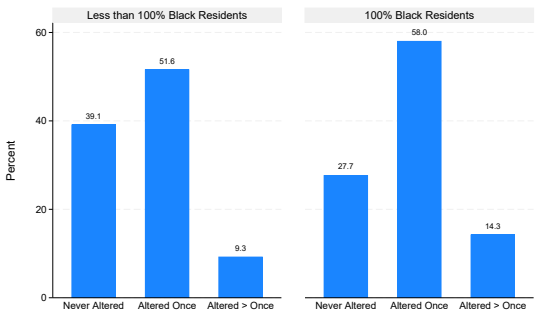
C: PROPERTY VALUE



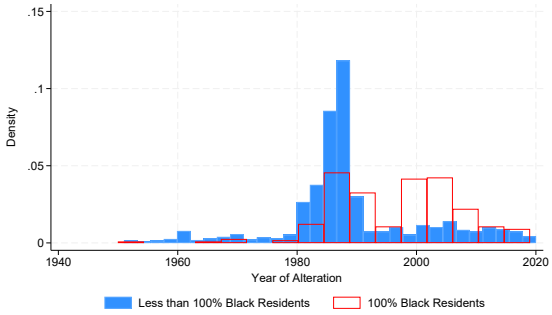
D: RANK OF RENT-TO-WAGES

Notes: These figures show binscatter plots absorbing property characteristics and the distance of the property to the nearest subway. The ranking in the rent-to-wage distribution against the ranking in the wage distribution, absorbs additionally individual characteristics (age, gender, employment status, and years of education). The rent-to-wage ratio is trimmed at the 5th and 95th percentiles.

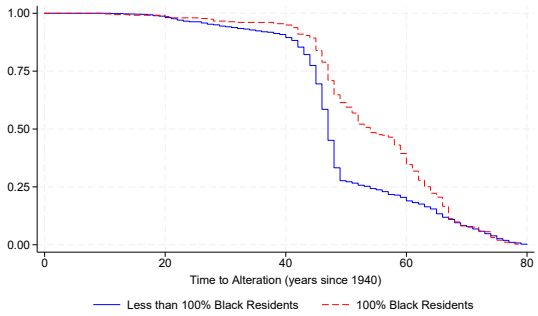
Figure 12: Property History by Race



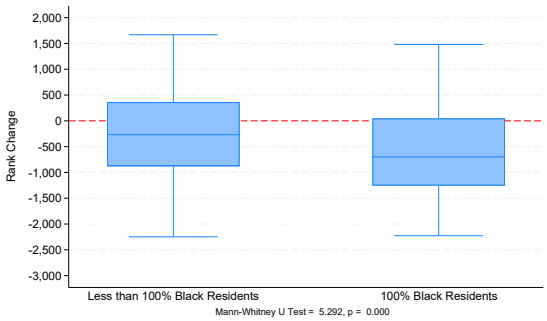
A: Alteration Status



B: Time to Alteration



C: Time to Alteration (Kaplan-Meier)



D: Rank Change in Value

Notes: These figures show the timing of alterations to the structure of properties that change its value based on links to the PLUTO (Primary Land Use Tax Lot Output) data. Panel D shows a boxplot of the distribution of the change in property value ranks between 1940 and 1980. We predict 1980 property values by applying the coefficients from a regression of 1940 property values on the principal components of the image vectors to the 1980 principal components. The Mann Whitney U test is under the null that the two groups have the same distribution.

Figure 13: Property Decay Between 1940 and 1980



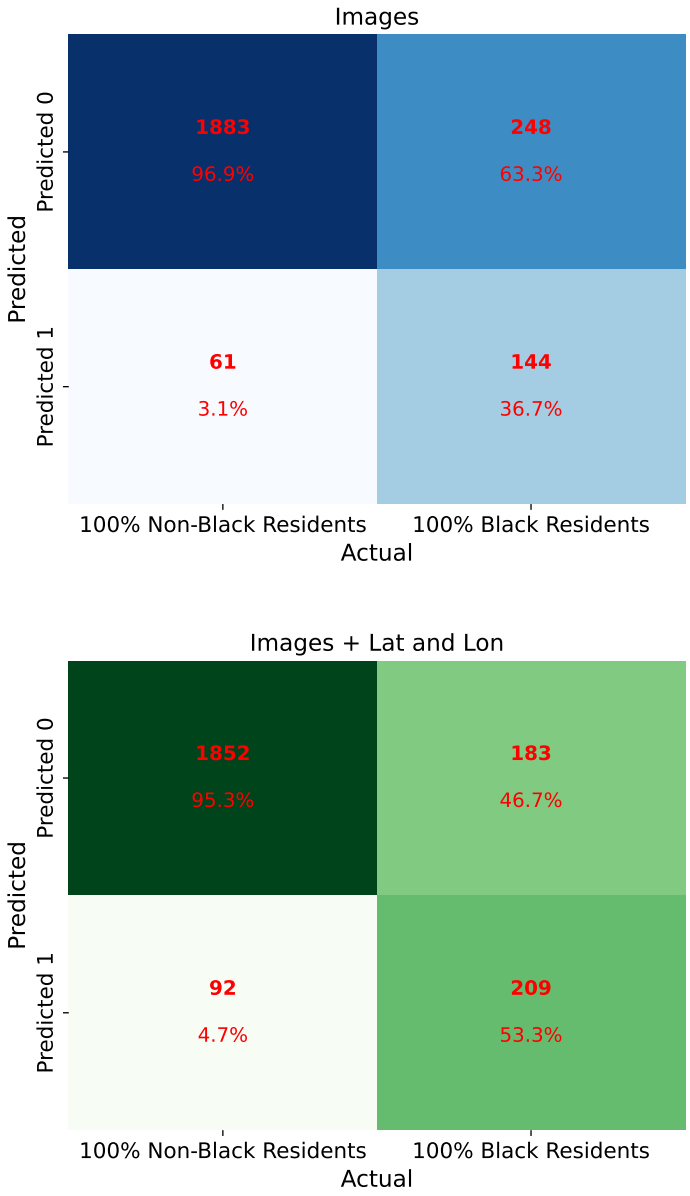
162 West 122 Street, Central Harlem



210 West 112th Street, Central Harlem

Notes: This properties housed Black residents in 1940 and show low similarity scores, based on cosine similarity between feature vectors extracted from ResNet for each property's 1940 image and its corresponding 1980 image.

FIGURE 14: PREDICTING 1940 PROPERTIES BY RACE USING 1940 IMAGES



Notes: These figures show a matrix comparing actual Black property status with predicted Black property status from a logit regression. The top figure uses 1940 image feature vectors alone, while the bottom figure includes both image feature vectors and geographic coordinates (latitude and longitude). Properties with a predicted probability ≥ 0.5 are classified as Black. In the top figure, 36.7% of Black properties are predicted successfully. In the bottom figure, 53.3% are predicted successfully.

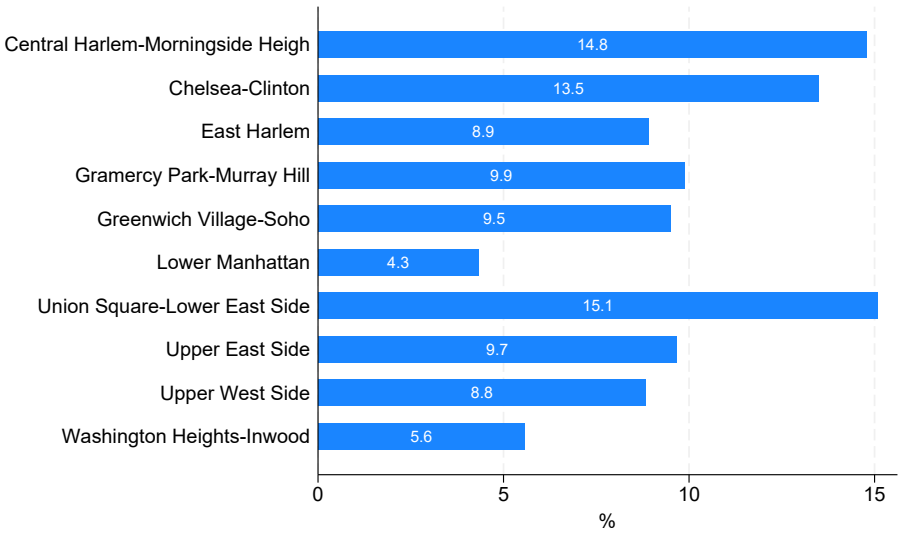
FIGURE 15: PREDICTING 1940 PROPERTIES BY RACE USING 1980 IMAGES



Notes: These figures show a matrix comparing actual Black property status with predicted Black property status from a logit regression. The top figure uses 1980 image feature vectors alone, while the bottom figure includes both image feature vectors and geographic coordinates (latitude and longitude). Properties with a predicted probability ≥ 0.5 are classified as Black. In the top figure, 35% of Black properties are predicted successfully. In the bottom figure, 58.4% are predicted successfully.

TABLE 1: TRANSACTIONS DATA DESCRIPTIVE STATISTICS

	Mean	SD	N
Type: Dwelling	0.206	0.405	23690
Type: Loft	0.089	0.285	23690
Type: Other	0.229	0.420	23690
Type: Tenement	0.475	0.499	23690
Construction: Brick	0.631	0.483	23690
Construction: Stone	0.131	0.337	23690
Construction: Other	0.238	0.426	23690
Feature: None	0.611	0.488	23690
Feature: Store	0.389	0.488	23690
1 Story	0.010	0.098	23690
2 Story	0.027	0.161	23690
3 Story	0.161	0.368	23690
4 Story	0.197	0.398	23690
5 Story	0.298	0.458	23690
6 Stories and Over	0.307	0.461	23690
Square Footage (Lot, in thousands)	18.728	897.790	21825
Square Footage (Lot and Building, in thousands)	81.958	2715.151	19771
Lot Shape	2.458	1.089	21878
Property Transaction Value	40300.970	80769.752	23690
Distance to Nearest Subway (miles)	0.264	0.196	23690



Notes: This table and figure show descriptive statistics on properties transacted in the *Real Estate Record and Builders' Guide* between 1912 and 1939 and the share of these transactions by neighborhood.

Table 2: Hedonic Regressions - Main Periods

	(1) 1912-1939	(2) 1910s	(3) 1920s	(4) 1930s
Log Square Footage	0.338***	0.314***	0.282***	0.438***
	(0.019)	(0.037)	(0.028)	(0.030)
Lot Shape	0.061***	0.028	0.056***	0.074***
	(0.009)	(0.020)	(0.013)	(0.013)
Foreclosure=1	-0.227***	-0.152***	-0.565***	-0.146***
	(0.017)	(0.028)	(0.035)	(0.027)
Building Type (base=Tenement)				
Dwelling	0.263***	0.289***	0.203***	0.304***
	(0.023)	(0.041)	(0.035)	(0.042)
Loft	0.369***	0.451***	0.373***	0.293***
	(0.031)	(0.061)	(0.049)	(0.050)
Other	0.680***	0.641***	0.661***	0.663***
	(0.032)	(0.064)	(0.055)	(0.052)
Construction Material (base=Brick)				
Other	-0.376***	-0.284***	-0.369***	-0.379***
	(0.055)	(0.082)	(0.086)	(0.141)
Stone	0.143***	0.143***	0.189***	0.098***
	(0.017)	(0.031)	(0.028)	(0.030)
Additional Features (base=None)				
Store	0.131***	0.078**	0.094***	0.183***
	(0.018)	(0.034)	(0.030)	(0.031)
Number of Stories (base=Six and Over)				
1	-0.121	-0.619***	-0.154	0.217
	(0.095)	(0.169)	(0.161)	(0.150)
2	-0.357***	-0.614***	-0.473***	-0.013
	(0.058)	(0.110)	(0.090)	(0.098)
3	-0.559***	-0.795***	-0.658***	-0.244***
	(0.039)	(0.075)	(0.060)	(0.066)
4	-0.313***	-0.467***	-0.380***	-0.129**
	(0.033)	(0.063)	(0.053)	(0.053)
5	-0.230***	-0.364***	-0.253***	-0.100**
	(0.027)	(0.051)	(0.045)	(0.044)
Neighborhood (base=Union Sq.-Lwr. E. Side)				
Central Harlem-Morningside Heights	-0.096***	-0.176***	-0.105**	-0.058
	(0.026)	(0.046)	(0.042)	(0.046)
Chelsea-Clinton	0.362***	0.236***	0.325***	0.429***
	(0.028)	(0.052)	(0.043)	(0.052)
East Harlem	-0.070***	-0.094**	-0.194***	0.012
	(0.026)	(0.047)	(0.044)	(0.047)
Gramercy Park-Murray Hill	0.423***	0.234***	0.352***	0.573***
	(0.031)	(0.062)	(0.048)	(0.055)
Greenwich Village-Soho	0.018	0.012	-0.032	0.060
	(0.030)	(0.057)	(0.047)	(0.053)
Lower Manhattan	0.242***	0.178*	0.108	0.490***
	(0.050)	(0.091)	(0.077)	(0.092)
Upper East Side	0.364***	0.177***	0.294***	0.484***
	(0.030)	(0.058)	(0.046)	(0.055)
Upper West Side	0.277***	0.098	0.272***	0.350***
	(0.033)	(0.063)	(0.050)	(0.056)
Washington Heights-Inwood	0.035	-0.106	-0.013	0.110
	(0.040)	(0.070)	(0.065)	(0.067)
Location				
Log Miles to Nearest Subway	-0.152***	-0.136***	-0.169***	-0.149***
	(0.012)	(0.021)	(0.020)	(0.020)
Mean Dep Var.	9.887	9.745	10.171	9.700
R-sq (adj.)	0.288	0.273	0.259	0.277
Observations	19771	4891	7361	7519
Year × Quarter FE	Yes	Yes	Yes	Yes

Notes: This table reports coefficients from regressions where the dependent variable is the log of the property transaction value. Robust standard errors in parentheses. *p<0.1, **p<0.05, ***p<0.01.

Table 3: Returns: Random Forest Predictions, 1940

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Net Rental Yields							
Black Household Head	0.015***	0.013**	0.013**	0.014***	0.014***	0.014***	0.007
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Mean Dep Var.	0.16	0.16	0.16	0.16	0.16	0.16	0.16
R-sq (adj.)	0.00	0.01	0.01	0.01	0.01	0.01	0.10
Panel B: Net Rent							
Black Household Head	-0.029	-0.052	-0.010	0.038	0.060	0.067	0.039
	(0.093)	(0.093)	(0.092)	(0.092)	(0.092)	(0.098)	(0.081)
Mean Dep Var.	8.25	8.25	8.25	8.25	8.25	8.25	8.25
R-sq (adj.)	-0.00	0.00	0.00	0.01	0.01	0.01	0.13
Panel C: Property Value							
Black Household Head	-0.196***	-0.206***	-0.167***	-0.150***	-0.129**	-0.164***	-0.085***
	(0.059)	(0.058)	(0.057)	(0.054)	(0.054)	(0.055)	(0.024)
Mean Dep Var.	10.53	10.53	10.53	10.53	10.53	10.53	10.53
R-sq (adj.)	0.01	0.02	0.04	0.10	0.10	0.12	0.77
Observations	12275	12275	12275	12275	12275	12275	12275
Properties	2889	2889	2889	2889	2889	2889	2889
Baseline Individual Controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Wage Controls	No	No	Yes	No	Yes	Yes	Yes
Education Controls	No	No	No	Yes	Yes	Yes	Yes
Distance to Subway	No	No	No	No	No	Yes	Yes
Property Controls	No	No	No	No	No	No	Yes

Notes: This table reports coefficients from regressions where the dependent variable is the inverse hyperbolic sine transformed net rental yield. Standard errors clustered by property in parentheses. *p<0.1, **p<0.05, ***p<0.01.

Table 4: Returns: Random Forest Predictions, 1930

	(1)	(2)	(3)	(4)	(5)
Panel A: Net Rental Yields					
Black Household Head	0.044***	0.041***	0.039***	0.038***	0.030***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Mean Dep Var.	0.09	0.09	0.09	0.09	0.09
R-sq (adj.)	0.03	0.04	0.04	0.07	0.21
Panel B: Net Rent					
Black Household Head	0.859***	0.783***	0.721***	0.704***	0.372**
	(0.166)	(0.166)	(0.167)	(0.166)	(0.154)
Mean Dep Var.	7.44	7.44	7.44	7.44	7.44
R-sq (adj.)	0.01	0.01	0.01	0.02	0.12
Panel C: Property Value					
Black Household Head	-0.114**	-0.128***	-0.155***	-0.160***	-0.144***
	(0.046)	(0.046)	(0.046)	(0.046)	(0.023)
Mean Dep Var.	11.09	11.09	11.09	11.09	11.09
R-sq (adj.)	0.01	0.01	0.04	0.07	0.70
Observations	9229	9229	9229	9229	9229
Properties	2701	2701	2701	2701	2701
Baseline Individual Controls	No	Yes	Yes	Yes	Yes
Literacy Control	No	No	Yes	Yes	Yes
Distance to Subway	No	No	No	Yes	Yes
Property Controls	No	No	No	No	Yes

Notes: This table reports coefficients from regressions where the dependent variable is the inverse hyperbolic sine transformed net rental yield. Standard errors clustered by property in parentheses. *p<0.1, **p<0.05, ***p<0.01.

Table 5: Returns: Random Forest Predictions Using Images, 1940

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Net Rental Yields						
Black Household Head	0.024***	0.021***	0.022***	0.022***	0.023***	0.022***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Mean Dep Var.	0.15	0.15	0.15	0.15	0.15	0.15
R-sq (adj.)	0.01	0.02	0.02	0.02	0.02	0.02
Panel B: Net Rent						
Black Household Head	0.112***	0.068**	0.074**	0.076**	0.081***	0.081***
	(0.029)	(0.030)	(0.030)	(0.030)	(0.030)	(0.031)
Mean Dep Var.	7.89	7.89	7.89	7.89	7.89	7.89
R-sq (adj.)	0.00	0.00	0.00	0.00	0.00	0.00
Panel C: Property Value						
Black Household Head	-0.212***	-0.215***	-0.211***	-0.205***	-0.203***	-0.204***
	(0.006)	(0.007)	(0.007)	(0.006)	(0.006)	(0.007)
Mean Dep Var.	10.26	10.26	10.26	10.26	10.26	10.26
R-sq (adj.)	0.10	0.11	0.11	0.12	0.12	0.12
Observations	54547	54547	54547	54547	54547	54547
Properties	14060	14060	14060	14060	14060	14060
Baseline Individual Controls	No	Yes	Yes	Yes	Yes	Yes
Wage Controls	No	No	Yes	No	Yes	Yes
Education Controls	No	No	No	Yes	Yes	Yes
Distance to Subway	No	No	No	No	No	Yes
Property Controls	No	No	No	No	No	No

Notes: This table reports coefficients from regressions where the dependent variable is the inverse hyperbolic sine transformed net rental yield. Standard errors clustered by property in parentheses. *p<0.1, **p<0.05, ***p<0.01.

Table 6: The Timing of Property Alteration by Race

	(1)	(2)	(3)	(4)
Year Built PLUTO	-0.119***	-0.116***	1.009***	1.009***
	(0.021)	(0.021)	(0.002)	(0.002)
100% Black Residents	4.610***		0.749***	
	(0.950)		(0.055)	
Share Residents Black		4.958***		0.736***
		(0.995)		(0.059)
Mean Dep Var.	50.64	50.64	50.64	50.64
R-sq (adj.)	0.14	0.14		
Observations (Properties)	1395	1395	1395	1395
Estimation	OLS	OLS	COX	COX

Notes: This table reports OLS coefficients from regressions where the dependent variable is the time, in years, since 1940 when the first recorded alteration occurred for each property and Cox proportional hazards models, where the time to the event of a property alteration is measured in years relative to the baseline year of 1940. All specifications control for property characteristics and spatial characteristics as well as a full set of dummy variables for redlining districts. Robust standard errors in parentheses. *p<0.1, **p<0.05, ***p<0.01.

Table 7: Cosine Similarity Between 1940 and 1980 Property Images

	(1)	(2)
Year Built PLUTO	0.005***	0.005***
	(0.001)	(0.001)
100% Black Residents	-0.381***	
	(0.062)	
Share Residents Black		-0.362***
		(0.060)
Mean Dep Var.	-0.06	-0.06
R-sq (adj.)	0.03	0.03
Observations (Properties)	1963	1963

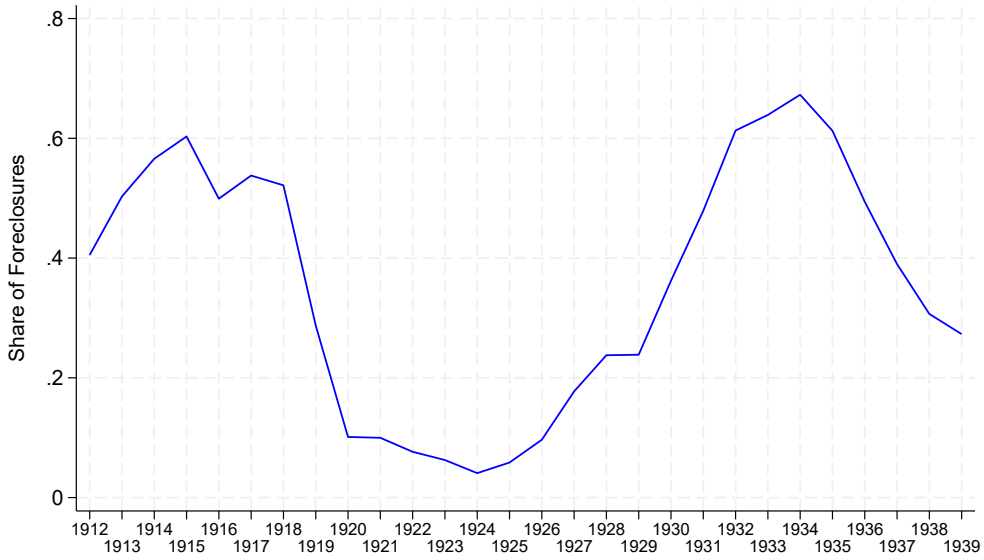
Notes: This table reports OLS coefficients from regressions where the dependent variable is the cosine similarity between feature vectors extracted from ResNet for each property image in 1940 and its corresponding image in 1980. All specifications include a full set of dummy variables for redlining districts. Robust standard errors in parentheses. *p<0.1, **p<0.05, ***p<0.01.

Online Appendix

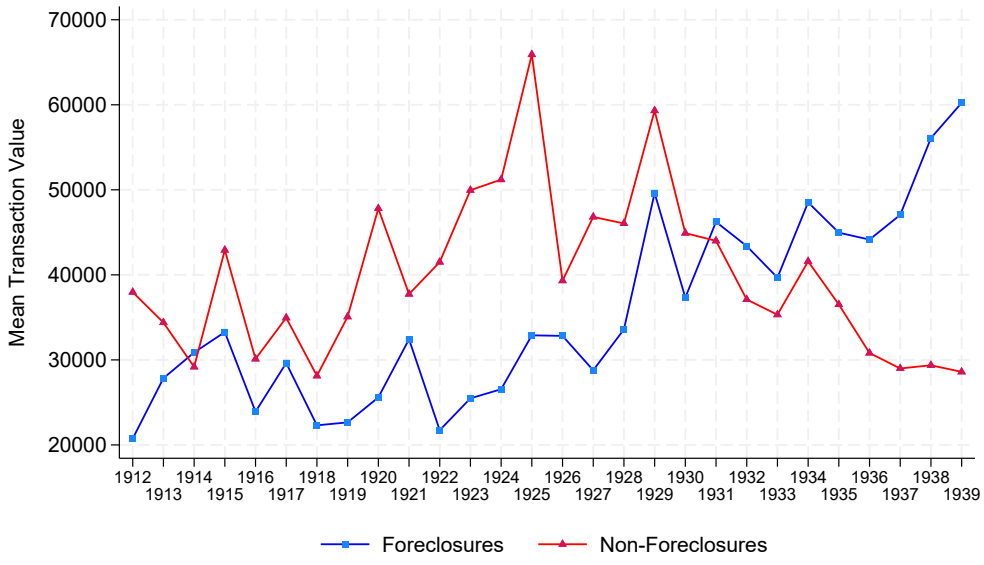
Race, Rental Yields, and Housing Decay in Manhattan

Tom Nicholas Christophe Spaenjers

FIGURE A1: FORECLOSURES, 1912-1939



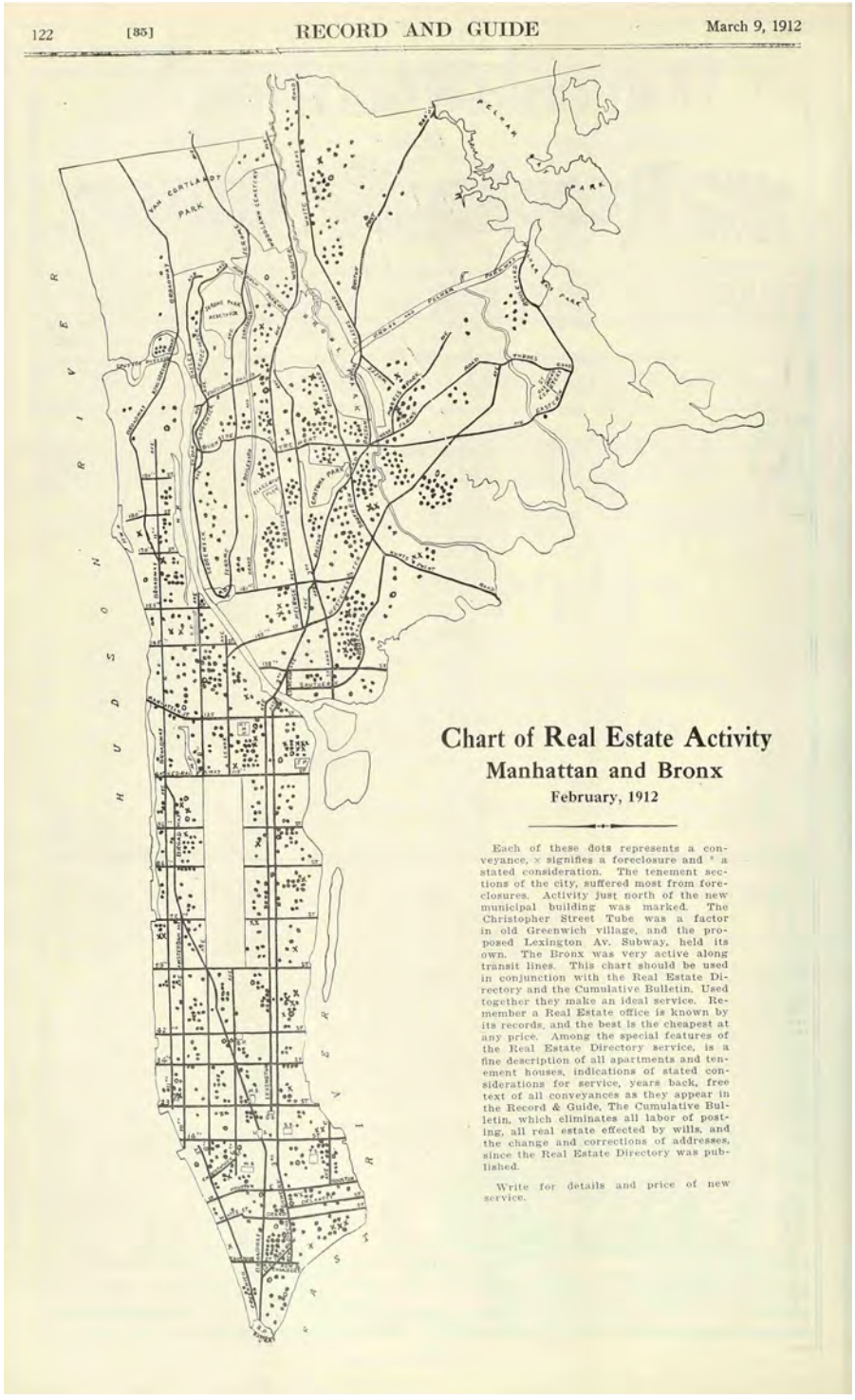
A: SHARE



B: VALUE

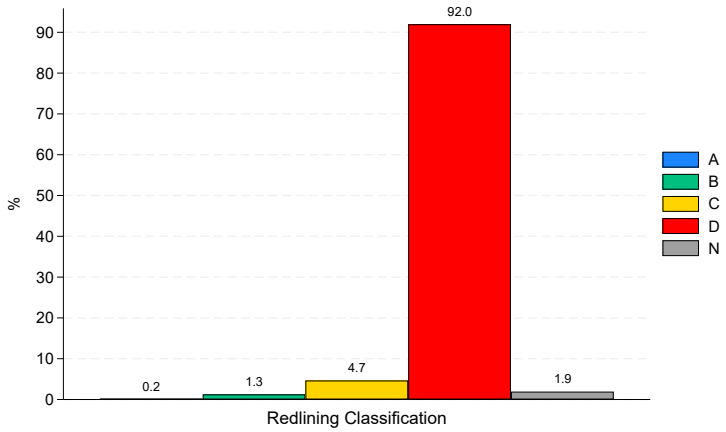
Notes: These figures show the number and average value of foreclosed property transactions between 1912 and 1939 from the *Real Estate Record and Builders' Guide*.

Figure A2: Verifying Foreclosure Counts

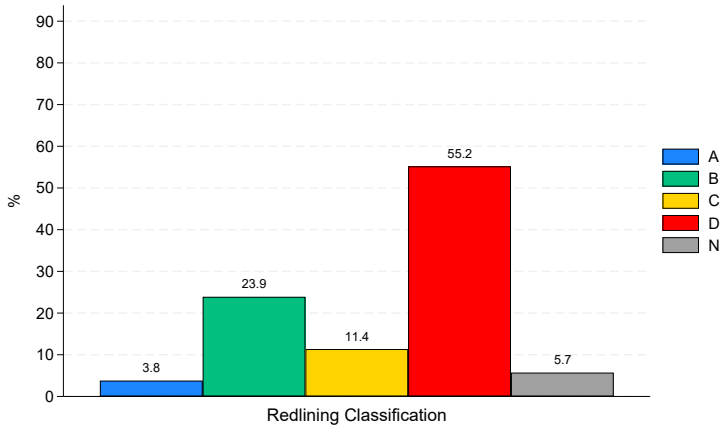


Notes: This figure show the number of foreclosed property transactions in 1912 from the *Real Estate Record and Builders' Guide*.

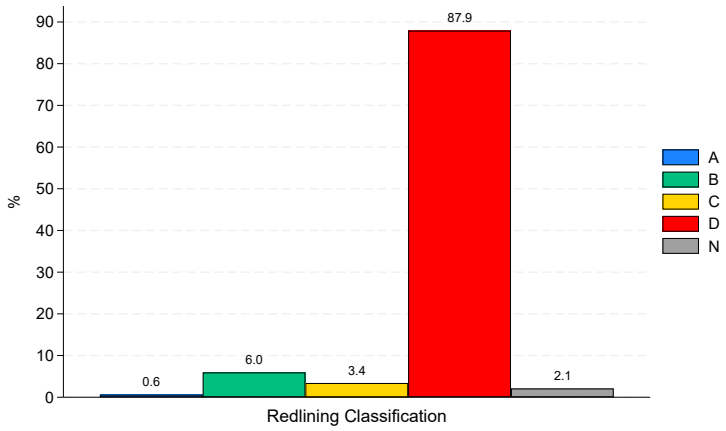
Figure A3: Location of Population by Redlining Area, 1940



A: Black



B: White



B: Other

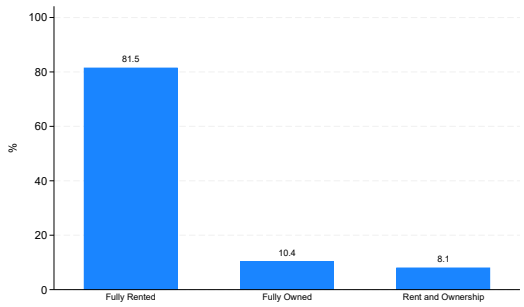
Notes: These figures show the distribution of the population of Manhattan by race based on the categories A (best), B (still desirable), C (declining), and D (hazardous) in redlining maps, originally developed by the Home Owners' Loan Corporation to assess the"risk" associated with mortgage lending in neighborhoods. The category "N" represents unclassified areas.

FIGURE A4: PROPERTIES IN THE CENSUS, 1930 AND 1940

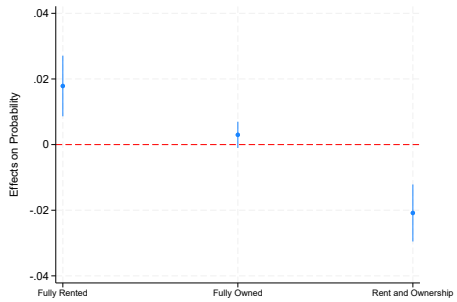


Notes: These maps shows geocoded locations of residential properties from the 1930 Census (top map) and the 1940 Census (bottom map). Shaded areas in the 1940 map are Grade D areas or "redlining" areas on HOLC maps created during the late 1930s and early 1940s.

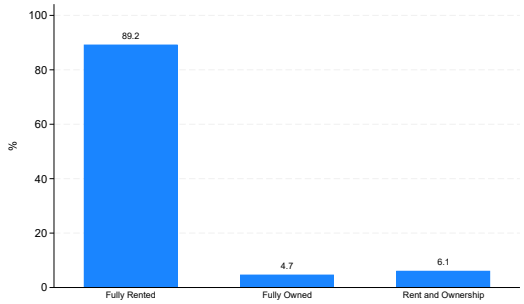
Figure A5: Property Types, 1930 and 1940



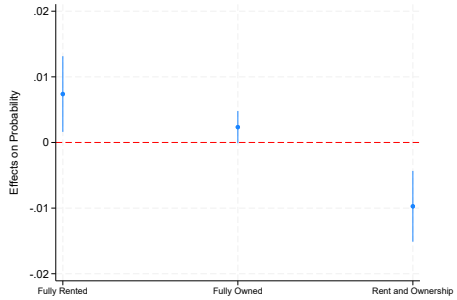
A: 1930 Property Type



B: 1930 Property Type by Race



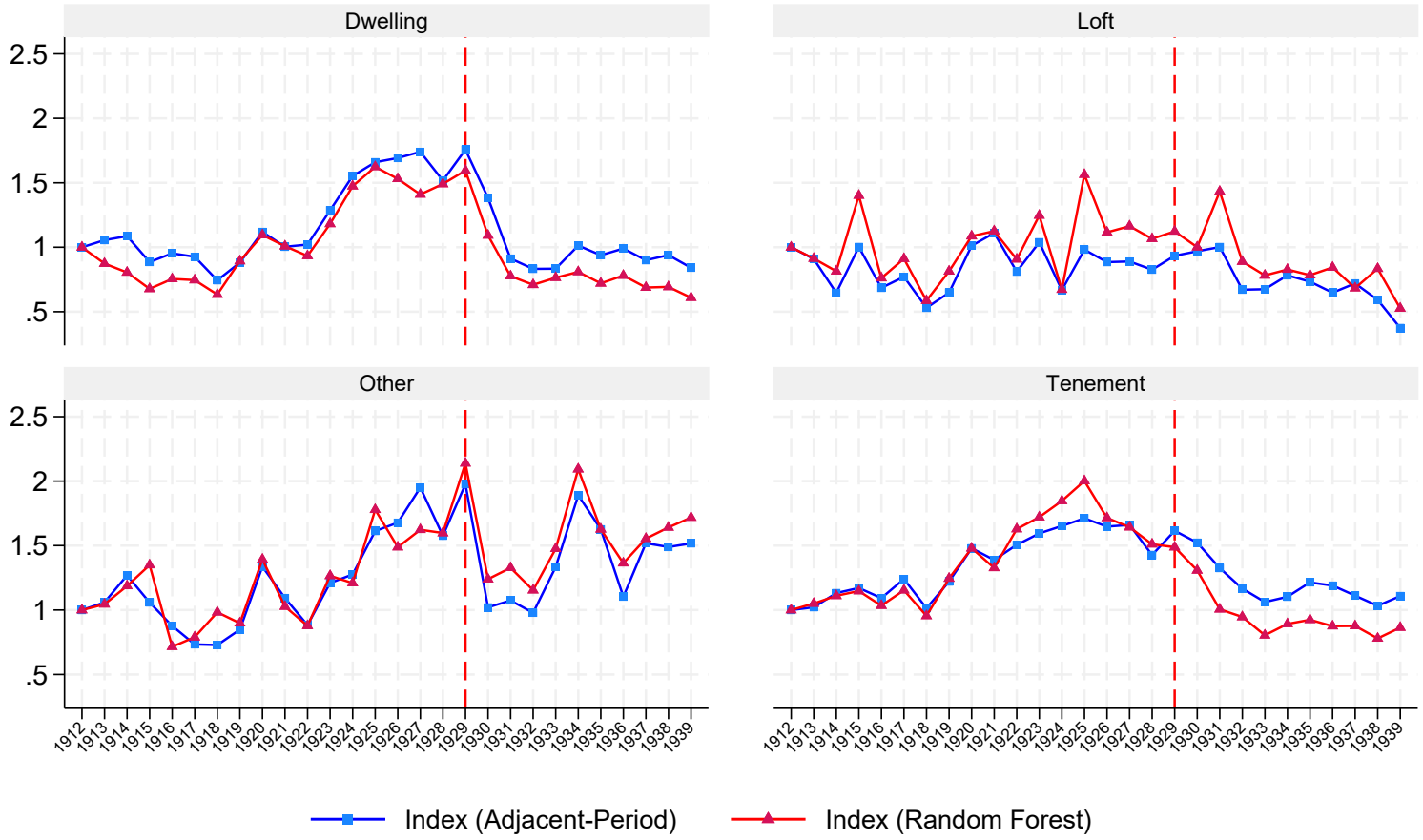
C: 1940 Property Type



D: 1940 Property Type by Race

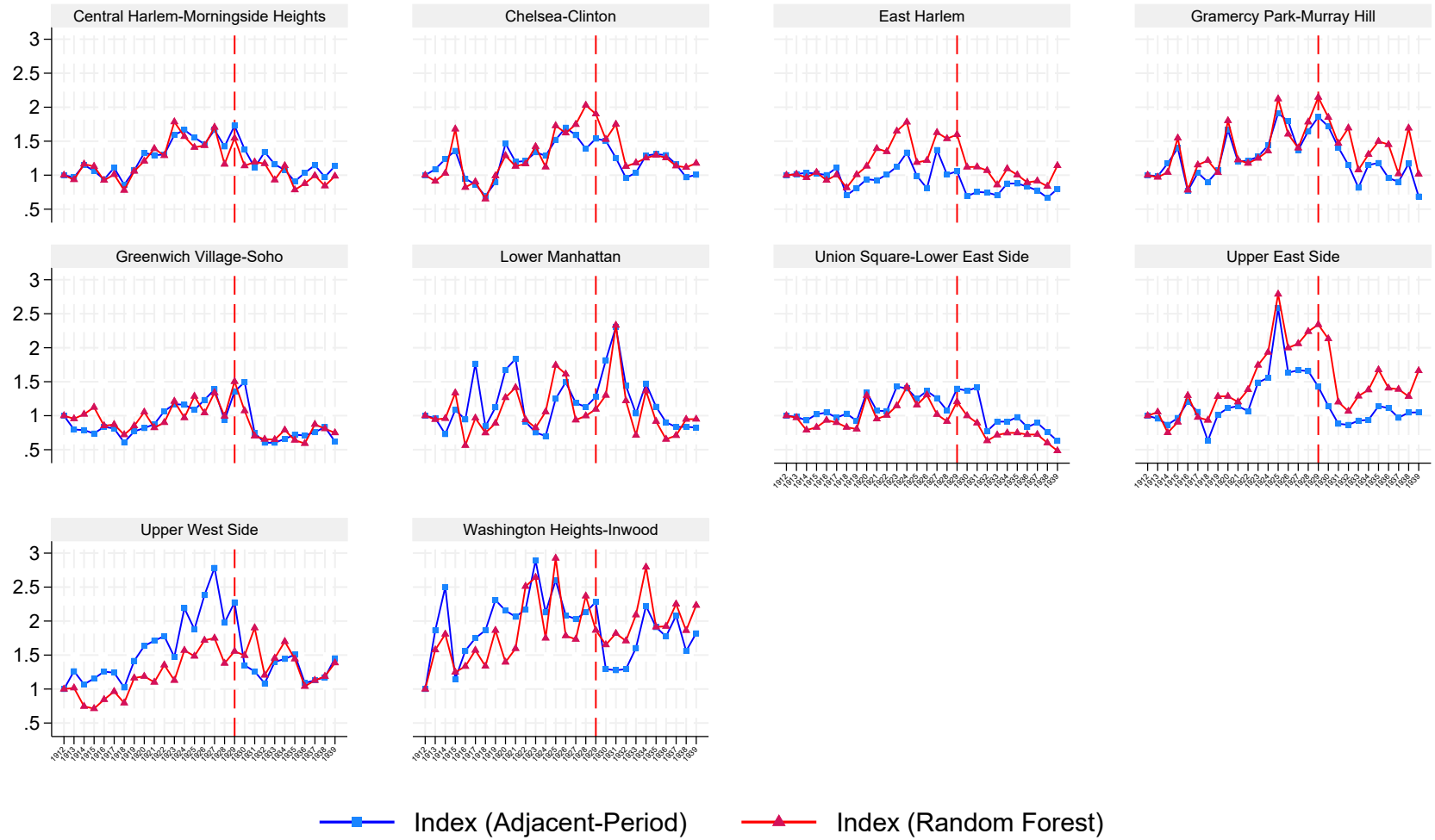
Notes: These figures show the share of properties linked from the *Real Estate Record and Builders' Guide* to the 1930 and 1940 Census that are classified as fully rented, fully owned or a mix of rent and ownership. Marginal effects of race on property type based on a multinomial logit. Marginal effects show the change in the probability of each property type associated with the household head being Black vs. non-Black. Specification controls for property characteristics, individual characteristics, and spatial characteristics.

Figure A6: Indexes by Property Type



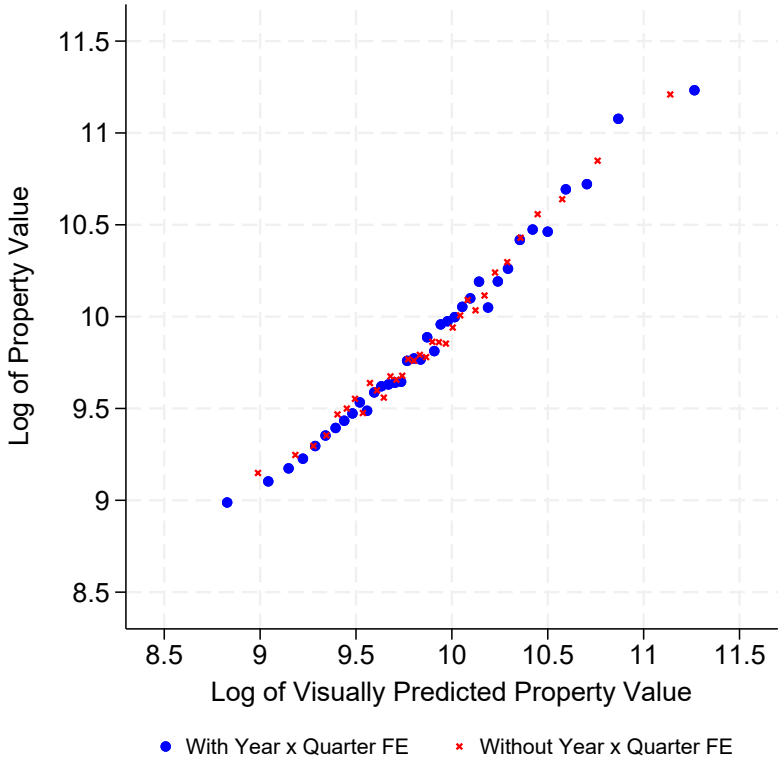
Notes: This figure shows indexes constructed by building type. The adjacent period model relies on adjacent time periods (e.g., 1912-1913, 1913-1914). The random forest model includes 100 decision trees. The indexes are normalized to one at the start of the period.

Figure A7: Indexes by Neighborhood



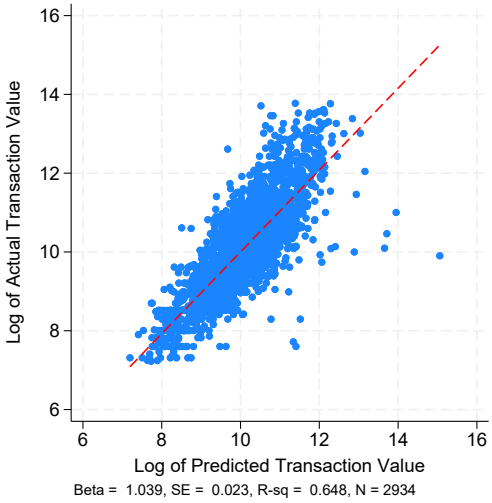
Notes: This figure shows indexes constructed by neighborhood. The adjacent period model relies on adjacent time periods (e.g., 1912-1913, 1913-1914). The random forest model includes 100 decision trees. The indexes are normalized to one at the start of the period.

FIGURE A8: USING VISUAL CHARACTERISTICS TO PREDICT PROPERTY VALUES

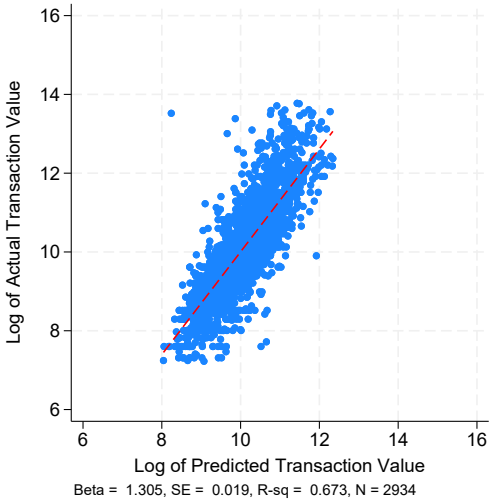


Notes: This figure shows a binscatter plot of predicted and realized property value transactions between 1912 and 1939 estimated using *only* the 100 principal components derived from visual features from 1940 photos of these properties extracted using ResNet. Plots are shown with and without year × quarter fixed effects.

Figure A9: Relation Between Predicted and Actual Property Value



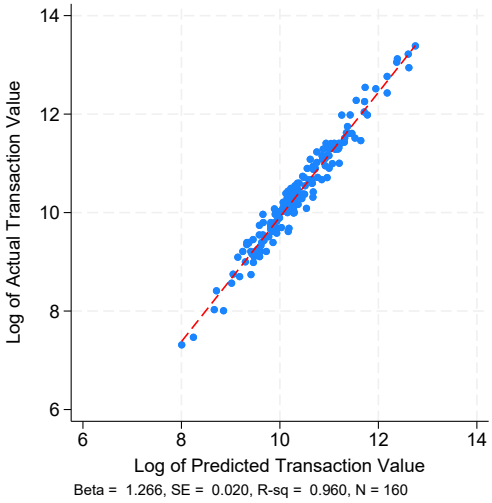
A: OLS



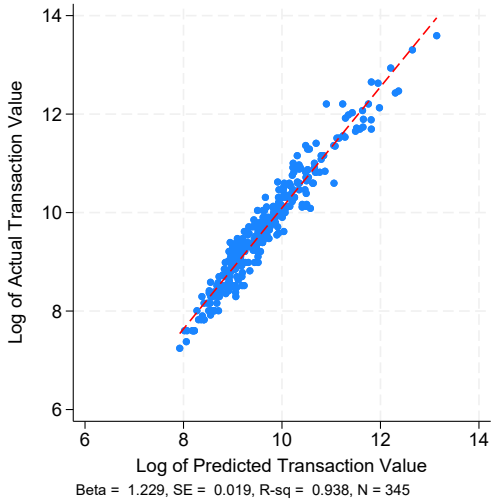
B: Random Forest

Notes: These figures show scatter plots of predicted and realized property value transactions estimated using an 80/20 training-test split for transactions occurring between 1912 and 1939. The model specification is described in the notes to Table A3.

FIGURE A10: PREDICTED PROPERTY VALUES IN-SAMPLE, 1930 AND 1939



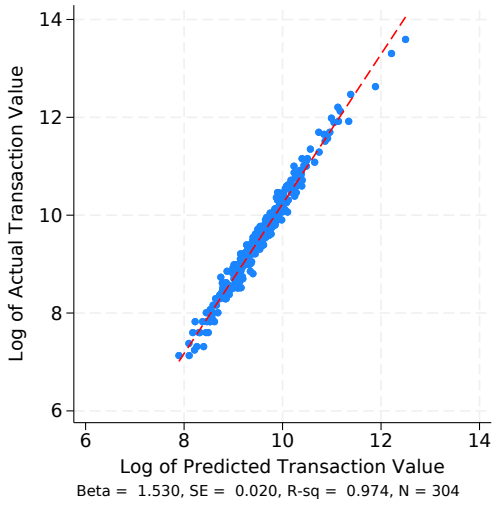
A: 1930 RANDOM FOREST



B: 1939 RANDOM FOREST

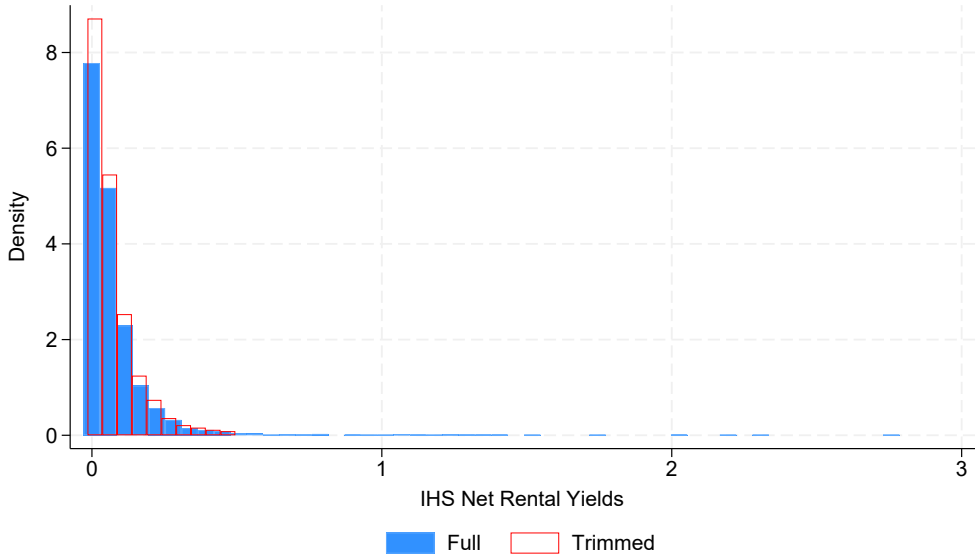
Notes: These figures show scatter plots comparing predicted and actual property transaction values, estimated using transactions that occurred in the five-year window before the target years of 1930 and 1939. Specifically, we use data from 1926–1930 and 1935–1939 to predict transaction values for the full cross-section of properties observed transacting between 1912 and 1939, as if they had occurred in 1930 and 1939, respectively. The predicted values are then plotted against the actual transaction values observed for these target years. We exclude foreclosures from the training model but include properties that experienced a foreclosure between 1912 and 1939 in the predicted set, treating them as if they transacted at market prices.

FIGURE A11: PREDICTED PROPERTY VALUES IN-SAMPLE USING IMAGES, 1939

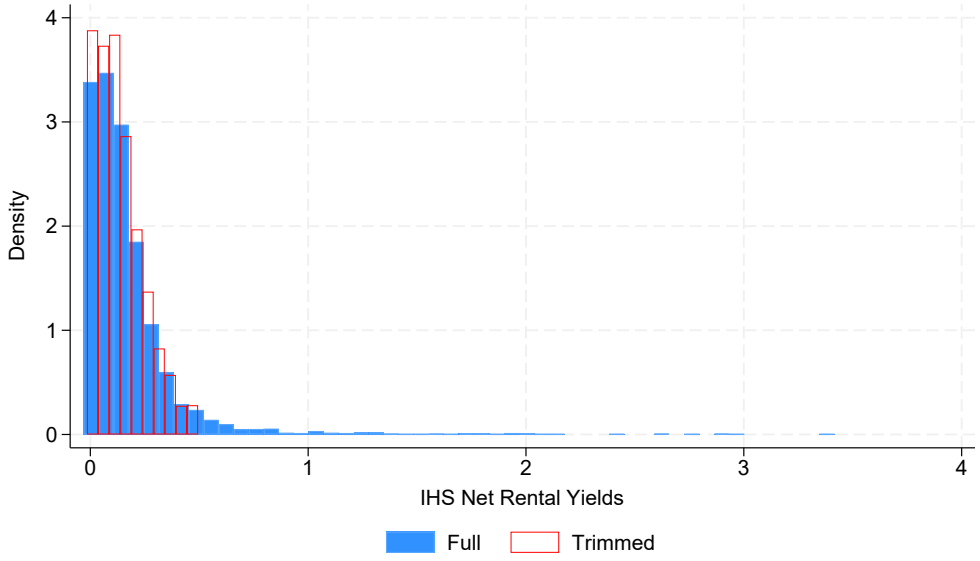


Notes: These figures show scatter plots comparing predicted and actual property transaction values, estimated using transactions that occurred in the five-year window before the target year of 1939. Specifically, we use image vector data from 1935–1939 to predict transaction values for the full cross-section of properties observed transacting between 1912 and 1939, as if they had occurred in 1939. The predicted values are then plotted against the actual transaction values observed for the target year. We exclude foreclosures from the training model but include properties that experienced a foreclosure between 1912 and 1939 in the predicted set, treating them as if they transacted at market prices.

Figure A12: Trimming Net Rental Yields



A: 1930



B: 1940

Notes: These figures show the full distribution of returns compared to the distribution trimmed at the 5th and 95th percentiles.

FIGURE A13: HIGHEST SIMILARITY SCORES: BLACK PROPERTIES 1940 AND 1980



Notes: This figure shows the 10 Black properties with the highest similarity scores, based on cosine similarity between feature vectors extracted from ResNet for each property's 1940 image and its corresponding 1980 image.

FIGURE A14: LOWEST SIMILARITY SCORES: BLACK PROPERTIES 1940 AND 1980



Notes: This figure shows the 10 Black properties with the lowest similarity scores, based on cosine similarity between feature vectors extracted from ResNet for each property's 1940 image and its corresponding 1980 image.

Table A1: Descriptive statistics, 1930

	Household Head is White		Household Head is Black		Household Head is Other	
	Mean	SD	Mean	SD	Mean	SD
Panel A: Property-Level						
Type: Dwelling	0.075	0.263	0.062	0.241	0.024	0.155
Type: Loft	0.015	0.121	0.010	0.100	0.012	0.110
Type: Other	0.107	0.309	0.079	0.270	0.024	0.155
Type: Tenement	0.803	0.398	0.849	0.358	0.939	0.241
Construction: Brick	0.833	0.373	0.829	0.376	0.878	0.329
Construction: Stone	0.009	0.097	0.004	0.061	0.000	0.000
Construction: Other	0.158	0.364	0.167	0.373	0.122	0.329
Feature: None	0.447	0.497	0.619	0.486	0.256	0.439
Feature: Store	0.553	0.497	0.381	0.486	0.744	0.439
1 Story	0.006	0.074	0.005	0.068	0.000	0.000
2 Story	0.008	0.087	0.005	0.068	0.000	0.000
3 Story	0.063	0.243	0.054	0.226	0.037	0.189
4 Story	0.136	0.343	0.056	0.229	0.159	0.367
5 Story	0.521	0.500	0.631	0.483	0.659	0.477
6 Stories and Over	0.267	0.442	0.250	0.433	0.146	0.356
Square Footage (Lot, in thousands)	48.879	2314.428	19.092	235.113	3.200	1.886
Square Footage (Lot and Building, in thousands)	111.201	4629.108	96.932	1175.597	16.068	11.529
Lot Dimensions	2.449	1.020	2.218	0.799	2.976	1.006
Property Value (Random Forest)	40835.891	33305.778	35809.362	26883.857	28288.191	15892.555
Property Value (OLS)	41355.375	37164.200	36513.790	28862.690	34446.385	13850.886
Property Rent (12 Months)	7232.579	11287.407	7143.025	6126.332	4685.268	5178.024
Distance to Nearest Subway 1930 (miles)	0.281	0.140	0.268	0.115	0.226	0.076
Panel B: Individual-Level						
Age	45.951	13.930	38.949	10.313	42.073	11.779
Male	0.738	0.440	0.677	0.468	0.963	0.189
Female	0.262	0.440	0.323	0.468	0.037	0.189
Employment Status: At Work	0.722	0.448	0.808	0.394	0.829	0.379
Employment Status: Unemployed	0.112	0.315	0.120	0.326	0.110	0.315
Employment Status: Not in Labor Force	0.166	0.372	0.071	0.258	0.061	0.241
Non-Literate	0.138	0.345	0.018	0.132	0.207	0.408
Literate	0.862	0.345	0.982	0.132	0.793	0.408

Table A2: Descriptive statistics, 1940

	Household Head is White		Household Head is Black		Household Head is Other	
	Mean	SD	Mean	SD	Mean	SD
Panel A: Property-Level						
Type: Dwelling	0.130	0.336	0.198	0.399	0.060	0.238
Type: Loft	0.017	0.129	0.006	0.078	0.017	0.130
Type: Other	0.131	0.337	0.085	0.280	0.043	0.203
Type: Tenement	0.723	0.448	0.710	0.454	0.880	0.326
Construction: Brick	0.812	0.390	0.731	0.444	0.863	0.345
Construction: Stone	0.006	0.078	0.008	0.087	0.000	0.000
Construction: Other	0.181	0.385	0.262	0.440	0.137	0.345
Feature: None	0.495	0.500	0.658	0.475	0.171	0.378
Feature: Store	0.505	0.500	0.342	0.475	0.829	0.378
1 Story	0.000	0.022	0.003	0.055	0.000	0.000
2 Story	0.008	0.087	0.007	0.081	0.026	0.159
3 Story	0.073	0.260	0.168	0.374	0.068	0.253
4 Story	0.150	0.357	0.081	0.273	0.154	0.362
5 Story	0.463	0.499	0.510	0.500	0.282	0.452
6 Stories and Over	0.306	0.461	0.232	0.422	0.470	0.501
Square Footage (Lot, in thousands)	36.525	1693.795	10.181	127.870	6.030	14.651
Square Footage (Lot and Building, in thousands)	120.905	3579.693	51.290	638.509	34.292	88.318
Lot Dimensions	2.390	0.994	2.180	0.700	2.701	1.124
Property Value (Random Forest)	30677.781	43547.184	22558.601	28592.921	16830.792	11717.757
Property Value (OLS)	49639.793	920916.587	26577.696	102947.698	28279.375	45936.462
Property Rent (12 Months)	7633.721	12699.402	5371.951	5595.080	4544.000	3884.072
Distance to Nearest Subway 1939 (miles)	0.230	0.131	0.179	0.066	0.212	0.108
Panel B: Individual-Level						
Age	47.605	14.352	41.532	11.331	40.906	10.481
Male	0.713	0.452	0.601	0.490	0.966	0.182
Female	0.287	0.452	0.399	0.490	0.034	0.182
Employment Status: At Work	0.614	0.487	0.667	0.471	0.761	0.429
Employment Status: Unemployed	0.106	0.308	0.104	0.305	0.128	0.336
Employment Status: Not in Labor Force	0.280	0.449	0.229	0.420	0.111	0.316
Wage	927.893	1275.276	566.769	731.859	676.453	783.716
Years of Schooling	7.586	4.542	7.406	3.386	4.256	4.981

Table A3: Property Value Prediction: Out-of-Sample Tests

	Model Performance			
	MAE	MedAE	MPE	MedPE
OLS	27158	6478	-31.3	-6.8
Random Forest	24834	5874	-22.9	-3.6

Notes: This table presents model performance metrics for predicting property transaction values, estimated using an 80/20 training-test split for transactions occurring between 1912 and 1939. The model specification predicts the log of property value based on the ratio of value to assessed value, square footage, physical dimensions, indicators for property type, construction type, architectural style, property features, foreclosure classification, latitude and longitude and year.

Table A4: Gross Returns, 1940

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Black	0.019***	0.017**	0.017**	0.019***	0.019***	0.019***	0.009
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)
Mean Dep Var.	0.26	0.26	0.26	0.26	0.26	0.26	0.26
R-sq (adj.)	0.00	0.01	0.01	0.01	0.01	0.01	0.10
Observations	12275	12275	12275	12275	12275	12275	12275
Properties	2889	2889	2889	2889	2889	2889	2889
Baseline Individual Controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Wage Controls	No	No	Yes	No	Yes	Yes	Yes
Education Controls	No	No	No	Yes	Yes	Yes	Yes
Distance to Subway	No	No	No	No	No	Yes	Yes
Property Controls	No	No	No	No	No	No	Yes

Notes: This table reports coefficients from regressions where the dependent variable is the inverse hyperbolic sine transformed gross rental yield. Standard errors clustered by property in parentheses. *p<0.1, **p<0.05, ***p<0.01.

Table A5: Rank Regressions by Race, 1940

	(1)	(2)	(3)	(4)
Household Wage Rank	-0.784***	-0.796***	-0.813***	-0.813***
	(0.013)	(0.010)	(0.009)	(0.009)
Black=1	4.348***	1.729	1.477	1.897*
	(1.433)	(1.129)	(1.088)	(1.062)
Black=1 × Household Wage Rank	-0.097***	-0.094***	-0.080***	-0.080***
	(0.017)	(0.015)	(0.015)	(0.015)
Mean Dep Var.	41.71	41.71	41.71	41.71
R-sq (adj.)	0.63	0.71	0.73	0.73
Properties	3045	3045	3045	3045
Observations (Households)	10240	10240	10240	10240
Individual Controls	No	Yes	Yes	Yes
Property Controls	No	No	Yes	Yes
Distance to Subway	No	No	No	Yes

Notes: This table reports coefficients from regressions where the dependent variable is the ranking in the rent-to-wage distribution. Standard errors clustered by property in parentheses. *p<0.1, **p<0.05, ***p<0.01.