Racial Disparities in Housing Returns*

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Abstract

We document the existence of a racial gap in realized housing returns that is an order of magnitude larger than disparities arising from housing costs alone, and is driven almost entirely by differences in distressed home sales (i.e. foreclosures and short sales). Black and Hispanic homeowners are both more likely to experience a distressed sale and to live in neighborhoods where distressed sales erase more house value. Importantly, absent financial distress, houses owned by minorities do not appreciate at slower rates than houses owned by non-minorities. Racial differences in income stability and liquid wealth explain a large share of the differences in distress. We use quasi-experimental variation in loan modifications to show that policies that restructure mortgages for distressed minorities can increase housing returns and reduce the racial wealth gap.

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1 Introduction

Racial wealth disparities in the US are large and persistent. The wealth of the median black household is about one-tenth of median white wealth, and median black wealth has rarely exceeded \$20,000 since at least 1949.[1] At the same time, the black homeownership rate has increased dramatically over the last century, from 23% in 1920 to 45% in 2021 (Collins and Margo 2011; Callis et al. 2021). Given that housing is the single largest asset class held by middle-class households (Campbell, 2006), and that returns to housing often exceed those of alternative investments (Jordà et al., 2019), the wealth held by middle-class black Americans has remained puzzlingly low.

While homeownership represents an attractive savings vehicle for Americans, who benefit from federal mortgage guarantees and tax deductions, mortgaged homeownership is different than most other savings vehicles because it requires sufficient income stability and liquidity to make monthly mortgage payments. This requirement may be particularly relevant for disadvantaged minorities, who are more likely to be financially distressed.[2] However, there is little evidence on the extent to which this requirement limits the effectiveness of homeownership as a savings vehicle for minorities.

This study is the first to estimate the racial/ethnic gap in housing returns using administrative data on individual housing transactions.[3] In our sample, black and Hispanic homeowners realize returns that are 3.7 and 2.0 percentage points lower than white homeowners, respectively, a gap that is driven almost entirely by differences in distressed home sales (i.e. foreclosures and short sales). Higher rates of illiquidity and income instability among minorities can explain a large share of the underlying differences in financial distress. These results help explain why minority wealth has remained persistently low despite rising homeownership rates and decades of policies designed to improve homeownership opportunities for minorities.[4] Quasi-experimental variation from mortgage servicers shows that mortgage modifications substantially increase housing returns for distressed homeowners. Our findings suggest that policies that offer payment flexibility, and thus help minorities keep their homes when they become financially distressed, are important complements to policies that aim to narrow the wealth gap by promoting minority homeownership.

We document the existence of a substantial gap in housing returns using administrative data that links homeowner race and ethnicity to real estate transactions, which allow us to observe the purchase and sale prices received by each homeowner. We apply granular fixed effects to compare homeowners of different racial groups but who purchased and sold their homes in the same years in the same county. This comparison eliminates differences in returns due to the timing of transactions

[1] Kuhn et al. (2020) report wealth by race in 2016 dollars since 1949 from the Survey of Consumer Finances. Median black wealth briefly exceeded \$20,000 in the years prior to the Great Recession and the accompanying collapse in house prices. Bhutta et al. (2020) document similarly low levels of wealth for Hispanic households.

[2] Racial and ethnic disparities in financial distress were especially pronounced in the Great Recession, during which the foreclosure rate among new black and Hispanic homeowners was nearly double that of their white counterparts (Bocian et al., 2010).

[3] For conciseness, we henceforth use race to refer to race and ethnicity collectively.

[4] Policies promoting minority homeownership date back to the 1968 Fair Housing Act, and have been supported by Republican and Democratic policymakers alike (Bush 2004; Warren 2019). Most recently, housing policy under the Biden-Harris administration has had the explicit goal of narrowing the racial wealth gap (White House, 2021).

and sorting across broad geographic regions. We consider two complementary measures of housing returns: the unlevered return defined by dividing the sale price by the purchase price, and the levered return defined by the homeowner's realized cash flows.

Racial differences in distressed home sales (i.e. foreclosures and short sales) explain the gap in housing returns. Black and Hispanic homeowners are both more likely to experience a distressed sale and to live in neighborhoods where distressed sales carry larger sale price discounts.[5] Within distressed sales, unlevered annual returns are 3.8 and 2.7 percentage points lower for black and Hispanic homeowners, respectively. We provide evidence that these differences within distressed sales are a result of black and Hispanic homeowners living in shallower real estate markets in which distressed sales incur a higher penalty. In contrast, within regular sales (i.e. non-distressed sales), the black-white gap in unlevered returns is only 0.2 percentage points (94% smaller than the total gap), whereas Hispanic homeowners experience returns that are 0.7 percentage points higher than those of white homeowners. This finding implies that homes owned by minorities appreciate at least as quickly as those owned by non-minorities.

We find similar patterns when analyzing differences in levered returns, which take into account the fact that housing is typically purchased using debt. Our measure of levered returns allows us to capture both higher rates of leverage among minorities as well as lenders bearing the cost of underwater foreclosures. Annual levered returns for black and Hispanic homeowners are 16.5 and 7.6 percentage points lower than for white homeowners. As with unlevered returns, racial disparities in levered returns are driven by distressed sales. For the sample of non-distressed sales, higher rates of leverage allow black and Hispanic homeowners to realize levered returns that are 2.8 and 8.4 percentage points higher than white homeowners, respectively.

During the 20th century, minorities often faced less favorable neighborhood-level house price growth (Akbar et al., 2019). However, our finding that there is no racial gap in housing returns for regular sales implies that minorities are not currently disadvantaged by neighborhood-level differences in house price growth. Indeed, within both neighborhoods with many minority homeowners and neighborhoods with few minority homeowners, average housing returns for regular sales are very similar across racial groups. These findings are surprising in light of a previously documented pattern in which minority homeowners pay higher prices for homes, but subsequently suffer diminished home values as a result of discriminatory market forces (e.g. white flight; Akbar et al. 2019; Perry et al. 2018; Bayer et al. 2017). We reconcile our findings with those in prior studies by showing that in our sample period, minority homeowners were more exposed to rapid house price growth driven by gentrification, allowing some homeowners to achieve very high returns.[6]

The racial gap in housing returns is not driven by differences in demographic characteristics across racial groups such as income or family structure. While racial gaps in housing returns

[5] Recent work has shown that the majority of mortgage defaults occur among homeowners with positive amounts of home equity (Low 2020; Ganong and Noel 2020b), meaning that distressed home sales tend to eliminate substantial amounts of homeowner wealth because these sales entail large price discounts (Campbell et al., 2011).

[6] These findings are consistent with previous work documenting higher exposure to gentrification among minorities (Hwang and Sampson, 2014) and with the patterns of gentrification documented in Guerrieri et al. (2013).

are larger for lower-income and single-headed households, large gaps exist even within narrow demographic categories. This finding indicates that differences in demographics may exacerbate the racial gap in housing returns, but they do not fully explain it. The gap is also not fully attributable to the 2000s housing boom and bust, since the racial gap in returns exists even among homeowners who purchased their homes in the 1990s.

To help interpret the magnitude of the racial gap in returns, we conduct a simple counterfactual exercise that estimates the contribution of the gap to differences in housing wealth at retirement age. The estimated contribution is substantial: equalizing housing returns reduces the black-white gap in housing wealth at retirement by 39%. In contrast, equalizing rates of first-time home purchases over the life cycle has virtually no impact because the gap in returns nullifies the benefit of purchasing a home at an earlier age. Equalizing both returns and purchase rates reduces the gap by 50%. These calculations suggest that addressing the racial gap in returns is necessary in order for policies that promote homeownership to be effective in narrowing the racial wealth gap.

Why are black and Hispanic homeowners more likely to experience a distressed home sale, and subsequently realize lower housing returns? We show that differences in liquidity and income stability play a leading role in explaining differences in mortgage delinquency, which is a precursor to foreclosure. In a sample of homeowners in the Survey of Income and Program Participation (SIPP), which measures income, liquidity, and mortgage delinquency, we show that minority homeowners are substantially more illiquid and face more income instability than white homeowners. Moreover, controlling for liquid wealth and recent income shocks explains one-third of the raw black-white difference in mortgage delinquency, and nearly half of the Hispanic-white difference.

Since the racial gap in housing returns is created by underlying differences in liquidity and income stability, closing the gap likely requires addressing upstream disparities, such as labor market discrimination (Bertrand and Mullainathan 2004; Kline et al. 2021). Nonetheless, policies that help minority homeowners avoid distressed sales may still reduce the gap in the short term. We provide evidence in favor of one such policy: expanding the availability of mortgage modifications for distressed homeowners. One attractive feature of such an expansion is that it can be readily targeted on the basis of location or household characteristics to better reach distressed minorities.

We show that by avoiding a distressed sale, modifications result in substantial increases in housing returns for black, Hispanic, and white homeowners alike. We leverage quasi-experimental variation in servicer-specific propensities to modify mortgages in order to estimate the causal impact of modifications. Receiving a modification within 12 months following three months of non-payment reduces the likelihood of a distressed sale by 37 percentage points, and increases realized annual returns by 8.9 percentage points, with no evidence that the impacts are significantly smaller for minorities. A back-of-the envelope calculation suggests that even expanding modifications for minority neighborhoods (as opposed to minority households) can meaningfully reduce the gap in housing returns.

The racial gap in housing returns suggests that homeownership may be a less effective savings vehicle for minorities, motivating policy intervention to reduce distressed sales among minorities.

However, it remains possible that homeownership offers minorities particularly strong opportunities to build wealth other than through the value of their properties. For instance, purchasing a home may help minorities overcome barriers to moving to neighborhoods with better employment prospects and schools (Bergman et al., 2019). We merge our data with homeowner address histories to measure upgrades in neighborhood quality by race. We find that although home purchases carry sizeable improvements in neighborhood quality for minorities, these improvements fall short of the neighborhood quality experienced by white homeowners. Moreover, race- and income-specific measures of intergenerational mobility indicate that moves generally do not yield increases in neighborhood-specific intergenerational income mobility. Our findings suggest limited scope for neighborhood upgrades to accelerate wealth accumulation for minority homeowners faster than for white homeowners.

Our study contributes to four distinct literatures. First, we build on prior studies that have documented racial disparities in housing markets. Bayer et al. (2017), Ihlanfeldt and Mayock (2009), and Myers (2004) find that minority homeowners pay more for identical housing than white homeowners. Other studies have found that minorities pay higher housing costs through unfavorable tax assessments (Avenancio-León and Howard, 2019), interest rates and fees (Bartlett et al. 2019; Bhutta and Hizmo 2019; Fuster et al. 2020; Ambrose et al. 2020), and refinancing behavior (Gerardi et al., 2020). We show that the racial gap in housing returns is an order of magnitude larger in dollar terms than these previously documented disparities in housing costs.

Another strand of this literature documents racial disparities in house price appreciation (Flippen 2004; Anacker 2010; Faber and Ellen 2016; Kahn 2021). We contribute to this literature by showing that analyzing neighborhood-level differences in house price appreciation (and thus ignoring distressed sales) greatly underestimates differences in realized housing returns by race.[7]

Second, we build on research studying racial disparities in economic well-being, particularly studies documenting elevated rates of mortgage default among minority homeowners (Berkovec et al. 1994; Rugh and Massey 2010; Gascon et al. 2017; Gerardi et al. 2020). Our focus on income instability and illiquidity as key factors that drive racial differences in mortgage default relates to prior work studying racial differences in income shocks (Wrigley-Field and Seltzer 2020; Ganong et al. 2020; Ritter and Taylor 2011). We show that these factors result in disparities in housing wealth accumulation, connecting our findings to the large literature studying the racial wealth gap (Blau and Graham 1990; Barsky et al. 2002; Gittleman and Wolff 2004; Altonji and Doraszelski 2005; Hamilton and Darity Jr 2010; Kuhn and Ploj 2020).

Third, our finding that expanding mortgage modifications can reduce the racial wealth gap adds to prior work documenting the potential value of reforms to the current housing finance system, such as through alternative mortgage contracts (Shiller and Weiss, 1999) and homeowners'

[7] Our merged administrative data allow us to measure housing returns using realized purchase and sale prices. Previous work has typically measured housing returns based on neighborhood-level house price appreciation (e.g. Anacker 2010; Kahn 2021) or homeowner self-reports of home value (e.g. Flippen 2004; Faber and Ellen 2016). Because of inherent limitations in these measures of home value, these approaches do not capture the critical impact of distressed sales on racial gaps in housing returns.

insurance (Campbell et al., 2020). Our estimates of the impacts of mortgage modifications on housing returns build on Collins et al. (2015), who find that mortgage modifications reduce the risk of foreclosure for minorities.

Lastly, our study contributes to an emerging literature on differences in returns to wealth, including recent work documenting the existence of a gender gap in housing returns (Goldsmith-Pinkham and Shue, 2020). Other studies have documented the substantial heterogeneity in returns across the wealth distribution (Fagereng et al. 2020; Bach et al. 2020; Campbell et al. 2019). Our study illustrates how heterogeneity in returns to wealth can exacerbate racial inequality.

The remainder of this paper proceeds as follows. Section 2 describes the merged administrative data. Section 3 documents the racial gap in housing returns. Section 4 analyzes underlying disparities in income stability and liquidity. Section 5 measures differences in neighborhood upgrades. Section 6 estimates the impact of mortgage modifications on housing returns. Section 7 concludes.

2 Data

We use a series of novel data linkages performed by the Fisher Center for Real Estate and Urban Economics at UC Berkeley to document racial disparities in housing returns. At the center of our analysis dataset is a linkage between mortgage origination records that contain homeowners' self-reported race and ethnicity, and real estate transaction records that capture the sale prices of property and enable us to compute housing returns at the household level. This linkage is standard in the literature on racial dynamics in real estate markets, and we build on this linkage by leveraging additional merges to administrative datasets which capture a broad range of outcomes including migration, borrowing, loan delinquency, and mortgage modifications.

We observe homeowner race and ethnicity in the Home Mortgage Disclosure Act (HMDA) data. HMDA requires mortgage lenders to disclose certain information about mortgage originations, including the self-reported race and ethnicity of loan applicants. With the exception of mortgages originated by small financial institutions that are exempt from these reporting requirements, the HMDA data capture the near-universe of mortgage originations going back to the 1990s.

We measure property characteristics and sale prices using data collected from local government assessor and recorder offices by ATTOM, a private data provider. The function of local assessors is to determine the taxable value of properties, while local recorders document both real estate sales and loans secured by real estate. These data contain property sale prices, buyer and seller names, and information indicating whether a transaction was a distressed sale.

Loans in ATTOM are merged with loans in the HMDA records by matching on transaction year, Census tract, dollar amount, and lender name. This linkage is very similar to linkages between the HMDA data and property transaction records used in previous work (e.g. Bayer et al. 2017; Avenancio-León and Howard 2019). We restrict to HMDA loans that are unique on year, tract, amount, and lender name, and require an exact merge on year, tract, transaction amount (rounded to thousands), and a fuzzy string match on lender name.[8] Unless otherwise noted, the samples analyzed in this study are restricted to owner-occupied properties.

In order to analyze differences in housing returns, we develop an algorithm for identifying repeat sales of properties. This algorithm distinguishes transaction records that represent mortgages used to purchase a property, transfers of ownership, and property values from records that represent loan refinances. We identify property purchases by restricting to arm's length, full-consideration transactions that are recorded as home purchases in HMDA. To identify the future sale of the property, we examine the set of all future transactions of that property, drop transactions in which the new buyer's name is similar to the original buyer name, and select the first subsequent arm's length full-consideration transaction. We compute measures of string similarity and apply a natural language processing algorithm to classify names as individuals, trusts, and non-trust institutions (e.g. banks, governments). This measure of similarity allows us to restrict the merged transactions to those in which the seller in the second transaction is the same as the buyer in the first transaction, excluding distressed sales from the requirement because distressed sales are typically executed by institutions rather than individuals.

Table 1, Panel A presents summary statistics for our sample of repeat property sales, which is comprised of 6 million ownership spells occurring between 1990 and 2017. Due to the relatively poor coverage of the ATTOM recorder data prior to 2000 and in certain so-called non-disclosure states, about 97% of the ownership spells occur in or after 2000 in 40 states.[9] In this study, we restrict our analysis sample to three groups defined by the race and ethnicity reported by the primary loan applicant. The three groups are black non-Hispanic (7%), white non-Hispanic (78%), and Hispanic of any race (15%), henceforth black, white, and Hispanic.[10] Relying on the HMDA data to identify homeowner race and ethnicity requires us to exclude all-cash home purchases. To quantify the magnitude of this restriction, we use the American Community Survey (2013-2017) to compute the share of households who have been living in their current residences for less than two years and who have unpaid mortgages. According to this measure, 76.5%, 78.6%, and 76.7% of white, black, and Hispanic homeowners purchased their homes with a mortgage, respectively.

A key component of our analysis entails comparing regular sales to distressed sales. There are two main types of distressed sales: foreclosures and short sales. If a borrower stops making mortgage payments, the lender can foreclose on the home and sell it to recover the outstanding mortgage balance. In contrast, a short sale occurs when the lender allows the homeowner to sell their home for less than the outstanding mortgage balance but does not hold the homeowner liable

[8]We also allow December transactions to match with January transactions. Our study relies on a fuzzy string match for lender names using a natural language algorithm developed by the Real Estate and Financial Markets Laboratory at the Fisher Center for Real Estate and Urban Economics at UC Berkeley. This procedure follows that used by Avenancio-León and Howard (2019).

[9]Sourcing data on transactions from local recorder offices generates imperfect geographic coverage in the repeat sales sample because non-disclosure states do not require that real estate sale prices be recorded publicly. These states are Alaska, Idaho, Kansas, Louisiana, Mississippi, Missouri (some counties), Montana, New Mexico, North Dakota, Texas, Utah, and Wyoming.

[10]Since our focus in this study is on historically disadvantaged minorities, our main analysis excludes Asian homeowners, who represent 5.9% of observations. Appendix Table A1 presents results including Asian homeowners.

for the difference. Overall, 31% of the ownership spells in our analysis sample are distressed sales. As we show below, the rates of foreclosures and short sales in our data match external estimates, implying that this large share is a consequence of conditioning on observing the eventual sale of a purchased property.

In our data, foreclosures are readily identified from real estate transfer documents. For instance, foreclosures generate notices of default and records from foreclosure auctions that are collected by recorder offices and captured in the ATTOM data. Appendix Figure A1 depicts the aggregate foreclosure rate over time in our data. The foreclosure rates in our data are similar to those reported in Corbae and Quintin (2009) using data from the Mortgage Bankers Association National Delinquency Survey.[11]

We identify short sales using a flag in the ATTOM data, which is the result of a proprietary algorithm used to classify short sales. Appendix Figure A2, Panel A shows that we can closely replicate this algorithm by defining short sales as those that are likely to have yielded proceeds below the outstanding balance of the mortgage. In our repeat sales sample, 36% of distressed sales are classified as short sales. Panel B plots this percentage over time and shows that the ATTOM categorization closely tracks short sales measured in external survey data.[12] Since short sales by definition take place at prices below the outstanding principal balance, the patterns in Appendix Figure A2 suggest that the algorithm accurately identifies short sales. In addition, Zhang (2019) uses a sample of property transactions provided by DataQuick and also classifies 36% of distressed sales as short sales.[13]

To complement our analysis of housing returns in our repeat sales sample, we use a dataset of individual address histories from Infogroup (also known as the Infogroup US Consumer Data) to analyze neighborhood migration. Infogroup collects information about individual address histories from a variety of sources, including real estate transfers, voter registration files, and telephone directories. These data are typically used for business marketing purposes. The Infogroup dataset is comprised of a yearly panel of households from 2006 to 2019. Infogroup links households and individuals over time and space. Each record provides a household address and names of household members. We link these data to the ATTOM transaction records using names reported in property transaction records and addresses. This linkage results in a sample of 3 million homeowners whose prior address is captured in the Infogroup data (Figure 1, Panel B).

To examine a wide range of financial behaviors and outcomes for our study sample, we use a linkage created by the Fisher Center that links credit bureau and mortgage servicing records to the previously described datasets. The credit bureau and mortgage servicing records are contained in the Equifax Credit Risk Insight Servicing McDash Database (CRISM). The CRISM data contain

[11]Our quarterly foreclosure rates are somewhat lower than those in Corbae and Quintin (2009), likely due to differences in denominators (i.e. ownership spells vs. mortgages).

[12]The survey data come from a monthly survey of real estate agents and are reported in Campbell Communications (2011). These surveys are widely referenced by industry professionals (e.g. Mahon 2010).

[13]Ferreira and Gyourko (2015) take an alternative approach, categorizing short sales as those with sales proceeds below 90% of the unpaid principal balance. Replicating our analysis following this approach yields very similar results.

two components: mortgage servicing records from McDash and credit bureau records from Equifax. The McDash data contain information on both mortgage characteristics measured at origination (e.g. loan-to-value ratio, property value, and borrower credit scores) and loan performance information including monthly loan balance, payment amount, delinquency, and foreclosure. The Equifax data are comprised of information from the Equifax credit bureau records from borrowers of loans captured in the McDash data. The Equifax data are at the monthly level and capture a broad range of financial outcomes and behaviors, including balances and delinquencies on credit cards, auto loans, and mortgages, as well as accounts in collections.

The monthly credit bureau and mortgage servicing data begin in June 2005 and cover between 60 and 80 percent of the US mortgage market, depending on the month. The data merge we use is similar to merges between the CRISM and HMDA datasets used in the literature (e.g. Gerardi et al. 2020). To document racial disparities in financial distress, we construct a yearly panel comprised of the June credit and mortgage servicing records from each year between 2005 and 2017. This panel is comprised of 85 million loan-year observations (Table 1, Panel C).

To estimate the impacts of mortgage modifications, we use a linkage with mortgage records from Fannie Mae, Freddie Mac, and ABSNet. Fannie Mae and Freddie Mac (government-sponsored enterprises, or GSEs) publish publicly-available mortgage databases containing subsets of purchased or guaranteed single-family conventional fixed rate mortgages originated since 2000 and 1999, respectively. To complement these databases, we include loans in the ABSNet Loan database. The ABSNet data are sourced from reports to securitization trustees and cover over 90% of loans collateralized through private-label residential mortgage backed securities. In addition to observing loan modifications, these data sources also record the identity of the mortgage servicer.

As with the credit bureau and mortgage servicer records, we use a linkage created by the Fisher Center to link mortgage modifications in the GSE and ABSNet data to our main study sample. To focus on a sample of homeowners who are eligible to receive a mortgage modification, we construct a sample of loans that become 90 or more days past due. The linkage yields a sample of 1.2 million loans that became delinquent between 2000 and 2017 (Table 1, Panel D). See Appendix C for additional details on the linkages to the CRISM, GSE, and ABSNet datasets.

3 The Racial Gap in Housing Returns

In this section, we define our two primary measures of housing returns and describe our empirical strategy for estimating the racial gap in housing returns. We then present our estimates of the racial gap, along with various robustness exercises and an accompanying framework for estimating the contribution of the returns gap to observed differences in housing wealth at retirement.

3.1 Measuring Housing Returns

In order to estimate racial disparities in housing returns, we measure the annual rate of return to housing in two complementary ways: unlevered and levered returns. Unlevered returns have the advantage of being straightforward to accurately measure, while levered returns have the advantage of factoring in racial differences in leverage at home purchase.

We compute the annual unlevered rate of return for owner i, r_i^u using the following formula:

$$1 + r_i^u = \left(\frac{P_{i1}}{P_{i0}}\right)^{\frac{1}{T_{i1}-T_{i0}}} \tag{1}$$

In Equation 1, P_{i0} and P_{i1} are the property purchase and sale prices, respectively. $T_{i1} - T_{i0}$ denotes the length of the ownership spell in years. The main advantage of this formula is that it is both simple and well-measured in the the local recorder data. Moreover, measuring housing returns at the household level represents an advance over prior work, which has often relied on local price indices (e.g. Anacker 2010; Kahn 2021) or on homeowner self-reports of home value (e.g. Flippen 2004; Faber and Ellen 2016).

The primary limitations of analyzing unlevered returns are that it does not capture homeowner leverage or the limited liability of borrowers in the event of default. Black and Hispanic homeowners tend to purchase their homes with more leverage (i.e. with higher loan-to-value ratios). Ceteris paribus, more leverage corresponds to higher returns, meaning that Equation 1 may understate the true rate of return for black and Hispanic homeowners. Relatedly, lenders often have a limited ability to recoup losses associated with underwater home sales, meaning that Equation 1 may overestimate the magnitude of losses from distressed home sales.[14]

In order to capture both of these factors, we compute the levered rate of return for owner i as the interest rate that sets the net present value of cash flows equal to zero. Specifically, the monthly levered return is the value of r_i^l that solves the following equation:

$$0 = -DownPay_{i0} + \sum_{t=1}^{T_i-1} \frac{rent_{it} - pymt_{it}}{(1+r_i^l)^t} + \frac{\max\{0.01, rent_{iT} - pymt_{iT} + 0.95P_{iT} - UPB_{iT}\}}{(1+r_i^l)^{T_i}} \tag{2}$$

Equation 2 defines the levered return as that which sets a series of monthly cash flows spanning $T+1$ months to zero. In the above, $DownPay_{i0}$ denotes owner i's down payment, $rent_{it}$ denotes the implicit rent received in month t, $pymt_{it}$ denotes the actual housing payment, P_{iT} denotes the property sale price, and UPB_{iT} denotes the outstanding principal balance at the time of sale. We assume that homeowners pay transaction costs of 5% of the sale price when selling their homes. The max operator captures the assumption that the homeowner is not liable for the difference between the sale price and the outstanding balance, and setting a floor of \$0.01 ensures that r_i^l is well-defined.[15]

We rely on a number of imputation strategies to compute certain components of Equation 2.

[14] In certain "no-recourse" states, lenders are legally prohibited from holding homeowners responsible for any difference between the outstanding principal balance and the proceeds from a home sale. Even in states that allow recourse, pursuing such a judgment is costly and lenders may have a limited incentive to pursue this difference using a legal judgment.

[15] We also relax these assumptions by calculating the Net Present Value (NPV) of the cash flows defined in Equation 2, which does not require a positive final value in order to be well-defined. When calculating the NPV, we do not impose the floor on cash flows in the final period for non-distressed sales.

To measure the down payment, we calculate the difference between the sale price and the original loan amount in the recorder data, and add closing costs imputed using the 2019 HMDA data. The down payment is therefore computed as the sum of equity at origination and closing costs.

To compute the monthly principal and interest payment and the unpaid principal balance at sale, we assume a 30-year fixed interest fully-amortizing mortgage and impute interest rates using mortgages originated in the same county and quarter in the McDash mortgage servicing data, distinguishing between first and second liens. The monthly payment is the sum of three components: the estimated principal and interest payment; the imputed tax and insurance payment; and maintenance costs that are 1% of the property's purchase price. We impute rents using Fair Market Rents provided by the Department of Housing and Urban Development (HUD) and house prices from Zillow, inflated using annual rental growth from HUD.[16] See Appendix D for more details on imputation.

For both the levered and unlevered returns, we restrict the sample to ownership spells that last at least 12 months and winsorize at the 1% level. For the levered rate of return, we restrict to properties where the combined LTV at origination is 100% or less. Table 1 reports statistics for the unlevered and levered returns. Notably, there is large variation in realized returns: the standard deviations of unlevered and levered returns are 12.5% and 80.2%, respectively.

Analyzing levered returns allows us to factor in both leverage and no-recourse; however, measuring levered returns requires making several assumptions when imputing the unobserved components of Equation 2. In addition, we do not capture differences in the internal rate of return that may arise due to differential propensities to refinance mortgages (Gerardi et al., 2020), or differences in mortgage contracts (e.g. adjustable rate vs. interest-only). Therefore, we view unlevered and levered returns as complementary measures of the rate of return on housing. To the extent that analysis of both measures yields similar conclusions, analyzing both provides confidence that our results are not driven by the types of bias affecting only one of the two measures.

3.2 Estimating the Returns Gap

We measure the racial gap in housing returns using an empirical strategy that allows us to compare homeowners of different races, but who purchased and sold their homes in the same years and county. We estimate regressions of the following form:

$$r_i^{\{u,l\}} = \alpha_0 \mathbb{1}\{\text{Black}_i\} + \alpha_1 \mathbb{1}\{\text{Hispanic}_i\} + \mu_{c(i),y_0(i),y_1(i)} + \varepsilon_i \tag{3}$$

where $c(i)$ denotes homeowner i's county, $y_0(i)$ denotes the year in which homeowner i purchased her home, and $y_1(i)$ denotes the year in which she sold her home. This specification regresses annualized housing returns on race indicators for homeowner i and fixed effects that interact purchase year, sale year, and county. We estimate this equation for both levered and unlevered returns, as defined in Section 3.1.

[16] Note that our calculations do not take into account racial differences in housing costs within locations and time periods, such as differences in interest rates for homeowners who purchase within the same county and quarter.

We estimate large and highly statistically significant differences in the housing returns realized by black, Hispanic, and white homeowners. Figure 1, Panel A presents the coefficients derived from estimating Equation 3 for unlevered returns. Relative to white homeowners, the annual unlevered returns realized by black homeowners living in the same county are 3.7 percentage points lower, while those realized by Hispanic homeowners are 2.0 percentage points lower. These differences are large both relative to the 1.3% annual return realized by the average homeowner in the sample. Scaled by the standard deviations of returns of 12.5%, the black and Hispanic gaps are 0.30 and 0.16 standard deviations lower, respectively.

The gaps in housing returns are attributable to the house price penalties associated with distressed home sales (e.g. foreclosures and short sales). As discussed in Section 2, we classify distressed sales as those identified as foreclosures and short sales in the property transaction records. Figure 1, Panel B presents coefficients from a regression that interacts race indicators with an indicator for whether the property sale is classified as a distressed sale. The omitted category is defined as white homeowners with non-distressed sales. We find that differences in returns by race for homeowners who sell their homes under normal (i.e. non-distressed) conditions are almost non-existent relative to the overall gap. Black homeowners with non-distressed sales realize returns that are only 0.2 percentage points lower than those of white homeowners, and Hispanic homeowners with non-distressed sales realize returns that are 0.7 percentage points higher.

In contrast to non-distressed sales, there is a large racial gap in distressed home sales. The house price penalties associated with distressed home sales (relative to non-distressed sales) are well-documented, and the impact of these penalties can be seen in Figure 1, Panel B. Distressed home sales result in annualized rates of return that are 10.5, 9.5, and 6.8 percentage points lower for black, Hispanic, and white homeowners, relative to non-distressed home sales for white homeowners in the same county. This result indicates that the overall racial gap in housing returns is driven by two factors. First, minority homeowners are more likely to experience a distressed sale. Appendix Table A1 presents the numerical values resulting from estimating Equation 3 and shows that black and Hispanic homeowners are 23 and 14 percentage points more likely than white homeowners to experience a distressed sale, respectively. Second, minority homeowners experience larger house price penalties associated with distressed home sales, as indicated by the lower returns realized by minorities with distressed sales relative to white homeowners with distressed sales.

We find similar patterns when examining differences in levered returns. Figure 1, Panel C shows that black and Hispanic homeowners realize annual levered returns that are 16.5 and 7.6 percentage points lower, respectively, than white homeowners living in the same county. While these differences are larger than those for unlevered returns in level terms, the gaps are similar when scaled by the variance of returns, at 0.21 and 0.09 standard deviations, respectively. Figure 1, Panel D shows results interacting race indicators with a distressed sale indicator. Notably, black and Hispanic homeowners who sell their homes under normal conditions realize levered returns that are 2.8 and 8.4 percentage points higher than their white counterparts, respectively. These favorable levered returns (relative to unlevered returns) are driven by higher amounts of leverage among minority homeowners.[17] As with unlevered returns, the gap in levered returns appears to be driven entirely by distressed sales.

The finding that the racial gap in housing returns can be explained by distressed sales is novel, as is the finding that distressed home sales carry particularly severe house price penalties for black and Hispanic homeowners. This latter result can be explained by racial differences in the thickness of local housing markets. In particular, black and Hispanic homeowners appear to live in more illiquid housing markets where distressed home sales carry more severe house price penalties. To show this, Appendix Figure A6 estimates Equation 3 splitting the sample by sale type (regular vs. distressed) and by quintile of the median days on the market of homes sold in each ZIP code from Zillow (2018). The racial gap in housing returns for distressed home sales increases substantially with housing market illiquidity. For instance, the black-white gap in distressed sales is about twice as large in the most illiquid markets relative to the least illiquid markets. Consistent with the interpretation that these patterns are driven by housing market liquidity, distressed white homeowners in illiquid markets also experience lower returns than distressed white homeowners in relatively liquid markets; moreover, these patterns are absent in the sample of non-distressed sales.

Two additional findings support the conclusion that racial differences in distressed sale discounts are driven by housing market liquidity. First, the differences in discounts are largely eliminated when comparing homeowners within Census blocks (Appendix Figure A7). Second, differences in discounts are not driven by racial differences in the composition of distressed sales. Previous research has shown that short sales carry more modest discounts than foreclosures (Zhang, 2019), suggesting that compositional differences could drive the difference in distressed sale discounts. However, the differences in distressed sale discounts exist within both foreclosures and short sales (Appendix Figure A8).

Our estimates of the racial gap in returns among regular sales (Figure 1, Panel B) are consistent with the findings in previous studies that have analyzed local house price indices. Kahn (2021) studies racial differences in housing returns using house price indices from Zillow and finds that black homeowners earn slightly lower returns than the average homeowner, while Hispanic homeowners earn higher returns than average.[18] Our results indicate that due to higher rates of distressed sales among black and Hispanic homeowners and the fact that local-level indices do not capture the pivotal impacts of distressed sales, previous approaches have greatly underestimated the racial gap in housing returns. Similar reasoning applies to the use of home values reported by homeowners (e.g. Flippen 2004), since homeowners presumably report the value of their homes if sold under non-distressed conditions.

To provide further evidence on the limited role played by differences in neighborhood-level house price growth, Figure 2 analyzes unlevered returns by neighborhood racial composition. Specifically,

[17] Appendix Figure A5 plots the distribution of combined-loan-to-value ratio at purchase by race.

[18] Specifically, Kahn (2021) computes returns for each racial group using a shift-share approach that takes weighted averages of county- and zip code-specific returns computed using Zillow's Home Value Indices. Weights correspond to the share of homeowners of a particular racial group who purchase homes in a given location. In Appendix Figure A9, we show that measuring returns using Zillow's indices underestimates the returns to regular sales and overestimates the returns to distressed sales.

we estimate Equation 3, interacting race indicators with quintiles of the 2010 white share of homeowners in each Census tract (quintiles assigned within each county). Figure 2, Panel A, shows that the size of the racial gap is substantially larger in neighborhoods with more minorities; however, Panel B, which further interacts race and neighborhood quintile with an indicator for distressed sale, shows that there is no racial gap in returns for regular sales, regardless of neighborhood racial composition.[19] These results demonstrate that the racial gap in housing returns is not primarily a result of lower levels of house price growth in minority neighborhoods, but rather of higher rates of distressed sales among minorities coupled with higher distressed sale penalties in minority neighborhoods.

In theory, the racial gap we document could arise solely from differences in household characteristics by race. For instance, if lower-income homeowners were to receive lower returns on average, one would observe lower returns for black homeowners even if homeowners of different races and similar incomes realized similar returns. To evaluate whether this is the case, we estimate Equation 3 by interacting the race indicators with household characteristics.

We find that minorities experience lower housing returns even conditional on demographics, but that the racial gap tends to be larger within more economically vulnerable demographic categories (e.g. low-income households). These patterns are illustrated in Figure 3, which presents the results of regressions that interact homeowner race with demographic categories. For example, the black-white gap in unlevered housing returns is approximately twice as large in the lowest income tercile relative to the highest income tercile, and for couples relative to single-headed households.[20] At the same time, the differences in housing returns among white homeowners in different demographic categories are generally modest. For example, white homeowners of different incomes experience nearly identical returns. One notable exception are homeowners in the lowest credit score tercile. White homeowners in the lowest credit score tercile experience substantially lower returns than higher-credit score white homeowners (on par with returns of black and Hispanic homeowners in the highest tercile of credit scores). Taken together, these findings indicate that while the racial gap in returns varies across demographic groups, the gap is not solely driven by differences in observable household characteristics.[21]

3.3 The Role of Gentrification

The finding that there is no racial gap in housing returns for regular sales is somewhat surprising in light of an emerging body of work that suggests that minority homeowners may "buy high and sell low." Akbar et al. (2019) use US Census data starting in 1930 to show that black families entering a previously-white neighborhood paid a house price premium of 28%, only to see the value of their

[19]Appendix Figure A10 presents the analogous results for levered returns.

[20]This finding is consistent with adjustments to labor supply providing additional insurance against income shocks for multiple-earner households (Blundell et al., 2016).

[21]Appendix Figure A11 presents results split by urban vs. rural, loan-to-value at origination, debt-to-income ratio, property size, and whether the mortgage is an FHA loan and yields a similar conclusion: the racial returns gap does not arise solely due to racial differences in household characteristics.

homes fall as white homeowners left the neighborhood. Analyzing modern-day housing markets, Bayer et al. (2017) show that black and Hispanic homebuyers pay more for houses than their white counterparts, and Perry et al. (2018) document substantial undervaluation of properties in black neighborhoods.

We reconcile our findings with these previous studies by showing that in recent years, minority homeowners have been more exposed to rapid house price growth associated with historical patterns of gentrification. Higher exposure among minorities to rapid house price growth is evident when analyzing trends in local house price indices. Appendix Figure A12, plots the distribution of Census tract house price growth (measured using FHFA repeat-sales house price indices; Bogin et al. 2019) between 2001 and 2017 by neighborhood racial composition and shows that minority Census tracts are more likely to experience very rapid increases in house price growth. We illustrate a similar pattern within our main analysis data in Appendix Table A2, which shows that the variance of returns is larger for black and Hispanic homeowners, even within non-distressed sales.

We show that returns among minorities for regular sales are particularly high relative to white homeowners at higher quantiles of housing returns. Appendix Table A3 presents estimates of marginal effects at the average at various quantiles of the distribution of unlevered returns using the quantile regression methods in Schmidt and Zhu (2016). The finding that the marginal effects associated with indicators for black and Hispanic homeowners are substantially larger at higher quantiles provides further evidence that the returns realized by minority homeowners are buoyed by areas experiencing rapid house price growth.[22]

Lastly, we show that minority homeowners are more exposed to previously studied measures of gentrification. Guerrieri et al. (2013) analyze two measures of exposure to gentrification measured at the ZIP code level. The first measure is an indicator that a ZIP code's median house price in 2000 is below the median within the corresponding MSA. The second measure is the distance to the nearest ZIP code in the highest quartile of house prices in the corresponding MSA, for ZIP codes with below-median house prices. Intuitively, cheaper neighborhoods close to higher-priced neighborhoods should be those most exposed to gentrification.

Black and Hispanic homeowners are more exposed to gentrification, measured using the percent of homeowners in low-price ZIP codes. In Appendix Table A4, we present the average exposure according to these measures of gentrification for black, Hispanic, and white homeowners in our sample. Black homeowners living in lower-price ZIP codes appear to be more exposed to gentrification in terms of their proximity to high-price ZIP codes than either Hispanic or white homeowners. In Appendix Table A5, we estimate Equation 3, interacting race indicators with these two measures of gentrification. Focusing on the sample of regular sales, we find that for all racial groups exposure to gentrification is associated with higher returns. Living in a neighborhood where house prices were low in 2000, and being closer to a high-price neighborhood is associated with realizing higher returns (conditional on experiencing a non-distressed sale).

[22]Due to computational constraints, we estimate quantile regressions on a restricted sample using purchase year-by-state fixed effects, which precludes a direct comparison to our main results.

Taken together, our findings indicate that on average, homes owned by minorities appreciate at least as quickly as those owned by non-minorities, but that this average masks differences in the variance of returns that are partly driven by differential exposure to gentrification. Our findings are consistent with other studies documenting higher exposure to gentrification in minority neighborhoods (Hwang and Sampson, 2014), and help reconcile our results with prior work suggesting that minority neighborhoods may be disadvantaged in housing markets.

3.4 Robustness and Interpretation

In this subsection, we address various issues concerning the interpretation of the racial gap in housing returns.

Alternative Fixed Effects.—Our preferred specification applies county-by-purchase year-by-sale year fixed effects in order to eliminate differences due to the timing of transactions. However, racial gaps arising from differences in timing may themselves be of interest. In Appendix Figure A13, we present estimates with less granular fixed effects. The raw gaps in unlevered returns are 5.8 and 5.5 percentage points for black and Hispanic homeowners, respectively. Comparing the estimates in Appendix Figure A13 indicates that the difference between the raw gaps and those in our preferred specification is mostly due to differences in the purchase year, as opposed to differences in location or sale year.

To evaluate the extent to which gaps in housing returns exist among homeowners in the same neighborhood, Appendix Figure A13 also presents estimates using more granular fixed effects. Controlling for purchase year, sale year, and Census tract reduces the gap in unlevered returns to 1.6 percentage points for black homeowners and 0.9 percentage points for Hispanic homeowners, respectively. Substituting Census blocks for Census tracts results in further reductions to 1.1 percentage points and 0.5 percentage points, respectively. Note that these smaller gaps do not affect the overall interpretation of our baseline results. As shown in Appendix Figure A13, Panel C, these finer fixed effects absorb much of the variation in the likelihood of experiencing a distressed sale. For instance, within counties, black homeowners are 23 percentage points more likely than white homeowners to experience a distressed sale, but only 9 percentage points more likely within Census blocks. Therefore, the reduction in the gap in housing returns cannot be interpreted as indicating that neighborhood-level differences in house price appreciation are responsible for the gaps in housing returns. This is particularly the case given that the more granular fixed effects restrict the estimation to location-year bins in which sales by multiple races are observed, which disproportionately excludes tracts with more minorities (in which distressed sales are disproportionately concentrated) biasing the estimated gaps towards zero.

Distressed Sale Discounts.—It may be tempting to diminish the importance of the racial gap because it is created by differences in distressed sales. In particular, one could conclude that distressed home sales do not destroy housing wealth because the proceeds of most distressed home sales are not sufficient to cover the outstanding loan balance. However, it is important to distinguish between the realized distressed sale proceeds and the value of the property if not sold in a distressed sale. Low (2020) and Ganong and Noel (2020b) show that the majority of homeowners who default have positive equity. At the same time, much of that equity is destroyed after a distressed sale. We illustrate this fact in our sample in Appendix Figure A9 by plotting the difference between a property's actual sale price and its value imputed by inflating its original purchase price using Zillow's ZIP code Home Value Index, suggesting a distressed sale discount of 30% for white homeowners, 38% for black homeowners, and 39% for Hispanic homeowners. This finding is roughly in line with estimates of foreclosure discounts from prior work (e.g. Campbell et al. 2011). Thus, the distressed sales that drive the returns gap directly erode black and Hispanic wealth, meaning that the racial gap in housing returns translates into real differences in wealth accumulation.

The Great Recession.—A second potential concern is that our results may largely pertain to the extraordinary housing market conditions prevalent during the Great Recession, which occurred roughly in the middle of our sample window. We show that minority homeowners would likely have experienced lower returns even in the absence of these extraordinary conditions. Appendix Figure A14 estimates Equation 3 by purchase year (Panel A) and by sale year (Panel B), and Appendix Figure A15 presents estimates within each purchase year-by-sale year cell as a heat map. While racial gaps are larger during the Great Recession, black and Hispanic homeowners realize substantially lower returns in every period outside of the Great Recession, with the exception of Hispanic homeowners who purchased and sold their properties between 2010 and 2017 or who sold their properties at the height of the housing boom. Even minority homeowners who purchased their homes in the 1990s (and thus were relatively less exposed to the house price volatility in the 2000s) realize lower returns. The reason for this can be seen in the aggregate foreclosure rates by race presented in Appendix Figure A1. Black and Hispanic homeowners have experienced higher foreclosure rates since the 1990s as well as after the Great Recession. Collectively, these patterns indicate that lower returns among minority homeowners are not confined to economic downturns.

Finite-Sample Bias.—An issue we face in estimating racial gaps is that we must do so within a finite sample window. Our sample contains ownership spells occurring between 1990 and 2017, with about 97% occurring between 2000 and 2017. Consequently, our analysis entails a common form of censoring bias resulting from our inability to observe returns for homeowners who purchased homes within our sample window but had not yet sold as of 2017. We show that this bias is unlikely to change the finding that minority homeowners experience substantially lower returns. Figure 3 presents results split by length of ownership spell. Large returns gaps exist even among minorities who have owned their property for 11 or more years. However, returns gaps are smaller among longer ownership tenures, suggesting that finite sample bias may lead us to overestimate the size of the racial gap in returns. In Appendix E, we attempt to bound this bias by re-weighting our estimates according to the observed distribution of ownership lengths. The strictest adjustment that assumes no racial differences in returns outside of our sample window shrinks our estimated gaps by about half. While this is a substantial reduction in percentage terms, the adjusted estimates still represent very large differences in housing returns and are many times larger in dollar terms than previously documented disparities in housing markets, discussed below.

Net Present Value.—Our definition of the internal levered rate of return in Equation 2 factors in many relevant cash flows, but it does not take into account substantial indirect costs associated with foreclosure that have been documented in previous work (Diamond et al. 2020; Ganong and Noel 2020b). Moreover, imposing a positive floor on terminal cash flows mechanically limits the losses of homeowners who voluntarily choose to sell an underwater property at a loss. As a result, we may underestimate the size of the racial gap in returns. To relax these assumptions, we define measures of the net present value (NPV) of the home purchase, calculated using the same cash flows in Equation 2, but relaxing the floor on cash flows in the final period for non-distressed sales. Appendix Table A1, Panel A presents the results of estimating Equation 3 for unlevered returns, levered returns, and the NPV scaled as a percentage of upfront costs. We present results under three different assumptions about the additional costs of foreclosures: no additional costs, a $50,000 cost paid at foreclosure, and a $100,000 cost paid at foreclosure, the latter of which corresponds to the consumption-equivalent utility cost of foreclosure from Ganong and Noel (2020b). Panel B presents analogous results, interacting race indicators with the sale type. The results for the NPV regressions are qualitatively similar as those for the levered and unlevered returns, and quantitatively similar when scaled by the standard deviations of each outcome.

Home Improvements.—We do not directly observe expenditures on home improvements that would affect the true return on housing by race. To evaluate the likely quantitative significance of this factor, we draw on home repair and home improvement expenditures reported in the Panel Study of Income Dynamics (2001-2017). Appendix Figure A16 plots these expenditures as an annual percentage of house value by race. While there do not appear to be meaningful differences in home repair expenditures by race, white homeowners spend somewhat more on home improvements than black and Hispanic homeowners, on the order of one-half of a percentage point. While this difference is non-trivial relative to the average gaps (3.7 and 2.0 percentage points for black and Hispanic homeowners, respectively), it does not change the overall interpretation of our results, given that there is no racial gap among non-distressed sales. However, it may help explain why minority homeowners with non-distressed sales do not realize higher returns despite of being more exposed to rapid house price growth (as discussed in Section 3.3).

Comparison to Other Disparities.—In dollar terms, the size of the gap in housing returns is substantially larger than many of the other racial disparities in housing markets documented in the literature. For instance, Bayer et al. (2017) document that black and Hispanic homeowners pay around 1.7% more for comparable houses (or $3,400 for a $200,000 house). Bartlett et al. (2019) document racial discrimination at mortgage origination resulting in interest rates that are 7.88 basis points higher for minority homeowners, while Gerardi et al. (2020) document post-origination interest rate disparities due to differences in refinancing behavior of over 40 basis points (a difference on the order of $500 annually for a $200,000 home). Avenancio-León and Howard (2019) find that inflated property assessments result in annual property tax costs that are $300-$390 higher for minorities. In our sample, the average tenure length is 5.3 years. For that ownership spell, even our adjusted black-white gap of 1.8% per year for a $200,000 house corresponds to a difference of $3,663 per year. Thus, this channel appears to be orders of magnitude larger than other gaps identified in previous work.

3.5 Racial Transitions and Institutional Buyers

To what extent are minority homeowners who live in distressed neighborhoods able to take advantage of the availability of discounted homes being sold at foreclosure auctions? In principle, if all real estate transactions occur within race (e.g. Hispanic sellers only selling to Hispanic buyers) and foreclosures do not entail substantial depreciation, then higher rates of distressed sales need not depress housing returns for minority homeowners. To evaluate this possibility, we examine racial property transitions by analyzing the ownership spell that occurs following the original spell in our repeat sales sample. Using a sample of sequential ownership spells where race is observed in the HMDA data, Appendix Table A6 shows that within the sample of distressed sales, 79% of white homeowners sell to a white buyer, 31% of black homeowners sell to a black buyer, and 39% of Hispanic homeowners sell to a Hispanic buyer. Thus, the majority of minority home sales appear to involve buyers of a different race or ethnicity.

What role do buyers outside of the neighborhood play in housing transitions? We use the sample of sequential ownership spells to examine how the characteristics of the second homeowner differ by the race of the first homeowner and by the sale type. In Appendix Table A7, we find that distressed homes are more likely to be purchased by investors rather than owner-occupiers. White-owned distressed homes are about 13 percentage points more likely to be purchased by an institutional buyer, and 5 percentage points less likely to be occupied by the next owner. These homes are also more likely to be flipped—they are held by the subsequent owner for 16 months less than white-owned non-distressed homes. Institutional buyers appear to have an even larger presence in buying minority-owned distressed homes: they are 7 and 5 percentage points more likely to buy distressed black-owned and Hispanic-owned homes, respectively, relative to a white-owned distressed home.

It is important to note that purchasing a distressed home can require substantial additional investment in order to counteract recent property depreciation. Since we do not observe this investment, we are unable to measure the net discount associated with distressed home sales. Nonetheless, our results suggest that net discounts associated with distressed properties owned by minorities, to the extent that they exist, may disproportionately benefit outside investors and buyers of other racial groups.

3.6 Disparate Returns and the Racial Housing Wealth Gap

We now estimate the contribution of racial gaps in housing returns to wealth disparities using a simple wealth accumulation equation that allows us to estimate a variety of counterfactual wealth gaps. We compute average wealth held in the primary home at retirement age by a household of race $r \in \{black, white\}$ using the following equation:

$$\hat{H}_r^{65} = \left(\sum_{t=25}^{65} p_r^t \times R_r^{(65-t)} \right) H_r^{ft} \tag{4}$$

In the preceding equation, p_r^t denotes the unconditional probability of becoming a first time home buyer at age t for race r, R_r denotes the annual return on housing for race r, and H_r^{ft} is the average value of houses purchased by first-time home buyers of race r. Simply put, Equation 4 models average primary housing wealth at retirement as the average value of households' first home at purchase, inflated by the race-specific housing returns and weighted by the probability of making a first home purchase at a given age. We do not explicitly model transitions out of homeownership through distressed sales, which are captured in the race-specific returns R_r. In addition, this framework assumes that average house sizes do not vary with age at first home purchase, which is consistent with the patterns in the data used to calibrate Equation 4.

We draw on a sample of households in the Panel Study of Income Dynamics (PSID) 2001-2017 to calibrate several components of Equation 4. We exploit the panel structure of the PSID to estimate age- and race-specific transition probabilities p_t^r and home values H_r^{ft} (normalized to 2016 dollars). We focus on black and white homeowners because both groups have sufficiently large samples in the PSID. See Appendix C.2 for more details on the PSID sample. We take a conservative approach to calibrating race-specific housing returns, and estimate inflation-adjusted returns using the correction for finite-sample bias, which is discussed in detail in Appendix E. This approach yields annual real returns of 0.376% for white homeowners and annual real returns of -1.374% for black homeowners. From the PSID, average home value at first home purchase is \$208,621 for white homeowners and \$142,587 for black homeowners.[23]

Despite its simplicity, Equation 4 yields estimates of primary housing wealth at retirement that are similar to those observed in the PSID sample. As reported in Table 2, this framework yields average housing wealth at retirement for black households of \$77,419, which closely matches the average of \$81,713 estimated from households in the PSID aged 63-67. The black-white wealth gap is \$135,359, which is similar to but somewhat smaller than the gap of \$167,956 in the sample.[24]

Equation 4 allows us to measure the contribution of the gap in housing returns to the gap in

[23] To compute p_r^t, we first estimate the transition probability of becoming a first-time home buyer at age t for race r, denoted by q_r^t. Let N_r^t denote the share of households of race r and age t who have never been homeowners. Then we can compute the transition probabilities as $p_r^t = N_r^t q_r^t$. We compute p_r^{25} as the share of households aged 25 who are homeowners.

[24] One potential reason why we underestimate white housing wealth is that since white homeowners have relatively more non-housing wealth, they have more scope to eventually buy a more expensive primary home, converting non-housing wealth into housing wealth.

housing wealth by estimating counterfactual housing wealth at retirement under varying assumptions about R_r, p_r^t, and H_r^{ft}. Specifically, we examine the change in the estimated gap in housing wealth under counterfactuals in which we allow black homeowners to realize the same returns, transition probabilities, and initial home values as white homeowners. The results of these counterfactual exercises are reported in Table 2. Equalizing housing returns reduces the gap by 39%. In contrast, equalizing transition probabilities reduces the gap by only about 1%, and equalizing both transition probabilities and initial home values reduces the gap by only 28%. Equalizing both returns and transition probabilities reduces the gap by 50%.

The results of this exercise indicate that the gap in housing returns can explain a quantitatively large share of observed differences in housing wealth and that equalizing housing returns can substantially reduce racial wealth disparities. Housing wealth held in the primary home comprises 43% of total net wealth for the average retirement-age black household in our PSID sample, implying that the gap in housing returns can explain a large share of the overall racial wealth gap. While the homeownership rate among white households is substantially higher than that of black households, our results indicate that the potential benefits of higher homeownership rates among black households are almost entirely eroded by their substantially lower returns. This finding illustrates both the limitations of policies that focus solely on promoting homeownership and the potential value of policies that help minorities stay in their homes.

4 Racial Disparities in Financial Distress

The finding that distressed home sales disproportionately erode the wealth of minority homeowners begs the question, why are minority homeowners more likely to experience a distressed home sale? We address this question by analyzing credit bureau and mortgage servicing records linked to our analysis sample. These data sources allow us to measure and decompose the racial differences in financial distress that underlie racial differences in distressed home sales. We present evidence that these differences are driven by higher rates of illiquidity and income instability among minority homeowners.

4.1 Measuring Disparities in Financial Distress

In order to analyze the sources of racial disparities in financial distress, we link our analysis sample to credit bureau records provided by Equifax and mortgage servicing records provided by McDash. The annual snapshots from these data sources allow us to define two measures of financial distress. The first measure is an indicator that a homeowner is 90 or more days past due on their mortgage, captured in the McDash servicing data. The second measure is an indicator that a homeowner has a non-mortgage loan (e.g. credit card) 90 or more days past due, or an account in third party collections, captured in the Equifax credit bureau data.

Loan default offers a better measure of underlying financial distress than distressed home sales because non-payment reflects homeowner decisions, whereas distressed sales in large part reflect lenders' willingness to foreclose or accept a short sale.[25] Default is a clear indicator that a homeowner is in financial distress. Mortgage default places homeowners at risk of foreclosure and eviction, and unpaid balances on non-mortgage loans may be sent to collections, which can subject homeowners to frequent and often invasive attempts to collect debt, including lawsuits. Moreover, loan default is reflected on homeowners' credit reports and thus visible to potential lenders and employers.[26]

In line with our finding that minorities are more likely to experience a distressed sale, we find that minority homeowners are more likely to be financially distressed. Figure 4 plots the incidence of financial distress against homeowners' current combined loan-to-value ratio, which represents the share of the property's value that is owned by the homeowner. In both Panel A (mortgage default) and Panel B (non-mortgage default), black and Hispanic homeowners exhibit strikingly high rates of financial distress, both in absolute terms and relative to white homeowners. About one-third of black homeowners whose home equity is equal to their outstanding principal balance (CLTV=50%) have a non-mortgage loan 90 or more days past due or in collections. The racial disparities in financial distress exist at all levels of combined loan-to-income, implying that accumulating home equity does not fully insulate minority homeowners from financially distress.[27]

As a first step towards identifying the causes of higher rates of financial distress (and thus distressed home sales) among minority homeowners, we conduct a decomposition exercise to identify the factors that can account for these differences. We decompose the racial differences in financial distress by estimating regressions of the following form:

$$\mathbb{1}\{\text{Distress}_{it}\} = \alpha_0 \mathbb{1}\{\text{Black}_i\} + \alpha_1 \mathbb{1}\{\text{Hispanic}_i\} + X_{it}'\beta + \mu_t + \varepsilon_{it} \tag{5}$$

The outcome in Equation 5 is an indicator that homeowner i experiences financial distress in month t. X_{it} denotes a vector of homeowner, mortgage, and property characteristics, and μ_t denotes month fixed effects. Measuring the impact of sequentially expanding the set of controls X_{it} on $\hat{\alpha}_0$ and $\hat{\alpha}_1$ allows us to decompose racial differences in financial distress into components that can be explained by the factors captured in X_{it}.

The detailed financial outcomes in our linked dataset allow us to evaluate a number of potential factors underlying differences in financial distress. First, minority homeowners may face mortgage terms that are relatively unfavorable (e.g. due to discrimination in lending). Second, minority homeowners may live in neighborhoods that are characterized by adverse economic conditions, such as negative house price shocks. Third, factors that are upstream of the home purchase decision

[25] While 90-day delinquency is a standard measure of default, an alternative approach to measuring differences in financial distress is to look at transition probabilities between payment statuses (e.g. likelihood of transitioning from 30 days past due to current). In Appendix Table A8, we present the full transition matrix of mortgage statuses by race, which indicates that black and Hispanic homeowners are less likely than white homeowners to catch up on their payments after becoming delinquent.

[26] Dobbie et al. (2020) document that the removal of bankruptcy flags on credit reports results in large increases in credit access and small increases in employment.

[27] Appendix Figure A17 presents a version of the figure that includes homeowners with combined loan-to-value ratios greater than 100%, and Appendix Figure A18 documents higher rates of financial distress among minorities for auto loans, student loans, and credit cards.

(e.g. higher levels of income instability) may make minorities more vulnerable to negative shocks to household balance sheets.[28]

We find that differences in financial distress can be largely explained by factors upstream of the home purchase decision, whereas neighborhood and loan characteristics account for a relatively small share. Figure 5, Panel A presents the results of estimating Equation 5 for mortgage default. The raw racial gaps in financial distress measured by mortgage default are 3.1 percentage points and 2.1 percentage points for black and Hispanic homeowners, respectively. The majority of this disparity is explainable by three borrower characteristics: income, credit score, and the presence of a co-applicant. These factors are upstream of the home purchase decision in the sense that they reflect homeowner characteristics that are determined prior to taking out the mortgage, and can explain 56% and 38% of the gap in distress for black and Hispanic homeowners, respectively. Only 9% of the black-white disparity is explained when controlling for mortgage characteristics, and an additional 16% can be attributed to neighborhood characteristics in the form of Census tract and block fixed effects. Even when controlling for a comprehensive range of individual, mortgage, and neighborhood characteristics, black and Hispanic homeowners are about one-third more likely to default on their mortgages than their white counterparts.[29]

Upstream factors appear to play an even larger role for non-mortgage default, presented in Figure 5, Panel B. Income, credit score, and family composition explain 67% and 72% of the gap for black and Hispanic homeowners, respectively. Neighborhood and loan characteristics appear to have an even weaker influence on non-mortgage default than on mortgage default.

Our results demonstrate the existence of high levels of financial distress among minorities, which underlie the differences in distressed sales that generate the racial gap in housing returns.[30] The results in Figure 5 suggest that differences in financial distress are unlikely to be caused by differences in mortgage terms, or by neighborhood-specific economic conditions. One limitation of this exercise is that the credit bureau and mortgage servicing data do not contain time-varying measures of income and liquidity. To overcome this limitation, we draw on a sample of homeowners in the Survey of Income and Program Participation, which allows us to directly analyze the relationship between racial differences in liquidity and income stability and racial disparities in financial distress.

[28] A fourth potential explanation for racial differences in distressed sales is that minority homeowners are more likely to strategically default on their mortgages; however, this explanation is rejected by Figure 4, since above-water minority homeowners are more likely to default even conditional on loan-to-value ratio.

[29] The results in Figure 5 are based on a sample of homeowners with CLTV $\leq$ 120%, and excludes homeowners with multiple mortgages (for whom the data do not permit CLTV to be calculated). Appendix Figure A19 repeats the analysis with the excluded groups and finds qualitatively similar patterns. For investors, current year-by-origination year-by county fixed effects proxy for both CLTV and upstream labor market factors given the strong correlation between local labor market shocks and house price shocks during the Great Recession.

[30] Our findings build on prior research documenting elevated rates of loan default among minorities (Gerardi et al. 2020; Butler et al. 2020; Jackson and Reynolds 2013). Moreover, the finding that the bulk of differences in financial distress can be attributed to upstream factors echoes Charles and Hurst (2002), who find that racial differences in transitions to homeownership are largely attributable to pre-existing differences in income, family structure, and transfers.

4.2 The Role of Liquidity and Income Stability

The decomposition exercise in the previous subsection suggests that factors that are upstream of the home purchase decision are important determinants of higher rates of financial distress among minority homeowners. In this section, we analyze the role of liquid wealth holdings and income instability, both of which are likely to be strongly influenced by upstream factors (e.g. labor market disparities, intergenerational transfers). This analysis is guided by recent research demonstrating that liquidity plays a key role for mortgage default (Ganong and Noel, 2020a), as well as in accounting for racial differences in consumption responses to income shocks (Ganong et al., 2020). We provide evidence that racial differences in liquid wealth holdings and income instability can explain observed disparities in financial distress, relying on both our merged administrative data as well as external data from the Survey of Income and Program Participation.

Evidence from SIPP.—We demonstrate the existence of large racial disparities in liquidity and income stability using a sample of homeowners in the the Survey of Income and Program Participation (SIPP), surveyed between 1992 and 2017. Appendix C.2 provides more details on the construction of the SIPP sample. The SIPP data have the advantage of containing time-varying measures of income and liquidity, which are not contained in our linked analysis dataset. The SIPP data reveal that among homeowners, the racial gap in liquid wealth is even larger than the gap in total net wealth. Figure 6 plots median total wealth (Panel A) and liquid wealth (Panel B) as a share of annual household income, by the race and age of the household head. The difference between the disparities in net wealth and liquid wealth are striking. While racial disparities exist for both measures of wealth, the proportional gap in net wealth is roughly constant over the life cycle, while the gap in liquid wealth increases dramatically. At less than 20% of annual earnings for almost all age groups, median wealth among black and Hispanic homeowners is strikingly low.[31]

Similarly, minorities have lower and less stable incomes than white homeowners. Figure 6 plots median income over the life cycle (Panel C) and the likelihood of transitioning to unemployment as a function of income (Panel D). Not only do minority homeowners earn substantially less income at all ages, they are also 2 to 4 percentage points more likely to experience a transition to unemployment, at all levels of pre-unemployment income. Together, the patterns illustrated in Figure 6 demonstrate the existence of disparities in income and liquidity that have the potential to explain the observed racial disparities in financial distress. These findings contribute to a growing literature documenting racial differences in income volatility (Wrigley-Field and Seltzer 2020; Hardy et al. 2018; Elvira and Zatzick 2002). In addition, the importance of income volatility for mortgage default and wealth accumulation is in line with recent evidence that a large share of mortgage defaults can be attributed to income shocks and other adverse life events (Ganong and Noel, 2020b).

We show that controlling for income stability and liquidity can explain a large share of racial differences in mortgage delinquency measured in the SIPP data. Homeowners in SIPP were asked

[31] Liquid wealth for minority homeowners is small in dollar terms as well: median liquid wealth for black and Hispanic homeowners is $2,400 and $5,400, respectively (Appendix Figure A20). Ganong et al. (2020) document similar gaps in a sample of banked individuals and in the SCF.

whether they have missed mortgage payments in the last 12 months. Table 3 shows that non-Hispanic black homeowners are 4.7 percentage points more likely to have missed mortgage payments, relative to a mean of 5.4% for non-Hispanic white homeowners. Hispanic homeowners are 3.2 percentage points more likely to have missed mortgage payments. Controlling for liquidity and unemployment in the prior year substantially reduces the estimated coefficients on indicators that the household head is black or Hispanic: Column 3 shows that the coefficients are 3.1 and 1.7 percentage points for black and Hispanic homeowners, respectively. Comparing the difference in the coefficients in Columns 1 and 3 implies that liquidity and income stability can explain about 33% and 47% of the racial gap in delinquency for black and Hispanic homeowners, respectively. Columns 4 through 6 repeat the same exercise but include controls for the level of household income, current loan-to-value, and family composition. Even including these additional controls, liquidity and income stability can explain 21% and 40% of the gap for black and Hispanic homeowners, respectively.

Evidence from Monthly Payment Changes.—To complement the analysis using the SIPP data, we provide further evidence on the role of liquidity by analyzing homeowner responses to quasi-experimental changes in monthly mortgage payments. Specifically, we apply the methodology developed in Wong (2020) to estimate event studies at the monthly level around changes to property tax and insurance payments (a.k.a. escrow payments), which can be interpreted as a shock to household liquidity. The advantage of analyzing responses to monthly payments in the linked administrative data, relative to our analysis using the SIPP data, is that the linked administrative data allow us to precisely measure both the liquidity shocks and mortgage delinquency. In the SIPP data, measures of mortgage delinquency, income, and liquidity are self-reported by respondents and therefore likely subject to nontrivial amounts of measurement error. Appendix Section F discusses this approach in detail.

Appendix Figure A22 plots event study coefficients and shows that in response to a 10% increase in monthly mortgage payments, black and Hispanic homeowners exhibit increases in mortgage delinquency of about 1.3 and 0.8 percentage points over the following twelve months, respectively. White homeowners exhibit an increase of only 0.5 percentage points, indicating that minority homeowners are more vulnerable than white homeowners to similarly-sized shocks to liquidity.

In addition, controlling for income, debt-to-income at mortgage origination, and credit score at mortgage origination explains 57% (65%) of the black-white (Hispanic-white) differences in the delinquency response to liquidity shocks (Appendix Table A9). Note that credit score at origination is designed to predict repayment ability, and is therefore likely to be correlated with income stability and liquidity. These results, which indicate that minority homeowners are more vulnerable to liquidity shocks, are consistent with recent evidence that liquidity is a key driver of mortgage default (Ganong and Noel 2020a; Ganong and Noel 2020b) and of racial differences in responses to income shocks (Ganong et al. 2020).

Seasonal Distress.—Another complementary source of evidence in support of the role of liquidity comes from the aggregate time series pattern of financial distress. Loan delinquency exhibits a seasonal pattern among minority homeowners that suggests higher sensitivity to liquidity shocks. Appendix Figure A24 presents the monthly share of homeowners with open mortgages in the credit bureau sample that are delinquent, by race, for the lowest quintile of household income measured at loan origination. Mortgage delinquency appears to be highly seasonal, especially for black and Hispanic homeowners. The troughs of delinquency occur between March and May of each year, which are precisely the months in which most tax filers receive their tax refunds. This behavior is consistent with previous evidence that households use tax rebates to pay down debts (Agarwal et al., 2007) and provides additional evidence that liquidity shocks are an especially important determinant of mortgage delinquency for minorities, even conditional on household income.

4.3 Interpreting Differences in Liquidity and Income Stability

While our results indicate that lower levels of liquidity and income stability make minority homeowners more financially distressed and more likely to default on their mortgages, an outstanding question is why minority homeowners have less liquidity. The extremely low levels of liquidity among minority homeowners is puzzling, particularly given that minority homeowners have less liquidity even as a share of their incomes (Figure 6, Panel B). We provide suggestive evidence from our sample of homeowners in the PSID and find that many factors are likely at play (see Appendix C.2 for details on the PSID sample). The lower incomes and higher income instability among minorities illustrated in Figure 6 likely contribute to lower levels of liquidity, particularly in light of recent work documenting the importance of job stability for wealth accumulation (Kuhn and Ploj, 2020) and that modest income gaps can translate into large wealth gaps (Aliprantis et al., 2019).

In spite of higher levels of income volatility among black homeowners, Appendix Figure A25, Panel A shows that black and white savings rates appear to be roughly similar conditional on income, consistent with previous findings in Gittleman and Wolff (2004). Financial outflows measured by mortgage interest paid (Panel B) and inheritances (Panel C) both appear to be less favorable for black homeowners. Moreover, black homeowners have a lower share of their financial wealth held in stocks (Panel D), indicating that returns to financial savings may be lower.

Together, the disparities documented in this section indicate that a combination of factors—such as lower incomes and higher income volatility, higher housing costs, lower intergenerational wealth transmission, and lower returns to saving—contribute to higher rates of mortgage default and distressed sales among minority homeowners. These findings suggest that distressed home sales are an important channel that amplifies the impacts of racial labor market disparities on the racial wealth gap, implying that addressing upstream disparities (e.g. disparities in labor market outcomes) is necessary in order to fully close the racial gaps in both housing returns and wealth.

5 Non-Financial Returns to Homeownership

Thus far, our analysis has focused on the financial returns to homeownership; however, homeownership carries many benefits that are not captured by financial returns. For instance, homeownership may provide an opportunity to locate in neighborhoods with desirable amenities, such as local public schools, and previous research has indicated that neighborhoods can have a causal impact on intergenerational income mobility (Chetty et al., 2016). Since households may encounter significant barriers to finding and accessing desirable neighborhoods (Bergman et al., 2019), homeownership could help to surmount these barriers. Together, these facts raise the possibility that there are substantial non-financial returns to homeownership, and that these non-financial returns contribute to household wealth accumulation. To the extent that these non-financial returns differ by race, they may compensate for the gap in financial returns to housing that we document in Section 3.

While estimating the total impact of homeownership on saving and wealth accumulation is outside of the scope of this study, we analyze one potential dimension of non-financial returns in the form of the neighborhood upgrades realized upon home purchase. We combine address histories for our analysis sample with data from Chetty et al. (2018) that measures neighborhood-level characteristics, including measures of intergenerational mobility. We use the Infogroup address histories linked to our main analysis dataset to identify the previous address of of each household. These data allow us to compare the characteristics of neighborhoods from which homeowners depart upon purchasing a home to those of the neighborhoods to which they move. The change in neighborhood characteristics represents one category of non-financial returns to homeownership.

We find that while homeowners of all racial groups move to higher-quality neighborhoods on average, the upgrades realized by minority homeowners are limited. In Figure 7, we plot the average size of neighborhood upgrades by race, as a function of income (homeowners are binned into deciles of income computed within-race). Figure 7, Panel A depicts improvements in neighborhood poverty, as measured by the share of individuals in the Census tract below the federal poverty line in the 2006-2010 American Community Surveys. This figure shows that homebuyers of all races and incomes appear to be moving to lower-poverty neighborhoods. Black and Hispanic homeowners move to neighborhoods with poverty rates that are 2-3 percentage points lower than their previous neighborhood, compared to only about 1 percentage point for white homeowners. However, despite minority homebuyers achieving larger absolute gains than their white counterparts, black and Hispanic homebuyers of similar incomes move to higher-poverty neighborhoods than white homebuyers of similar incomes. This pattern is especially pronounced at lower levels of income, at which the average poverty rate of the neighborhoods to which minorities move is higher than even that of the neighborhoods from which white homeowners depart.

Figure 7, Panel B illustrates a similar pattern for school quality, measured using 2013 school district standardized 3rd grade math test scores in grade equivalent units. Homebuyers of nearly all race and income groups move to school districts with higher test scores, but homebuying does not appear to allow black and Hispanic homebuyers to catch up to white homebuyers. The average minority homeowner arrives in a neighborhood with lower-quality schools than the neighborhood from which the average white homeowner with a similar income departs.

Because poverty level and school quality measure neighborhood quality based off of the average characteristics of residents, they are not ideal measures of the benefits realized by individual households. For example, moving a family to a district with high test scores does not guarantee that the children's test scores will improve. To measure household-specific non-financial returns to homeownership, we use the race- and income-specific estimates of intergenerational mobility and incarceration rates from Chetty et al. (2018). We assign each homeowner the statistic that pertains to their tract, race, and income percentile in the national distribution of income measured in 2015 dollars reported in the HMDA data.

Strikingly, we find no evidence of neighborhood upgrading when neighborhood quality is measured using race- and income-specific statistics. Panel C presents results for intergenerational mobility, measured as the mean rank in the national income distribution of children born to parents of a given race and income percentile. There is effectively no average change in neighborhood intergenerational mobility for any race or income group. Similarly, Panel C presents results for incarceration, measured as the share of male children born in 1978-1983 in each tract that are incarcerated in 2010. All income and racial groups experience negligible changes in local race- and income-specific incarceration rates. This is especially notable for lower-income black homebuyers who live in areas with the highest incarceration rates of black men.[32]

While the migration patterns we document confirm that homebuying allows households to realize substantial upgrades in terms of neighborhood quality, the upgrades realized by minorities are limited in two ways. First, the improvements in neighborhood poverty and school quality are not sizeable enough to allow minority homeowners to catch up to white homeowners. Second, homebuying does not appear to result in any average increases in intergenerational mobility or reductions in incarceration. These results suggest limited scope for improvements in neighborhoods to increase wealth accumulation for minority homeowners beyond those realized by white homeowners. While there remain other channels through which homeownership can increase wealth accumulation,[33] the large magnitude of the racial gap in housing returns coupled with the limited gains in neighborhood quality suggest that the total impact of homeownership on wealth accumulation is lower for black and Hispanic homeowners.

6 Policy

In this section, we discuss how our findings relate to longstanding policy efforts to increase minority homeownership, and estimate causal impacts of mortgage modifications on housing returns

[32]These results are based on a sample of homebuyers that includes households that owned their previous property. Our data only allow us to observe whether a household is a first-time homebuyer through the linkage with the Fannie Mae and Freddie Mac mortgage records, which explicitly capture this information but are only linked for a subset of homeowners. Appendix Figure A26 repeats these exercises for the sample of first-time homebuyers and yields similar results albeit with some loss in precision.

[33]For instance, recent work suggests that homeownership can serve as a commitment device to save through mortgage amortization (Bernstein and Koudijs, 2021).

to show that policies that promote mortgage modifications can greatly increase the efficacy of homeownership as a savings vehicle for minorities.

6.1 Housing Policy and Racial Disparities

Since at least the 1968 Fair Housing Act, homeownership has been a key tool in the policy effort to combat racial economic inequality, and Republican and Democratic politicians alike have advocated for policies that increase homeownership among minorities (e.g. Bush 2004; Warren 2019). Housing has offered historically favorable returns (Jordà et al., 2019), and represents the single-largest asset class for middle-class American households (Campbell, 2006). Perhaps as a result, recent policy efforts to narrow the racial wealth gap have included proposals to expand homeownership opportunities among minorities (White House, 2021).

Policies designed to expand homeownership opportunities among minorities typically fall into one of two categories: those that make it easier for households to purchase homes, and those that help homeowners stay in their homes when they become financially distressed (e.g. following a job loss). Most recent proposals fall into the first category, such as the 2020 proposals by then-Senators Kamala Harris and Elizabeth Warren to provide down payment assistance to homebuyers in formerly redlined areas (Capps and Mock, 2019). However, our findings suggest that such policies are limited in their ability to help minorities build wealth because they do little to help financially distressed homeowners avoid a foreclosure or short sale.[34]

Far less attention has been paid in recent years to policies that help distressed minority homeowners stay in their homes. Given our findings, such policies have the potential to mitigate racial gaps in housing returns. In this section, we analyze the potential value of a targeted expansion of mortgage modifications, which are specifically designed to help distressed homeowners.

When homeowners become unable to afford their current mortgage (e.g. after becoming unemployed), mortgage servicers can modify the terms of the mortgage. Servicers can reduce monthly payments through a combination of principal forbearance, interest rate reductions, and term extensions. Notably, large-scale government intervention in restructuring mortgages has ample precedent in the modification subsidies provided by the Home Affordable Modification Program (HAMP) in 2009 and mandatory payment forbearance mandated by the CARES Act in 2020.[35]

Mortgage modifications are seemingly well-suited to avoiding the erasure of minority housing wealth created by distressed sales. Previous research has found that modifications are useful for avoiding mortgage default (Ganong and Noel, 2020a), a precursor to distressed sales. Moreover, because minority homeowners are more likely to default, they receive a disproportionately large share of modifications. Appendix Figure A27 shows that throughout the financial crisis and Great Recession, black and Hispanic homeowners each accounted for approximately 20% of loan modifications,

[34] To the extent that down payment assistance increases liquid wealth holdings, these policies may help some homeowners self-insure against negative shocks. However, these policies are designed to make homebuying more accessible to households with little liquid wealth, a group that are likely to be particularly vulnerable to such shocks.

[35] As documented in Agarwal et al. (2017), HAMP prevented about 600,000 foreclosures between 2009 and 2012 by subsidizing modifications through incentive payments to servicers, borrowers, and investors.

despite only comprising about 7% and 13% of open mortgages, respectively.

Interestingly, mortgage servicers appear to disproportionately target modifications to black (and to some extent Hispanic) homeowners despite the absence of any policy incentives to do so. In Appendix Section G, we show that black homeowners are 2.5 to 6.4 percentage points more likely than observationally similar white homeowners to receive a modification. These patterns hold even controlling for the homeowner's neighborhood and servicer, suggesting that servicers internalize part of the larger distressed sale discounts among minority homeowners.

While these findings are encouraging, they are not sufficient to conclude that modifications are effective for reducing the racial gap in housing returns. First, reductions in default need not increase housing returns. For instance, by prolonging (or merely postponing) the foreclosure process for some homeowners, modifications could exacerbate property depreciation and actually lower housing returns. Second, it is possible that modifications are less beneficial for minority homeowners, particularly considering that minorities experience higher levels of financial fragility. Therefore, evaluating the efficacy of mortgage modifications as a policy tool for preventing distressed sales from eroding minority wealth requires directly estimating the impact of mortgage modifications on housing returns.

6.2 The Impact of Mortgage Modifications on Housing Returns

To estimate the impact of modifications on housing returns, we leverage quasi-experimental variation in servicers' propensities to modify mortgages. This variation is motivated by previous work that has shown that servicers' propensities to modify mortgages vary both across servicers and within servicers over time (Agarwal et al. 2017; Aiello 2019; Korgaonkar 2020). In the Fannie Mae, Freddie Mac, and ABSNet Loan databases, we observe the identities of servicers and the provision of modifications. To construct a measure of servicer modification propensity, we turn to a sample of homeowners who have become 90 days delinquent on their mortgages and estimate equations of the following form:

$$\mathbb{1}\{\text{Mod}_{it}\} = \mu_{f(i)} + \gamma_{s(i),t} + \varepsilon_i \tag{6}$$

In Equation 6, i denotes homeowner, t denotes year, $\mu_{f(i)}$ denotes a vector of fixed effects that includes fixed effects for the Census tract interacted with origination year and current year; the source of the data (i.e. Fannie Mae, Freddie Mac, or ABSNet); deciles of credit score at origination; an indicator that the loan is interest-only; and an indicator that the loan is a negative amortization loan. The vector also includes fixed effects capturing deciles of the original loan amount, current LTV, and years remaining in the loan term, and an indicator that the loan is an an adjustable-rate mortgage. $\gamma_{s(i),t}$ denotes servicer-by-year fixed effects. The outcome is defined as an indicator that the loan received a modification within 12 months of becoming 90 days delinquent. We estimate a separate $\gamma_{s(i),t}$ for each state, restricting the sample to loans outside of that state and outside of any ZIP codes and commuting zones that overlap with that state. The estimated $\hat{\gamma}_{s(i),t}$ provide a plausibly exogenous measure of servicer propensities to modify loans.

We use our estimated propensities of servicer $s(i)$ in year t to modify the mortgage of delinquent homeowner i to instrument for an indicator that homeowner i receives a modification. Specifically, we estimate the following specification by 2SLS, using $\hat{\gamma}_{s(i),t}$ as an instrument for $\mathbb{1}\{\text{Mod}_{it}\}$:

$$r_i = \alpha_0 \mathbb{1}\{\text{Mod}_{it}\} + \mu_{f(i)} + \varepsilon_i \tag{7}$$

Equation 7 regresses an outcome r_i (e.g. the rate of return realized by homeowner i) on indicators that i received a modification within twelve months of default interacted with race indicators. $\mu_{f(i)}$ denotes a vector of fixed effects. In our baseline specification, this vector includes interacted fixed effects for Census tract, purchase year, year of default, and indicators for interest-only loan and negative amortization loan, as well as servicer fixed effects. Under the exclusion assumption that the servicer modification propensity affects realized returns only through receipt of modification, estimating Equation 7 by 2SLS recovers the causal impacts of modification receipt by race. The exclusion assumption is plausibly satisfied in this setting because homeowners are unlikely to be aware of their mortgage servicer's propensity to modify loans. Moreover, the inclusion of servicer fixed effects controls for potential bias from systematic sorting into servicers and leverages within-servicer over-time differences in modification propensities.

Table 4 presents our estimates of the impact of modifications on housing returns derived by estimating Equation 7. Column 1 presents naive OLS estimates, which indicate that a modification for a white homeowner is associated with a 3.2 percentage point increase in housing returns (and with slightly higher returns for black and Hispanic homeowners). These estimates cannot be interpreted as causal because receipt of a modification is likely a function of expected homeowner outcomes. For instance, servicers may allocate modifications to homeowners who are most at risk of continuing to default, or in distressed neighborhoods where foreclosures are particularly costly, both of which would bias the OLS estimates downwards. We proceed to estimate our specification by 2SLS to remove these sources of bias. Column 2 presents the first stage equation estimated by OLS, which results in a highly statistically significant coefficient on the servicer instrument, indicating that the instrument relevance assumption is satisfied.

The 2SLS estimates indicate that modifications reduce the likelihood of experiencing a distressed home sale for all racial groups. Table 4, Column 2 presents 2SLS estimates of the impacts of modifications on an indicator that the ownership spell ends in a distressed sale, with properties that have not been sold as of 2018 defined as not experiencing a distressed sale. In this baseline specification, we interact the instrument and endogenous variables with race indicators. Receiving a modification causes a highly statistically significant 37 percentage point reduction in the probability of experiencing a distressed sale for white homeowners. The small and statistically insignificant coefficients on the interactions with race indicators indicate similar impacts for black and Hispanic homeowners. These findings are consistent with Collins et al. (2015), who find similar associations between modification and foreclosure across racial and ethnic groups in a sample of subprime loans originated between 2004 and 2006.

As previously discussed, reducing distressed sales need not increase housing returns. Nevertheless, we find that modifications increase housing returns for black, white, and Hispanic homeowners alike. Table 4, Column 3 presents estimates for our main outcome of interest: annual unlevered housing returns. Modification increases annual returns by 8.9 percentage points for white homeowners, with no significant evidence of smaller impacts on returns for black homeowners, and moderately higher impacts for Hispanic homeowners. This finding implies that modifications have economically large impacts on housing returns for minorities. In addition, the 2SLS estimates are larger than those in Column 1, confirming the existence of downward bias in the OLS estimates.

We conduct three sets of robustness exercises in order to validate our research design. First, one potential issue with our estimates of the impacts of modifications on housing returns is that they may be be biased downwards because we cannot compute the returns for properties that were not sold before 2018. To gauge the magnitude of this bias, we compute returns for unsold properties by imputing their value as of 2018 using county-level FHFA house price indices (Bogin et al., 2019). In Table 4, Column 5, we estimate an increase of 10.6 percentage points in annualized returns, confirming the existence of downward bias but suggesting that its magnitude is modest.

In our second robustness exercise, we evaluate the sensitivity of our estimates to alternative sets of control variables. In Table 5, we interact our baseline fixed effects with terciles of credit score at origination (Column 2), loan-to-value ratio at default (Column 3), and income at loan origination (Column 4). The estimated impacts of modifications are quantitatively similar across specifications. Third, we conduct a placebo exercise in which we regress the outcome of interest (e.g. indicator for a distressed sale) on a vector of characteristics measured prior to default and use the predicted values to define an index.[36] Intuitively, if our exclusion restriction is valid, then the modification instrument should have no impacts on these outcomes measured prior to default. Forming an index using these predicted values is a concise way to summarize the relationship between the vector of characteristics and the outcome. Appendix Table A11 presents the results of regressing the index on our reduced form specification (i.e. on the instrument, its interactions with race indicators, and baseline covariates) and shows that the estimated coefficients are small and statistically insignificant for all coefficients.

We provide evidence of heterogeneous impacts of modifications, suggesting that policies that promote modifications could be made more cost-effective by targeting specific types of homeowners. Table 5, Columns 5 and 6 interact the modification indicator with measures of market distress and family size, respectively. For each homeowner i who is first delinquent in year t, we compute the share of property sales in year t (excluding the sale of homeowner i) that are distressed sales. We define homeowners in distressed tracts as those in the top quartile of this measure. Similarly, we define single applicants as those whose loan application registered in the HMDA data does not include a co-applicant. The impact of modifications on unlevered returns is 4.4 percentage points larger in

[36] The characteristics include loan type (i.e. conventional, FHA, VA) fixed effects; loan purpose (i.e. purchase or refinance) fixed effects; indicators for adjustable rate, interest-only, and negative amortization; fixed effects for deciles of credit score, income, interest rate, and loan amount at origination; current year fixed effects, and data source (i.e. Fannie Mae, Freddie Mac, or ABSNet) fixed effects.

distressed tracts and 3.1 percentage points larger for single-applicant households, significant at the 0.1% and 5% levels, respectively. These results suggest that policies that promote modifications may be productively targeted towards certain vulnerable neighborhoods and households.

6.3 Interpretation and Discussion

The results presented in this section indicate that providing mortgage modifications to minority homeowners can increase housing returns and thus reduce the racial gap in housing returns. However, targeting minority homeowners themselves may not prove politically feasible. We conduct a back-of-the-envelope calculation to assess the potential impacts of policies that target minority neighborhoods instead of minority homeowners. Consider a policy that extends modifications to half of distressed homeowners in the decile of neighborhoods with the highest share of black homeowners. Re-weighting our sample to reflect the reduction in distressed sales shrinks the estimated black-white gap in housing returns from 3.71 to 3.26 percentage points.[37] An analogous calculation for Hispanic homeowners reduces the Hispanic-white gap from 1.96 to 1.69 percentage points.

This calculation illustrates both the value and limitations of an expansion in mortgage modifications. While the calculation indicates that even policies that target minority neighborhoods can have meaningful impacts on the racial gap in housing returns, it also ignores important considerations of moral hazard and adverse selection that are very likely to influence homeowner responses to a large-scale expansion of modifications. Moreover, an expansion in modifications of any plausible size would not be able to fully close the racial gap in housing returns, implying that closing the gap likely requires addressing upstream racial disparities, such as those leading to worse labor market outcomes for minorities.

Nonetheless, an expansion in modifications may offer a politically feasible short-term policy solution, echoing recent proposals to expand homeownership opportunities in formerly-redlined minority neighborhoods (Capps and Mock, 2019). The recent government mandate of mortgage forbearance through the CARES Act indicates that large-scale restructuring of mortgages is not only possible, it also need not be especially costly (Cherry et al., 2021). Since previous research indicates that monthly payment reductions are the key benefits of modifications, a large-scale expansion may only require implicit government loans to lower payments and lengthen terms for distressed homeowners (Ganong and Noel, 2020a). Expanding modifications could also ameliorate the well-documented negative house price externalities on nearby properties associated with distressed sales (Campbell et al. 2011; Anenberg and Kung 2014), and the corresponding reduction in foreclosures could yield additional economic benefits through residential investment and consumer demand (Mian et al., 2015).

Government incentives to modify mortgages are not the only policy that offers these desirable properties. An alternative method of restructuring mortgages for distressed homeowners would

[37] Neighborhood black/Hispanic share is defined as the share of mortgaged homeowners in a Census tract identifying as black/Hispanic in the 2010 Census. Dividing our estimate of the effect of a modification on the likelihood of a distressed sale (-0.34) by the share of defaulted loans not receiving a modification and ending in a distressed sale (0.68) implies that the extra modifications yield a 24.8% reduction in distressed sales.

be through the alternative mortgage contracts proposed by Campbell et al. (2020), which would offer homeowners the option of lowering their mortgage payments and extending their terms during economic downturns. Similar benefits could be realized through privately-provided insurance contracts. Shiller and Weiss (1999) propose insurance contracts that trigger payments to homeowners in response to life events (e.g. divorce). Given the patterns we document in this paper, policies that restructure housing costs to help distressed minorities keep their homes have the potential to narrow the racial gap in housing returns, and by extension the racial wealth gap.

7 Conclusion

Homeownership has long been a central part of the American dream, and is the primary savings vehicle for middle-class households in the US. Over the last century, there have been enormous changes to the homeownership opportunities available to historically disadvantaged minorities, including legal prohibitions on discrimination in housing; however, minority wealth has remained remarkably low. While policies that increase minority homeownership are widely viewed as helping minorities build wealth, we show that the financial returns to homeownership for minorities are severely limited by high rates of financial distress.

Our findings highlight the importance of policies that help homeowners stay in their homes in times of financial distress or avoid financial distress altogether, as complements to policies that help households purchase homes. By preventing distressed home sales, policies that accommodate financial distress may have large benefits for the wealth accumulation of minorities. Moreover, since higher rates of illiquidity and income instability underlie higher rates of distressed home sales among minorities, fully closing the gap likely requires addressing labor market disparities. Nonetheless, policies that increase liquid wealth among minorities, such as baby bonds and reparations, may mitigate the racial gap in housing returns.

Lastly, there is no reason why financial distress should only impact the returns on housing wealth. It may be the case that assets that are typically acquired using leverage may yield less net value to minorities in general. Indeed, Figure 8 shows that rates of delinquency for student loans and auto loans are higher for black and Hispanic homeowners in our sample.[38] If the mechanisms we document are general in nature, attempts to improve economic outcomes for minorities by expanding access to leveraged assets may be inherently limited in their efficacy without efforts to address the root causes of financial distress.

[38]Delinquency on auto loans puts the borrower at risk of having their car repossessed, while delinquency on student loans may result in wage garnishment and becoming ineligible for loan deferment, forbearance, and additional federal student aid. Both types of delinquency can negatively harm credit access through lower credit scores.

References

S. Agarwal, C. Liu, and N. S. Souleles. The Reaction of Consumer Spending and Debt to Tax Rebates—evidence From Consumer Credit Data. *Journal of Political Economy*, 115(6):986–1019, 2007.

S. Agarwal, G. Amromin, I. Ben-David, S. Chomsisengphet, T. Piskorski, and A. Seru. Policy Intervention in Debt Renegotiation: Evidence From the Home Affordable Modification Program. *Journal of Political Economy*, 125(3):654–712, 2017.

D. Aiello. Financially Constrained Mortgage Servicers. *Available at SSRN 3063513*, 2019.

P. A. Akbar, S. Li, A. Shertzer, and R. P. Walsh. Racial Segregation in Housing Markets and the Erosion of Black Wealth. Technical report, National Bureau of Economic Research, 2019.

D. Aliprantis, D. Carroll, and E. R. Young. The Dynamics of the Racial Wealth Gap. 2019.

J. G. Altonji and U. Doraszelski. The Role of Permanent Income and Demographics in Black/White Differences in Wealth. *Journal of Human Resources*, 40(1):1–30, 2005.

B. W. Ambrose, J. Conklin, and L. A. Lopez. Does Borrower and Broker Race Affect the Cost of Mortgage Credit? *Review of Financial Studies (Forthcoming)*, 2020.

K. B. Anacker. Still Paying the Race Tax? Analyzing Property Values in Homogeneous and Mixed-Race Suburbs. *Journal of Urban Affairs*, 32(1):55–77, 2010.

E. Anenberg and E. Kung. Estimates of the Size and Source of Price Declines Due to Nearby Foreclosures. *American Economic Review*, 104(8):2527–51, 2014.

C. Avenancio-León and T. Howard. The Assessment Gap: Racial Inequalities in Property Taxation. *Available at SSRN 3465010*, 2019.

L. Bach, L. E. Calvet, and P. Sodini. Rich Pickings? Risk, Return, and Skill in Household Wealth. *American Economic Review*, 110(9):2703–47, 2020.

R. Barsky, J. Bound, K. K. Charles, and J. P. Lupton. Accounting for the Black–White Wealth Gap: A Nonparametric Approach. *Journal of the American Statistical Association*, 97(459): 663–673, 2002.

R. Bartlett, A. Morse, R. Stanton, and N. Wallace. Consumer-Lending Discrimination in the FinTech Era. Technical report, National Bureau of Economic Research, 2019.

P. Bayer, M. Casey, F. Ferreira, and R. McMillan. Racial and Ethnic Price Differentials in the Housing Market. *Journal of Urban Economics*, 102:91–105, 2017.

P. Bergman, R. Chetty, S. DeLuca, N. Hendren, L. F. Katz, and C. Palmer. Creating Moves to Opportunity: Experimental Evidence on Barriers to Neighborhood Choice. Technical report, National Bureau of Economic Research, 2019.

J. A. Berkovec, G. B. Canner, S. A. Gabriel, and T. H. Hannan. Race, Redlining, and Residential Mortgage Loan Performance. *The Journal of Real Estate Finance and Economics*, 9(3):263–294, 1994.

A. Bernstein and P. Koudijs. The Mortgage Piggy Bank: Building Wealth Through Amortization. Technical report, National Bureau of Economic Research, 2021.

M. Bertrand and S. Mullainathan. Are Emily and Greg More Employable Than Lakisha and Jamal? A Field Experiment on Labor Market Discrimination. *American economic review*, 94(4): 991–1013, 2004.

N. Bhutta and A. Hizmo. Do Minorities Pay More for Mortgages? *The Review of Financial Studies*, 2019.

N. Bhutta, A. C. Chang, L. J. Dettling, and J. W. Hsu. Disparities in Wealth by Race and Ethnicity in the 2019 Survey of Consumer Finances. Technical report, Washington: Board of Governors of the Federal Reserve System, September 2020. FEDS Notes https://doi.org/10.17016/2380-7172.2797.

F. D. Blau and J. W. Graham. Black-White Differences in Wealth and Asset Composition. *The Quarterly Journal of Economics*, 105(2):321–339, 1990.

R. Blundell, L. Pistaferri, and I. Saporta-Eksten. Consumption Inequality and Family Labor Supply. *American Economic Review*, 106(2):387–435, 2016.

D. G. Bocian, W. Li, and K. S. Ernst. Foreclosures by Race and Ethnicity. *Center for Responsible Lending*, pages 4–6, 2010.

A. Bogin, W. Doerner, and W. Larson. Local House Price Dynamics: New Indices and Stylized Facts. *Real Estate Economics*, 47(2):365–398, 2019.

G. W. Bush. Remarks by the President in a Conversation on Homeownership. Archived at Wayback Machine (https://web.archive.org/), http://www.whitehouse.gov/news/releases/2004/03/20040326-15.html, 2004. Published 2004-03-26.

A. W. Butler, E. J. Mayer, and J. Weston. Racial Discrimination in the Auto Loan Market. *Available at SSRN 3301009*, 2020.

R. Callis, P. Holley, and D. Truver. Quarterly Residential Vacancies and Homeownership, First Quarter 2021 (Report No. CB21-56). *Retrieved from the United States Census Bureau website: https://www. census. gov/housing/hvs/files/currenthvspress. pdf*, 2021.

J. Y. Campbell. Household Finance. *The Journal of Finance*, 61(4):1553–1604, 2006.

J. Y. Campbell, S. Giglio, and P. Pathak. Forced Sales and House Prices. *American Economic Review*, 101(5):2108–31, 2011.

J. Y. Campbell, T. Ramadorai, and B. Ranish. Do the Rich Get Richer in the Stock Market? Evidence From India. *American Economic Review: Insights*, 1(2):225–40, 2019.

J. Y. Campbell, N. Clara, and J. F. Cocco. Structuring Mortgages for Macroeconomic Stability. Technical report, National Bureau of Economic Research, 2020.

Campbell Communications. Tracking Real Estate Market Conditions Using the HousingPulse Survey. Link, 2011. Accessed 2021-09-01.

K. Capps and B. Mock. Who Will Presidential Candidates' Redlining Plans Actually Benefit? *Link*, 2019.

CFPB. Regulation X § 1024.17 Escrow accounts. Link, 2019. Accessed 2019-10-1.

K. K. Charles and E. Hurst. The Transition to Home Ownership and the Black-White Wealth Gap. *Review of Economics and Statistics*, 84(2):281–297, 2002.

S. F. Cherry, E. X. Jiang, G. Matvos, T. Piskorski, and A. Seru. Government and Private Household Debt Relief during COVID-19. Technical report, National Bureau of Economic Research, 2021.

R. Chetty, N. Hendren, and L. F. Katz. The Effects of Exposure to Better Neighborhoods on Children: New Evidence From the Moving to Opportunity Experiment. *American Economic Review*, 106(4):855–902, 2016.

R. Chetty, L. Sándor, and A. Szeidl. The Effect of Housing on Portfolio Choice. *The Journal of Finance*, 72(3):1171–1212, 2017.

R. Chetty, J. N. Friedman, N. Hendren, M. R. Jones, and S. R. Porter. The Opportunity Atlas: Mapping the Childhood Roots of Social Mobility. Technical report, National Bureau of Economic Research, 2018.

J. M. Collins, C. K. Reid, and C. Urban. Sustaining Homeownership After Delinquency: The Effectiveness of Loan Modifications by Race and Ethnicity. *Cityscape*, 17(1):163–188, 2015.

W. J. Collins and R. A. Margo. Race and Home Ownership From the End of the Civil War to the Present. *American Economic Review*, 101(3):355–59, 2011.

D. Corbae and E. Quintin. Mortgage Innovation and the Foreclosure Boom. *Unpublished paper, University of Texas at Austin*, 2009.

Corelogic. Escrow vs. Non-Escrow Mortgages: The Trend is Clear. Link, 2017. Published 2017-06-21.

R. Diamond, A. Guren, and R. Tan. The Effect of Foreclosures on Homeowners, Tenants, and Landlords. Technical report, National Bureau of Economic Research, 2020.

W. Dobbie, P. Goldsmith-Pinkham, N. Mahoney, and J. Song. Bad Credit, No Problem? Credit and Labor Market Consequences of Bad Credit Reports. *The Journal of Finance*, 75(5):2377–2419, 2020.

M. M. Elvira and C. D. Zatzick. Who's Displaced First? The Role of Race in Layoff Decisions. *Industrial Relations: A Journal of Economy and Society*, 41(2):329–361, 2002.

J. W. Faber and I. G. Ellen. Race and the Housing Cycle: Differences in Home Equity Trends Among Long-Term Homeowners. *Housing Policy Debate*, 26(3):456–473, 2016.

A. Fagereng, L. Guiso, D. Malacrino, and L. Pistaferri. Heterogeneity and Persistence in Returns to Wealth. *Econometrica*, 88(1):115–170, 2020.

F. Ferreira and J. Gyourko. A new look at the us foreclosure crisis: Panel data evidence of prime and subprime borrowers from 1997 to 2012. Technical report, National Bureau of Economic Research, 2015.

C. Flippen. Unequal Returns to Housing Investments? A Study of Real Housing Appreciation Among Black, White, and Hispanic Households. *Social Forces*, 82(4):1523–1551, 2004.

A. Fuster, P. Goldsmith-Pinkham, T. Ramadorai, and A. Walther. Predictably Unequal? The Effects of Machine Learning on Credit Markets. *The Effects of Machine Learning on Credit Markets (October 1, 2020)*, 2020.

P. Ganong and P. Noel. Liquidity Versus Wealth in Household Debt Obligations: Evidence From Housing Policy in the Great Recession. *American Economic Review*, 110(10):3100–3138, 2020a.

P. Ganong and P. J. Noel. Why Do Borrowers Default on Mortgages? A New Method for Causal Attribution. Technical report, National Bureau of Economic Research, 2020b.

P. Ganong, D. Jones, P. Noel, F. Greig, D. Farrell, and C. Wheat. Wealth, Race, and Consumption Smoothing of Typical Income Shocks. *NBER Working Paper*, (w27552), 2020.

C. S. Gascon, L. Ricketts, and D. Schlagenhauf. The Homeownership Experience of Minorities During the Great Recession. 2017.

K. Gerardi, P. Willen, D. H. Zhang, et al. Mortgage Prepayment, Race, and Monetary Policy. Technical report, 2020.

M. Gittleman and E. N. Wolff. Racial Differences in Patterns of Wealth Accumulation. *Journal of Human Resources*, 39(1):193–227, 2004.

P. Goldsmith-Pinkham and K. Shue. The Gender Gap in Housing Returns. Technical report, National Bureau of Economic Research, 2020.

V. Guerrieri, D. Hartley, and E. Hurst. Endogenous Gentrification and Housing Price Dynamics. *Journal of Public Economics*, 100:45–60, 2013.

D. Hamilton and W. Darity Jr. Can 'Baby Bonds' Eliminate the Racial Wealth Gap in Putative Post-Racial America? *The Review of Black Political Economy*, 37(3-4):207–216, 2010.

B. Hardy, J. Morduch, W. Darity Jr., and D. Hamilton. Wealth Inequality, Income Volatility, and Race. *Working Paper*, 2018.

J. Hwang and R. J. Sampson. Divergent Pathways of Gentrification: Racial Inequality and the Social Order of Renewal in Chicago Neighborhoods. *American Sociological Review*, 79(4):726–751, 2014.

K. Ihlanfeldt and T. Mayock. Price Discrimination in the Housing Market. *Journal of Urban Economics*, 66(2):125–140, 2009.

B. A. Jackson and J. R. Reynolds. The Price of Opportunity: Race, Student Loan Debt, and College Achievement. *Sociological Inquiry*, 83(3):335–368, 2013.

Ò. Jordà, K. Knoll, D. Kuvshinov, M. Schularick, and A. M. Taylor. The Rate of Return on Everything, 1870–2015. *The Quarterly Journal of Economics*, 134(3):1225–1298, 2019.

M. E. Kahn. Racial and Ethnic Differences in the Financial Returns to Home Purchases From 2007 to 2020. Technical report, National Bureau of Economic Research, 2021.

P. M. Kline, E. K. Rose, and C. R. Walters. Systemic Discrimination Among Large US Employers. Technical report, National Bureau of Economic Research, 2021.

S. Korgaonkar. The Limited Benefits of Mortgage Renegotiation. *Available at SSRN 2924981*, 2020.

M. Kuhn and G. Ploj. Job Stability, Earnings Dynamics, and Life-Cycle Savings. 2020.

M. Kuhn, M. Schularick, and U. I. Steins. Income and Wealth Inequality in America, 1949–2016. *Journal of Political Economy*, 128(9):3469–3519, 2020.

D. Low. Estimating the Home Equity of Foreclosed Homeowners. *Link*, 2020.

J. Mahon. Short Sales Stand Tall. Federal Reserve Bank of Minneapolis Link, 2010. Accessed 2021-09-01.

A. Mian, A. Sufi, and F. Trebbi. Foreclosures, House Prices, and the Real Economy. *The Journal of Finance*, 70(6):2587–2634, 2015.

C. K. Myers. Discrimination and Neighborhood Effects: Understanding Racial Differentials in US Housing Prices. *Journal of Urban Economics*, 56(2):279–302, 2004.

A. Perry, J. Rothwell, and D. Harshbarger. The Devaluation of Assets in Black Neighborhoods. *Library Catalog: www.brookings.edu*, 2018.

J. A. Ritter and L. J. Taylor. Racial Disparity in Unemployment. *The Review of Economics and Statistics*, 93(1):30–42, 2011.

J. S. Rugh and D. S. Massey. Racial Segregation and the American Foreclosure Crisis. *American Sociological Review*, 75(5):629–651, 2010.

L. Schmidt and Y. Zhu. Quantile Spacings: A Simple Method for the Joint Estimation of Multiple Quantiles Without Crossing. *Available at SSRN 2220901*, 2016.

R. J. Shiller and A. N. Weiss. Home Equity Insurance. *The Journal of Real Estate Finance and Economics*, 19(1):21–47, 1999.

E. Warren. Warren and Colleagues Reintroduce Historic Legislation to Confront America's Housing Crisis. Link, 2019. Published 2019-03-13.

White House. Fact Sheet: Biden-Harris Administration Announces New Actions to Build Black Wealth and Narrow the Racial Wealth Gap. Link, 2021. Published 2021-06-01.

F. Wong. Mad as Hell: Property Taxes and Financial Distress. *Available at SSRN 3645481*, 2020.

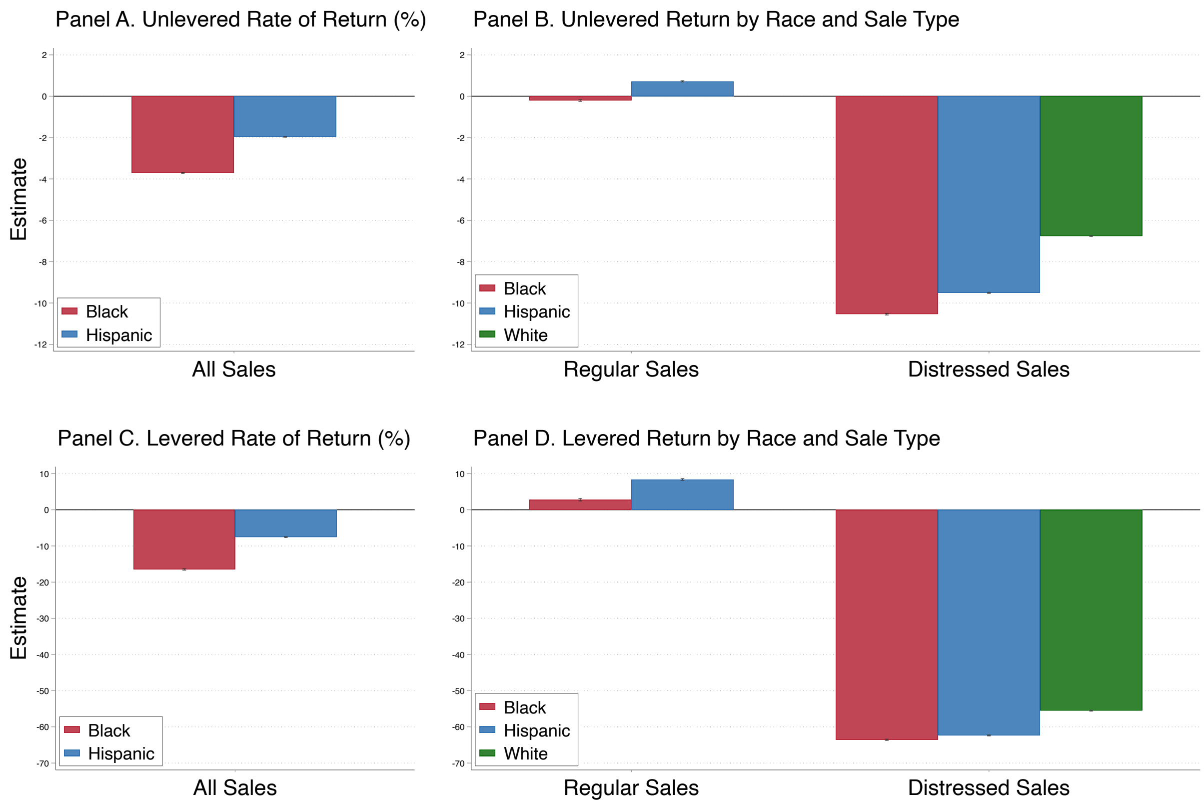
E. Wrigley-Field and N. Seltzer. Unequally Insecure: Rising Black/White Disparities in Job Displacement, 1981-2017. *Washington Center for Equitable Growth Working Paper Series. Washington, DC*, 2020.

C. Zhang. A shortage of short sales: Explaining the underutilization of a foreclosure alternative. 2019.

Zillow. Zillow Data. Data World, 2018. Accessed 2021-05-12.

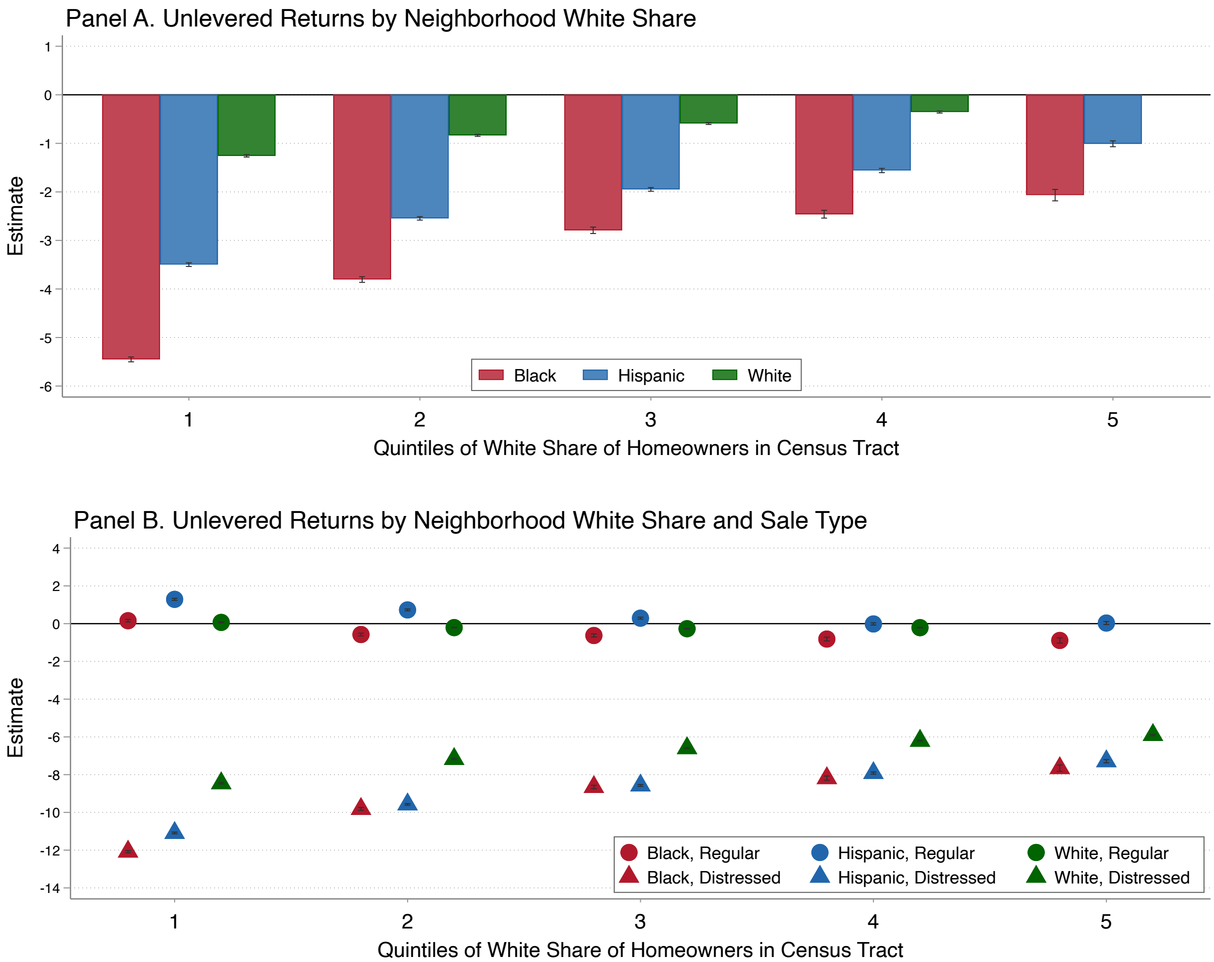
Zillow. What Is Zillow's Buyer-Seller Index, and How Is It Computed? Link, 2019. Accessed 2021-05-12.

Figure 1: Racial Gap in Housing Returns



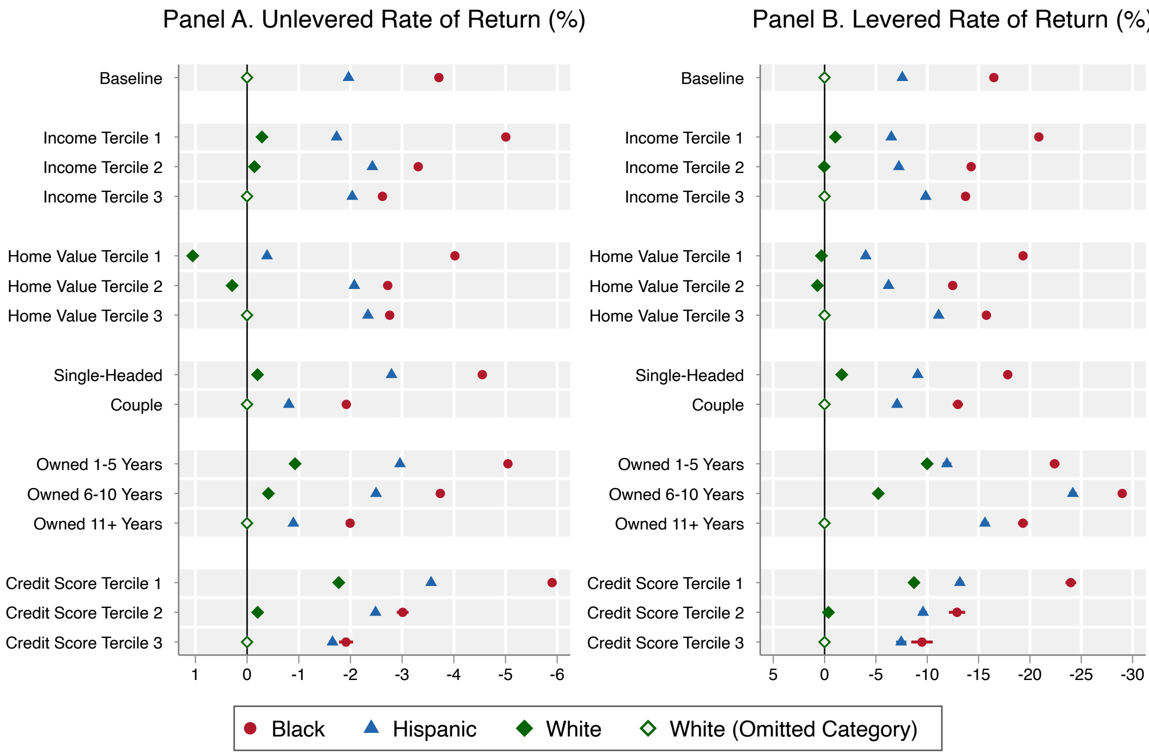
Notes: These figures present estimates of the racial gap in housing returns from four regression specifications that compare homeowners living in the same county and buying and selling their homes in the same year (Equation 3). In Panels A and B, housing returns are measured as the annualized unlevered return (i.e. sale price divided by purchase price). Panel A presents regression coefficients corresponding to indicators for black and Hispanic homeowners, with white homeowners as the omitted category. Coefficients indicate that annual unlevered returns are 3.7 and 2.0 percentage points lower for black and Hispanic homeowners, respectively, relative to white homeowners. Panel B interacts race/ethnicity indicators with an indicator that the homeowner experienced a distressed sale (i.e. foreclosure or short sale). Coefficients indicate that relative to white homeowners, annual unlevered returns for regular (i.e. non-distressed) sales are only 0.2 percentage points lower for black homeowners and 0.7 percentage points higher for Hispanic homeowners, implying that the gap estimated in Panel A is driven almost entirely by distressed sales. The specifications in Panels C and D mirror those in A and B, but estimate the annualized levered return, measured using each homeowner's internal rate of return. Coefficients in Panel C indicate that annual levered returns for black and Hispanic homeowners are 16.5 and 7.6 percentage points lower, respectively, than those of white homeowners. Coefficients in Panel D indicate that within regular sales, black and Hispanic homeowners realize levered returns that are 2.8 and 8.4 percentage points higher, respectively, than those of white homeowners. Data are from sample of homeowners with observed purchase and sale prices (i.e. repeat sales sample) described in Section 2. Table 1 in the Online Appendix presents numerical values and additional statistics.

Figure 2: Racial Gaps by Neighborhood Demographics and Sale Type



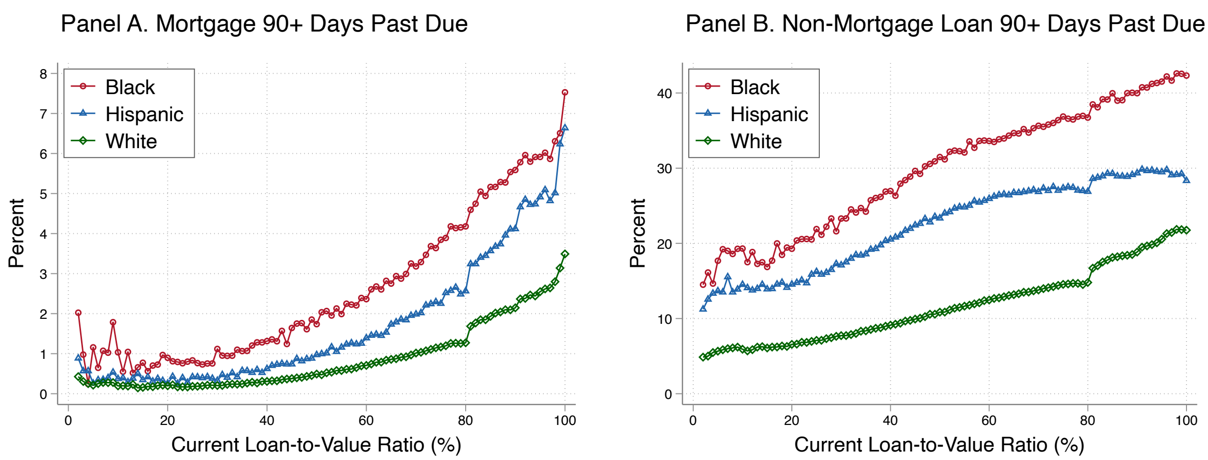
Notes: These figures present estimates of racial gaps in annualized unlevered housing returns (i.e. sale price divided by purchase price) from two regression specifications that compare homeowners living in the same county and buying and selling their homes in the same year (Equation 3). Panel A presents regression coefficients that interact individual race/ethnicity with quintiles of the white share of homeowners in the individual's Census tract. The omitted category is white homeowners in neighborhoods with the highest white share. Within the least-white tracts, the black-white difference in annual returns is about 4.2 percentage points. Within the most-white tracts, the black-white difference is 2.1 percentage points. Panel B presents regression coefficients that interact homeowner race/ethnicity with quintiles of the white share and homeowner's sale type (regular vs. distressed). The omitted category in Panel B is white homeowners in neighborhoods with the highest white share whose property sale is not distressed. Within regular sales, returns are similar across races and neighborhood demographics. In both panels, quintiles are assigned within each county, such that higher quintiles contain neighborhoods in each county with the highest share of white homeowners. Data are from sample of homeowners with observed purchase and sale prices (i.e. repeat sales sample) described in Section 2. Table 2 in the Online Appendix presents numerical values and additional statistics.

Figure 3: Heterogeneous Racial Gaps



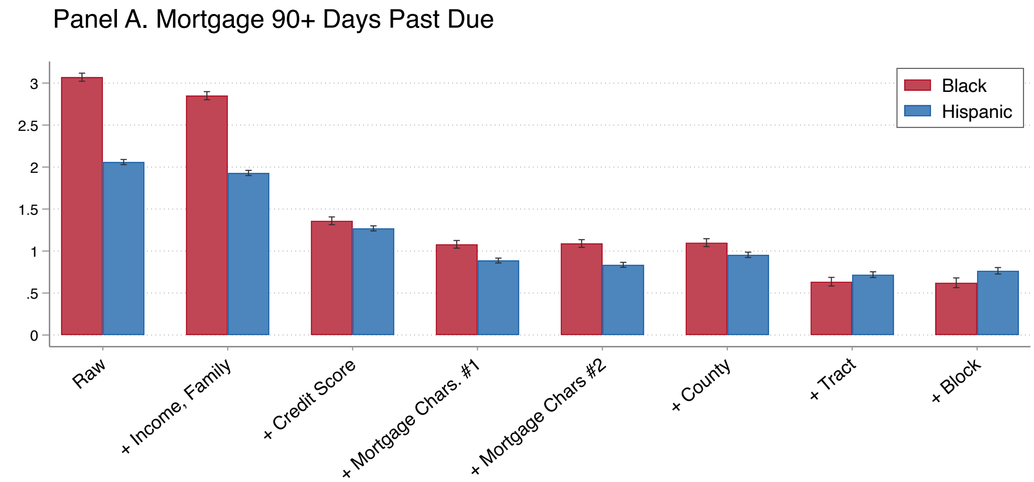
Notes: These figures document heterogeneity in the racial gap in housing returns for unlevered returns (Panel A) and levered returns (Panel B). Each dimension of heterogeneity provides estimates from a separate regression that compares homeowners living in the same county and buying and selling their homes in the same year (Equation 3). Points denote estimated coefficients of race/ethnicity indicators interacted with homeowner characteristics (e.g. indicators for income tercile). *Baseline* denotes the full analysis sample. *Income* denotes income measured at home purchase. *Home Value* denotes home purchase price. A *Single-Headed* household has no mortgage co-applicant in the HMDA data and only one individual listed in the Infogroup data. A *Couple* has a co-applicant in the HMDA data and more than one individual listed in the Infogroup data. Ownership length corresponds to the number of years between home purchase and sale. *Credit Score* corresponds to credit score at mortgage origination. Data are from sample of homeowners with observed purchase and sale prices (i.e. repeat sales sample) described in Section 2. Table 3 in the Online Appendix presents numerical values and additional statistics.

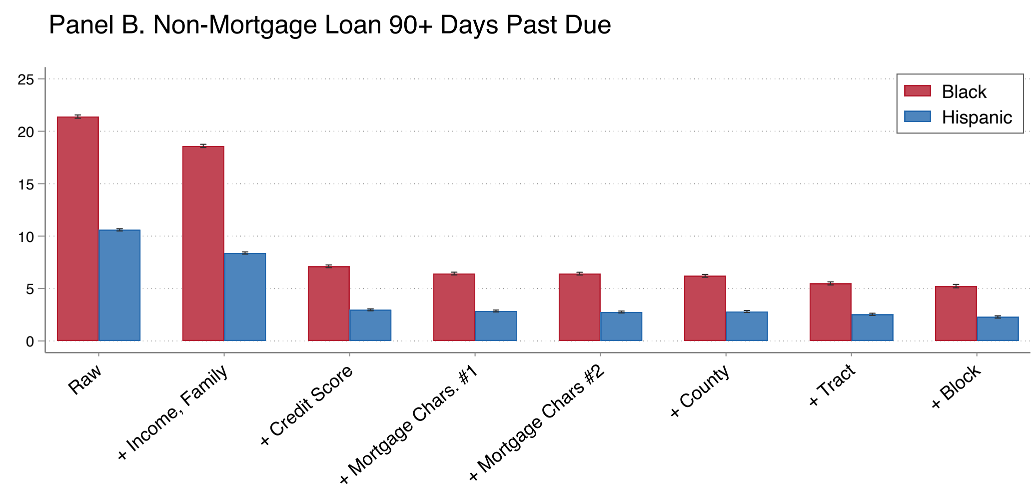
Figure 4: Measuring Racial Disparities in Financial Distress



Notes: These figures present rates of financial distress, measured by loan delinquency, as a function of homeowner race/ethnicity and current loan-to-value ratio. Panel A plots the percent of homeowners whose primary mortgage is 90 or more days past due. Panel B plots the percent of homeowners with at least one non-mortgage loan that is 90 or more days past due or an account in collections. Both panels document high rates of financial distress among minority homeowners, both in absolute terms and relative to white homeowners. Data are from a panel of homeowners with linked credit bureau and mortgage servicing records described in Section 2. Tables 4-6 in the Online Appendix present numerical values and additional statistics.

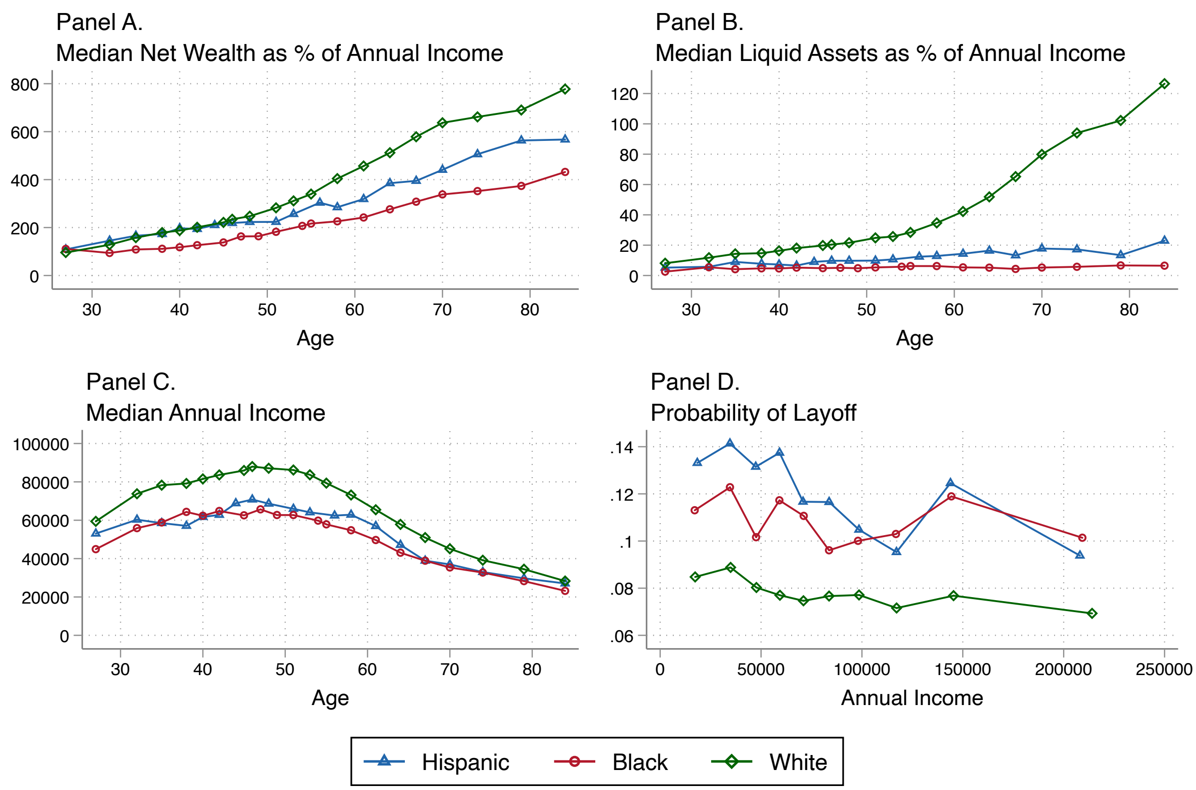
Figure 5: Decomposing Racial Disparities in Financial Distress





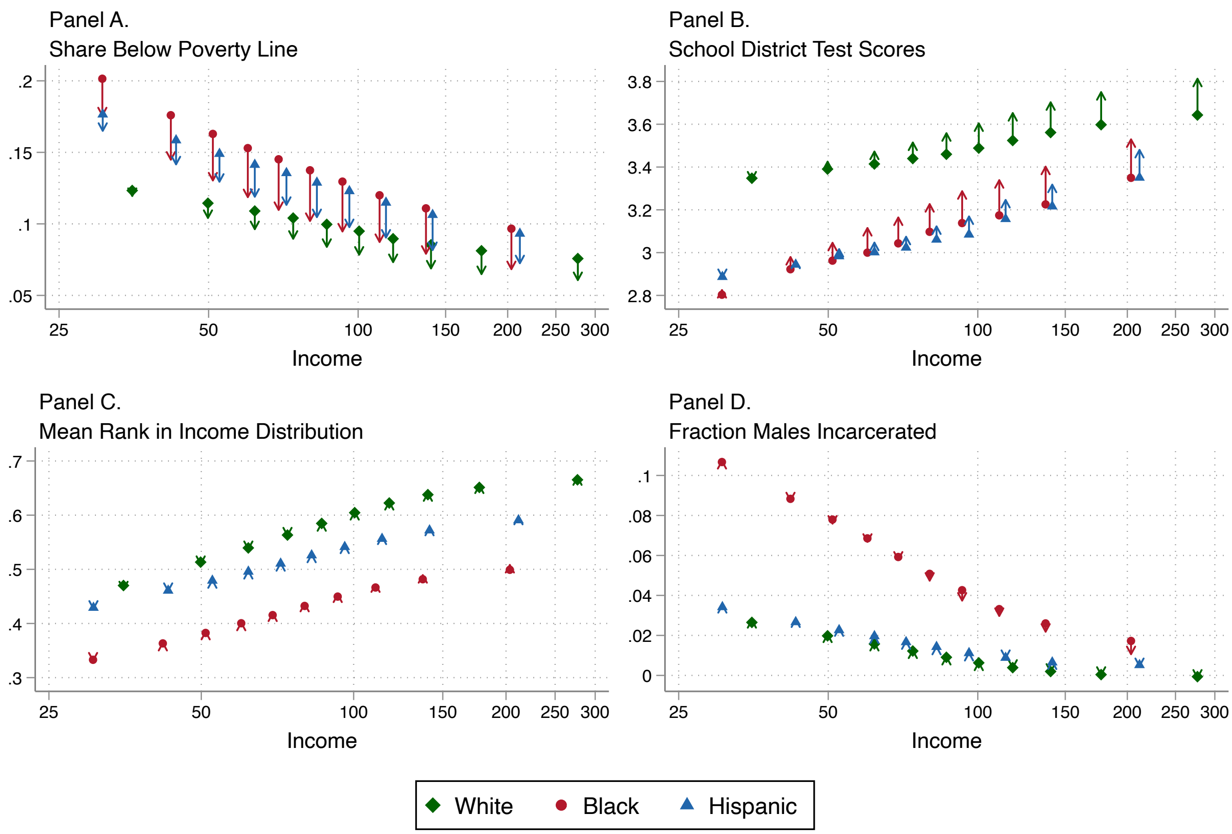
Notes: These figures present estimates of racial differences in financial distress controlling for a range of observable homeowner characteristics (Equation 5). These estimates offer a decomposition of racial differences into components that correspond to household, loan, and location characteristics, which attributes the majority of the racial differences to household characteristics that are determined prior to mortgage origination. In Panel A, the outcome is an indicator that the homeowner's primary mortgage is 90 or more days past due (sample mean=1.8%). In Panel B, the outcome is an indicator that the homeowner has a non-mortgage loan 90 or more days past due or an account in collections (sample mean=16.3%). Each bar corresponds to the coefficient on a race/ethnicity indicator. Each pair of bars correspond to a separate regression with a particular set of covariates. *Raw* denotes a regression of the outcome on race/ethnicity indicators and year fixed effects. *Income, Family* adds income decile fixed effects and fixed effects for family type (i.e. single female, single male, couple derived from HMDA mortgage application) in addition to year fixed effects. *Credit Score* adds 10-point credit score bins. *Mortgage Chars. #1* adds splines in original loan-to-value ratio and current combined loan-to-value ratio, and term-by-origination year fixed effects, property value decile fixed effects, and debt-to-income decile fixed effects. *Mortgage Chars. #2* adds in the log of estimated monthly payments, log interest rate, and indicators for interest-only loan, refinance, and adjustable rate mortgage. *County* adds in county fixed effects. *Tract* adds in Census tract fixed effects. *Block* adds in Census block fixed effects. Data are from a panel of homeowners with linked credit bureau and mortgage servicing records described in Section 2, restricted to homeowners with CLTV less than or equal to 120%. Table 7 in the Online Appendix presents numerical values and additional statistics.

Figure 6: Disparities in Wealth, Liquidity, and Income



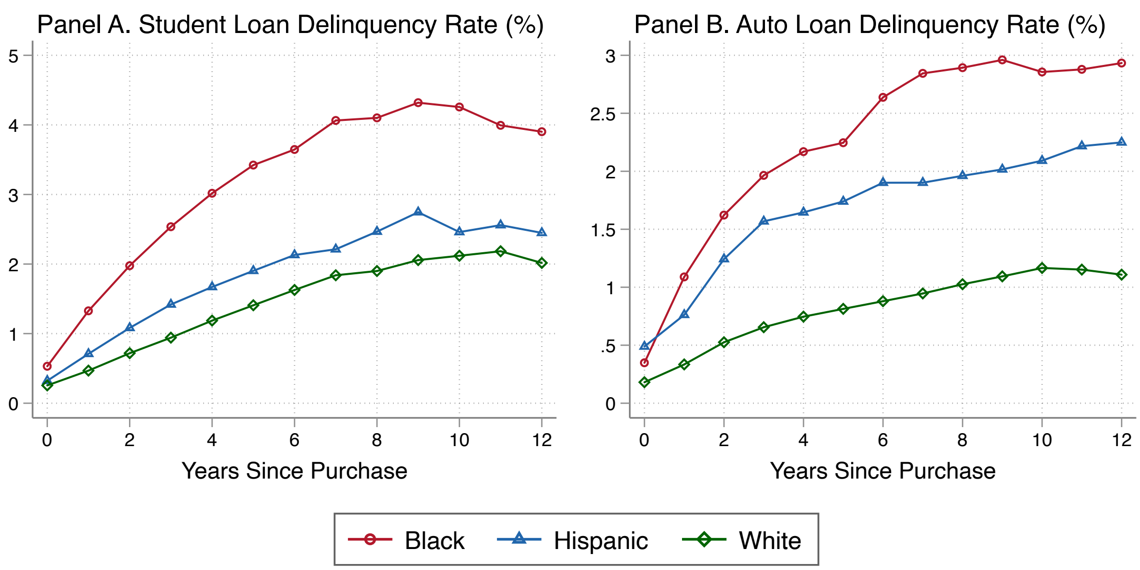
Notes: These figures present binned scatterplots that illustrate racial disparities in wealth, liquidity, and income among homeowners. Panel A plots median net wealth as a percentage of annual income as a function of age. Panel B plots median liquid wealth as a percentage of annual income as a function of age. Panel C plots median annual income as a function of age. Panel D plots the share of households who have experienced an unemployment spell in the previous 12 months as a function of income in the prior year, restricting to households aged 25 to 65 who were employed homeowners in the prior year. Data come from sample of homeowners in the Survey of Income and Program Participation (1990-2017) described in Section 4. Race/ethnicity and age are assigned according to the head of household. Dollar values are adjusted to 2016 levels. Tables 8 and 9 in the Online Appendix present numerical values and additional statistics.

Figure 7: Upgrades in Neighborhood Quality from Home Purchase



Notes: These figures depict changes in neighborhood quality associated with home purchases, illustrating the modest upgrades in neighborhood quality achieved by minority homeowners relative to the neighborhood quality achieved by white homeowners. Each panel corresponds to a different measure of neighborhood quality. Panel A measures the share of homeowners in the Census tract below the federal poverty line in the 2006-2010 ACS. Panel B measures school district standardized 3rd grade math test scores in 2013. Panel C measures the mean rank in the national income distribution of children born in 1978-1983 to parents of the same race/ethnicity and income percentile as that reported by the homeowner in their mortgage application. Panel D measures the 2010 incarceration rate of male children that were born in 1978-1983 to parents of the same race/ethnicity and income percentile as that reported by the homeowner in their mortgage application. In each panel, homeowners are binned by race/ethnicity and to decile of income at home purchase (deciles computed within race/ethnicity). The base of each arrow corresponds to the quality of neighborhoods from which homeowners depart and the head of each arrow corresponds to the neighborhoods at which homeowners arrive after purchase. Income is measured in 2015 dollars. Homeowner-level data on neighborhood migration come from sample of homeowners linked to address histories described in Section 2. Data on neighborhood characteristics come from Chetty et al. (2018). Table 10 in the Online Appendix presents numerical values and additional statistics.

Figure 8: Racial Disparities in Other Levered Assets



Notes: These figures present rates of loan delinquency by race/ethnicity as a function of the number of years since the homeowner purchased their home. These figures illustrate that in addition to being more likely to be delinquent on their mortgages, minority homeowners are also more likely to be delinquent on other types of loans that enable the levered purchase of assets. Panel A presents the delinquency rate on student loans and Panel B presents the delinquency rate on auto loans. Delinquency rates in both panels are conditional on the homeowner having an open (student or auto) loan. Data are from a panel of homeowners with linked credit bureau and mortgage servicing records described in Section 2. Table 11 in the Online Appendix presents numerical values and additional statistics.

Table 1: Summary Statistics

	Mean	SD	p10	p90
Panel A. Observed Purchase and Sale Prices				
(N = 6,106,936 Ownership Spells)				
Black Share	0.066			
Hispanic Share	0.149			
Income ($, Thousands)	92	125.3	35	157
Purchase Year	2005	4.0	2000	2011
Purchase Price ($, Thousands)	273	1091.4	98	495
Unlevered Return (%)	1.3	12.51	–14.0	15.7
Levered Return (%)	–6.7	80.19	–100.0	76.4
Length of Ownership (Months)	64	41.1	19	123
Combined Loan-to-Value Ratio at Purchase (%)	91	138.1	73	100
Share Distressed	0.311			
Panel B. Migration Histories				
(N = 3,310,906 Moves)				
Share Moving out of CZ	0.505			
Kilometers Moved Within CZ	11.2	15.26	1.1	26.9
Change in Test Scores (Grade Equivalent Units)	0.10	0.953	–1.05	1.32
Change in Poverty Rate (%)	–1.54	9.879	–12.80	8.75
Panel C. Credit Bureau and Servicing Records				
(N = 56,460,765 Loan-Years)				
Mortgage 30+ Days Delinquent	0.081			
Mortgage 90+ Days Delinquent	0.047			
Any Non-Mortgage Loan 30+ Days Delinquent	0.202			
Any Non-Mortgage Loan 90+ Days Delinquent	0.186			
Panel D. Mortgage Modifications Sample				
(N = 1,242,197 Delinquent Loans)				
Black Share	0.126			
Hispanic Share	0.258			
Delinquencies Ending in Modification	0.210			
Delinquencies Ending in Foreclosure	0.616			
Delinquencies Ending in Self-Cure	0.154			

Notes: This table presents summary statistics from our main analysis samples. Panel A presents statistics at the level of the ownership spell for owner-occupied properties for which both the purchase and sale prices are observed (i.e. repeat sales). Panel B presents statistics on characteristics of neighborhood moves associated with home purchases using the address histories from Infogroup. Panel C presents statistics at the loan-year level for a panel of homeowners with outcomes linked to CRISM mortgage servicing and credit bureau records. Outcomes in the yearly panel are measured as of each June. Panel D presents statistics at the loan level for a sample of loans that are observed in the GSE and ABSNet mortgage databases, which contain information about mortgage modifications. The sample is restricted to homeowners that become 90 or more days past due on their mortgages.

Table 2: Contribution of Returns Gap to Housing Wealth Disparities at Retirement Age

	PSID	**Model**	**Counterfactuals**			
	(1)	(2)	(3)	(4)	(5)	(6)
Black Wealth at Retirement	$81,713	$77,419	$130,085	$78,738	$115,203	$145,428
White-Black Difference	$167,956	$135,359	$82,693	$134,040	$97,575	$67,350
% Reduction in Gap	-	0%	38.91%	0.97%	27.91%	50.24%
Equal Returns	-		X			X
Equal Transition Rates	-			X	X	X
Equal Purchase Values	-				X	

Notes: This table presents estimates from our wealth accumulation equation (Equation 4). This equation allows us to compute the average household's housing wealth at retirement age by race, along with actual and counterfactual differences between black and white households. These estimates illustrate the contribution of the gap in housing returns to observed racial wealth disparities at retirement. Column 1 presents estimates from households aged 63-67 in the PSID, including non-homeowners with no housing wealth. Column 2 presents baseline estimates for households at age 65 from the wealth accumulation equation, incorporating estimates of the racial gap in housing returns presented in Section 3 and purchase amounts and rates of first-time home purchases from the PSID. Columns 3 through 6 present estimates of counterfactual wealth disparities by equalizing annual housing returns, rates of first-time home purchases, and home values at purchase by race.

Table 3: Liquidity, Income Stability, and Racial Disparities in Mortgage Delinquency

	(1)	(2)	(3)	(4)	(5)	(6)
Black	4.67***	3.39***	3.12***	3.42***	3.24***	2.69***
	(0.34)	(0.34)	(0.34)	(0.33)	(0.33)	(0.33)
Hispanic	3.18***	1.90***	1.67***	1.12**	1.06**	0.67
	(0.41)	(0.41)	(0.40)	(0.39)	(0.39)	(0.39)
Log Liquid Assets		–1.03***	–0.84***			–0.50***
		(0.03)	(0.03)			(0.03)
Unemployed			4.98***		3.93***	4.14***
			(0.29)		(0.27)	(0.29)
Unemp.×Log Liquid Assets			–1.37***			–1.39***
			(0.12)			(0.12)
Current LTV				5.93***	5.83***	5.01***
				(0.22)	(0.22)	(0.22)
Log Household Income				–2.28***	–2.17***	–1.52***
				(0.10)	(0.09)	(0.09)
Married				–1.11***	–0.96***	–0.64***
				(0.17)	(0.17)	(0.17)
# Household Members				1.09***	0.89***	0.73***
				(0.07)	(0.06)	(0.06)
Constant	2.90***	3.94***	3.31***	23.45***	22.30***	16.32***
	(0.07)	(0.09)	(0.08)	(0.99)	(0.97)	(0.96)
Observations	136,725	136,725	136,725	136,236	136,236	136,236

Notes: This table presents regressions of an indicator that a household has been delinquent on its mortgage in the past 12 months on different sets of covariates. Results in this table illustrate that the racial/ethnic differences in mortgage delinquency can be partly explained by differences in liquidity and income stability. *Log Liquid Assets* includes deposits, bonds, and stocks, and is demeaned. *Unemployed* indicates that the household has experienced unemployment in the last 12 months. *Current LTV* denotes the household's current loan-to-value ratio. Data come from a sample of homeowners in the Survey of Income and Program Participation (1992-2017) described in Section 4. Race/ethnicity is assigned according to the head of household. All specifications include state-by-year fixed effects. Standard errors are clustered at the household level and reported in parentheses. *** $p<0.001$, ** $p<0.01$, * $p<0.05$

Table 4: Impacts of Modifications on Distressed Sales and Housing Returns

Outcome	Unlevered Return (1)	Modification (2)	Distressed Sale (3)	Unlevered Return (4)	Imputed Return (5)
Servicer Instrument		0.610***			
		(0.0256)			
Modification	3.234***		–0.369***	8.911***	10.63***
	(0.147)		(0.0526)	(1.466)	(1.041)
Black × Modification	0.788*		0.112	–1.591	–2.338
	(0.345)		(0.0700)	(2.420)	(1.459)
Hispanic × Modification	1.146***		0.0369	3.135*	3.119**
	(0.213)		(0.0511)	(1.482)	(1.112)
Outcome Mean	–16.96	0.185	0.737	–16.96	–12.56
N	90,240	131,783	131,783	90,240	131,477
Specification	OLS	OLS	2SLS	2SLS	2SLS

Notes: This table presents estimated treatment effects of mortgage modifications. Results indicate that modifications reduce the likelihood of distressed sales and increase housing returns for homeowners of all racial groups. Column 1 presents OLS estimates of th impact of modifications on unlevered returns. Column 2 presents the first stage OLS regression of modification on the servicer instrument. Columns 3 through 5 present treatment effects of modifications interacting the servicer instrument and modification indicator with race/ethnicity indicators. The outcome in Columns 1 and 4 is the unlevered rate of return. The outcome in Column 2 is an indicator that a homeowner receives a modification within 12 months of default. The outcome in Column 3 is an indicator that the ownership spell ends in a distressed sale. The outcome in Column 5 is the unlevered return, imputing the value of properties that had not sold by December 2017 using county-level house price indices. *Modification* denotes an indicator that a homeowner receives a modification within 12 months of default. All specifications include interacted fixed effects for purchase year, default year, tract, an indicator for negative amortization loan, and an indicator for interest-only loan. Data comprised of homeowners who have become delinquent and are observed in the Fannie Mae, Freddie Mac, and ABSNet data, described in Section 2. *** $p<0.001$, ** $p<0.01$, * $p<0.05$

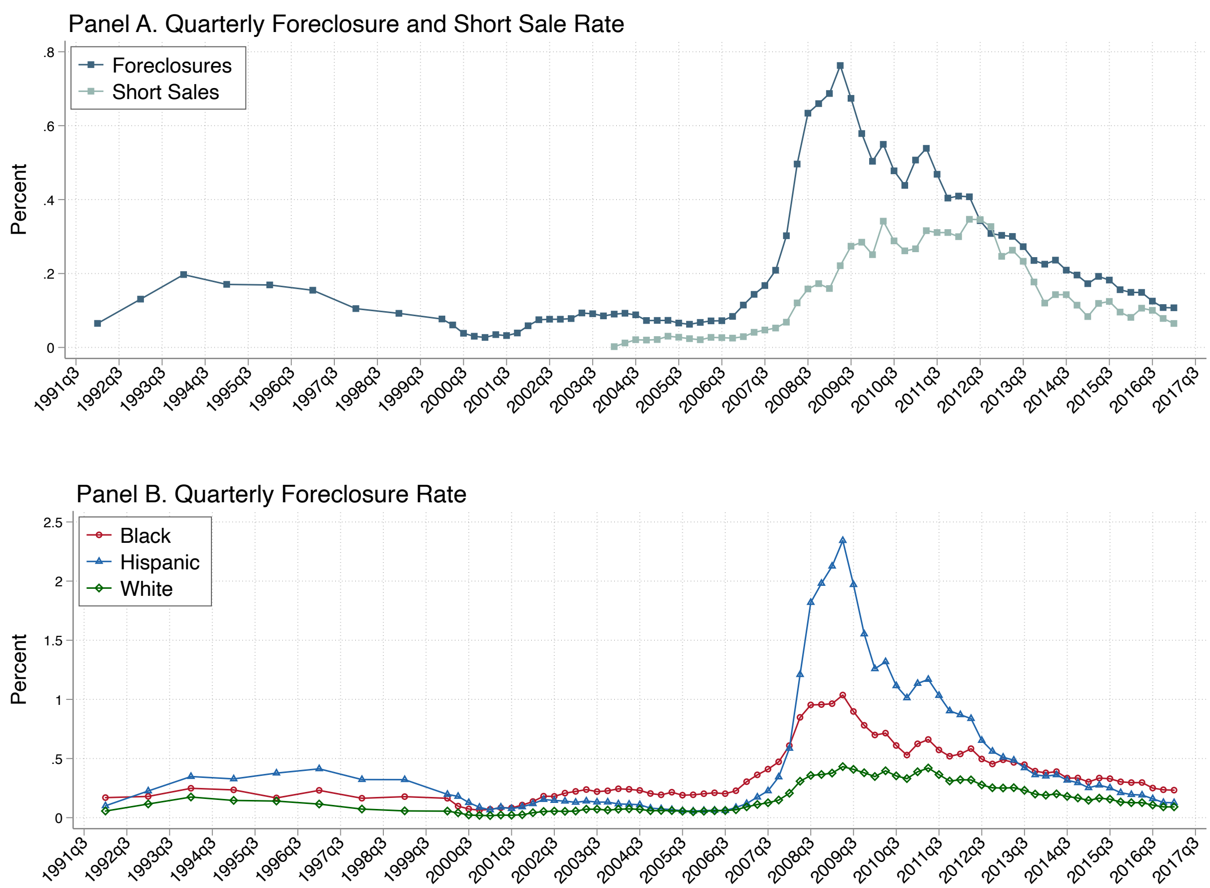
Table 5: Impacts of Modifications, Robustness and Heterogeneity Analysis

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Distressed Sale						
Modification	–0.369***	–0.313***	–0.433***	–0.308***	–0.283***	–0.301***
	(0.0526)	(0.0692)	(0.0603)	(0.0628)	(0.0472)	(0.0523)
Black × Mod.	0.112	0.139	0.102	0.136		
	(0.0700)	(0.0883)	(0.0822)	(0.0867)		
Hispanic × Mod.	0.0369	0.0539	0.110	0.0230		
	(0.0511)	(0.0715)	(0.0590)	(0.0656)		
Distressed Tract × Mod.					–0.103*	
					(0.0414)	
Single Applicant × Mod.						–0.0527
						(0.0493)
Outcome Mean	0.737	0.753	0.757	0.756	0.738	0.737
N	131783	72870	103458	81512	131720	131783
Panel B. Unlevered Return						
Modification	8.911***	7.778***	11.40***	7.451***	7.902***	8.233***
	(1.466)	(2.102)	(1.830)	(1.634)	(1.420)	(1.409)
Black × Mod.	–1.591	–0.568	–1.705	0.802		
	(2.420)	(3.250)	(2.904)	(3.068)		
Hispanic × Mod.	3.135*	3.894	2.781	6.503***		
	(1.482)	(2.110)	(1.796)	(1.898)		
Distressed Tract × Mod.					4.372***	
					(1.231)	
Single Applicant × Mod.						3.076*
						(1.421)
Outcome Mean	–16.96	–18.01	–17.86	–17.84	–16.96	–16.96
N	90240	49838	72749	56664	90234	90240
Controls	Baseline	Score	LTV	Income	Baseline	Baseline

Notes: This table presents robustness exercises for the analysis of the impacts of mortgage modifications along with heterogeneous impacts by neighborhood and household characteristics. The outcomes are an indicator that the ownership spell ends in a distressed sale (Panel A) and the unlevered rate of return (Panel B). Column 1 presents the baseline specification. Columns 2 through 4 interact baseline fixed effects with terciles of credit score at origination, LTV in the month of default, and income at origination, respectively. Column 5 presents heterogeneity results for distressed Census tracts, defined as the tract-years in the highest quartile of the distressed sales share of all sales. Column 6 presents heterogeneity results for an indicator that the household listed a single individual on their mortgage application. The baseline specification includes interacted fixed effects for purchase year, default year, tract, indicator for negative amortization loan, and indicator for interest-only loan. Data comprised of homeowners who have become delinquent and are observed in the Fannie Mae, Freddie Mac, and ABSNet data, described in Section 2. *** $p<0.001$, ** $p<0.01$, * $p<0.05$

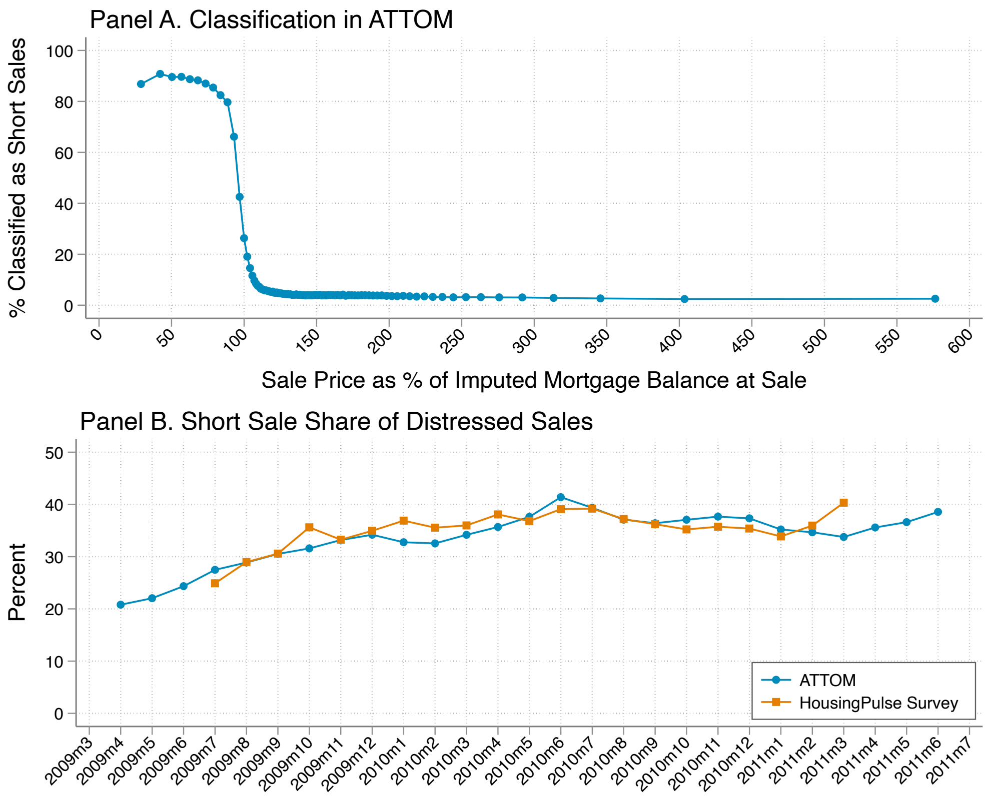
A Appendix Figures

Figure A1: Time Series of Aggregate Distressed Sales



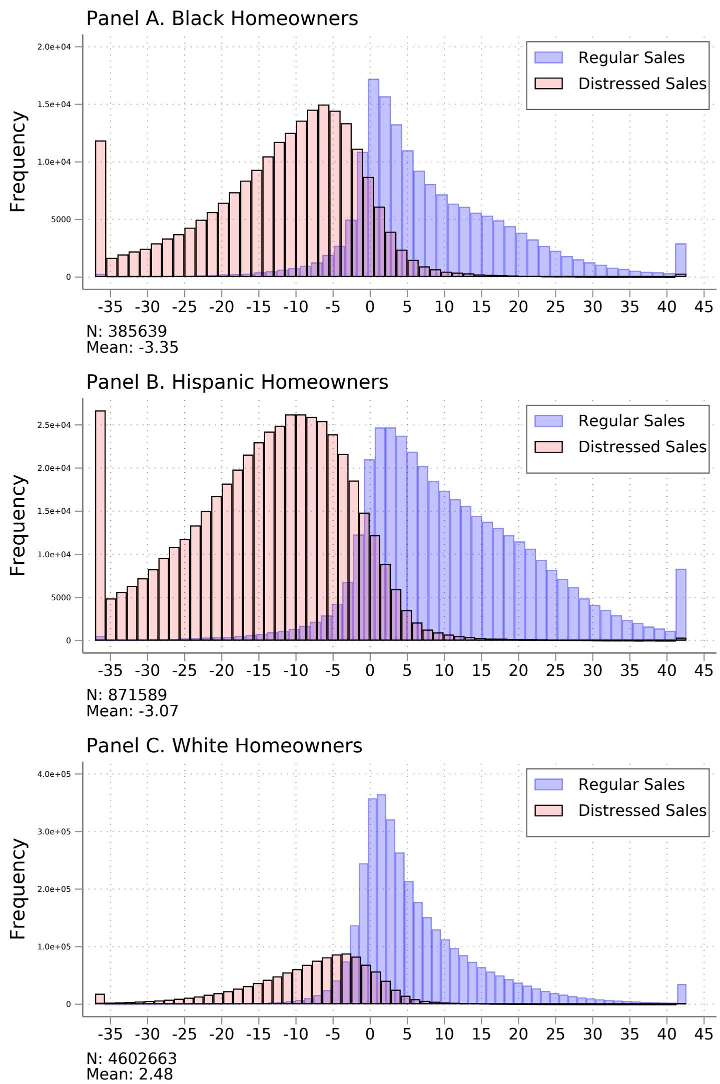
Notes: These figures plot aggregate quarterly trends in distressed sales from 1992 to 2017, and illustrate higher rates of distressed sales among minority homeowners throughout this period. Panel A plots quarterly foreclosure and short sale rates, defined as the percent of ownership spells beginning prior to a given quarter and ending in a foreclosure or short sale in that quarter. Panel B plots the quarterly foreclosure rate by race/ethnicity. The sample starting in 2000Q1 has 448 million property-quarters, and the sample prior to 2000Q1 contains 3.5 million property-quarters. Data are from sample of homeowners with observed purchase prices, including homeowners with no observed sale as of 2017.

Figure A2: Short Sale Classification



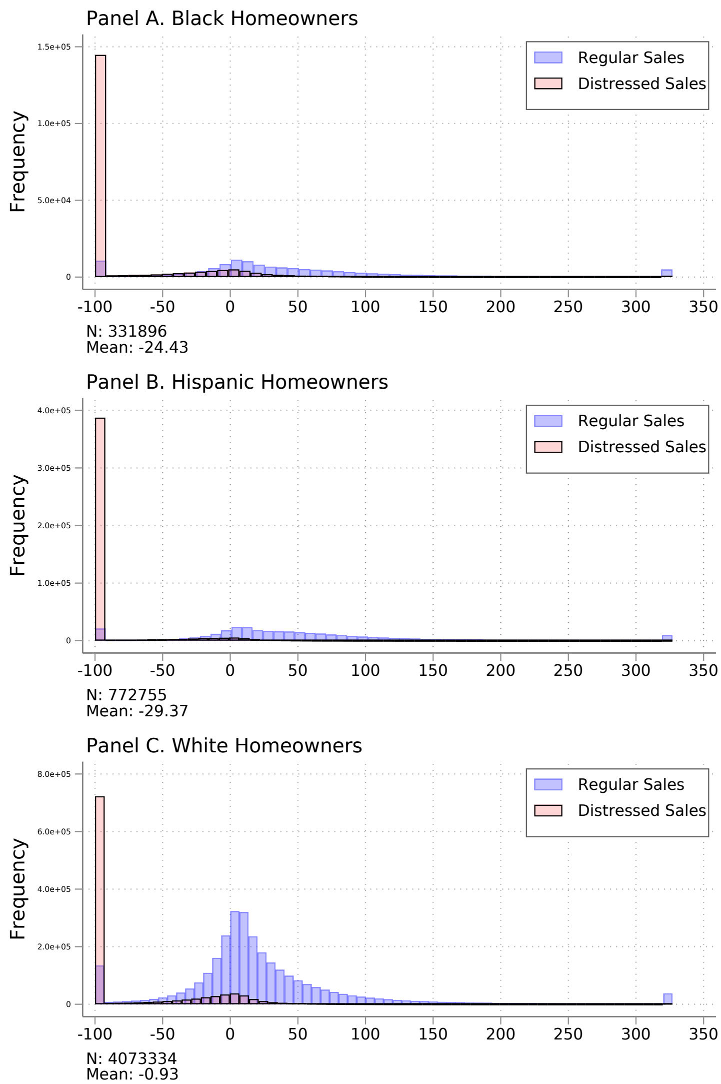
Notes: This figure illustrates the algorithm used to identify short sales and compares the results of that algorithm to an external measure of short sales. Panel A plots the percent of property sales that are classified by ATTOM as short sales, as a function of the sale price as a percentage of the imputed mortgage balance at sale. Sample excludes sales classified as foreclosures based on the sale documentation. Data are from a sample of homeowners with observed purchase and sale prices (i.e. repeat sales sample) described in Section 2. Panel B plots the percentage of distressed sales that are classified as short sales by ATTOM in the repeat sales sample, along with the percentage classified as short sales in the HousingPulse Survey as reported in Campbell Communications (2011). See Appendix Section D for discussion of imputation of mortgage balance at sale.

Figure A3: Distribution of Unlevered Rate of Return



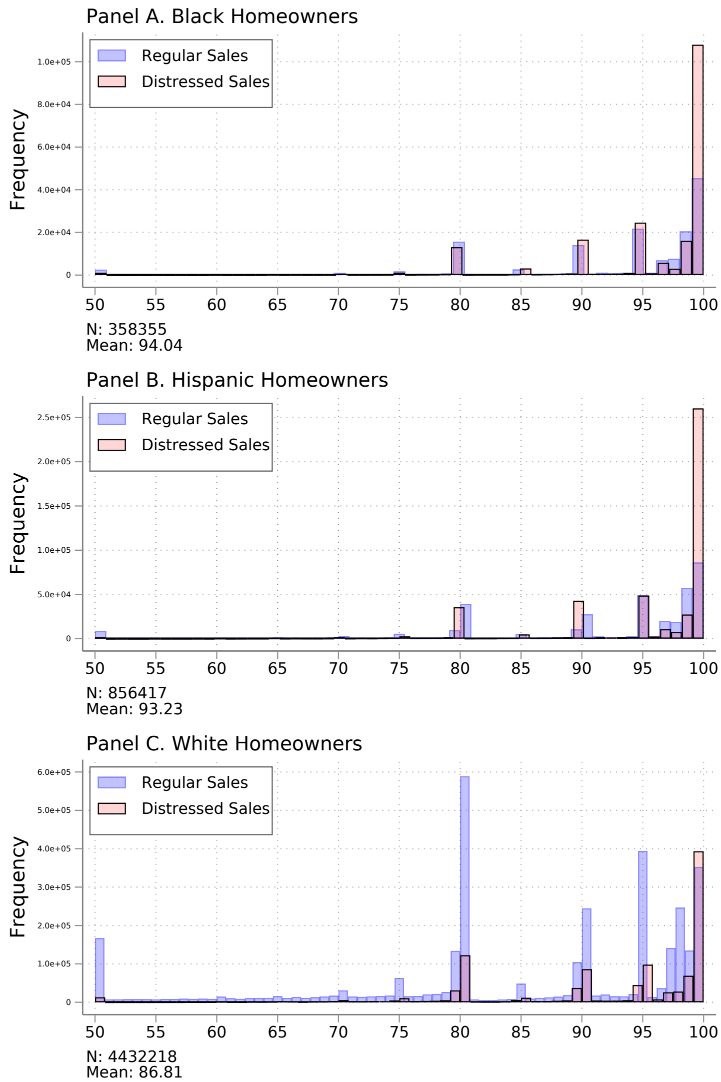
Notes: These figures plot the distribution of annualized unlevered returns (i.e. sale price divided by purchase price, Equation 1). Distributions are plotted separately for black homeowners (Panel A), Hispanic homeowners (Panel B), and white homeowners (Panel C). For each race/ethnicity, the distributions for regular sales and distressed sales are also presented separately. Data are from sample of homeowners with observed purchase and sale prices (i.e. repeat sales sample) described in Section 2.

Figure A4: Distribution of Levered Rate of Return



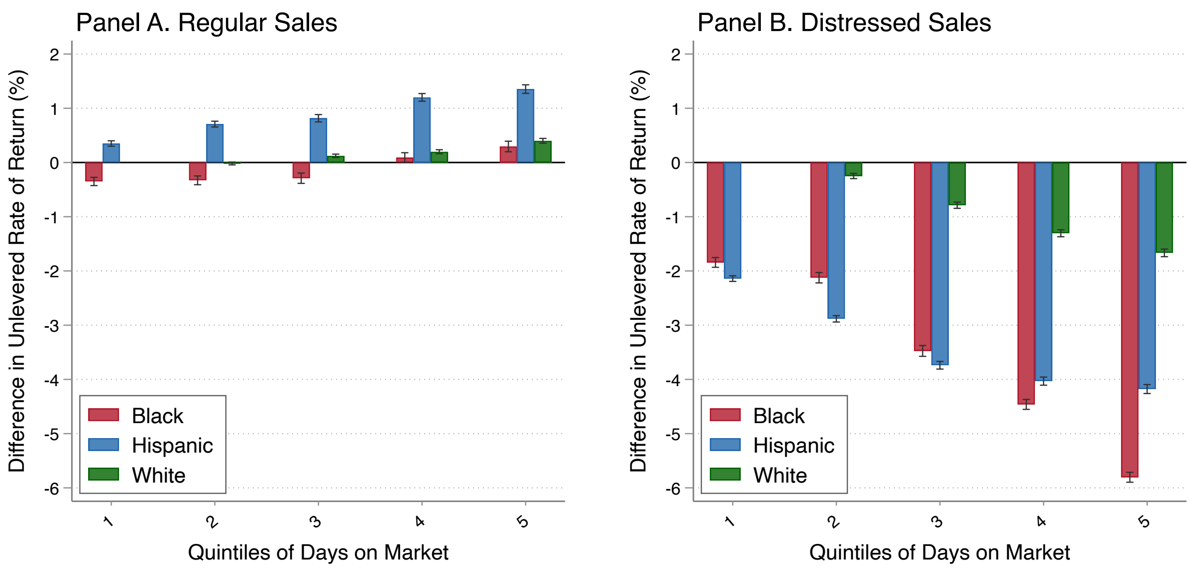
Notes: These figures plot the distribution of annualized levered returns (i.e. sale price divided by purchase price, Equation 2). Distributions are plotted separately for black homeowners (Panel A), Hispanic homeowners (Panel B), and white homeowners (Panel C). For each race/ethnicity, the distributions for regular sales and distressed sales are also presented separately. Data are from sample of homeowners with observed purchase and sale prices (i.e. repeat sales sample) described in Section 2.

Figure A5: Distribution of Combined Loan-to-Value at Purchase



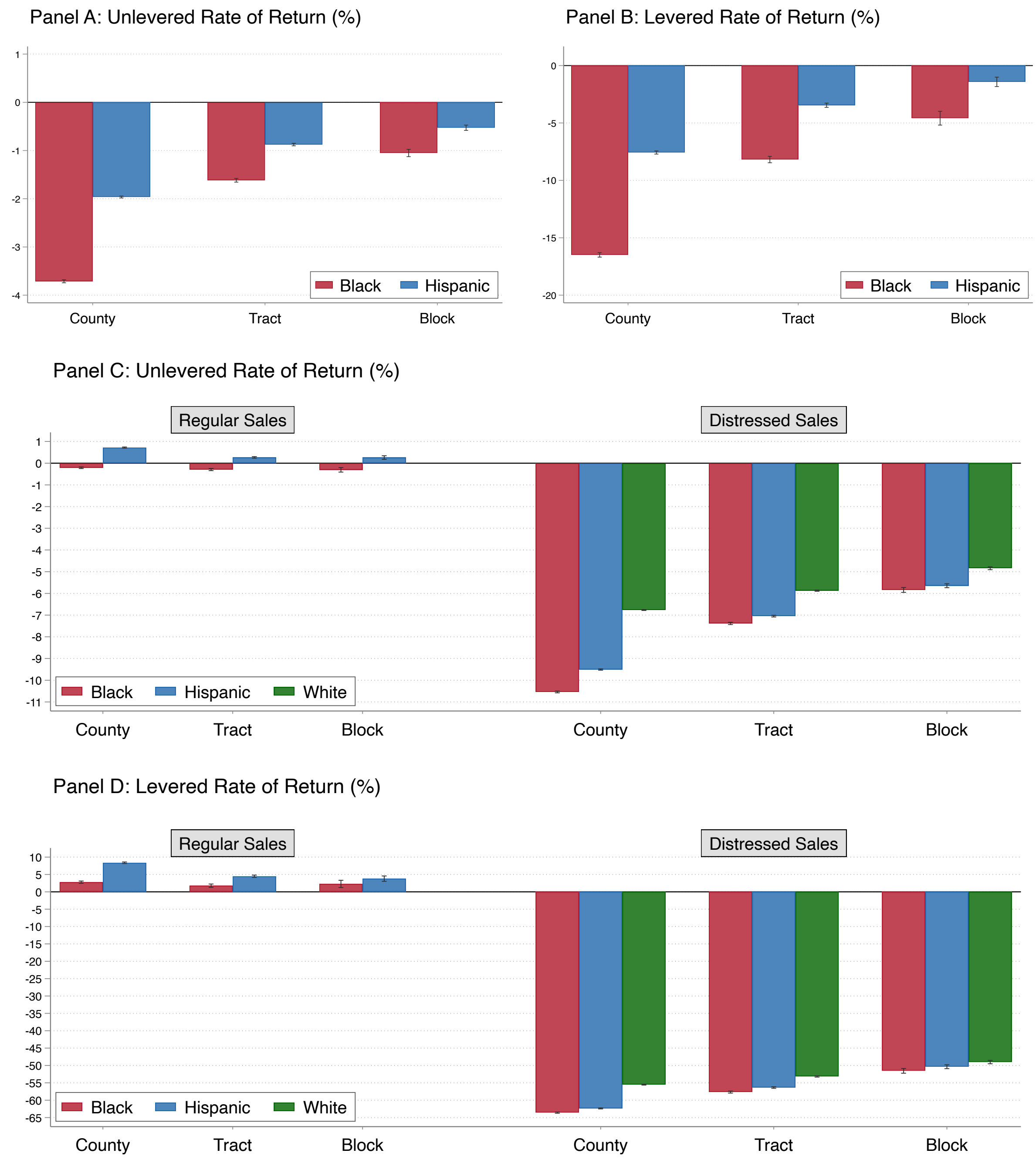
Notes: These figures plot the distribution of combined loan-to-value ratio at origination, winsorized from below at 50%. Distributions are plotted separately for black homeowners (Panel A), Hispanic homeowners (Panel B), and white homeowners (Panel C). For each race/ethnicity, the distributions for regular sales and distressed sales are also presented separately. Data are from sample of homeowners with observed purchase and sale prices (i.e. repeat sales sample) described in Section 2.

Figure A6: Heterogeneity in Unlevered Returns by Housing Market Depth



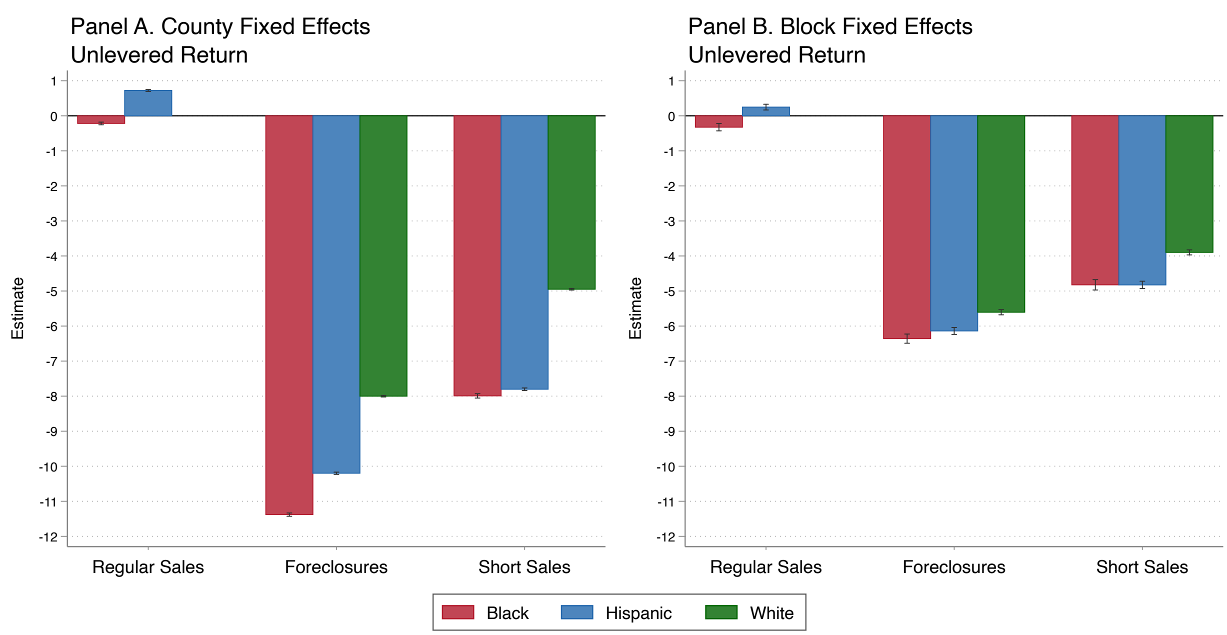
Notes: These figures present estimates of racial gaps in annualized unlevered housing returns from two regression specifications that compare homeowners living in the same county and buying and selling their homes in the same year (Equation 3). Both panels present regression coefficients that interact individual race/ethnicity with quintiles of the median days on market of homes sold in a ZIP code, reported by Zillow (Zillow, 2019). Panel A presents results from a sample of regular sales and Panel B presents results from a sample of distressed sales. Data are from sample of homeowners with observed purchase and sale prices (i.e. repeat sales sample) described in Section 2.

Figure A7: Racial Gap in Housing Returns



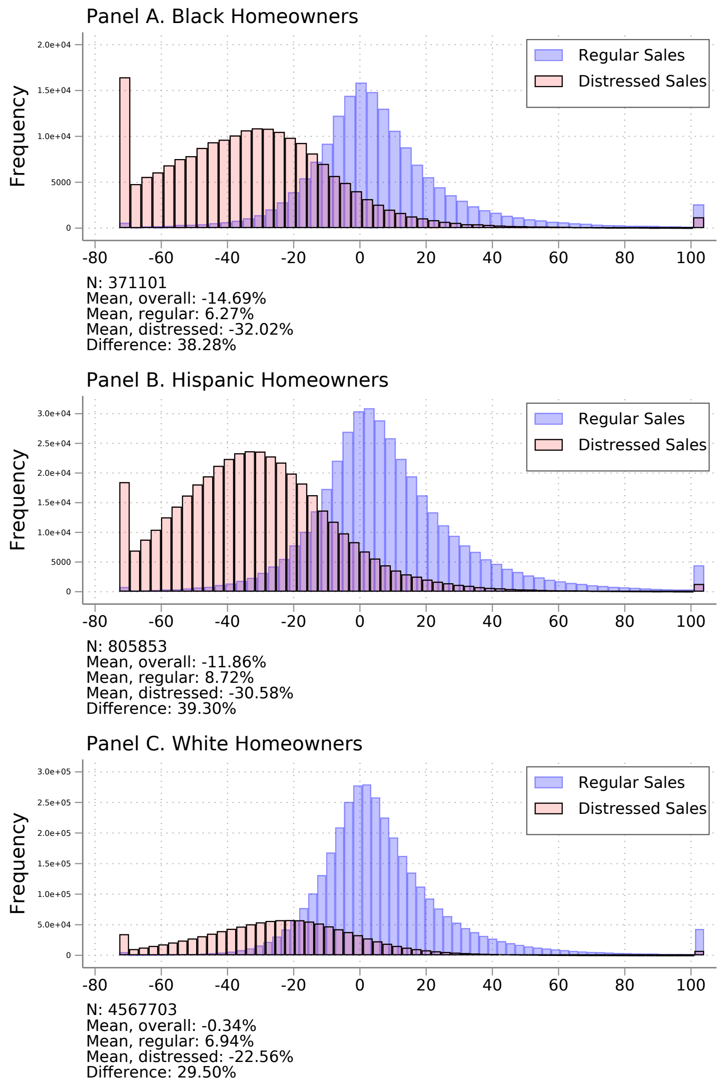
Notes: These figures present estimates of racial gaps in housing returns. Each pair/trio of bars corresponds to a separate regression and indicates estimated coefficients of black and Hispanic indicators from Equation 3. *County* denotes regressions with purchase year-by-sale year-by-county fixed effects. Regressions labeled *Tract* substitute county fixed effects for Census tract fixed effects, and *Block* regressions substitute county fixed effects for Census block fixed effects. The outcome in Panels A and C is the unlevered rate of return (Equation 1), and the outcome in Panels B and D is the levered rate of return (Equation 2). In Panels A and B, the omitted category corresponds to white homeowners. Panels C and D interact race/ethnicity coefficients with an indicator that the property was sold in a distressed sale, such that the omitted category corresponds to white homeowners who sold their property in a regular sale (i.e. non-foreclosure, non-short sale). Data are from sample of homeowners with observed purchase and sale prices (i.e. repeat sales sample) described in Section 2.

Figure A8: Gap in Housing Returns by Distressed Sale Type



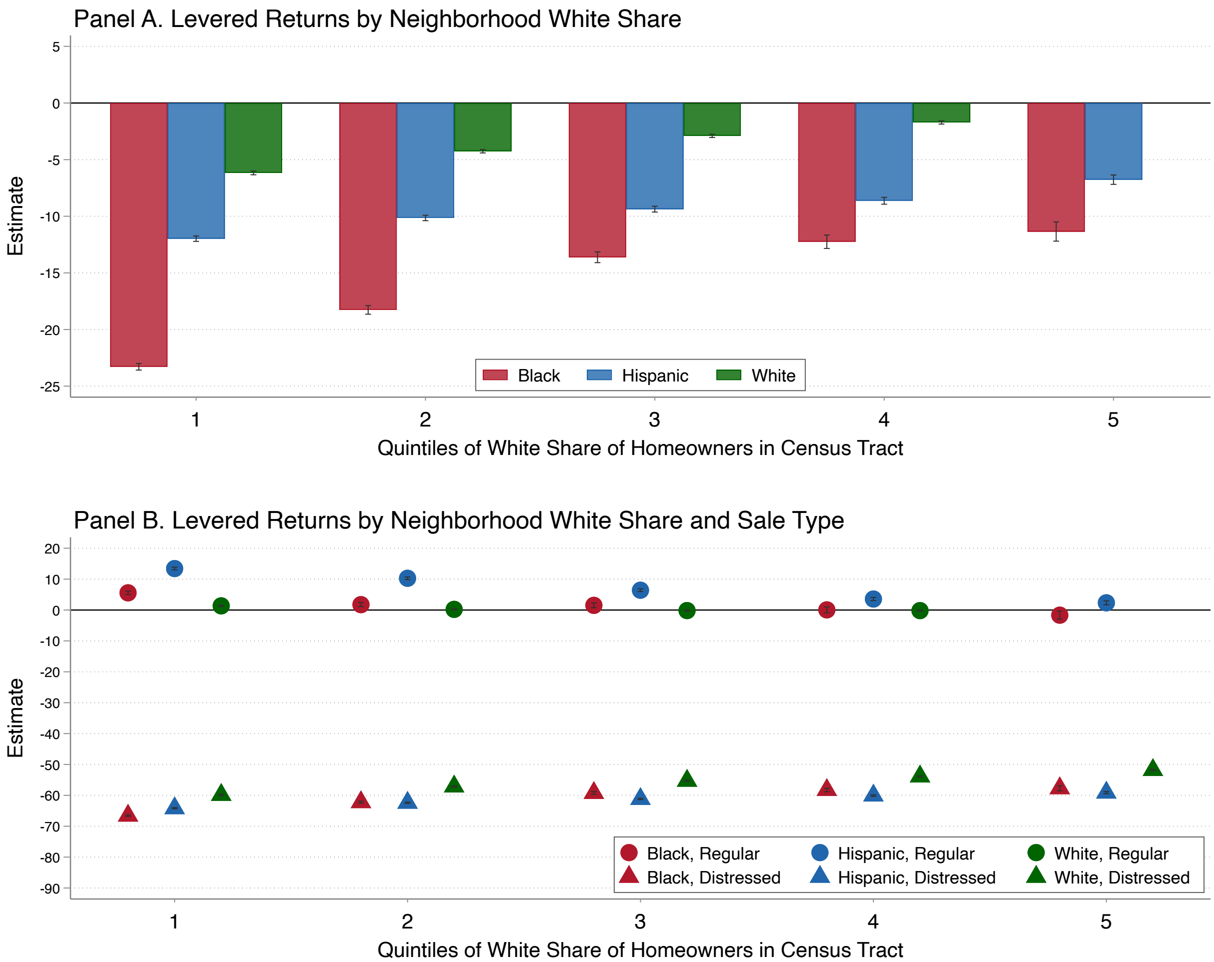
Notes: These figures present estimates of racial gaps in housing returns. Each panel contains estimates from a separate regression (Equation 3). Bars depict estimated coefficients of black and Hispanic indicators interacted with the sale type (regular, foreclosure, short sale). The specification in Panel A includes purchase year-by-sale year-by-county fixed effects. The specification in Panel B includes purchase-year-by-sale year-by-Census block fixed effects. The outcome in both panels is the unlevered rate of return (Equation 1)/ethnicity. Data are from sample of homeowners with observed purchase and sale prices (i.e. repeat sales sample) described in Section 2.

Figure A9: Distribution of Difference between Sale Price and Predicted Price (% of Predicted Price)



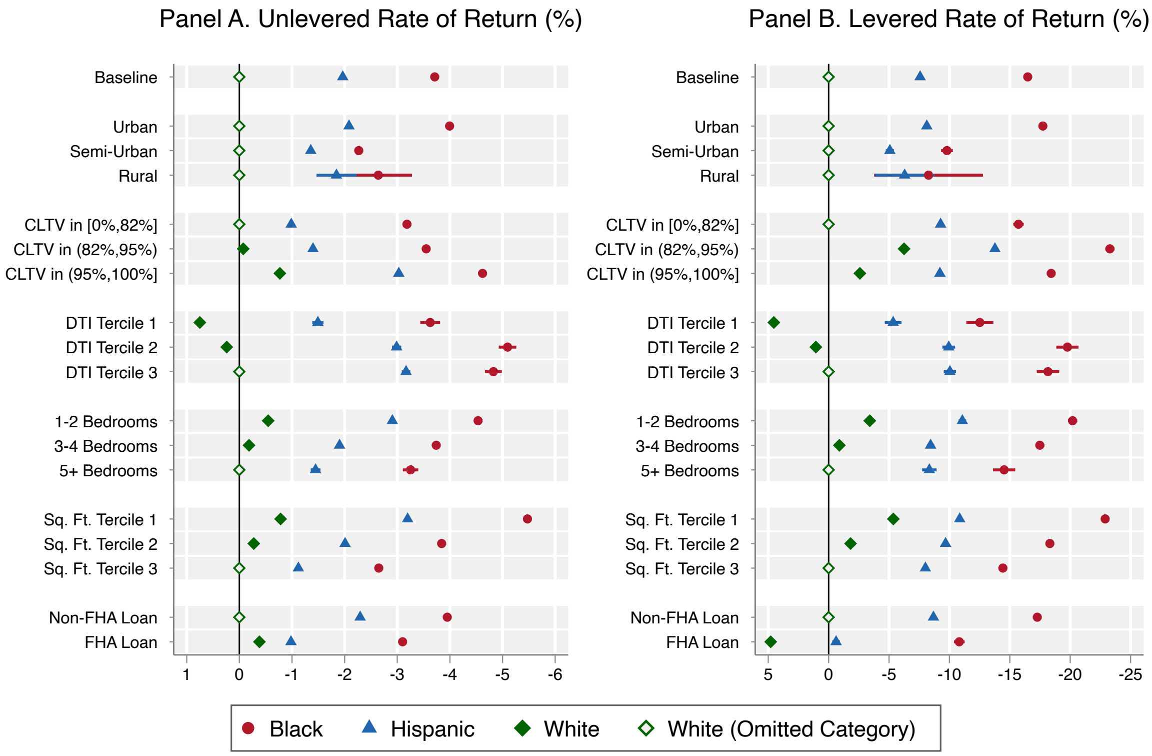
Notes: These figures plot the distribution of the difference between the actual sale price homeowners receive and the predicted sale price as a percentage of the predicted sale price (i.e. $\frac{P^{actual}}{P^{predicted}} - 1$). Predicted sale price is constructed by inflating purchase price to its value at the time of sale using Zillow's Home Value Index. Differences are winsorized at the 1% level. Distributions are plotted separately for black homeowners (Panel A), Hispanic homeowners (Panel B), and white homeowners (Panel C). For each race/ethnicity, the distributions for regular sales and distressed sales are also presented separately. Data are from sample of homeowners with observed purchase and sale prices (i.e. repeat sales sample) described in Section 2.

Figure A10: Racial Gaps by Neighborhood Demographics and Sale Type



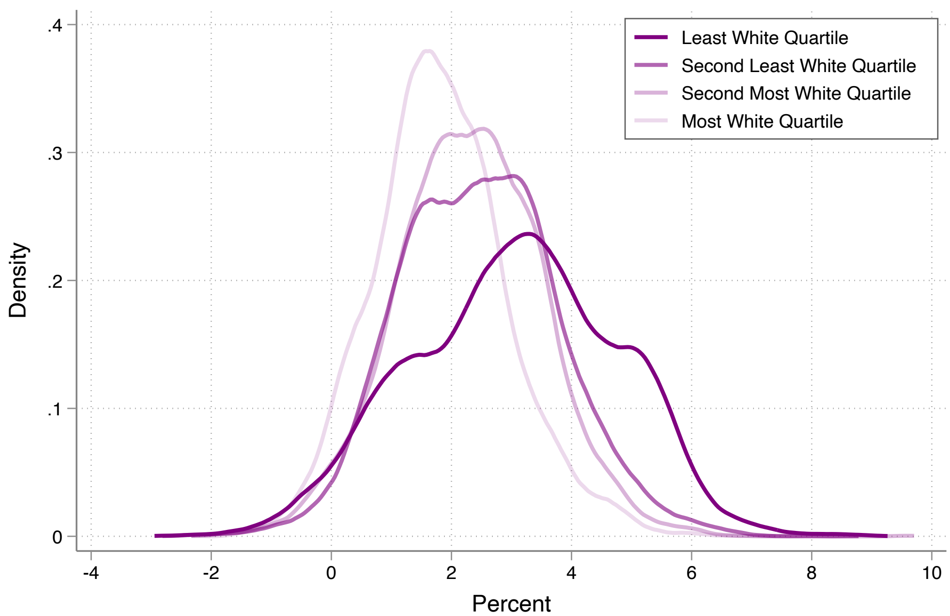
Notes: These figures present estimates of racial gaps in annualized levered housing returns (i.e. the internal rate of return) from two regression specifications that compare homeowners living in the same county and buying and selling their homes in the same year (Equation 3). Panel A presents regression coefficients that interact individual race/ethnicity with quintiles of the white share of homeowners in the individual's Census tract. The omitted category is white homeowners in neighborhoods with the highest white share. Within the most-white tracts, the black-white difference is 2.1 percentage points. Panel B presents regression coefficients that interact homeowner race/ethnicity with quintiles of the white share and homeowner's sale type (regular vs. distressed). The omitted category in Panel B is white homeowners in neighborhoods with the highest white share whose property sale is not distressed. Within regular sales, returns are similar across races and neighborhood demographics. In both panels, quintiles are assigned within each county, such that higher quintiles contain neighborhoods in each county with the highest share of white homeowners. Data are from sample of homeowners with observed purchase and sale prices (i.e. repeat sales sample) described in Section 2. Table 1 in the Online Appendix presents numerical values and additional statistics.

Figure A11: Heterogeneous Racial Gaps



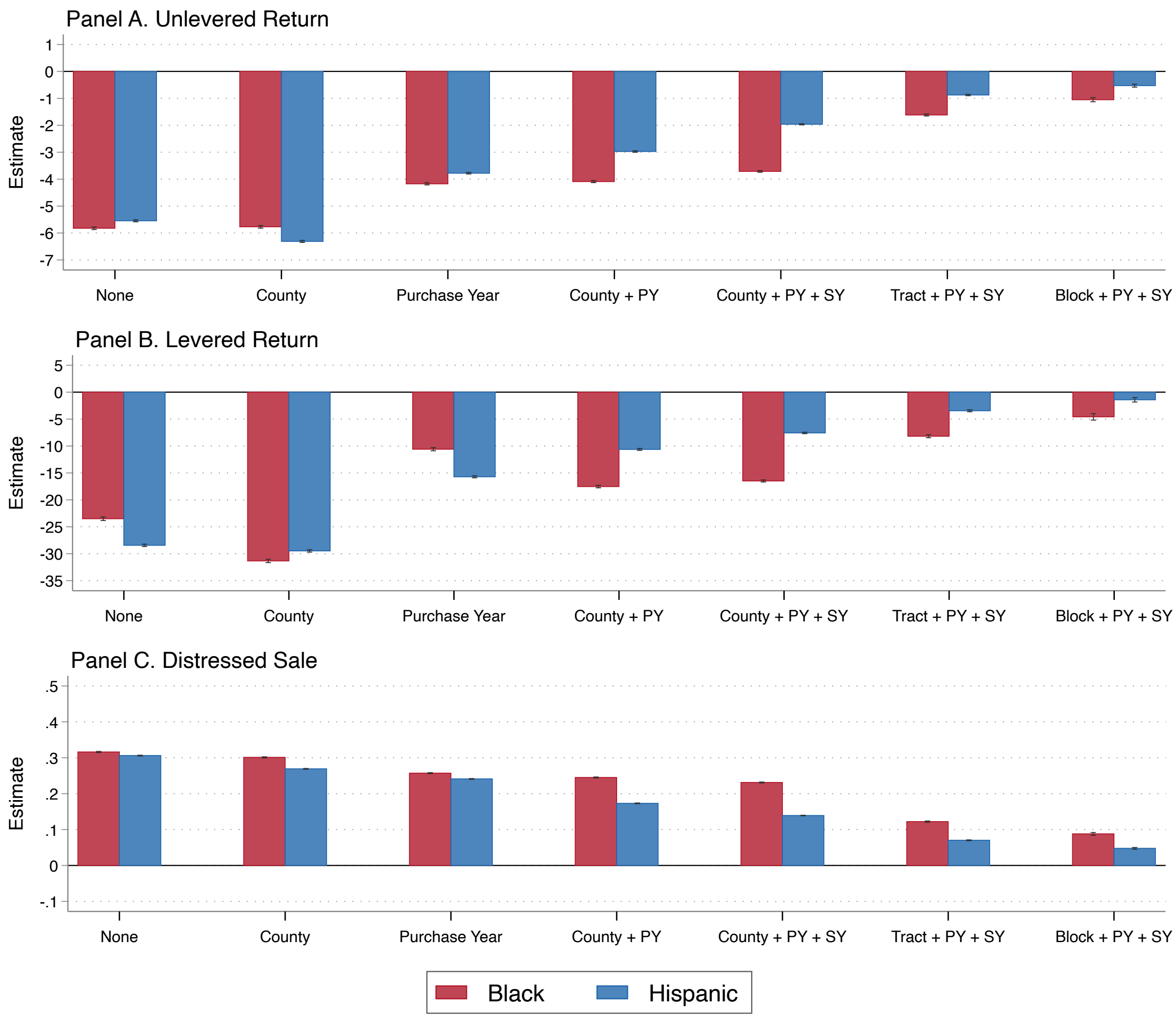
Notes: These figures document heterogeneity in the racial gap in housing returns for unlevered returns (Panel A) and levered returns (Panel B). Each dimension of heterogeneity provides estimates from a separate regression that compares homeowners living in the same county and buying and selling their homes in the same year (Equation 3). Points denote estimated coefficients of race/ethnicity indicators interacted with homeowner characteristics (e.g. indicators for income tercile). *Baseline* denotes the full analysis sample. *Urban* denotes tracts in which all constituent Census blocks are urban, according to 2010 Census definitions. *Semi-urban* denotes tracts with some urban and some rural blocks. *Rural* denotes tracts with only rural blocks. *CLTV* denotes combined loan-to-value ratio at origination. *DTI* denotes back-end debt-to-income ratio measured at origination from the McDash Servicing Records. *Sq. Ft.* denotes interior square footage. *FHA Loan* denotes that the mortgage is identified as a loan from the Federal Housing Administration in the ATTOM data. Data are from sample of homeowners with observed purchase and sale prices (i.e. repeat sales sample) described in Section 2.

Figure A12: Average House Price Growth 2001-2017 by Census Tract Demographics



Notes: This figure presents the distribution of annual house price growth between 2001 and 2017 in kernel density form for US Census tracts. Tracts are categorized into quartiles of the share of homeowners in each tract identifying as white in the 2010 Census. Tract house price growth is measured using tract-level FHFA house price index. These distributions indicate that tracts with more minority homeowners were more exposed to rapid levels of house price growth between 2001 and 2017.

Figure A13: Racial Gap with Alternative Fixed Effects

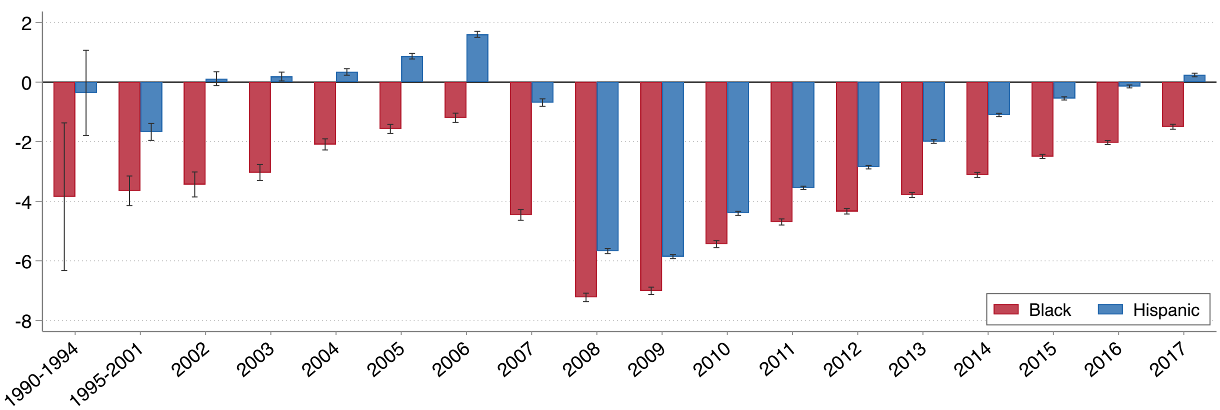


Notes: These figures present estimates of racial gaps in housing returns. Each pair of bars corresponds to a separate regression and indicates estimated coefficients of black and Hispanic indicators from Equation 3 using a particular set of fixed effects. PY denotes purchase year fixed effects, SY denotes sale year fixed effects, $County + PY$ denotes county-by-purchase year fixed effects, and so on. The outcome in Panel A is the unlevered rate of return (Equation 1), the outcome in Panel B is the levered rate of return (Equation 2), and the outcome in Panel C is an indicator that a homeowner experiences a distressed sale. Data are from sample of homeowners with observed purchase and sale prices (i.e. repeat sales sample) described in Section 2.

Figure A14: Heterogeneity in Unlevered Returns by Purchase and Sale Year

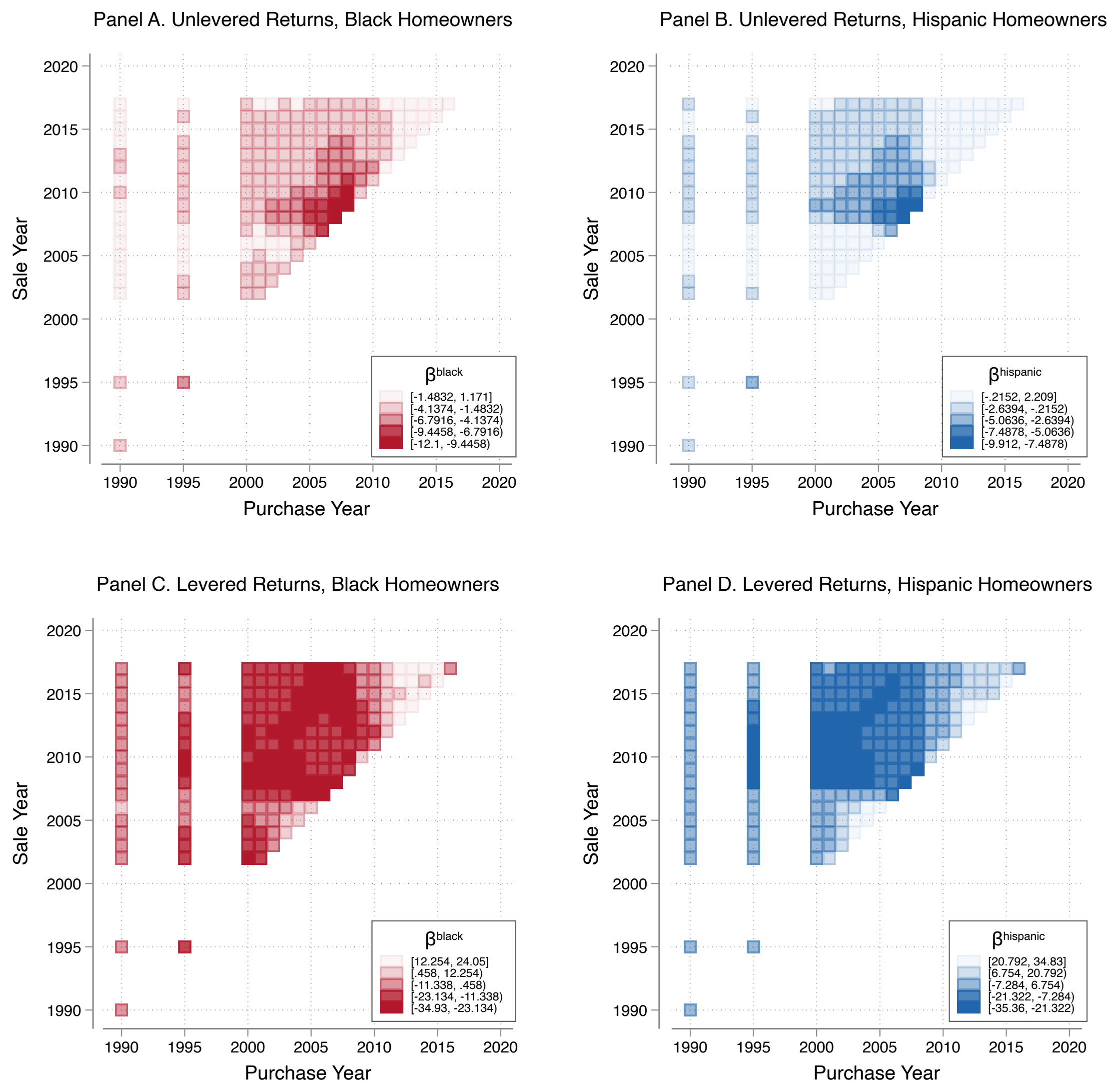
Panel A. Purchase Year

Panel B. Sale Year



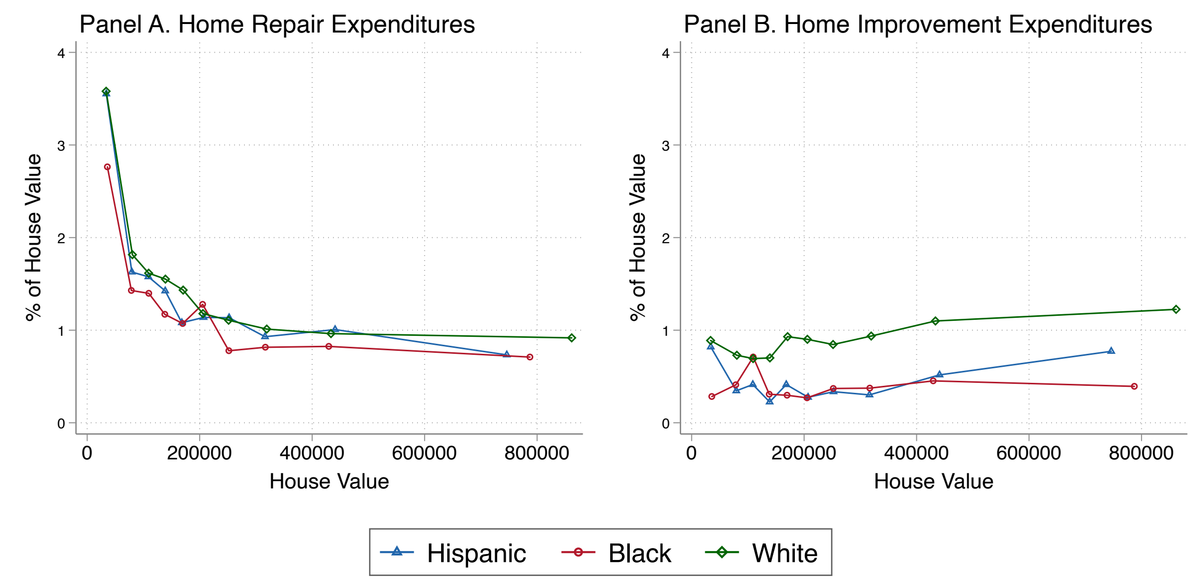
Notes: These figures present estimates of racial gaps in annualized unlevered housing returns from regression specifications that compare homeowners living in the same county and buying and selling their homes in the same year (Equation 3). Each pair of bars corresponds to a separate regression, and each bar denotes an estimated coefficient corresponding to a race/ethnicity indicator. In Panel A, each pair represents estimates from a subsample corresponding to homeowners who purchased their homes in a certain year. Panel B presents separate estimates for homeowners who sold their homes in certain years. Data are from sample of homeowners with observed purchase and sale prices (i.e. repeat sales sample) described in Section 2.

Figure A15: Heat Map of Returns Gap by Purchase and Sale Year



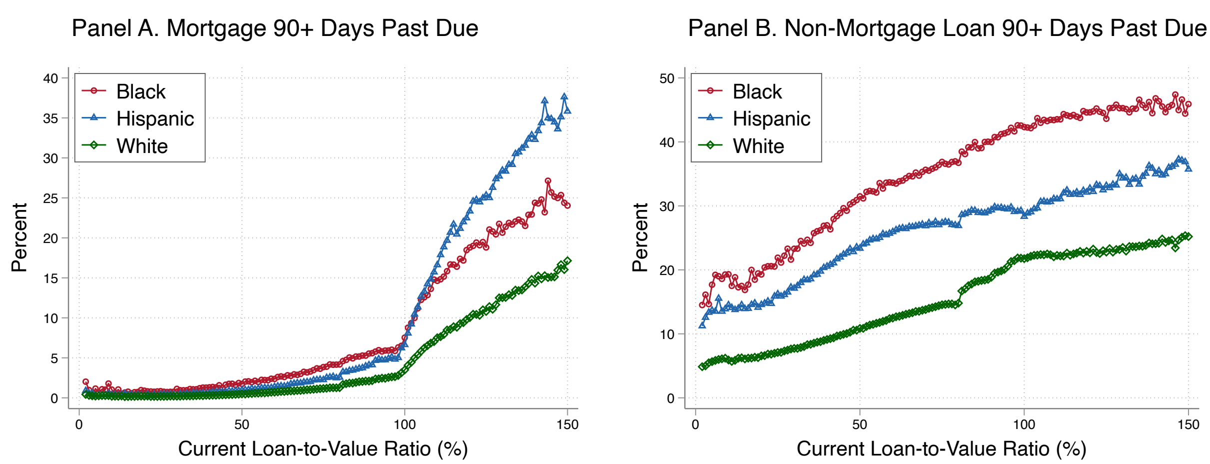
Notes: These figures present estimates of racial gaps in unlevered housing returns split by year of purchase and year of sale for unlevered returns (Panels A and B) and levered returns (Panels C and D). Within each panel, the color of a square indicates the size of the estimated coefficient, with each square corresponding to a coefficient for race/ethnicity indicators in separate regressions estimated within purchase year-by-sale year cells. Regressions are estimated as in Equation 3 with county fixed effects. For purchase year, 1990 denotes period 1990-1994 and 1995 denotes period 1995-1999. For sale year, 1990 denotes 1990-1994 and 1995 denotes 1995-2001. Data are from sample of homeowners with observed purchase and sale prices (i.e. repeat sales sample) described in Section 2.

Figure A16: Differences in Home Expenditures by Race



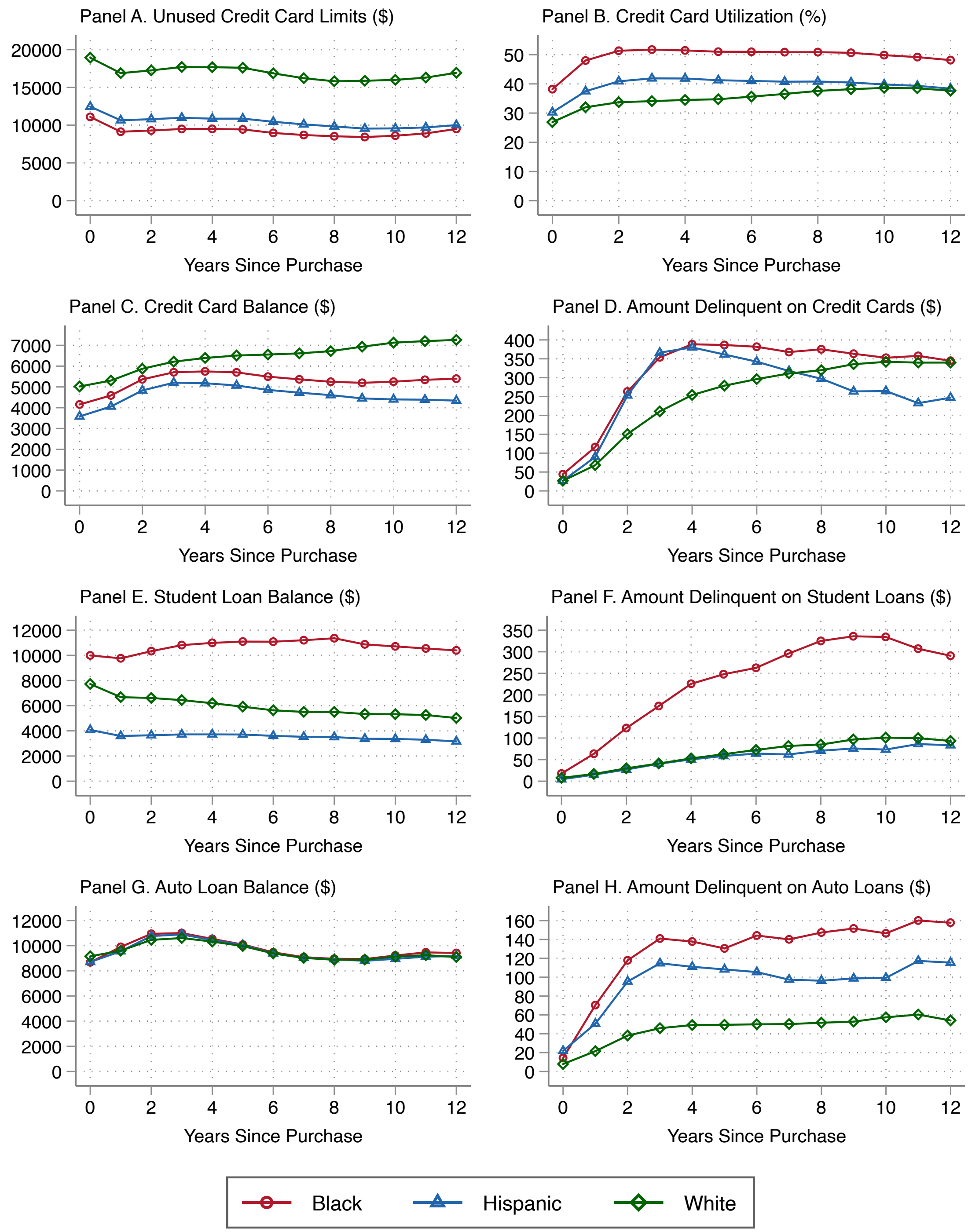
Notes: These figures present binned scatterplots of home repair expenditures during previous year as a percentage of current house value (Panel A) and annual expenditure on additions and improvements (averaging over prior two years) as a percentage of house value (Panel B). Data come from sample of homeowners in the Panel Study of Income Dynamics (2001-2017) described in Appendix Section C.2. Race/ethnicity assigned according to head of household.

Figure A17: Measuring Racial Disparities in Financial Distress



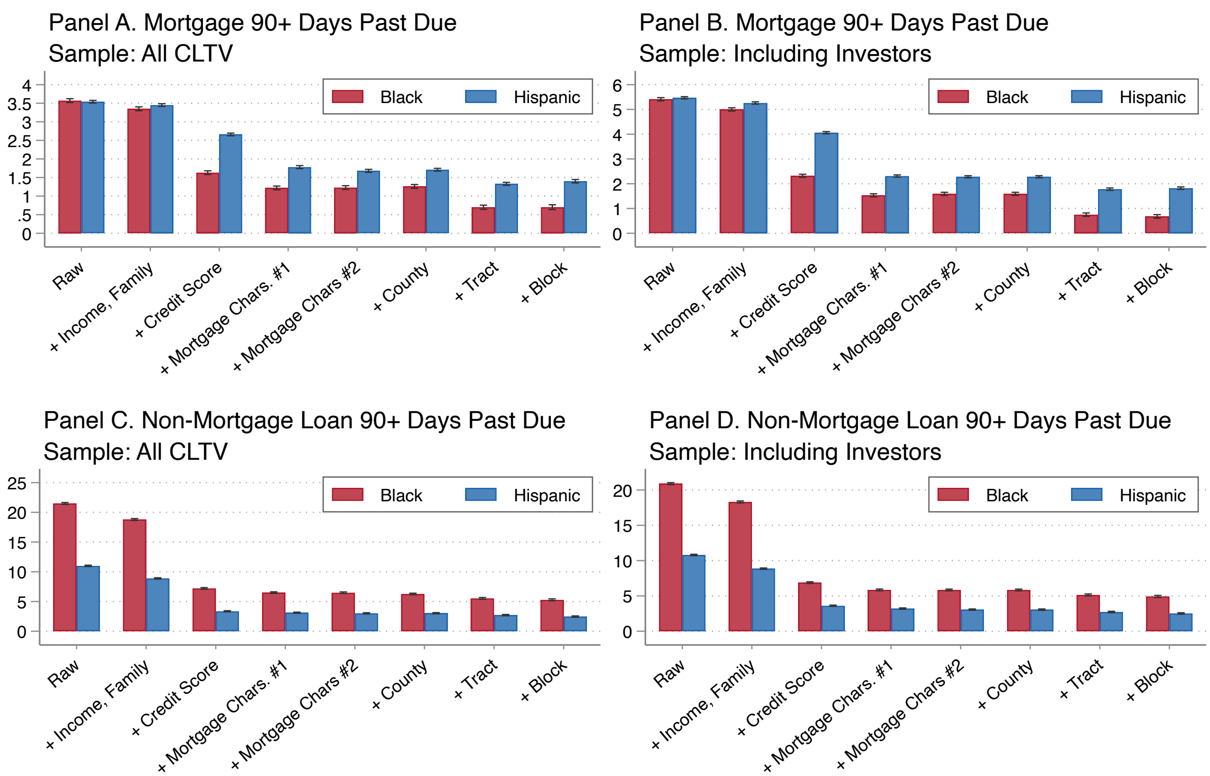
Notes: These figures present rates of financial distress, measured by loan delinquency, as a function of homeowner race/ethnicity and current loan-to-value ratio. These figures extend the horizontal axis in Figure 4 to include homeowners with combined loan-to-value ratio of up to 150%. Panel A plots the percent of homeowners whose primary mortgage is 90 or more days past due. Panel B plots the percent of homeowners with at least one non-mortgage loan that is 90 or more days past due or an account in collections. Both panels document high rates of financial distress among minority homeowners, both in absolute terms and relative to white homeowners. Data are from a panel of homeowners with linked credit bureau and mortgage servicing records described in Section 2.

Figure A18: Racial Disparities in Financial Distress by Tenure Length



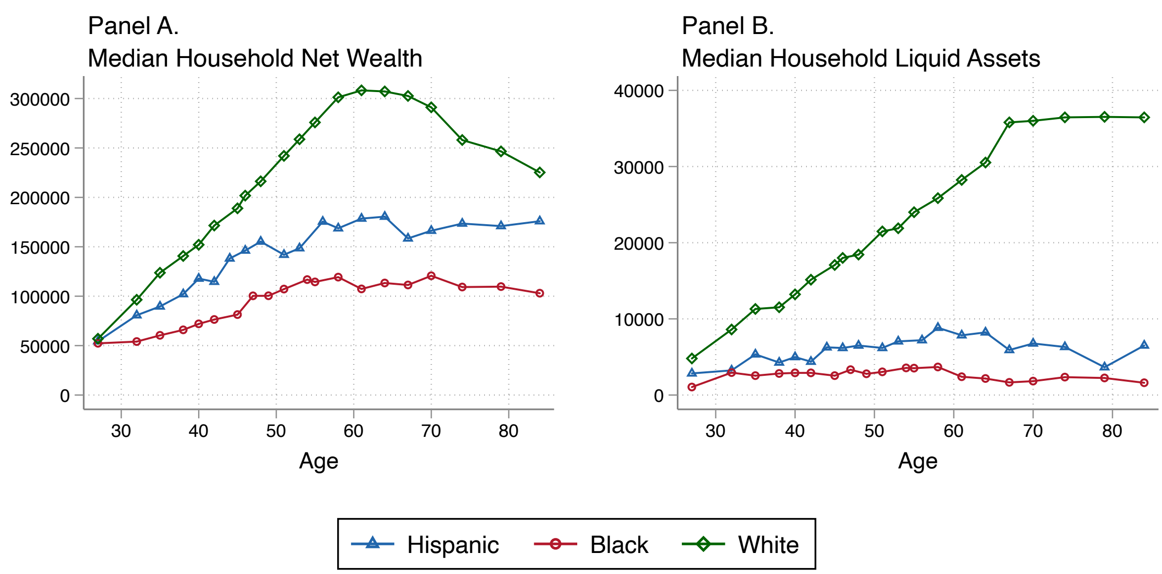
Notes: These figures present financial outcomes by race/ethnicity as a function of the number of months since home purchase. The financial outcomes are dollar amount of unused credit card limits (Panel A), credit card utilization in percent (Panel B), amount of credit card balances (Panel C), amount 30 or more days past due on credit cards (Panel D), amount of student loan balances (Panel E), amount 30 or more days past due on student loans (Panel F), amount of auto loan balances (Panel G), and amount 30 or more days past due on auto loans (Panel H). Credit card utilization is conditional on having an open credit card. Homeowners without credit cards are coded as having $0 in unused limits. Data are from a panel of homeowners with linked credit bureau and mortgage servicing records described in Section 2.

Figure A19: Racial Disparities in Financial Distress in Alternative Samples



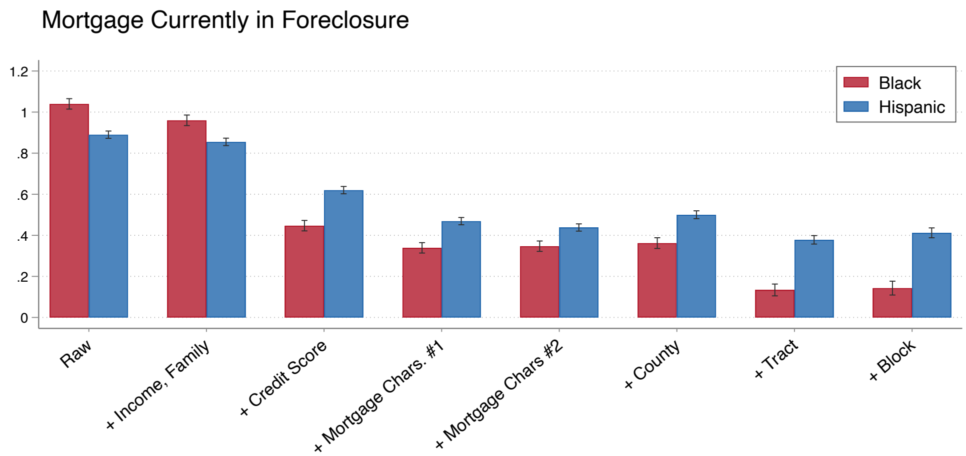
Notes: These figures present estimates of racial differences in financial distress controlling for a range of observable homeowner characteristics (Equation 5), and replicate Figure 5 for alternative samples. Panels A and C drop the restriction to homeowners with CLTV less than or equal to 120%. Panels B and D add in homeowners with multiple open first mortgages (for whom CLTV cannot be measured). The outcome in Panels A and B is an indicator that the homeowner's primary mortgage is 90 or more days past due. The outcome in Panels C and D is an indicator that the homeowner has a non-mortgage loan 90 or more days past due or an account in collections. Each bar corresponds to the coefficient on a race/ethnicity dummy. Each pair of bars correspond to a separate regression with an additional set of controls. *Raw* denotes regression with year fixed effects. *Income, Family* adds income decile fixed effects and fixed effects for family type (i.e. single female, single male, couple derived from HMDA mortgage application) in addition to year fixed effects. *Credit Score* adds 10 point credit score bins. *Mortgage Chars. #1* adds splines in original loan-to-value ratio and current combined loan-to-value ratio, and term-by-origination year fixed effects, property value decile fixed effects, and debt-to-income decile fixed effects. Since CLTV cannot be measured for the investor sample, Panels B and D instead include fixed effects for month-by-origination year-by county. *Mortgage Chars. #2* adds in the log of estimated monthly payments, log interest rate, and indicators for interest-only loan, refinance, and adjustable rate mortgage. *County* adds in county fixed effects. *Tract* adds in Census tract fixed effects. *Block* adds in Census block fixed effects. Data are from a panel of homeowners with linked credit bureau and mortgage servicing records described in Section 2.

Figure A20: Disparities in Wealth and Liquidity



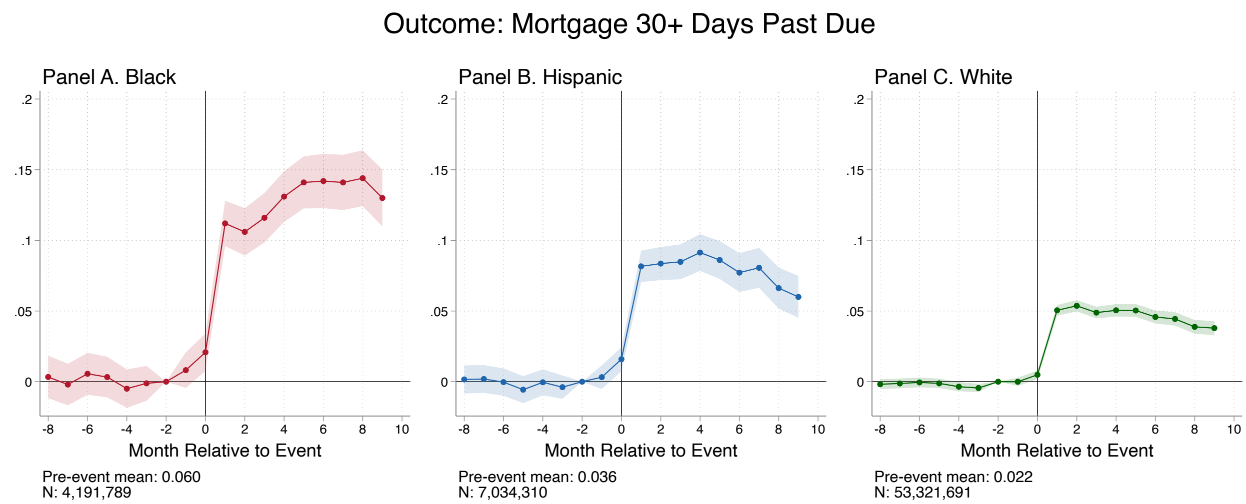
Notes: These figures present binned scatterplots that illustrate racial disparities in wealth, liquidity, and income among homeowners. Panel A plots median net wealth as a function of age. Panel B plots median liquid wealth as a function of age. Data come from sample of homeowners in the Survey of Income and Program Participation (1990-2017) described in Section 4. Race/ethnicity and age are assigned according to the head of household. Dollar values are adjusted to 2016 levels.

Figure A21: Racial Disparities in Foreclosure



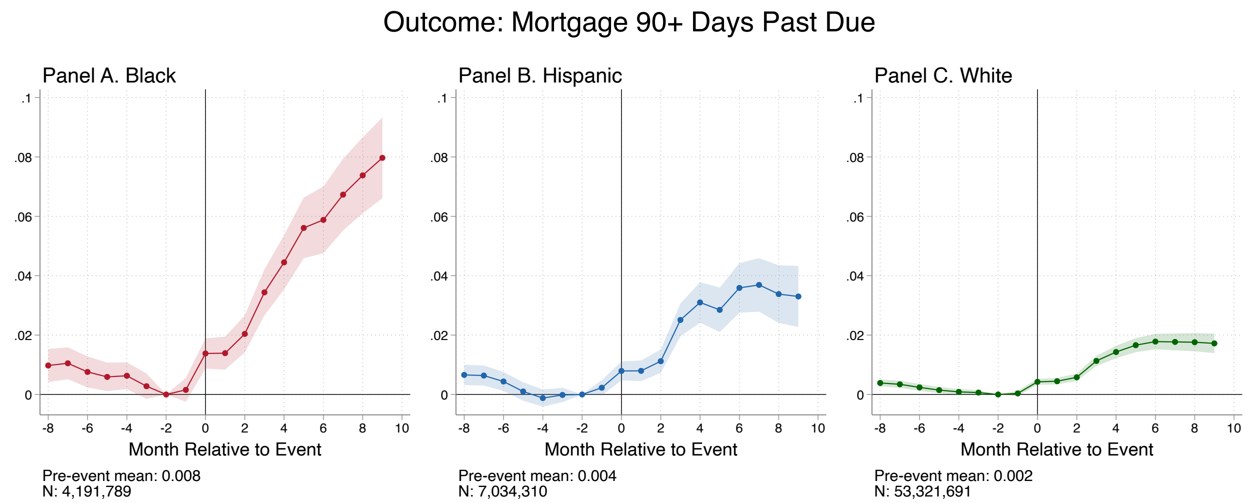
Notes: This figure presents estimates of racial differences in foreclosures controlling for a range of observable homeowner characteristics (Equation 5). The outcome is an indicator that the homeowner's primary mortgage is currently in foreclosure. Each bar corresponds to the coefficient on a race/ethnicity indicator. Each pair of bars correspond to a separate regression with a particular set of covariates. *Raw* denotes a regression of the outcome on race/ethnicity indicators and year fixed effects. *Income, Family* adds income decile fixed effects and fixed effects for family type (i.e. single female, single male, couple derived from HMDA mortgage application) in addition to year fixed effects. *Credit Score* adds 10 point credit score bins. *Mortgage Chars. #1* adds splines in original loan-to-value ratio and current combined loan-to-value ratio, and term-by-origination year fixed effects, property value decile fixed effects, and debt-to-income decile fixed effects. *Mortgage Chars. #2* adds in the log of estimated monthly payments, log interest rate, and indicators for interest-only loan, refinance, and adjustable rate mortgage. *County* adds in county fixed effects. *Tract* adds in Census tract fixed effects. *Block* adds in Census block fixed effects. Data are from a panel of homeowners with linked credit bureau and mortgage servicing records described in Section 2, restricted to homeowners with CLTV less than or equal to 120%.

Figure A22: Mortgage Delinquency Responses to Liquidity shocks



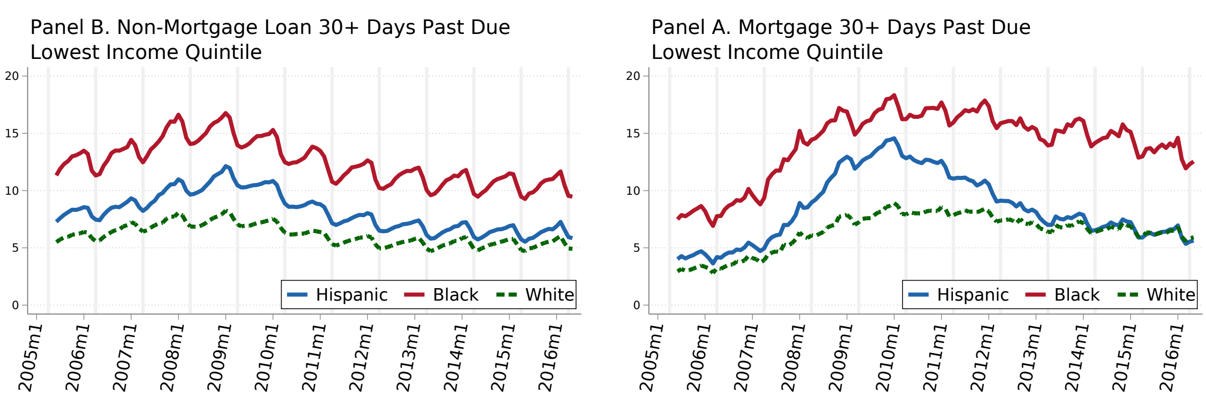
Notes: These figures depict the time path of monthly delinquency rates around a change in monthly tax and insurance payments that occurs at event time $t = 0$. Delinquency is defined as an indicator that the homeowner's primary mortgage is 30 or more days past due. Each panel corresponds to a different racial group. All panels present event study coefficients from Equation 8. Event time indicators are interacted with the percentage change in the total monthly payment created by the change in the monthly tax and insurance payment. Coefficients show that a 10% increase in monthly mortgage payments increases the delinquency rate by about 1.4 percentage points for black homeowners (Panel A), 0.8 percentage points for Hispanic homeowners (Panel B), and 0.5 percentage points for white homeowners (Panel C). The shaded region depicts 95 percent confidence intervals, with standard errors clustered at the loan level. Event coefficients are normalized to zero two months before the change ($t = -2$). Data come from panel of homeowners with linked credit bureau and mortgage servicing records who experience a change in their monthly tax and insurance payments. See Appendix Section F for more details on construction of event study sample.

Figure A23: Mortgage Default Responses to Liquidity shocks



Notes: These figures depict the time path of monthly default rates around a change in monthly tax and insurance payments that occurs at event time $t = 0$. Default rates are measured as an indicator that the homeowner's primary mortgage is 90 or more days past due. Each panel corresponds to a different racial group. All panels present event study coefficients from Equation 8. Event time indicators are interacted with the percentage change in the total monthly payment created by the change in the monthly tax and insurance payment. Coefficients show that after 10 months, a 10% increase in monthly mortgage payments increases the default rate by 0.8 percentage points for black homeowners (Panel A), 0.3 percentage points for Hispanic homeowners (Panel B), and 0.2 percentage points for white homeowners (Panel C). The shaded region depicts 95 percent confidence intervals, with standard errors clustered at the loan level. Event coefficients are normalized to zero two months before the change ($t = -2$). Data come from panel of homeowners with linked credit bureau and mortgage servicing records who experience a change in their monthly tax and insurance payments. See Appendix Section F for more details on construction of event study sample.

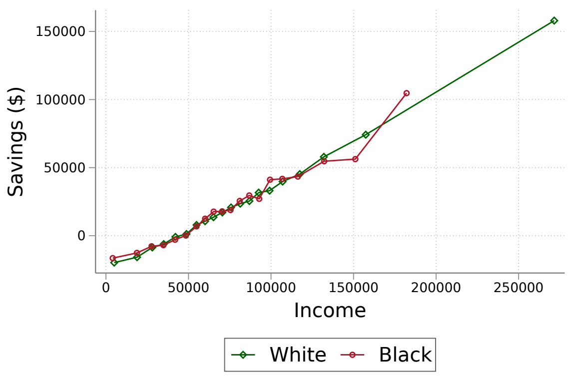
Figure A24: The Seasonality of Financial Distress



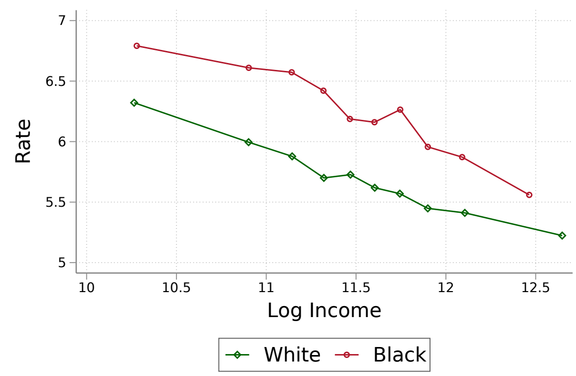
Notes: These figures depict the seasonality of financial distress by race/ethnicity, plotting the share of homeowners who are 30 or more days past due on a non-mortgage loan, excluding collections (Panel A) and 30 or more days past due on their mortgage (Panel B) over 2005-2016. Higher amounts of seasonality for black and Hispanic homeowners and lower levels of seasonality during months in which tax rebates are received (shaded gray bars) suggest that minorities are more sensitive to liquidity shocks. Data are from a monthly panel of homeowners with linked credit bureau and mortgage servicing records described in Section 2, restricted to the lowest quintile of homeowner income.

Figure A25: Household Financial Outcomes and Behaviors in the PSID

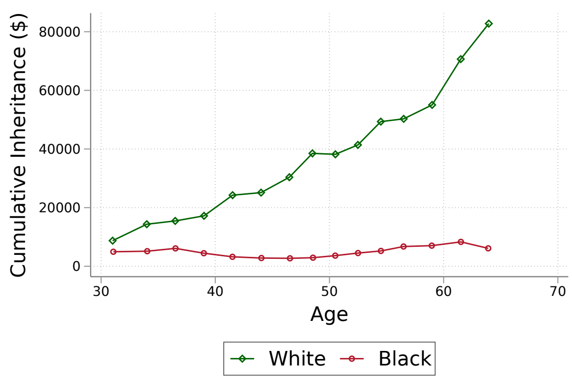
(a) Savings



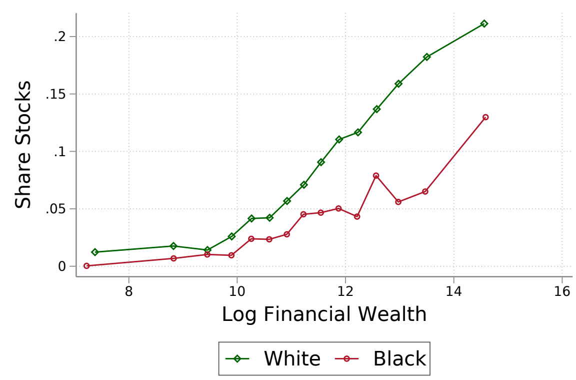
(b) Mortgage Interest Rate



(c) Inheritance

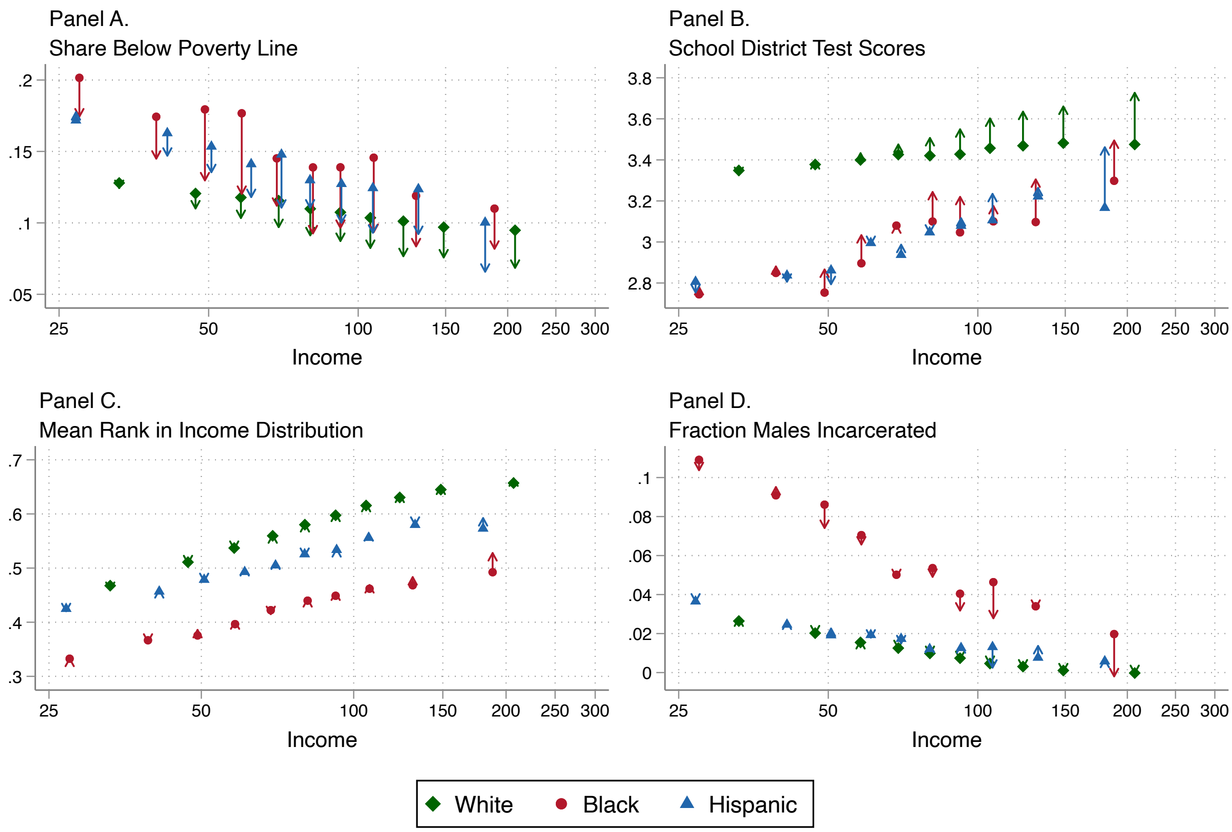


(d) Share of Wealth in Stocks



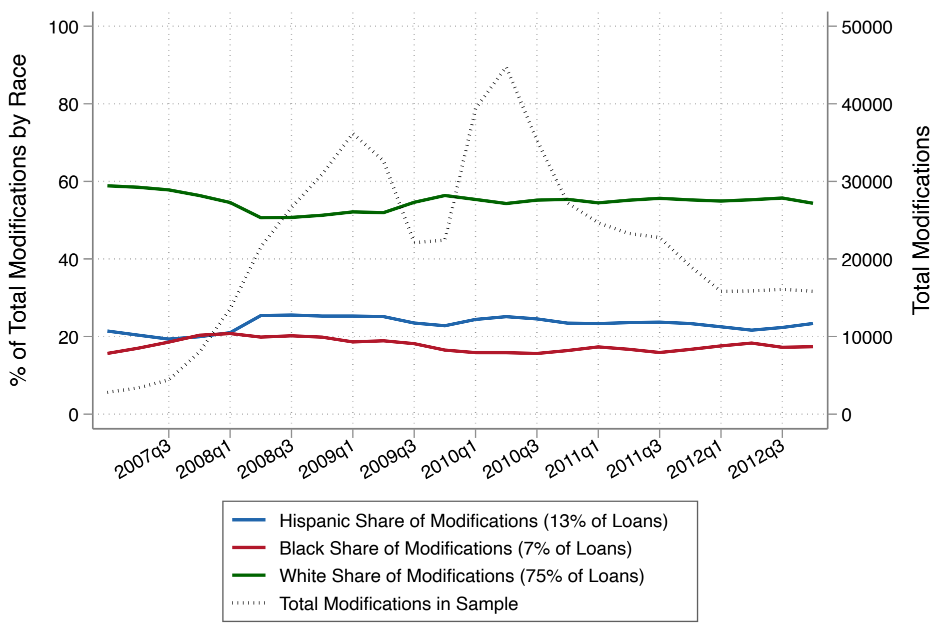
Notes: These figures present binned scatterplots of household financial behaviors and outcomes of homeowners by race, income, and age. Panel A presents the amount saved in the prior year (disposable income minus consumption) and residualizes by deciles of homeowner age. Panel B presents mortgage interest rate and includes linear controls for LTV and age, as well as state-year fixed effects. Panel C presents inheritance and gifts (cumulative through the panel window) without controls. Panel D presents the share of homeowner financial wealth held in stocks and residualizes by deciles of homeowner age. Race and age assigned according to reference person of household. Data come from sample of homeowners in the Panel Study of Income Dynamics (PSID) 2000-2017, restricted to household heads aged 30 to 65. See Appendix Section C.2 for more details on PSID sample. All dollar amounts normalized to 2016 dollars.

Figure A26: Upgrades in Neighborhood Quality Among First-Time Homebuyers



Notes: These figures depict changes in neighborhood quality associated with first-time home purchases and replicate the results in Figure 7 for a sample of first-time homebuyers. Each panel corresponds to a different measure of neighborhood quality. Panel A measures the share of homeowners in the Census tract below the federal poverty line in the 2006-2010 ACS. Panel B measures school district standardized 3rd grade test scores in 2013. Panel C measures the mean rank in the national income distribution of children born in 1978-1983 to parents of the same race/ethnicity and income percentile as that reported by the homeowner in their mortgage application. Panel D measures the 2010 incarceration rate of male children that were born in 1978-1983 to parents of the same race/ethnicity and income percentile as that reported by the homeowner in their mortgage application. In each panel, homeowners are binned by race/ethnicity and to decile of income at home purchase (deciles computed within race/ethnicity). The base of each arrow corresponds to the quality of neighborhoods from which homeowners depart and the head of each arrow corresponds to the neighborhoods at which homeowners arrive after purchase. Income is measured in 2015 dollars. Homeowner-level data on neighborhood migration come from sample of first-time homeowners linked to address histories described in Section 2 (N=61,996). First-time homebuying status is indicated in the Fannie Mae and Freddie Mac data Data on neighborhood characteristics come from Chetty et al. (2018).

Figure A27: Modifications During the Great Recession



Notes: This figure plots the aggregate quarterly time series of modification rates before, during, and after the Great Recession. The dashed line plots the total number of modifications observed in the sample. The solid lines plot the percent of total modifications received by race/ethnicity. These patterns indicate that black and Hispanic homeowners received a disproportionately large and approximately constant share of modifications throughout this time period, despite only accounting for 7% and 13% of owner-occupied mortgages, respectively. The data come from a sample of 6.4 million first-lien owner-occupied mortgages originated in or before 2008, contained in the Fannie Mae, Freddie Mac, and ABSNet Loan databases (described in Section 2) in which mortgage modifications can be observed.

B Appendix Tables

Table A1: Racial Disparities in Housing Returns

Outcome	Unlevered Return	Levered Return	NPV	NPV	NPV	Distressed Sale
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Baseline						
Black	–3.716	–16.49	–125.1	–279.0	–433.5	0.230
	(0.0157)	(0.0995)	(0.977)	(1.321)	(1.824)	(0.000671)
Hispanic	–1.982	–7.505	–112.8	–219.5	–327.0	0.137
	(0.0101)	(0.0680)	(0.836)	(1.071)	(1.390)	(0.000437)
Asian	–0.520	–4.893	–16.22	–24.75	–33.48	0.0410
	(0.0121)	(0.0827)	(1.062)	(1.307)	(1.627)	(0.000595)
Panel B. Interacted						
Black × Regular	–0.213	2.843	–1.219	–1.340	–1.683	
	(0.0194)	(0.170)	(1.463)	(1.516)	(1.599)	
Hispanic × Regular	0.724	8.525	60.04	51.69	42.20	
	(0.0133)	(0.111)	(1.056)	(1.118)	(1.211)	
Asian × Regular	–0.404	–2.691	2.050	–6.478	–15.06	
	(0.0136)	(0.102)	(0.989)	(1.034)	(1.104)	
Black × Distr.	–10.54	–63.71	–416.4	–846.7	–1278.3	
	(0.0205)	(0.0902)	(1.258)	(1.733)	(2.473)	
Hispanic × Distr.	–9.517	–62.50	–509.7	–905.4	–1301.9	
	(0.0142)	(0.0675)	(1.235)	(1.603)	(2.135)	
Asian × Distr.	–6.868	–58.37	–349.1	–602.0	–856.0	
	(0.0209)	(0.0985)	(2.271)	(2.935)	(3.799)	
White × Distr.	–6.765	–55.65	–330.0	–604.3	–879.3	
	(0.00956)	(0.0578)	(0.663)	(0.855)	(1.160)	
Outcome Mean	1.263	–7.403	–126.4	–238.8	–351.4	0.324
Outcome SD	12.51	79.54	671.9	836.5	1051.7	0.468
Addl. Forecl. Costs	-	-	$0	$50,000	$100,000	-
N	6,203,025	5,497,415	5,497,415	5,497,415	5,497,415	6,203,025

Notes: This table presents estimates of the racial gap in housing returns using five different measures of housing returns. Within each panel, columns correspond to separate regressions estimating Equation 3, which compares homeowners living in the same county and buying and selling their homes in the same years. *Distr.* is an indicator that a sale is a foreclosure or short sale. *Regular* is an indicator that a sale is a non-foreclosure, non-short sale. *Unlevered Return* and *Levered Return* denote annualized unlevered and levered rates of return in percentage terms, respectively. *NPV* denotes net present value as a percentage of up-front costs. *Distressed Sale* denotes an indicator that an ownership spell ended in a distressed sale. *Addl. Forecl. Costs* denotes assumed additional dollar cost of foreclosure paid in final month of homeownership spell. Data are from sample of homeowners with observed purchase and sale prices (i.e. repeat sales sample) described in Section 2.

Table A2: Standard Deviation of Returns by Race and Sale Type

	Unlevered Returns			Levered Returns		
	Black	Hispanic	White	Black	Hispanic	White
Panel A. All Sales						
Raw	14.98	16.87	10.94	94.10	93.23	75.15
Residualized	9.12	7.72	6.78	52.36	47.23	46.39
Panel B. Regular Sales						
Raw	11.08	11.81	8.89	92.90	87.74	66.26
Residualized	7.23	7.20	5.89	59.89	58.01	44.45
Panel C. Distressed Sales						
Raw	11.22	11.13	9.47	57.48	32.92	53.86
Residualized	7.69	6.68	6.52	21.88	16.88	27.91

Notes: This table presents the standard deviations of returns by race/ethnicity and sale type. Panel A presents statistics for all sales, Panel B presents statistics for regular sales, and Panel C presents statistics for distressed sales. *Raw* denotes the standard deviation of returns within race/ethnicity and sale type. *Residualized* denotes the standard deviation of residual returns from a regression of returns on purchase year-by-sale year-by county fixed effects. Data are from sample of homeowners with observed purchase and sale prices (i.e. repeat sales sample) described in Section 2.

Table A3: Quantile Regression Estimates of Marginal Effects at the Average

	Full Sample		Regular Sales		Distressed Sales	
	Black	Hispanic	Black	Hispanic	Black	Hispanic
	(1)	(2)	(4)	(3)	(5)	(6)
p10	–6.982	–5.299	–0.047	0.882	–6.066	–5.883
p25	–5.244	–4.044	0.486	1.461	–4.709	–5.001
p50	–3.571	–2.835	1.271	2.462	–3.171	–3.769
p75	–1.926	–1.282	1.861	3.040	–2.133	–2.746
p90	–1.391	–0.614	2.472	3.281	–1.578	–2.160
OLS	–4.192	–2.939	2.003	2.966	–3.794	–4.099
Outcome Mean	1.181	1.181	7.700	7.700	–10.78	–10.78
N	5,738,392	5,738,392	2,071,390	2,071,390	1,458,748	1,458,748

Notes: This table presents estimates of marginal effects at the average from quantile regressions using the method in Schmidt and Zhu (2016). Each column presents marginal effects for a race/ethnicity indicator. Columns 1 and 2 present estimates from a regression estimated on the full sample, while Columns 3 and 4 present estimates from a sample of regular sales and Columns 5 and 6 present estimates from a sample of distressed sales. All specifications control for state-by-purchase year fixed effects. Due to computational constraints, *Full Sample* is comprised of 500 largest state-by-purchase year cells, while *Distressed Sales* and *Regular Sales* are comprised of 100 largest state-by-purchase year cells. Data are from sample of homeowners with observed purchase and sale prices (i.e. repeat sales sample) described in Section 2.

Table A4: Exposure to Gentrification By Race

	Hispanic	Black	White
Percent in Low-Price ZIP Codes	63.38	63.11	36.04
Mean Distance to High-Price ZIP	5.91	5.02	4.13
Mean Distance for Below-Median ZIPs	7.43	6.16	7.24
Mean Distance for Above-Median ZIPs	3.29	3.09	2.38

Notes: This table presents measures of exposure to gentrification from Guerrieri et al. (2013). *Percent in Low-Price ZIP Codes* denotes the percentage of homeowners who live in ZIP codes with house prices below the median in the corresponding MSA. *Mean Distance to High-Price ZIP* denotes the mean distance in miles to the nearest ZIP code with house prices in the top quartile in the corresponding MSA. *Mean Distance for Below-Median ZIPs* gives this same distance but restricts the sample to homeowners in ZIP codes with house prices below the MSA median, while *Mean Distance for Above-Median ZIPs* restricts the sample to homeowners in ZIP codes with house prices above the MSA median. Data are from sample of homeowners with observed purchase and sale prices (i.e. repeat sales sample) described in Section 2.

Table A5: Unlevered Returns by Exposure to Gentrification

	All Sales	Distressed Sales	Regular Sales
	(1)	(2)	(3)
Black × Low Price	–4.364***	–3.029***	–0.0634*
	(0.0239)	(0.0264)	(0.0309)
Hispanic × Low Price	–2.116***	–2.143***	0.841***
	(0.0151)	(0.0185)	(0.0205)
Black × High Price	–1.660***	0.883***	–1.360***
	(0.0238)	(0.0320)	(0.0281)
Hispanic × High Price	–0.259***	1.060***	–0.409***
	(0.0160)	(0.0216)	(0.0205)
White × High Price	0.757***	2.471***	–0.642***
	(0.00880)	(0.0152)	(0.00916)
Black × Low Price × Distance	0.0652***	0.0382***	–0.0518***
	(0.00363)	(0.00417)	(0.00487)
Hispanic × Low Price × Distance	–0.0403***	–0.0623***	–0.0216***
	(0.00187)	(0.00221)	(0.00267)
White × Low Price × Distance	–0.0537***	–0.0461***	–0.0233***
	(0.00121)	(0.00183)	(0.00134)
Black × High Price × Distance	–0.125***	–0.150***	–0.0308***
	(0.00573)	(0.00734)	(0.00700)
Hispanic × High Price × Distance	–0.0775***	–0.0776***	–0.0122**
	(0.00345)	(0.00426)	(0.00472)
White × High Price × Distance	–0.104***	–0.165***	–0.00875***
	(0.00135)	(0.00249)	(0.00139)
Outcome Mean	1.306	–10.11	6.715
N	5,436,828	1,739,304	3,681,596

Notes: This table estimates unlevered returns by race/ethnicity, interacting race/ethnicity indicators with two measures of exposure to gentrification from Guerrieri et al. (2013). Each column presents coefficients from a separate regression corresponding to Equation 3. Column 1 presents estimates for the full sample. Column 2 presents estimates for the sample of distressed home sales. Column 3 presents esetimates for the sample of non-distressed home sales. *Low Price* denotes an indicator that the homeowner lives in a ZIP code with house prices below the median in the corresponding MSA. *Distance* denotes the mean distance in miles from the homeowner's ZIP code to the neareset ZIP code with house prices in the top quartile in the corresponding MSA, demeaned for ease of interpretation. Data are from sample of homeowners with observed purchase and sale prices (i.e. repeat sales sample) described in Section 2. *** p<0.001, ** p<0.01, * p<0.05

Table A6: Ownership Transitions by Race

	Race of Next Owner			
	White	Black	Hispanic	Asian
Panel A. All Sales				
White	81.04	3.97	8.62	6.05
Black	43.60	33.06	15.16	7.89
Hispanic	40.59	5.50	44.60	9.01
Asian	47.04	5.42	13.17	34.04
Panel B. Distressed Sales				
White	78.61	4.39	10.23	6.48
Black	45.06	31.36	14.49	8.85
Hispanic	44.32	5.48	38.56	11.39
Asian	48.04	5.94	14.72	30.97

Notes: This table presents the transition matrix of homeowner race/ethnicity across subsequent homeownership spells. Each number corresponds to the racial/ethnic percentages of subsequent owners conditional on original owner race/ethnicity. Panel A presents statistics for all sales, while Panel B presents statistics for distressed home sales. Data are from sample of homeowners with observed purchase and sale prices (i.e. repeat sales sample) described in Section 2.

Table A7: Characteristics of Next Ownership Spell

	Next Owner Tenure (1)	Institutional Next Owner (2)	Occupied by Next Owner (3)	White Next Owner (4)
Black	–6.571***	0.0213***	–0.00808***	–0.280***
	(0.173)	(0.000583)	(0.000890)	(0.00158)
Hispanic	–6.050***	0.000201	0.00816***	–0.276***
	(0.113)	(0.000337)	(0.000631)	(0.00109)
Distressed	–15.80***	0.125***	–0.0452***	–0.0526***
	(0.0801)	(0.000421)	(0.000576)	(0.000765)
Black × Distressed	1.006***	0.0727***	–0.0224***	0.0214***
	(0.213)	(0.00116)	(0.00168)	(0.00258)
Hisp. × Distressed	1.972***	0.0483***	–0.0173***	0.0383***
	(0.145)	(0.000791)	(0.00120)	(0.00179)
Outcome Mean	47.16	0.0818	0.909	0.735
N	1,576,940	6,084,819	3,394,966	3,068,085

Notes: This table presents estimates of Equation 3 for outcomes pertaining to the ownership spell immediately following the current spell, applying purchase year-by-sale year-by-county fixed effects. *Distressed* denotes an indicator that the current spell ends in a foreclosure or short sale. Each column corresponds to a separate regression and outcome. *Next Owner Tenure* is the number of months that the next owner holds the property. *Institutional Next Owner* is an indicator that the next owner's name is classified as a non-trust institution. *Occupied by Next Owner* is an indicator that the next owner lives in the property (i.e. the property is labeled as owner-occupied in the HMDA data). *White Next Owner* is an indicator that the next owner identifies as white. Data are from sample of homeowners with observed purchase and sale prices (i.e. repeat sales sample) described in Section 2. *** $p<0.001$, ** $p<0.01$, * $p<0.05$

Table A8: Mortgage Status Transitions by Race

	Status in t-1					
	Current	30 DPD	60 DPD	90 DPD	120 DPD	Forcl.
Panel A. Black						
Current	**97.96**	31.51	9.94	6.76	6.95	3.69
30 DPD	2.02	**53.50**	18.82	4.39	0.84	0.48
60 DPD	0.01	14.87	**43.29**	11.95	1.03	0.20
90 DPD	0.00	0.10	26.82	**25.42**	2.25	0.14
120+ DPD	0.00	0.01	0.23	39.92	**77.84**	5.95
Foreclosure	0.00	0.01	0.90	11.56	11.08	**89.54**
Panel B. Hispanic						
Current	**98.54**	32.70	9.27	5.59	7.02	2.68
30 DPD	1.45	**50.53**	15.94	3.34	0.80	0.27
60 DPD	0.01	16.67	**41.51**	9.39	0.88	0.11
90 DPD	0.00	0.08	31.76	**21.30**	1.63	0.07
120+ DPD	0.00	0.01	0.17	41.06	**74.05**	4.11
Foreclosure	0.00	0.01	1.35	19.32	15.62	**92.75**
Panel C. White						
Current	**99.10**	36.18	11.33	6.55	5.76	2.90
30 DPD	0.90	**48.55**	16.60	3.58	0.85	0.37
60 DPD	0.00	15.17	**39.05**	9.41	0.90	0.11
90 DPD	0.00	0.07	31.45	**20.73**	1.85	0.10
120+ DPD	0.00	0.01	0.17	41.10	**74.13**	3.97
Foreclosure	0.00	0.01	1.40	18.64	16.51	**92.54**

Notes: This table presents the transition matrix of payment status by homeowner race/ethnicity. Each number denotes the percent of mortgages with payment status at time t that had a given payment status at time $t-1$. Payment status 120 DPD indicates mortgage pyament is 120 or more days past due but not in foreclosure. Data are from a panel of homeowners with linked credit bureau and mortgage servicing records described in Section 2.

Table A9: Responses to Monthly Mortgage Payment Shocks

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Payment ($)						
Post $\times \Delta E_i$	1410.3	1508.2	1507.9	1512.4		
	(3.289)	(1.249)	(1.247)	(1.625)		
Post $\times \Delta E_i \times$ Black	–269.1	4.917	10.79	11.41	12.11	–0.317
	(7.130)	(3.187)	(3.188)	(3.384)	(3.543)	(3.839)
Post $\times \Delta E_i \times$ Hispanic	–133.1	–4.497	4.420	3.237	4.540	14.40
	(7.170)	(2.777)	(2.799)	(2.958)	(3.337)	(3.529)
Panel B. Delinquency						
Post $\times \Delta E_i$	0.0395	0.0362	0.0366	0.0270		
	(0.00198)	(0.00207)	(0.00207)	(0.00263)		
Post $\times \Delta E_i \times$ Black	0.0967	0.0918	0.0842	0.0366	0.0315	0.0134
	(0.00841)	(0.00862)	(0.00862)	(0.00895)	(0.00926)	(0.0107)
Post $\times \Delta E_i \times$ Hispanic	0.0597	0.0534	0.0422	0.0141	0.0202	0.00580
	(0.00643)	(0.00655)	(0.00661)	(0.00681)	(0.00744)	(0.00832)
Panel C. Default						
Post $\times \Delta E_i$	0.00779	0.00547	0.00569	0.000123		
	(0.00106)	(0.00109)	(0.00110)	(0.00134)		
Post $\times \Delta E_i \times$ Black	0.0383	0.0337	0.0301	0.0124	0.00970	0.00205
	(0.00465)	(0.00458)	(0.00457)	(0.00466)	(0.00479)	(0.00541)
Post $\times \Delta E_i \times$ Hispanic	0.0283	0.0245	0.0191	0.00996	0.0133	0.00943
	(0.00356)	(0.00350)	(0.00352)	(0.00359)	(0.00395)	(0.00436)
Number of Loans	1,717,772	1,709,089	1,709,089	1,567,776	1,567,776	1,567,776
Controls						
Monthly Payment		X	X	X	X	X
Income			X	X	X	X
Credit Score				X	X	X
Geography FE	None	None	None	None	County	Tract

Notes: This table presents differences-in-differences estimates of the impacts of monthly payment changes on the dollar value of monthly payments (Panel A); an indicator that the mortgage is 30 or more days past due (Panel B); and an indicator that the mortgage is 90 or more days past due (Panel C). Each column corresponds to a separate specification. In the differences-in-difference framework, the pre-period corresponds to event months -5 through -2, and the post-period corresponds to event months 1 through 8. Event months are defined as in event studies (Equation 8). ΔE denotes the payment shock. Coefficients can be interpreted as impacts of a 100% increase in monthly payments. Standard errors are in parentheses. All specifications include loan and event time fixed effects. Each additional control variable normalized by subtracting its mean and is interacted with Post$\times \Delta E$: *Monthly Payment* denotes the dollar value of monthly payment prior to payment increase, *Income* denotes log income at origination and log debt-to-income ratio, and *Credit Score* denotes a quartic in credit score at origination. Geographic fixed effects are interacted with Post$\times \Delta E$. Data from panel of homeowners with linked credit bureau and mortgage servicing records who experience a change in their monthly tax and insurance payments described in Appendix Section F.

Table A10: Differential Modification and Foreclosure Rates by Race

	(1)	(2)	(3)	(4)	(5)
Panel A. Modified					
Black	6.442***	5.800***	5.051***	3.890***	2.506**
	(0.116)	(0.121)	(0.143)	(0.327)	(0.899)
Hispanic	–0.687***	0.881***	1.574***	0.176	–0.167
	(0.0837)	(0.0898)	(0.109)	(0.214)	(0.558)
Panel B. Foreclosed					
Black	–3.170***	–4.535***	–4.181***	–4.080***	–2.808**
	(0.134)	(0.138)	(0.166)	(0.373)	(1.002)
Hispanic	7.374***	2.028***	0.628***	1.480***	2.048**
	(0.0974)	(0.103)	(0.125)	(0.243)	(0.629)
Panel C. Self-Cured					
Black	–3.780***	–1.669***	–1.075***	0.173	0.585
	(0.0965)	(0.100)	(0.114)	(0.215)	(0.567)
Hispanic	–6.124***	–2.040***	–1.524***	–0.836***	–1.007**
	(0.0664)	(0.0696)	(0.0791)	(0.128)	(0.319)
N	1,242,197	1,144,514	957,325	335,485	55,341
Controls	Baseline	Borrower, Mortgage	County-Time, Servicer FE	Tract-Time FE	Servicer-Tract-Time FE

Notes: This table presents regressions in which the outcomes capture the events following a homeowner becoming 90 days delinquent on their mortgage, and shows that minorities are more likely to receive a loan modification after becoming delinquent. The three outcomes are *Modified* (Panel A), an indicator that the delinquency resulted in the homeowner's loan terms being modified (μ = 24%); *Foreclosed*, an indicator that the delinquency resulted in a foreclosure (μ = 56%); and *Self-Cured*, an indicator that the delinquency resulted in the homeowner becoming current or paying off the loan (μ = 18%). The specification in Column 1 includes fixed effects for the quarter of default. Column 2 interacts quarter of default with origination year, adds fixed effects for number of years remaining in term, indicators for the mortgage being an ARM, interest-only, or negative-amortization, and adds decile fixed effects for current LTV, original credit score, original income, and original loan amount. Column 3 applies tract-by-quarter of default-by-origination year fixed effects and adds a servicer fixed effect to the controls in (2). Column 4 applies tract-by-quarter of default-by-origination year fixed effects in addition to the controls in (3). Column 5 applies servicer-by-tract-by-quarter of default-by-origination year fixed effects in addition to the controls in (3). Data comprised of homeowners who have become delinquent and are observed in the Fannie Mae, Freddie Mac, and ABSNet data, described in Section 6. Coefficients are scaled by 100 and are interperetable as the percentage point differences in the likelihood of each outcome. *** p<0.001, ** p<0.01, * p<0.05

Table A11: Modification Treatment Effects Placebo Outcomes

	Distressed Sale (1)	Unlevered Return (2)	Imputed Return (3)
$\hat{\gamma}_{s(i),t}$	0.00494	-0.157	-0.261
	(0.00578)	(0.295)	(0.187)
Black $\times\hat{\gamma}_{s(i),t}$	-0.0192	-0.603	0.200
	(0.0101)	(0.498)	(0.316)
Hispanic $\times\hat{\gamma}_{s(i),t}$	-0.00317	-0.277	0.0361
	(0.00644)	(0.304)	(0.207)
Outcome Mean	0.632	-14.02	-9.436
N	131783	90240	131477

Notes: This table presents placebo exercises for the analysis of the impacts of mortgage modifications. Each column estimates the reduced-form impact of the server instrument and its interactions with race/ethnicity indicators on placebo outcomes. The placebo outcomes are defined using the predicted values from a regression of the true outcome (e.g. indicator that ownership spell ends in a distressed sale) on a vector of individual characteristics measured prior to the realization of the true outcome. The vector of characteristics includes loan type (i.e. conventional, FHA, VA); loan purpose; indicators for ARM, interest-only, and negative amortization; term; deciles of credit score, income, interest rate, and amount at origination; current year, and data source (i.e. Fannie Mae, Freddie Mac, ABSNet). Each placebo regression includes interacted fixed effects for purchase year, default year, tract, indicator for negative amortization loan, and indicator for interest-only loan. Data comprised of homeowners who have become delinquent and are observed in the Fannie Mae, Freddie Mac, and ABSNet data, described in Section 6. *** $p<0.001$, ** $p<0.01$, * $p<0.05$

C Data Appendix

C.1 Merged Administrative Data

This section provides additional details on our merged administrative dataset described in Section 2. The merged HMDA-ATTOM-Infogroup dataset forms the foundation of our analysis sample and allow us to provide precise estimates of racial disparities in housing returns. However, these datasets lack a number of variables of interest, such as measures of underlying financial well-being, certain mortgage characteristics, and loan modifications. In order to observe these variables, we turn to linkages with the CRISM, GSE, and ABSNet datasets. These additional datasets allow us to observe important information on our study sample; however, unlike the core HMDA-ATTOM-Infogroup dataset, the use of the CRISM, GSE, and ABSNet datasets entails non-negligible amounts of measurement error generated by imprecision in the merges. In this section, we provide more details on these merges and the strategies used to minimize measurement error.

We rely on a k-nearest neighbors algorithm developed by the Fisher Center at UC Berkeley to link the core HMDA-ATTOM-Infogroup dataset with the CRISM, GSE, and ABSNet datasets. To create the linkage to the CRISM dataset, the algorithm proceeds as follows. Within each US county, the algorithm creates a stable linkage between transactions in ATTOM and loans in McDash, matching records ("neighbors") along a vector of attributes. These attributes include the loan amount, the value of the property, the origination date, the purpose of the loan (e.g. purchase or refinance), whether the loan ended in distress (e.g. foreclosure), the loan lien type, the interest rate, and the date the loan was paid off. The same algorithm is used for the linkage with the GSE and ABSNet datasets, with a similar vector of matched attributes (e.g. loan amount, property value, origination date).

We apply a number of sample restrictions to mitigate the potential impact of measurement error. First, we restrict to matches for which the algorithm chose the nearest neighbor (e.g. as opposed to the second-nearest neighbor). Second, we restrict to matches for which there are no other close matches. Our measure of match closeness comes from a score generated by the algorithm that denotes the closeness of the match along the vector of matched attributes. For the merge with the CRISM data, the 10th, 25th, 50th, and 75th percentiles of this score are 210, 597, 899, and 1,959, respectively (lower scores denote closer matches). For the merge with the GSE and ABSNet data, the 10th, 25th, 50th, and 75th percentiles of this score are 435, 499, 824, and 1,929, respectively. We drop any match with a neighbor with a score within 200 of the score of the chosen match. Third, we restrict our analysis to matches with scores at or below 2,000 (approximately the 75th percentile of the score).

The merge score provides a convenient way to test whether measurement error significantly impacts our results. We replicate our analyses that use the CRISM, GSE, and ABSNet datasets using more stringent restrictions on merge quality, restricting to matches with a score of 700 or less (slightly below the median score). The results from this replication exercise are available upon request. Comparing the results of this exercise to the main results, our findings are largely unchanged with some loss in precision due to the use of a smaller sample. The robustness to these sample choices indicates that measurement error is not likely to significantly affect the conclusions we draw from the analysis using the CRISM, GSE, and ABSNet data sources.

C.2 External Data Sources

This section provides additional details on the construction of the external data sources from the Survey of Income and Program Participation (SIPP) and the Panel Study of Income Dynamics (PSID).

For the SIPP sample, we draw on waves between 1991 and 2018. All results use the person weights, and dollar-denominated values are deflated to 2016 dollars. In Table 3, we restrict the sample to homeowners with positive liquid wealth, and in Appendix Figure A25, we restrict to homeowners between ages 20 and 65. Our final sample includes 1.1 million observations corresponding to 423 thousand households, with households defined as the unique combination of SIPP sample units/address IDs, and family IDs.

To construct a liquid wealth variable, we follow Chetty et al. (2017) and define liquid wealth as the sum of assets held in stocks, bonds, checking accounts, and savings accounts, excluding retirement, accounting for changes to variable construction and variable names across panels in some years. We winsorize this variable at the 1% level. Our annual unemployment variable is an indicator that measures whether in the prior 12 months, any earner in the household had no job in a month, was on layoff, or was looking for work in all weeks. Income is the annualized monthly income for the household, and delinquency corresponds to the question, "Was there any time in the past 12 months when (you/your household) did not pay the full amount of the rent or mortgage?"

For the PSID sample, we construct a dataset at the family (household) level using PSID waves between 2001 and 2017. We restrict the sample to households who are consistently reported in the survey for consecutive panels. That is, we drop 8,252 observations (1,593 households) that have gaps in the years for which data is provided. All results use the Core/Immigrant family longitudinal weights, and dollar-denominated values are deflated to 2016 dollars. In Appendix Figure A25, we restrict the sample to households whose reference person is between the ages of 30 and 65. Our combined sample includes 68,582 observations (14,554 households) for the years 2001 to 2017.

D Constructing the Internal Levered Rate of Return

This section describes the calculations used to estimate the levered (internal) rate of return (Equation 2). This is the return that satisfies the following equation:

$$0 = -DownPay_{i0} + \sum_{t=1}^{T_i-1} \frac{rent_{it} - pymt_{it}}{(1+r_i^l)^t} + \frac{\max\{0.01, rent_{iT} - pymt_{iT} + 0.95P_{iT} - UPB_{iT}\}}{(1+r_i^l)^{T_i}}$$

We draw on a variety of data sources to compute each component of this equation. Table C1 provides summary statistics on the imputed variables described in this section. $DownPay_{i0}$ denotes the homeowner's down payment and is the sum of initial equity and closing costs. Equity is measured directly as the difference between purchase price and loan values in the ATTOM dataset. To estimate closing costs, we use the 2019 HMDA data, which contain information about closing costs paid for originated mortgages. We restrict to owner-occupied, first-lien, purchase mortgages with LTV less than or equal to 100% and loan amounts less than or equal to $1,245,000 (corresponding to the 99th percentile). We compute total closing costs as total loan costs minus lender credits. We then regress closing costs on the loan amount within three LTV bins: (0,82%], (82% to 95%), and [95%,100%].[39] We then impute closing costs for each transaction in ATTOM using the coefficients from these regressions.

To impute monthly rents $rent_{it}$, we first measure median annual county-level rental costs using HUD fair market rents.[40] We measure median county house prices using Zillow's Home Value Index (ZHVI). Dividing the ZHVI house values by the HUD Fair Market rents and winsorizing at the 1% level yields price-to-value ratios at the county-by-year level. For each transaction, we derive $rent_{it}$ by applying the price-to-rent ratio in the year of purchase to the property's purchase price, and inflating rents using annual changes in HUD fair market rents.

Monthly housing costs $pymt_{it}$ are comprised of two components: principal and interest payments and tax and insurance payments (i.e. escrow). To impute monthly mortgage payments (and UPB_{iT}), we apply standard amortization formulas assuming a 30-year term. We impute interest rates using a sample of fixed interest mortgages measured in McDash. We impute interest rates separately for first- and second-lien mortgages. For first-lien mortgages, we regress interest rates on the full interaction of LTV and the three LTV bins used to calculate closing costs as well as closing quarter-by-county fixed effects. For second-lien mortgages, we regress interest rate on LTV and the interaction of two LTV bins (corresponding to a cutoff of 20% LTV), as well as closing year-by-state fixed effects.[41] For missing county-quarter cells, we impute using the mean value in that quarter. We then impute interest rates for each transaction in ATTOM using the coefficients and fixed effects from these regressions.

To impute escrow payments, we use a sample of first-lien mortgages where escrow is observed in the McDash data. We measure escrow payments 18 months after the closing month and regress

[39] These categories allow our calculations to reflect higher closing costs for higher-LTV mortgages (e.g. due to higher mortgage insurance costs).

[40] In cases where fair market rents reflect the the 40th or 45th percentile of rents, we inflate using the ratios of these quantiles from the distribution of rental costs reported in the 2011 PSID.

[41] Coarser fixed effects for second liens are used to compensate for relatively fewer observations of second lien mortgages.

escrow payment as a share of property value on LTV, an indicator that the LTV is greater than 82%, their interaction, and closing year by county fixed effects. We use the predicted values from this regression to impute escrow payments in the main data. If the mortgage was originated before 1998, we impute using the 1998 values due to limited temporal coverage in the McDash data.

Lastly, we assume that 5% of the sale price goes towards paying closing costs, and that in the event of a foreclosure, there is no surplus revenue to be redistributed to the property owner (i.e. the final term evaluates to 0.01). This latter assumption is justified by the fact that in the Freddie Mac single-family loan database, only about 3% of foreclosures have net sales proceeds listed as covered (i.e. there exist surplus funds that could potentially be returned to the homeowner). Imposing a floor of \$0.01 ensures that r^l is well-defined.

Table C1: Summary Statistics for Imputed Values

	Mean	SD	p10	p90
Interest Rate, First Lien	0.061	0.0102	0.045	0.072
Interest Rate, Second Lien	0.067	0.0203	0.038	0.096
Principal and Interest Payment	1417	1231.6	541	2589
Escrow Payment	397	1162.9	158	681
Monthly Rent	1515	7748.0	643	2560
Price-to-Rent Ratio	15.39	5.610	8.96	23.58
Closing Costs	4314	1112.7	3313	5590

Notes: This table presents summary statistics for the imputed values used to construct the internal rate of return (Equation 2). See Appendix Section D for more details.

E Adjustment for Finite-Sample Bias

We estimate racial returns gaps using a sample of properties that were purchased and sold between 1990 and 2017. While this approach allows us to accurately measure realized returns, not being able to observe realized returns for properties that have not yet been sold means that our estimates likely differ from the difference in returns unconditional on the length of ownership. In this section, we implement a strategy to re-weight our estimates to account for this difference and to provide plausible bounds on the unconditional returns gap.

The importance of considering different realized returns among properties whose sales are unobserved is apparent when examining heterogeneity in the size of the racial returns gap by tenure length. Figure E1 presents estimates from Equation 3 split by the number of years the owner has held the property. We restrict to 17-year gaps because the vast majority of our sample is contained in the 2000-2017 window. Panel A presents results for the unlevered rate of return and Panel B presents results for the levered return. The estimated racial gaps vary substantially by tenure length, and tend to be smaller for longer ownership spells. This finding suggests that the racial returns gaps are likely to be smaller among the set of properties whose sale is not observed in the sample because it will occur at some point in the future.

In order to derive estimates of the returns gap that are interpretable as the expected disparity in returns unconditional on property sale within a given window, we can extrapolate the racial gap in returns for longer tenure lengths and reweight our estimates to match the empirically-observed distribution of tenure lengths. The theoretical (unobserved) statistic of interest is the difference in unconditional expected returns between black or Hispanic homeowners and white homeowners. To approximate this difference and to assess the sensitivity of our baseline estimates to adjusting for the previously described source of bias, we compute the following for $r \in \{black, Hispanic\}$:

$$\begin{aligned}\Delta_r &\equiv E[R_i|race(i) = r] - E[R_i|race(i) = white] \\ &= \sum_{t=1}^{T} Pr[tenure(i) = t, race(i) = r] \times E[R_i|tenure(i) = t, race(i) = r] \\ &\quad - \sum_{t=1}^{T} Pr[tenure(i) = t, race(i) = white] \times E[R_i|tenure(i) = t, race(i) = white] \\ &\cong \sum_{t=1}^{T} Pr[tenure(i) = t]\hat{\beta}_t^r\end{aligned}$$

In the above equation, R_i denotes the returns for homeowner i, $\hat{\beta}_t^{\{black,Hispanic\}}$ denotes the estimated racial returns gap for the sample of ownership spells of length t, and $Pr[tenure(i) = t]$ denotes the unconditional probability that homeowner i experiences tenure length t.

To estimate $Pr[tenure(i) = t]$, we can use standard tools from survival analysis. The blue line in Figure E2 plots non-parametric Kaplan-Meier estimates of the survivor curve for our sample of ownership spells in ATTOM. Given that the vast majority of ownership spells in our sample occur between 2000 and 2017, we need to extrapolate the survivor curve in order to estimate $Pr[tenure(i) = t]$ for $t > 17$. To do this, we draw on the distribution of tenure length for a sample of new homeowners in the PSID between 1968 and 2017. The survivor curve estimated from a sample of homeowners in the PSID is plotted in the solid red line in Figure E2. Notably, the survivor curve for PSID tenures is below that of ATTOM tenures because PSID tenures capture the length of occupancy, i.e. the number of years a homeowner lives in that property, whereas the ATTOM tenures capture the length of property ownership. It appears to be common for renters to purchase a home and retain ownership of that property after moving into a new home. To accommodate this difference in definitions, we extrapolate the ATTOM survivor curve by inflating the value of the PSID curve evaluated at a tenure length of 17 years to match the ATTOM curve. We use the actual and extrapolated values of the survival curve to define $Pr[tenure(i) = t]$ for $t <= 49$.

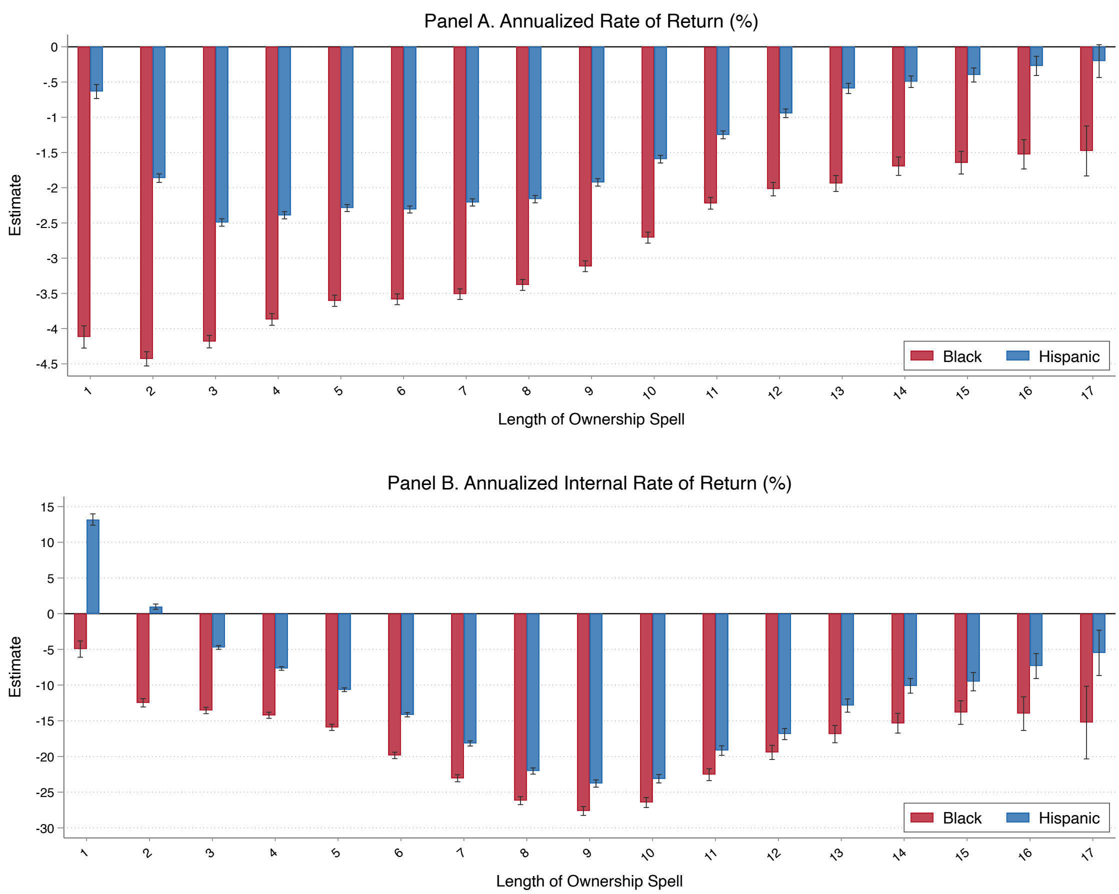
In order to apply our adjustment, we must also extrapolate $\beta_t^{\{black,Hispanic\}}$ for $k > 17$. To assess a range of plausible estimates, we estimate $\Delta_{\{black,Hispanic\}}$ for three sets of assumptions.[42] The first case assumes that $\beta_t^{\{black,Hispanic\}} = \beta_{17}^{\{black,Hispanic\}}$ for $t > 17$. Given that the estimated gaps tend to diminish at longer tenures, this case provides a plausible upper bound on $\Delta_{\{black,Hispanic\}}$. A second case provides a lower bound estimate, in which we assume that $\beta_t^{\{black,Hispanic\}} = 0$ for $t > 17$. The third case offers a middle ground, in which we assume $\beta_t^{\{black,Hispanic\}} = 0$ for $t \geq 30$ (corresponding to a standard mortgage term), and linearly impute between $\beta_{17}^{\{black,Hispanic\}}$ and

[42] In each case, we assume that $\beta_t^{\{black,Hispanic\}} = \beta_{49}^{\{black,Hispanic\}}$ for $t > 49$.

$\beta_{30}^{\{black,Hispanic\}}$.

Table D1 presents adjusted estimates of the racial returns gap. Each number corresponds to an estimate of $\Delta_{\{black,Hispanic\}}$ at baseline (Column 1), applying the upper bound assumption (Column 2), linearly extrapolating (Column 3) and applying the lower bound assumption (Column 4). Adjusting for the finite sample window reduces the size of the gaps by about one-third to one-half. Notably, even under the implausible stringent lower bound assumptions, the estimated gaps in returns are economically large, and remain larger in dollar terms than the previously documented racial gaps discussed in Section 3.

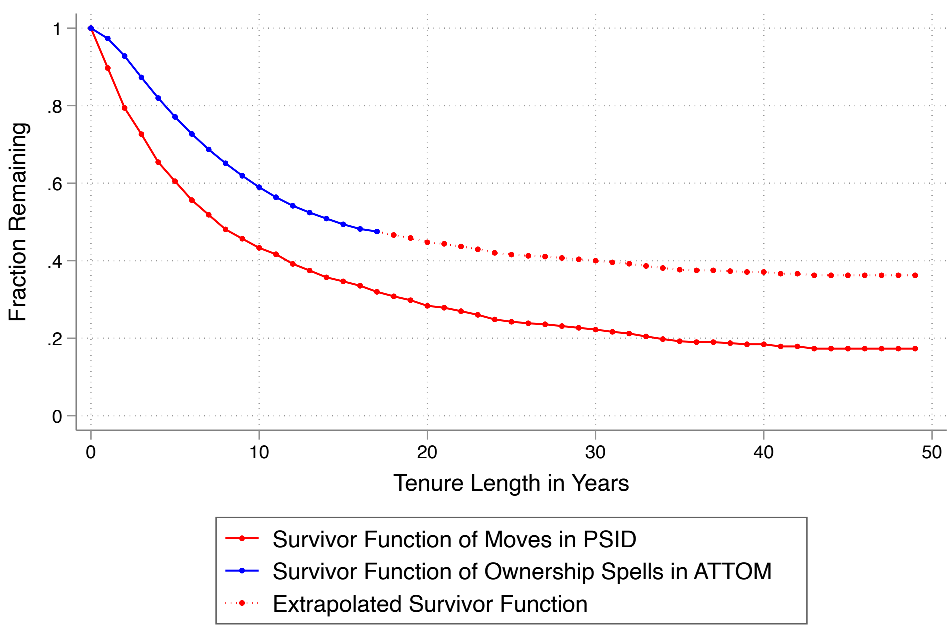
Figure E1: Heterogeneity by Length of Ownership Tenure



Notes: These figures present estimates of racial gaps in housing returns. Each pair of bars corresponds to a separate regression and indicates coefficients of black and Hispanic indicators from Equation 3. Regressions include purchase year-by-sale year-by-county fixed effects. The outcome in Panel A is the unlevered rate of return (Equation 1), and the outcome in Panel B is the levered rate of return (Equation 2). Each pair of coefficients corresponds to a subsample defined by the number of years the owner held the property (i.e. the length of the ownership spell). Data are from sample of homeowners with observed purchase and sale prices (i.e. repeat sales sample) described in Section 2.

Lastly, in order to implement our wealth accounting framework (Equation 4), we require estimates of inflation-adjusted returns for black and white homeowners. To compute average inflation-adjusted returns for white homeowners, we must extrapolate returns for tenure lengths outside of our 1990-2017 window. We compute the average inflation-adjusted return for white homeowners with tenure lengths between 18 and 27 years in our sample, which is 1.3% per year. Because annual housing returns appear to be roughly constant at longer tenures, the average return for tenures between 18 and 27 years is very similar to the average return of 1.2% for tenures lasting 17 years. We therefore assume that returns are 1.3% for white homeowners with tenure lengths greater than 27 years, and compute a weighted average of returns by tenure length, with weights corresponding to unconditional tenure length probabilities estimated using the previously described survival analysis. This yields an average inflation-adjusted return of 0.38% per year for white homeowners. We then estimate the black-white gap in inflation-adjusted housing returns by tenure length and adjust for finite-sample bias. We use the middle-ground estimate that assumes $\beta_t^{\{black,Hispanic\}} = 0$ for $t \geq 30$ and linearly impute between β_{17}^{black} and β_{30}^{black}. Subtracting the adjusted black-white gap from the average returns for white homeowners yields an average inflation-adjusted return of -1.4% per year for black homeowners.

Figure E2: Survivor Functions in ATTOM and PSID



Notes: This figure plots Kaplan-Meier estimates of survivor curves associated with ownership and occupancy spells. The blue line plots the estimated survivor curves from ownership spells occurring between 2000 and 2017. The solid red line plots estimated survivor curves from occupancy spells for homeowners in PSID between 1968 and 2017. The dotted red line plots the extrapolated survivor curve derived by inflating the value of the PSID curve evaluated at a tenure length of 17 years to match the ATTOM curve. Appendix E presents more details on the adjustment for finite-sample bias.

Table D1: Adjusted Estimates of Returns Gap

	Unadjusted (1)	Upper Bound (2)	Linear Extrap. (3)	Lower Bound (4)
Panel A. Unlevered Rate of Return				
Black	-3.71	-2.44	-1.80	-1.74
Hispanic	-1.96	-1.03	-0.94	-0.94
Panel B. Levered Rate of Return				
Black	-16.49	-16.64	-10.04	-9.40
Hispanic	-7.57	-8.50	-6.12	-5.89

Notes: This table presents estimates of the racial gap in housing returns returns adjusted for bias arising from the finite sample window. Each number corresponds to an estimate of the black-white or Hispanic-white difference in returns. Panel A presents figures for unlevered returns and panel B presents figures for levered returns. Column 1 presents baseline unadjusted estimates, and Columns 2 through 4 correspond to different assumptions concerning out-of-sample returns gaps. See Appendix E for details.

F Delinquency Responses to Monthly Payment Changes

This section describes the methodology we use to show that minority homeowners are more likely to become delinquent in response to an increase in their monthly payments. This analysis applies the methodology originally developed by Wong (2020) to analyze differences in responses by race and ethnicity using changes in monthly payments.

We interpret responses to changes in monthly payments as responses to liquidity shocks. Homeowners must satisfy their monthly mortgage payments in order to avoid foreclosure and eviction. While homeowners could change the amount of their monthly payment by refinancing their mortgage or selling their house, these responses take time and incur substantial fixed costs. Consequently, short-term responses to monthly payment shocks can be interpreted as responses to liquidity shocks. This interpretation is also supported by a large body of evidence indicating that liquidity is a key determinant of mortgage default (Ganong and Noel, 2020a).

The advantage of analyzing responses to monthly payments in the linked administrative data, relative to our analysis using the SIPP data, is that the linked administrative data allow us to estimate the impact of liquidity shocks on mortgage delinquency by race using precise measures of both shocks and responses. This is an improvement relative to the SIPP data, in which measures of mortgage delinquency, income, and liquidity are self-reported by respondents and therefore likely subject to nontrivial amounts of measurement error.

We leverage an institutional feature of mortgage payment arrangements that generates quasi-experimental variation in monthly payments. Monthly mortgage payments are comprised of two distinct components: principal and interest payments and escrow payments. Escrow payments are used by approximately four-fifths of mortgaged homeowners to pay property taxes and insurance (Corelogic, 2017). Escrow accounts are maintained by mortgage servicers and offer homeowners the convenience of paying their property taxes, homeowner's insurance, and mortgage insurance in monthly installments together with their regular mortgage principal and interest payments. Mortgage servicers then pay taxes and insurance to governments and insurers on behalf of the homeowner.

Mortgage servicers must update the level of escrow payments once a year to reflect changes in property tax and insurance payments. The calculation of these updates performed by mortgage servicers is subject to stringent regulations (CFPB, 2019), which generate a specific pattern of payment amounts in the data: for each homeowner, escrow payments are constant for twelve months before and after annual escrow updates. We analyze the causal impacts of changes to monthly payments using the quasi-experimental variation generated by annual escrow updates. Specifically, we estimate event studies of the following form:

$$y_{it} = \alpha_i + \gamma_s + \sum_{s \neq -2} \beta_s 1[t = e_i + s](\Delta E_i) + \varepsilon_{it} \tag{8}$$

In Equation 8, y_{it} denotes an outcome for homeowner i in month t. α_i and γ_s denote homeowner and event time fixed effects, respectively. ΔE_i denotes the percent change to monthly payments due to the escrow update, defined by $\Delta E_i = \frac{escrow_1 - escrow_0}{escrow_0 + P\&I_0}$. The identification assumption required to identify β_s, the effect of a monthly payment increase at event time s, is that the outcomes of homeowners with small increases and decreases to their monthly payment represent a valid counterfactual for the potential outcomes of homeowners with large increases in monthly payments. This assumption can be validated by evaluating the presence of common trends (i.e. whether $\hat{\beta}_s = 0$ for $s < 0$). Note that the identification in the original methodology developed by Wong (2020) pertains only to changes in property taxes, rather than changes in escrow payments which include both taxes and insurance. Our assumptions are somewhat stronger since homeowners may be more able to adjust their insurance payments than their property taxes. We estimate Equation 8 on a monthly panel of homeowners with escrow accounts.[43]

We find that minority homeowners are particularly sensitive to liquidity shocks in the form of changes in monthly payments. Figure A22 plots the results of estimating the event study regressions (Equation 8) separately by race. The event studies indicate that black and Hispanic homeowners are significantly more sensitive to similarly-sized shocks than white homeowners. Panel A shows that a 10% increase in monthly mortgage payments increases the delinquency rate by about 1.3 percentage points for black homeowners, 0.8 percentage points for Hispanic homeowners, and 0.5 percentage points for white homeowners. Note that while these racial differences are large in absolute terms, these increases are similar relative to baseline levels of mortgage delinquency (about 22 percent for all three groups). Minority homeowners also demonstrate more sensitivity to shocks when the outcome is defined as 90-day delinquency, presented in Appendix Figure A23.

We show that the higher sensitivity of minority homeowners can be statistically accounted for

[43]Because escrow payment amounts are typically constant for twelve months following an annual update, it is straightforward to identify the month in which monthly payments change to reflect increases in annual property taxes or insurance payments. Specifically, for each homeowner, we define a regular update as two successive twelve month sequences of constant escrow payments (in the notation of Equation 8, twelve months of $escrow_0$ followed by twelve months of $escrow_1$). We define at most one event for each homeowner i by selecting the largest change in escrow payments that follows this pattern.

by factors that are upstream of the home purchase decision, and that are likely correlated with liquid wealth holdings and income stability. Appendix Table A9 shows that controlling for income and debt-to-income at mortgage origination reduces the difference in sensitivity relative to white homeowners by about 8% for black homeowners and 18% for Hispanic homeowners, and controlling for credit score at mortgage origination reduces the difference by about 49% for black homeowners and 47% for Hispanic homeowners. Notably, credit score at origination is designed to predict repayment ability, and as such is likely correlated with income stability and liquidity. Controlling for Census tract reduces the difference by 24% for black homeowners and 10% for Hispanic homeowners. While this exercise should be interpreted as strictly correlative, it is consistent with the results in Figure 5 that indicate that most of the racial differences in financial distress can be explained, in a statistical sense, by differences in observable financial and neighborhood-level characteristics.[44]

G Differences in Receipt of Mortgage Modification by Race and Ethnicity

In this section, we present evidence that black and Hispanic homeowners are more likely to receive mortgage modifications than observationally similar white homeowners. Our findings are similar to those in Collins et al. (2015), who document similar patterns in a sample of subprime loans originated between 2004 and 2006.

We link homeowners in our administrative datasets to the mortgage records contained in the Fannie Mae, Freddie Mac, and ABSNet datasets. For this sample, we can observe both the occurrence of a modification as well as the identity of the homeowner's servicer. We restrict the sample to homeowners who become 90 or more days past due on their mortgage and classify the outcome of their first 90 day delinquency into one of three categories: modified, foreclosed, or self-cured. We directly observe modifications and foreclosures, and we define a loan as self-cured if the borrower makes three consecutive payments or pays off the loan. The outcome of the delinquency is defined as whichever of these three events occurs first.[45]

We show estimate the following equation:

$$\mathbb{1}\{\text{Delinquency Outcome}_i\} = \alpha_0 \mathbb{1}\{\text{Black}_i\} + \alpha_1 \mathbb{1}\{\text{Hispanic}_i\} + \mu_{f(i)} + \varepsilon_i \tag{9}$$

The outcome is defined as an indicator that the 90 day delinquency of homeowner i ended in modification, foreclosure, or self-cure. $\mu_{f(i)}$ denotes fixed effects which vary by specification. The values of $\hat{\alpha}_0$ and $\hat{\alpha}_1$ capture the extent to which delinquent black and Hispanic homeowners are more or less likely than white homeowners to end their delinquency in a given outcome.

Table A10, Column 1 estimates a baseline version of Equation 9 with fixed effects for quarter of default, and shows that black homeowners are about 6 percentage points more likely to receive a modification relative to white homeowners. The black-white difference is driven by relatively lower foreclosure and self-cure rates. Hispanic homeowners are slightly less likely to receive a modification,

[44] This finding is similar to those in Ganong et al. (2020), who find that differences in liquidity can explain racial differences in marginal propensity to consume.

[45] Note that a small fraction of loans (less than 2%) end in bankruptcy or repurchase. These observations are kept in the analysis dataset but not captured in the three main categories of outcomes.

and appear to be much less likely to self-cure. Adding in granular fixed effects that capture borrower characteristics (e.g. credit score, income) and mortgage characteristics (e.g. current LTV, origination year, interest type) results in a 5.1 and 1.6 percentage point higher modification rates for black and Hispanic homeowners, respectively (Column 3). Notably, even when comparing homeowners within the same servicer, Census tract, and time period, black homeowners are 2.5 percentage points more likely to receive a modification than white homeowners (with no statistically significant difference between Hispanic and white homeowners).

These results indicate that even conditional on defaulting on payments as well as a wide range of observables, black (and to some extent Hispanic) homeowners appear to receive favorable treatment from mortgage servicers. This behavior is consistent with mortgage servicers internalizing the higher house price penalties associated with foreclosures on minority-owned properties. This type of discrimination could arise from an equilibrium in which mortgage servicers attempt to maximize value for investors and anticipate that the value of avoiding a foreclosure for a black or Hispanic homeowner is higher than for a white homeowner.