RACIAL AND ETHNIC DIFFERENCES IN THE FINANCIAL RETURNS TO HOME PURCHASES

Matthew E. Kahn

WORKING PAPER 28759

NBER WORKING PAPER SERIES

RACIAL AND ETHNIC DIFFERENCES IN THE FINANCIAL RETURNS TO HOME PURCHASES

Matthew E. Kahn

Working Paper 28759
http://www.nber.org/papers/w28759

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
May 2021, Revised August 2023

I thank Linna Zhu and two anonymous reviewers and participants at the June 2023 University of Wisconsin Conference for helpful comments. The views expressed herein are those of the author and do not necessarily reflect the views of the National Bureau of Economic Research.

Racial and Ethnic Differences in the Financial Returns to Home Purchases
Matthew E. Kahn
NBER Working Paper No. 28759
May 2021, Revised August 2023
JEL No. R21,R3,R31

ABSTRACT

The racial and ethnic composition of home buyers varies across geographic locations. Since home prices grow at different rates across counties and within counties, these place based bets yield different average rates of return for different demographic groups. I estimate these differential returns by combining micro data from HMDA with zip code level data from Zillow. Based on this index of housing returns from 2010 to 2022, I find that at the national level that Asian buyers earn higher returns than other groups. For California buyers and for Los Angeles buyers, Black people earn roughly the same average rate of return but face a higher standard deviation in returns than other groups.

Matthew E. Kahn
Department of Economics
University of Southern California
3620 South Vermont Ave.
Kaprielian (KAP) Hall, 300
Los Angeles, CA 90089-0253
and NBER
kahnme@usc.edu

Introduction

There is a large racial wealth gap in the United States such that the average white household has ten times as much wealth as the average Black household (McIntosh, Moss, Nunn and Shambaugh 2020).[1] One important determinant of one's wealth is the average rate of return to one's asset portfolio. Housing wealth continues to be an important part of a majority of American's asset portfolio. Based on data from the 2001 Survey of Consumer Finances, Di (2003) estimates that residential real estate represents 27% of average household wealth.

The indivisibility of housing means that homeowners are less likely to hold as diversified a portfolio as they would have had they rented. Much of a home owner's wealth is tied to a place based bet whose ex-post returns depends on how the local economy and local quality of life evolves over time. During a time of rising income inequality, increased international investment in coastal city real estate and regulatory limits to building housing in Superstar Cities, there are large differences in price appreciation across U.S local housing markets (Gyourko, Mayer and Sinai 2013). Based on Zillow price index data, U.S real estate increased in nominal terms by 197% from January 2000 to April 2023. Over that same time period, residential metropolitan level area real estate prices increased by 297% in San Francisco, 213% in Seattle but only by 107% in Chicago and 83% in Cleveland. Who has gained from the spatially concentrated housing boom in high amenity areas and in the Superstar tech cities (Gyourko, Mayer and Sinai 2013)?

The indivisibility of housing creates a type of binding hedonic bundling constraint. Unlike with stocks, one cannot form a convex portfolio of investing small amounts of money in different homes. Hedonic bundling means that such households cannot build a spatially diversified housing portfolio (Rosen 2002).

[1] Blau and Graham (1990) use 1976 and 1978 NLSY data on young men and women to measure the composition of racial differences in wealth. They find that young Black families hold 18 percent of the wealth of white families. They posit that intergenerational transfers of wealth are a major reason for the racial wealth gap they observe in the 1970s, while finding less evidence for differences in accumulating wealth through home and business ownership.

Given this constraint, different demographic groups tend to make different place based bets with respect to investing their wealth. For example, Asians and Hispanics are much more likely to buy homes in California than Black people and Black people are more likely to buy homes in Georgia than other demographic groups. If all home prices grew at the same national rate then there would be no wealth consequences due to place based bets on real estate. In this case, home owners would obtain a different "dividend flow" of local amenities from where they own but the rate of return would be the same across groups. But, home prices grow at different rates across geographic units such as counties or zip codes.

To measure the economic consequences of the hedonic bundling problem, this paper presents a shift share analysis of the returns to home purchases to calculate differences across demographic groups in the nominal returns to ownership. To study demographic differences in realized real estate returns, I use two different datasets. I use micro data from the 2007 to 2017 HMDA loan files to identify the count of home buyers who obtain a loan by geographic area by demographic group by year of purchase. The HMDA micro data provide the demographic information to create the shift share weights. The shift share calculation combines the HMDA weights with Zillow price index data by geographic area and by purchase year to calculate the annual average rate of return for the average person in a demographic group who buys a home in a given year using a FHA loan.

My paper contributed to an emerging literature that studies how the rate of return to real estate varies across demographic groups. Gender differences in the rate of return have been documented (Goldsmith-Pinkham and Shue 2023, O'Connor et. al 2018). Other research has independently investigated racial differences in the returns to housing. In an important contribution, Kermani and Wong (2021) assemble several data sets to document the fundamental role that distressed asset sales play in lowering the economic returns earned by black and Hispanic homeowners. They find that their realized returns that are 3.7 and 2.0 percentage points lower than white homeowners, respectively. They argue that this gap is driven almost entirely by differences in distressed home sales (i.e. foreclosures and short sales). They also document that Black buyers are more likely to borrow more to finance their homes. Such leveraged households have on average earned a higher rate of return.

My study complements their study. I mainly focus on describing differences in the geography of home ownership. My study builds on the descriptive study presented by Zonta (2019). She presents a series of detailed maps of specific cities such as Chicago documenting that Black buyers tend to buy in majority Black neighborhoods. My empirical findings generalize and update her results.

I focus on unleveraged returns and I assume that owners of property in a given zip code earn the same rate of return. Given the year when different people buy their home, I estimate their annual rate of return under different holding patterns (i.e owning the home for 5 years or 10 years or longer). An analysis that focuses on a specific home buyer's return is a conditional analysis that is based on the selected buy and sell date. My analysis conditions on the buy date but does not require information on the sell date.

My approach to estimating average returns captures the concept of comparing "place based bets" holding all other factors **constant**. Based on this index of housing returns, I find that at the national level that Asian buyers earn higher returns than other groups. For California buyers and for Los Angeles buyers, Black people earn roughly the same average rate of return but face a higher standard deviation in returns than other groups.

Some Descriptive Facts

Throughout this paper, I rely on Zillow's Home Value Index (ZHVI).[2] I take the monthly data available at https://www.zillow.com/research/data/ and I calculate annual averages for the years 1996 to 2020. The units are nominal dollars. Given that Zillow data are produced by a private company, it is important to double check the data's quality. FHFA provides its own home price index by state/year/quarter.[3] Over the years 1996 to 2020, the correlation between

---

[2] Gorback and Keys (2020) document that there is a high correlation between using the Zillow ZHVI and their own micro panel data approach for estimating geographic price indices. Such cross-data set robustness checks raise my confidence that the Zillow data can be used to describe cross-group average returns differentials.

[3] The data are available here

https://www.fhfa.gov/DataTools/Downloads/Documents/HPI/HPI_AT_state.txt the state/year average FHFA index and the ZHVI is .87. For the 1206 data points, the correlation between the annual percent change in each index is .958.

Given this fact, I proceed with using the ZHVI data. The Zillow data coverage of counties changes over time. In 1996, there are 1017 counties in the data. My shift share analysis starts in the year 2007. By 2007, Zillow reports ZHVI data for 2165 counties. These counties were home to 94.17% of the nation's population in the year 2000. By 2020, the Zillow data cover 2861 counties. These 2861 counties were home to 99.43% of the nation's population in the year 2000. As counties enter the Zillow sample, I use these data over time in the shift share analysis I report below. While the Zillow data do not represent a balanced panel, the counties that eventually enter the Zillow sample in later years are the smaller counties. Based on year 2000 census data, the average population size of counties not always in the Zillow data is 39,842. The average year 2000 county population size for counties always in the Zillow data from 1996 to 2020 is 202,981.

In Figure One, I report the ZHVI index for the years 1996 to 2020 for the entire nation and the metropolitan areas of Los Angeles, San Francisco and Seattle. I chose these three markets to highlight price dynamics across local markets. Back in 1996, San Francisco's real estate was the most expensive but the differences in prices across the four categories were small. Over the 25 years, a divergence emerges. San Francisco's real estate has appreciated by much more than the national average and so has real estate in Los Angeles and Seattle.

To further explore the geography of Zillow's ZHVI dynamics, in Figure Two I report each state's average annual percentage change in the ZHVI and I graph this against the state's standard deviation of the average annual percentage change in the ZHVI. There is a positive correlation such that higher returns states feature a greater standard deviation. California stands out as having one of the highest rates of return. Louisiana and Ohio are at the other end featuring low returns and a low standard deviation.

In the shift-share calculations presented below, I use HMDA micro data to construct the demographic shares. The HMDA micro data that are available from 2007 to 2017.[4] For a

[4] The data are posted at https://www.consumerfinance.gov/data-research/hmda/historic-data/.

discussion of why the HMDA data were created see Munnell, Tootell, Browne and McEneaney (1996). "[5] There is a low minimum threshold of loans such that banks that issue more loans than this threshold must provide their data for the HMDA database.

I focus on the observations for loans for home purchases for owner occupied housing for 1 to 4 family dwellings. Foreign buyers who borrow from foreign banks and cash buyers are not included in the data set. In Figure Three, I use the Zillow Data and the HMDA data by calendar year to create the average price paid for housing for four different demographic groups; All buyers, Asian Buyers, Black buyers and Hispanic buyers. I weight the annual nominal Zillow data by zip code by the share of each demographic group who purchase housing in that zip code. For example, if 1.5% of all Asian buyers in 2009 purchased a home in zip code 90210, then Zillow's overall home price index for zip code 90210 would receive a weight of .015 in calculating the average Asian home price index presented in Figure Three. As shown in Figure Three, Asian home buyers have purchased housing in zip codes where housing is more expensive than the average home buyer and this differential has grown in recent years.

In Table One, I use the micro HMDA data from 2007, 2009, 2011, 2013, 2015, and 2017 to report the percentage of home buyers who purchase in each state. Both depository and non-depository institutions must report. They report single and multifamily, purchase, home improvement. They report if they issued more than 25 loans.

In Table One, the rows in each column sum to 100. Based on the HMDA data, 9.93% of all buyers purchase a California home. In contrast only 4.94% of Black buyers purchase in California. 27.8% of Asian home buyers and 22.5% of Hispanic home buyers purchase in California. The contrast between California and Georgia is illustrative. Based on the HMDA data, only 3.37% of all buyers purchase a Georgia home but 10.16% of Black people purchase a home there. Texas offers another distinctive data point as 9.64% of Asians and 9.57% of Black

[5] "The Home Mortgage Disclosure Act (HMDA) requires many financial institutions to maintain, report, and publicly disclose loan-level information about mortgages. These data help show whether lenders are serving the housing needs of their communities; they give public officials information that helps them make decisions and policies; and they shed light on lending patterns that could be discriminatory." (source https://www.consumerfinance.gov/data-research/hmda/).

people buy a home there. In contrast, 19.13% of Hispanics purchase a home there.[6] Drilling down to the zip code level, consider Beverly Hills (zip code 90210). In 2015, the HMDA data lists 145 observations for this zip code; eleven borrowers were Asian, four were Black and none were Hispanic.

Table Two reports similar data but focuses on home buyers who purchase in a metropolitan area. Consider San Francisco. Only 1.47% of all metropolitan home buyers purchase in San Francisco. Only .66% of Black metropolitan home buyers purchased there. In contrast, 6.77% of Asian metropolitan home buyers purchased there. The Seattle shares reveal a similar pattern. In contrast, 1% of Asians buy a home in the Detroit metropolitan area and 2.02% of Black people purchase a home there.

As a first step to use both the Zillow ZHVI data and the HMDA micro data, I calculate average home prices paid by demographic group by purchase year. I take the ZHVI index each year at the county level and then at the zip code level, and I calculate the weighted average of this index using the demographic shares by year. This yields each group's average price paid for housing in nominal dollars. The average home price using the Zillow county/year level data is calculated using this formula for demographic group D in year t for county g. The zip code calculations use a similar formula.

$$Average\ Price_{Dt} = \sum_{g=1}^{G} Share_{gtD} * Zillow_{gt} \qquad (1)$$

Table Three reports the results. In every year from 2007 to 2017, Asian home buyers are purchasing in more expensive counties and zip codes. Black home buyers are purchasing homes in the lease expensive counties and zip codes. Based on the zip code level data, the average Asian home buyer is spending roughly twice as much on housing than the average Black home buyer.[7]

---

[6] For long run trends in racial differences in home ownership and residential segregation trends see Collins and Margo (2001, 2003) and Cutler, Glaeser and Vigdor (1999).

[7] Bayer, Ferreira, and Ross (2018) examine the role of lenders in explaining racial and ethnic differences in high cost mortgages. They find that after controlling for a variety of borrower and loan characteristics,

Calculating Average Nominal Returns to Home Ownership

Define g to indicate a geographical unit such as a county or a zip code. There are G total counties and there are Z total zip codes. Define t as the year of house purchase and f as the year when the owner sells the home. Define D to indicate one's demographic group. In this study, D will indicate either; the entire population of buyers, an Asian buy, a Black buyer, or a Hispanic buyer. Define $Share_{gtD}$ as the share of home buyers of type D who purchase in location g at time t. At each point in time t, these shares sum across geographic locations to 1.

Define $\Delta Zillow_{gtf}$ as the nominal percent change in the Zillow index at location g from time t to time f. I will report weighted returns on home purchases broken out by demographic group (D) and year of purchase (t) and year of sale (f). The average home price percentage change using the Zillow zipcode/year level data is calculated using this formula. I divide the percentage change from the purchase year t to the sell year f by (f-t) to yield the annual average nominal returns by demographic group, by purchase year and by sales year. Equation (2) presents my algebra equation.[8]

$$Average\ Returns_{Dtf} = \sum_{g=1}^{Z} Share_{gtD} * \Delta Zillow_{gtf} \qquad (2)$$

I am making several assumptions. First, I am ignoring the fact that the home buyer received a loan for the home. As documented above, the demographic differences in loan

Black borrowers are nine percentage points more likely of having a high cost loan than comparable white borrowers. They identify high risk lenders using an ex-post foreclosure risk measure and find that including this explanatory variable accounts for between 75 and 90 percent of the racial and ethnic differences in high cost mortgages.

[8] In results available on request, I have also calculated these rate of return indices based on county level versions of equation (2). The national results are quite similar to those based on the zip code aggregation approach.

amounts are small once I include zip code fixed effects. Larger loans in more volatile housing markets increase the returns and the risk for the asset buyer. Second, I am assuming that the Zillow price index represents the purchase price of the asset that the buyer buys and sells at. This perfect competition assumption means that all demographic groups pay the same price for a home in the same geographic area at the same point in time.[9] This assumption rules out differential price discrimination across demographic groups. I am assuming that Black people do not pay more for the same house than Asians or Hispanics when they buy a home in the same geographic area at a given point in time.[10] If Black people do pay more for housing than the rest of the population and then sell at the market price, then my approach over-states their average rates of return. I calculate the level of average returns across groups for any given t,f pair and I am also interested in comparing how average returns differ by t and f for a given demographic group.

Table Four reports the main results.[11] Each row of the matrix is a different home purchase year and home sale year. If a person buys in 2007 and sells in 2010, then the asset is held for three years. I report the average annual nominal rate of return using the zip code level shift share. The results are similar using the county level weights and these are available on

---

[9] It is important to highlight several strong assumptions that have been maintained throughout this analysis. The first assumption is that the Zillow home price growth series accurately captures each demographic group's neighborhood average rate of return. If this assumption is false, then my approach suffers from measurement error.

[10] Economic history research documents that this assumption was false in the past. Using pre-war Census data from 1930 and 1940, Akbar, Shertzer, and Walsh (2019) found that Blacks paid a rent price premium of roughly 50 percent for housing on blocks that had formerly been majority white relative to whites in comparable housing on comparable blocks that had not undergone this racial transition. They also found that Black families who bought homes on racially transitioning blocks that were still majority white paid 28 percent more than white families did on the same block. However, after these early moving Black families purchased their homes at elevated prices, the price then decreased in price by 10 percent below the non-premium price once the block became majority Black.

[11] To simplify the Table, I do not report the standard deviations of average returns in this Table. It is important to note that HMDA represents the universe of loans. This table does not report estimation results. Instead, it reports calculations based on the shift share formulas presented above. I do not know the confidence intervals on the Zillow ZHVI price indices.

request. The average rate of return is calculated for all buyers, and then separately for Asian, Black, and Hispanic buyers. In the year 2012, whites represent 81% of the data points in the HMDA loan sample (and 60% of the population), the Asians have a 5.6 HMDA share (5.6% of the population), Black home buyers have a 5.3% HMDA share(12.2% of the population) and Hispanics represent 9.1% of the HMDA observations (18% of the population).

Table Four reports 87 year of purchase and year of sale entries. Each entry represents the average of the annual percent change in the home's nominal value. The mean and standard deviation for All home buyers is .047 and .041. The mean and standard deviation for Asian home buyers is .054 and .042. The mean and standard deviation for Black home buyers is .048 and .051. The mean and standard deviation for Hispanic home buyers is .059 and .054. Those who purchased in the peak year of 2007 earn low average annual nominal returns. Consider the row of buyers who purchased in 2007 and sold in 2018.

In Figures Three and Four, I graph the average annual rate of return by year of purchase for All buyers, Asian Buyers, Black Buyers and Hispanic Buyers. Figure Three presents the results for those who sell after five years of ownership and Figure Four presents the same graph for those who sell after eight years of ownership. Starting from 2009 to 2014, Black home buyers are earning a lower annual rate of return than Asian and Hispanic buyers. The vertical difference represents the rate of return differential conditional on a given purchase year.

In Table Five, I use equation (2) to calculate cell specific average returns and standard deviations for different demographic categories and within those demographic categories, I stratify by geography. Each cell is calculated based on ten observations. Each cell entry is based on the assumption that a home buyer sells after holding the asset for five years. For example, a home buyer who purchases in 2016 then sells in 2021. In this case the HMDA weights are all from the year 2016 and Zillow rates of return are calculated based on the Zillow Zip Code index data from 2016 to 2021.   What differs across the cells for a given demographic group such as Black buyers is the geography. Consider the column showing the Northeast region. In this case, the summation is only over the zip codes in the Northeast and for any demographic group these sum to one within that region. In the column for Los Angeles, I limit recalculate equation (4) but the summation is only over zip codes in Los Angeles. Conditional on buying a home in Los Angeles in year t, what was the group's average rate of return between t and t+5, where t takes on the values 2007 to 2017. The mean and standard deviation are calculated across the ten entries for each cell.

In Table Five, I also report the standard deviations in returns by cell. This allows me to study the risk and return to holding a home for five years for different demographic groups purchasing real estate in different geographic areas. Several findings emerge. The first row replicates the national results and documents that Asian buyers earn a higher average rate of return and face a lower risk in returns than Black buyers. It is important to note that the results at the national level report results that only introduce one selection rule. Conditional that a person chose to buy a home, what is the average rate of return earned over a five year holding pattern. The other rows of the matrix report more select samples. For example, the California row reports results for those who bought a home in California. California homes are much more expensive than in the rest of the nation and require one to have both higher earnings and a greater capacity to borrow to finance the home.

This point matters because in Table Five, I document that there is not a racial gap in rates of return in California or Los Angeles. In these areas, Black buyers face a higher standard deviation in returns. It is important to note that this standard deviation is calculated based on the mean annual return for a given group who purchased in a given year within a given geography so the variation in returns is time series variation as one could hold a home from 2007 to 2012 or 2008 to 2013 and continuing to include buying in 2017 and selling in 2022.

In concluding this section, it is important to emphasize what my approach achieves. I view this approach as solving an index problem. The U.S has thousands of zip codes. Home buyers are buying homes in each of these zip codes, to collapse this vector into a scalar requires a set of index weights. I use Zillow zip code home price indices to collapse these vectors into scalars that can be compared across demographic groups. It is important to note that I find quantitatively similar results when I conduct this analysis at the county level. To further study this, I conduct an ANOVA analysis for 8400 zip codes located in the 276 counties that feature at least 200,000 people in the year 2000. I regress zip code annual price appreciation on county fixed effects for each year from 2007 to 2022. Across these 16 observations, the mean adjusted R2 is .61 and the standard deviation is .05. This suggests to me that local place based bets can be analyzed using either county or zip code data.

My approach studies the unleveraged rates of return to home ownership. While the HMDA micro data do not report the price of the home that is purchased, the data do report the loan amount. I use these data to estimate a linear regression for loan i in location j in year t.

$$\log(loan_{ijt}) = \mu_{jt} + B_{jt} * X_{jt} + U_{ijt} \qquad (3)$$

In Table Six, I present five estimates of this regression using the 2017 HMDA micro data. The regressions are identical except for the geographic fixed effect. In column (1), I do not include a fixed effect. In column (2), I include state fixed effects. In column (3), I include county fixed effects. In column (4), I include zip code fixed effects. In column (5), I include tract fixed effects. In these regressions, White buyers represent the omitted category. The key explanatory variables are dummy variables for whether the borrower is Hispanic, Asian or Black. Given that Asians are buying homes in the most expensive areas, it is not surprising that this group takes a larger loan than Whites. As I include more refined spatial fixed effects, the racial coefficients all shrink close to zero. I conclude that the different demographic groups are roughly equally leveraged in purchasing homes.[12]

Measuring Average Demographic Group Differences in the "Dividend" Flow from Home Ownership

Any asset owners gains both a dividend flow and the right to sell the asset in the future. In this section, I report some evidence on how the dividend flow of homeownership varies across demographic groups. Given that a home owner incurs extra costs that a renter does not, the opportunity cost of owning is to sacrifice some current consumption. At the same time, the

[12] Bayer, Ferreira, and Ross (2016) look at racial differences in home mortgage outcomes for individuals with similar credit and loan attributes in seven large markets in the US. Using a novel dataset that matched individual level HMDA records to public record transactions and proprietary credit score data for home mortgages originated between May and August in the years 2004 to 2007, they find that Black and Hispanic borrowers had much higher rates of delinquency and default following the 2008 crisis and that this effect was greatest for borrowers who purchased a home closest to the years preceding the crisis. Black and Hispanic households that purchased a home during this period and had similar credit scores, loan characteristics, housing type, demographics, neighborhood, and lender were about three percentage points more likely to enter foreclosure than similar white households.

home owner gains another short term stream of pride of ownership and a flow of services from living in a specific area. I know of no structural revealed preference studies estimating the "American Dream" pride of ownership utility parameter.

Using the zip code level HMDA data on home purchases by race and ethnic group, I study objective indicators of neighborhood quality. Are different racial and ethnic groups moving to similar neighborhoods as based on human capital and poverty rates? I use 2010 Census Data on each zip code's percent of the population whose income is below the poverty line and the percent of the adults in the zip code who are college graduates. In the equation below, I show how I use these data to calculate each HMDA home buyer's exposure to zip code poverty.

$$Average\ Neighborhood\ Exposure\ to\ Poverty_D = \sum_{g=1}^{Z} Share_{gD} * Poverty_g$$

Every zip code differs with respect to its poverty rate and college graduate share. I weight these shares by the empirical distribution of different HMDA home buyers across these zip codes. Table Seven reports the empirical distribution of neighborhood exposure based on the 2010 College graduate share and Table Eight reports the empirical distribution of neighborhood exposure based on the 2010 Poverty share.

Asian people tend to buy homes in the best zip codes based on these measures. Twenty five percent of Asian home buyers buy a home in a community where the college graduate share is greater than 51% and the median Asian home buyer lives in a community where the college graduate share is 36%. In contrast, 5% of Black home buyers live in a community with more than 50% of the adults having a college degree and the median Black home buyer lives in a community with 22.5% of neighboring adults having a college degree.

Future Research Directions

I have presented a descriptive analysis. Given where different groups purchase housing, I report their respective realized rates of return on these lumpy investments In this section, I sketch out relevant recent research for thinking about why different demographic groups demand different real estate assets. A more comprehensive approach would model the joint decision of a household to own versus rent, the metropolitan area where the household lives and the neighborhood within that metro area and the specific home that the household buys and its bidding for that home.[13]

The opportunity cost of owning is to rent. Renters maintain greater flexibility to move in response to shocks to employment, natural disaster risks, and changes in one's health. At the same time, renters face eviction risk and a recent literature has documented search frictions (Christensen and Timmins 2021). While it is intuitive that minorities face greater search frictions in home buying markets than in rental markets (since in the former one must find and finance a property), I know of no research documenting this. Given the costs associated with home ownership, if more Black people choose to rent rather than own they can afford to rent in better neighborhoods than the neighborhoods where they tend to buy housing in. DiPasquale and Kahn (1999) emphasize the tradeoffs households face between ownership, structure type and community quality. Higher quality communities as measured by local school quality, street safety, human capital of neighbors and proximity to high quality public transit and job centers are more expensive to live in. The hedonic pricing gradient confronts all market participants with having to prioritize their housing demands.

A local labor market's industrial structure plays a key role in determining who moves and remains in an area. Demographic data indicate that few Black people live in high tech cities ranging from Boston to San Francisco, Seattle, and Portland. The under-representation of African-Americans in tech jobs must play a role in explaining why this group is under-represented among home owners in these cities. Given commuting times are slow and given the

[13] From 1940 to 1980, the Black homeownership rate in metropolitan areas in the US rose from 19 percent to 46 percent while remaining relatively unchanged in the decades following and preceding this period. During the same period of 1940 to 1980, many whites in metropolitan areas suburbanized, leaving central cities. Boustan and Margo (2013) argue that this suburbanization of whites was a causal reason for the increase in Black homeownership rates in center cities as whites departing the city center reduced costs and barriers associated with homeowning in center cities. Their estimates suggest that every 1,000 white departures from city centers resulted in an increase in 87 Black owner-occupied homes. By using the construction of interstate highways that facilitated suburbanization, they find that 26 percent of the increase in Black homeownership in center cities can be attributed to white suburbanization.

desire to live in great “consumer cities”, the spatial concentration of firms in tech cities created a local real estate boom.

All home buyers must confront the hedonic bundling constraint because a given home cannot be divided into several smaller homes. This means that home buyers face a binding down-payment constraint and this constraint is binding for those who have not accumulated much wealth and during times in the leverage cycle when banks are stingy in terms of the loan to value ratio. Down-payment constraints in expensive markets will limit the ability of middle class households to bid for such housing (Acolin, Bricker, Calem and Wachter 2016, Bayer, Ferreira and Ross 2016, Haurin, Hendershott and Wachter 1996).

Access to mortgage finance affects the urban geography of home buying patterns. Using data from Chicago, Ouazad and Ranciere (2016) document that as mortgage credit access expanded over the years 2000 to 2006 that whites bid more for housing in non-Black areas in the metropolitan area. This research raises questions about the causal role that an area’s racial composition plays in determining the price path of locally tied assets such as businesses and homes see Perry, Rothwell and Harshbarger (2018).

We know little about the expectations of different groups about future home price appreciation and real estate risk (Dominitz and Manski 2011). Case, Shiller and Thompson’s (2012) work on surveying buyers and renters about their respective beliefs and how these expectations vary across different local markets would appear to be a promising research topic. In several Chinese cities, Zheng, Sun and Kahn (2016) interview renters about their beliefs about housing price appreciation in their city over the next year. Using a panel data set to interview the same people a year later reveals a positive correlation between optimistic baseline beliefs about home price growth and the propensity to subsequently buy an apartment.

This section’s discussion highlights that access to high paying jobs, access to finance, and housing market expectations all offer promising leads for future research studying the empirics of differences in the average rate of return to real estate investment.

Conclusion

Urban economic models such as the cross-city Rosen-Roback model and the Tiebout migration model emphasize the fundamental role of self-selection in determining who lives where across and within cities. This insight from urban economics has implications for the realized rates of return to home ownership because home buyers live in owner occupied units. This paper has explored the financial consequences of this bundling point. Asian home buyers, Black home buyers and the average home buyer are making different place based bets. While I have not presented a structural model of the joint choice of ownership and city and neighborhood choice, I have explored how the resulting geography of these place based bets. These recent buyers could have rented. Instead, they chose to make place based bets.

The geography of these bets plays a crucial role in determining their realized rates of return. This paper has explored this spatial asset pricing (Ortalo-Magne and Prat 2019). As an asset, a home purchase represents a place based bet that both local economic growth and local quality of life will flourish. As time passes, home owner can sell their asset and earn a realized rate of return on their investment. My simple strategy of using HMDA data by racial group aggregated to the zip code/purchase year level, allows me to conduct an index approach where I use these as index weights to collapse the Zillow vector of zip code rate of returns indices into a single number. This shift share number represents the average rate of return to housing from a given purchase date to any subsequent sales date. Over the years 2010 to 2022, Black home owners have earned a lower rate of return on their unleveraged investment in housing than the average buyer and Asian buyers have earned the highest rate of return. These estimates do vary by economic geography. In a local market such as the Los Angeles metropolitan area, I do not find a racial gap. I do find that Black buyers face a greater standard deviation of returns to home ownership. My findings complement the recent important study by Kermani and Wong (2021) that incorporates several real world features such as the fact that Black buyers are more likely to engage in distressed sales. A better understanding of household finance differences and labor market opportunities differences across demographic groups will inform this emerging literature documenting demographic differences in real estate asset returns.

References

Akbar PA, Li S, Shertzer A, Walsh RP. Racial segregation in housing markets and the erosion of black wealth. National Bureau of Economic Research Working Paper; 2019

Bayer P, Ferreira F, Ross SL. The vulnerability of minority homeowners in the housing boom and bust. American Economic Journal: Economic Policy. 2016 Feb;8(1):1-27.

Bayer P, Ferreira F, Ross SL. What drives racial and ethnic differences in high-cost mortgages? The role of high-risk lenders. The Review of Financial Studies. 2018 Jan 1;31(1):175-205.

Blau FD, Graham JW. Black-white differences in wealth and asset composition. The Quarterly Journal of Economics. 1990 May 1;105(2):321-39.

Boustan LP, Margo RA. A silver lining to white flight? White suburbanization and African–American homeownership, 1940–1980. Journal of Urban Economics. 2013 Nov 1;78:71-80.

Case KE, Shiller RJ, Thompson A. What have they been thinking? Home buyer behavior in hot and cold markets. National Bureau of Economic Research; 2012 Sep 21.

Christensen, Peter, and Christopher Timmins. *The damages and distortions from discrimination in the rental housing market*. No. w29049. National Bureau of Economic Research, 2021.

Collins WJ, Margo RA. Race and home ownership: A century-long view. Explorations in Economic history. 2001 Jan 1;38(1):68-92.

Collins WJ, Margo RA. Race and the value of owner-occupied housing, 1940–1990. Regional Science and Urban Economics. 2003 May 1;33(3):255-86.

Cutler DM, Glaeser EL, Vigdor JL. The rise and decline of the American ghetto. Journal of political economy. 1999 Jun;107(3):455-506.

Di Zhu X. Housing wealth and household net wealth in the United States: a new profile based on the recently released 2001 SCF data. Joint Center for Housing Studies, 2003.

DiPasquale D, Kahn ME. Measuring neighborhood investments: An examination of community choice. Real Estate Economics. 1999 Sep;27(3):389-424.

Dominitz J, Manski CF. Measuring and interpreting expectations of equity returns. Journal of Applied Econometrics. 2011 Apr;26(3):352-70.

Gyourko J, Mayer C, Sinai T. Superstar cities. American Economic Journal: Economic Policy. 2013 Nov;5(4):167-99.

Haurin DR, Morrow-Jones HA. The impact of real estate market knowledge on tenure choice: A comparison of black and white households. Housing Policy Debate. 2006 Jan 1;17(4):625-53.

Kermani, Amir, and Francis Wong. *Racial disparities in housing returns*. No. w29306. National Bureau of Economic Research, 2021.

McIntosh K, Moss E, Nunn R, Shambaugh J. Examining the Black-white wealth gap. Washington DC: Brooking Institutes. 2020.

Munnell AH, Tootell GM, Browne LE, McEneaney J. Mortgage lending in Boston: Interpreting HMDA data. The American Economic Review. 1996 Mar 1:25-53.

Ortalo-Magné, Francois, and Andrea Prat. "Spatial asset pricing: A first step." Economica

Ouazad A, Rancière R. Credit standards and segregation. Review of Economics and Statistics. 2016 Dec 1;98(5):880-96.

Goldsmith-Pinkham, Paul, and Kelly Shue. "The gender gap in housing returns." *The Journal of Finance* 78, no. 2 (2023): 1097-1145.

O'Connor, Sean, Brent Norwood, Myongjin Kim, and Leilei Shen. "Gender Price Differentials in the Housing Market: Evidence from a Repeat-Sales Approach." *Available at SSRN 3307563* (2018).

Perry A, Rothwell J, Harshbarger D. The devaluation of assets in black neighborhoods. Brookings. 2018

Rosen S. Markets and diversity. American Economic Review. 2002 Mar;92(1):1-5.

Zheng, Siqi, Weizeng Sun, and Matthew E. Kahn. "Investor confidence as a determinant of China's urban housing market dynamics." *Real Estate Economics* 44, no. 4 (2016): 814-845.

Zonta, Michela, Racial Disparities in Home Appreciation, 2019. Available at: https://www.americanprogress.org/issues/economy/reports/2019/07/15/469838/racial-disparities-home-appreciation/

Figure One

Nominal Home Price Index Dynamics

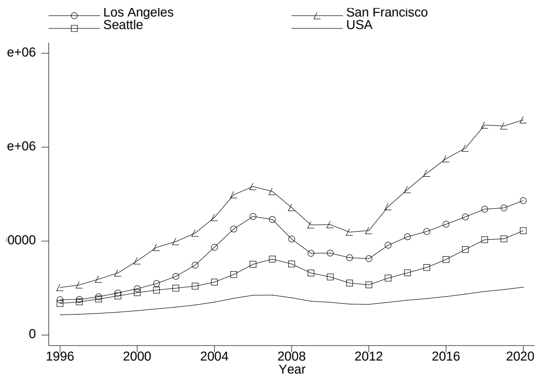
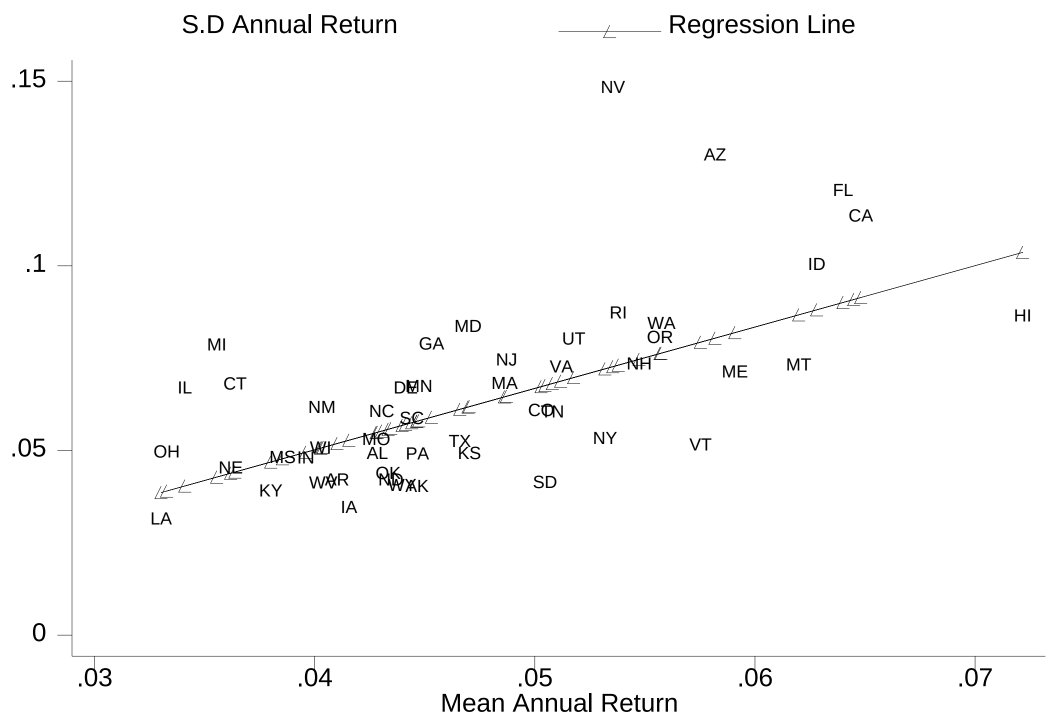


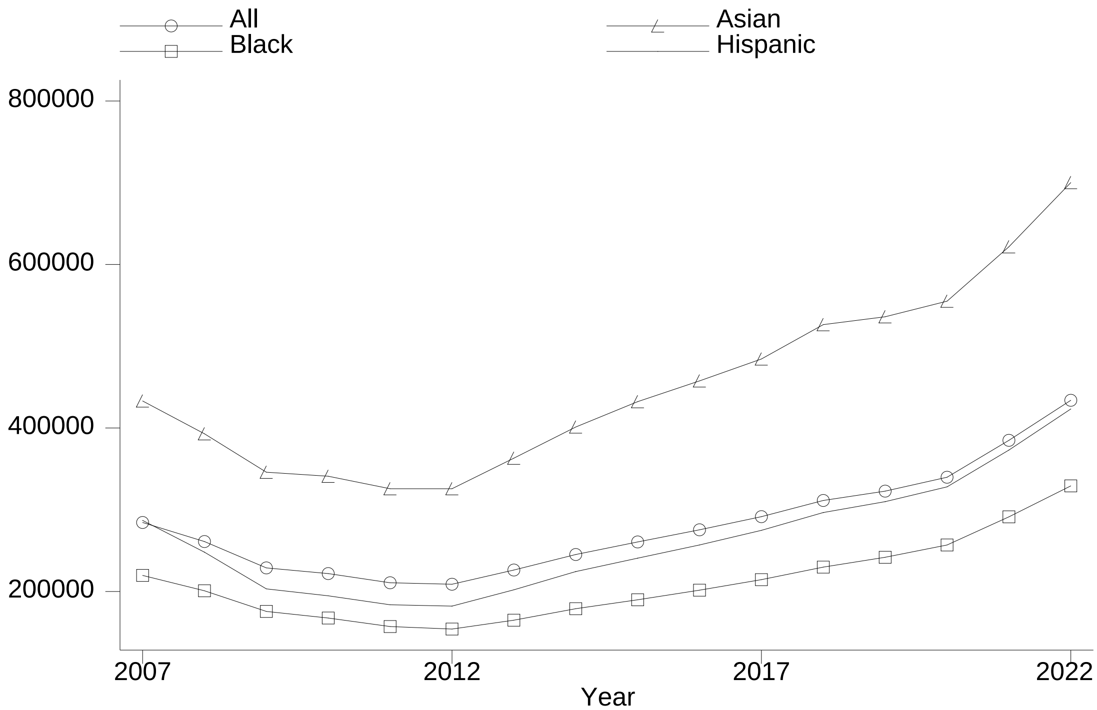
Figure Two

Cross-State Variation in the Mean and Standard Deviation of Housing Returns



State Level Summary Statistics for Housing Returns 2000 to 2022

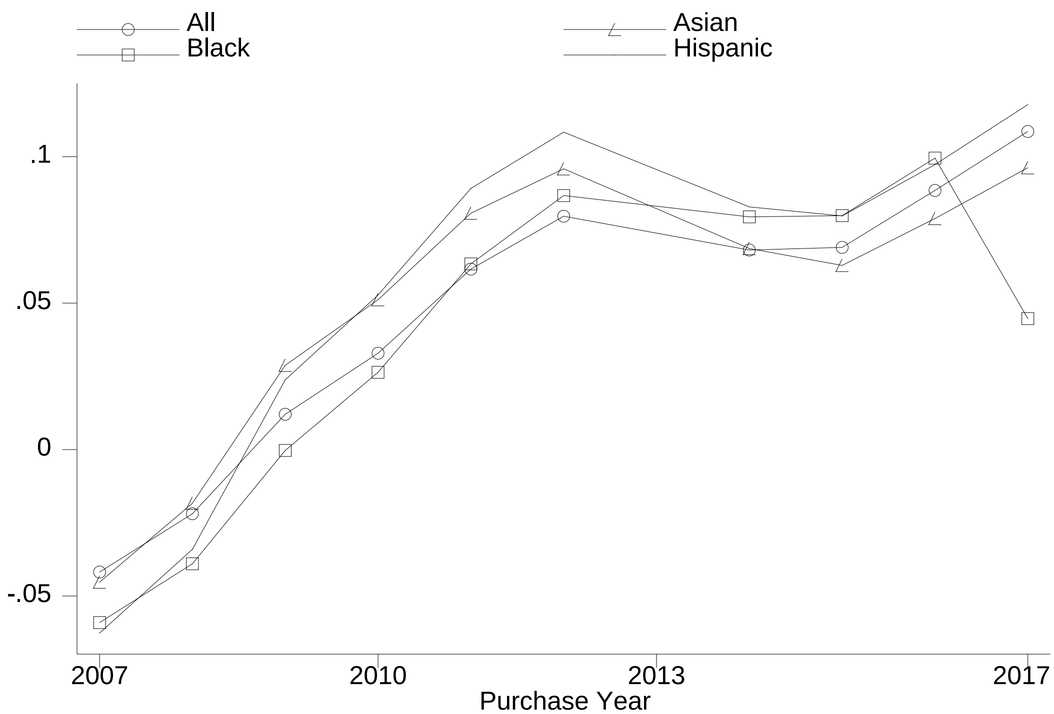
Figure Three



Weighted Average Zillow Zip Code Purchase Price (nominal $)

Figure Four

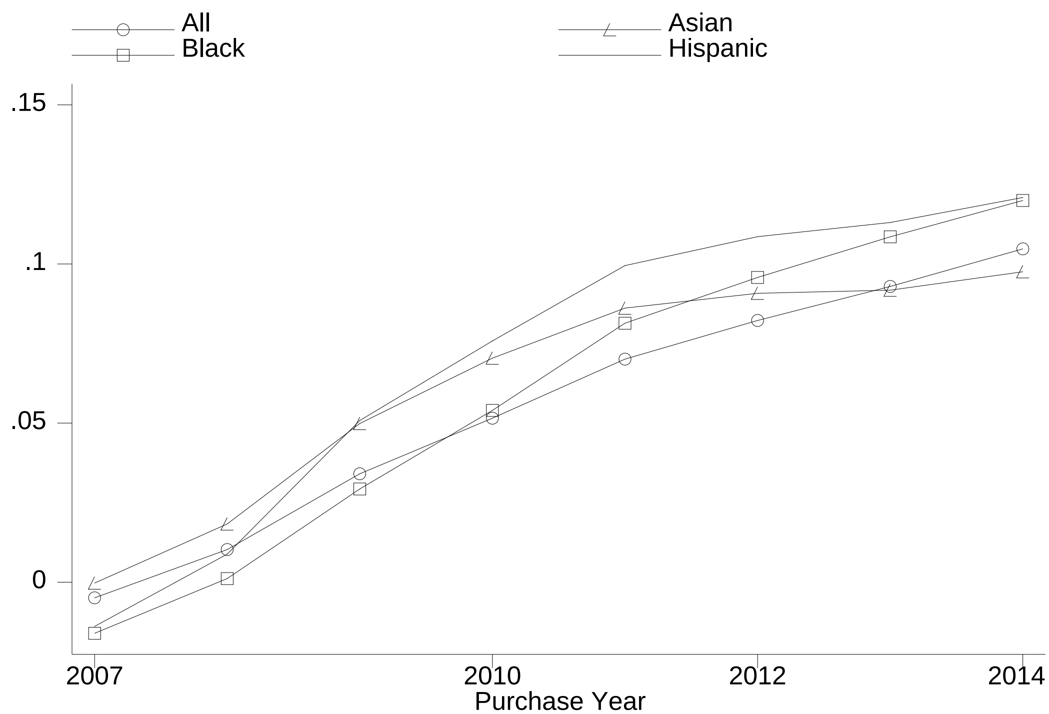
Shift Share Estimates of the Nominal Annual Rate of Return to Home Ownership



Nominal Average Annual Return After Holding for Five Years

Figure Five

Shift Share Estimates of the Nominal Annual Rate of Return to Home Ownership for Eight Years



Nominal Average Return by Purchase Year and Sell After 8 Years

Table One

The Distribution of Home Buyers Across States

State	All	Asian	Black	Hispanic
Alabama	1.42	0.42	3.12	0.32
Alaska	0.28	0.18	0.09	0.11
Arizona	2.76	1.66	1.14	5.18
Arkansas	0.89	0.26	1.02	0.49
California	9.93	27.8	4.94	22.51
Colorado	2.65	1.41	0.95	2.56
Connecticut	1.08	0.86	0.99	0.87
Delaware	0.31	0.22	0.75	0.15
District of Columbia	0.24	0.23	0.6	0.13
Florida	6.28	2.99	8.27	12.67
Georgia	3.37	3.08	10.16	2.01
Hawaii	0.31	2.17	0.11	0.13
Idaho	0.69	0.16	0.05	0.42
Illinois	3.95	4.03	4.08	4.18
Indiana	2.33	0.87	1.6	0.91
Iowa	1.13	0.39	0.23	0.35
Kansas	1	0.55	0.39	0.57
Kentucky	1.26	0.34	0.79	0.3
Louisiana	1.23	0.43	2.94	0.35
Maine	0.36	0.07	0.03	0.04
Maryland	2.05	2.63	6.49	1.35
Massachusetts	2.11	2.69	1.28	1.27
Michigan	2.9	1.45	2.55	0.76
Minnesota	2.08	1.67	0.86	0.56
Mississippi	0.63	0.16	1.81	0.12
Missouri	2.07	0.68	1.65	0.48
Montana	0.33	0.04	0.02	0.05
Nebraska	0.67	0.27	0.22	0.35
Nevada	1.16	1.62	0.85	2.17
New Hampshire	0.43	0.16	0.05	0.09
New Jersey	2.48	4.96	2.59	2.65
New Mexico	0.54	0.19	0.14	1.73
New York	3.95	6.69	3.82	2.69
North Carolina	3.46	2.1	5.94	1.78
North Dakota	0.27	0.05	0.03	0.04
Ohio	3.57	1.45	3.05	0.72
Oklahoma	1.24	0.5	0.71	0.67
Oregon	1.38	1.18	0.22	0.73
Pennsylvania	3.68	2.35	2.87	1.55

Rhode Island	0.3	0.13	0.17	0.28
South Carolina	1.7	0.51	2.85	0.53
South Dakota	0.31	0.05	0.04	0.05
Tennessee	2.31	0.79	2.91	0.68
Texas	9.02	9.64	9.57	19.13
Utah	1.32	0.54	0.13	1.05
Vermont	0.15	0.04	0.01	0.02
Virginia	3.17	3.99	5.21	1.94
Washington	2.83	4.62	0.96	1.59
West Virginia	0.41	0.07	0.14	0.05
Wisconsin	1.8	0.69	0.6	0.61
Wyoming	0.22	0.03	0.02	0.09

For each column, the rows to 100.

Table Two

The Distribution of Home Buyers Across Metro Areas

Name	MSA	All	Asian	Black	Hispanic
Atlanta, GA	520	2.54	2.8	8.27	1.49
Baltimore, MD	720	1.14	1.2	2.59	0.39
Boston, MA	1123	2.52	2.87	1.27	1.25
Chicago, IL	1600	3.5	3.92	4.03	4.43
Cleveland-Lorain-Elyria, OH	1680	0.75	0.27	0.89	0.22
Dallas, TX	1920	2.12	3.25	2.63	2.63
Denver, CO	2080	1.81	1.12	0.69	1.69
Detroit, MI	2160	1.63	1.01	2.02	0.34
Houston, TX	3360	2.6	3.78	3.48	4.9
Los Angeles-Long Beach, CA	4480	2.22	5.93	1.38	5.85
Miami, FL	5000	0.63	0.16	0.7	4.21
Minneapolis-St. Paul, MN-WI	5120	1.7	1.59	0.86	0.47
New York, NY	5600	4.67	10.67	4.88	4.63
Anaheim--Santa Ana, CA -X	5945	0.88	3.26	0.12	1.03
Philadelphia, PA-NJ	6160	1.91	1.89	2.61	0.89
Phoenix-Mesa, AZ	6200	2.22	1.43	0.89	3.61
Pittsburgh, PA	6280	0.78	0.32	0.35	0.08
Riverside-San Bernardino, CA	6780	1.72	2.2	1.23	5.87
St. Louis, MO-IL	7040	1.22	0.46	1.34	0.2
San Diego, CA	7320	1.1	1.89	0.4	1.63
San Francisco, CA	7360	1.47	6.77	0.66	1.24
Seattle-Bellevue-Everett, WA	7600	1.45	3.83	0.5	0.55
Tampa-St. Petersburg-Clearwater, FL	8280	1.21	0.62	1.15	1.59
Washington, DC-MD-VA-WV	8840	2.79	4.95	6.43	2.46
Other	9999	55.44	33.81	50.62	48.35

For each column, the rows to 100.

Table Three

Shift Share Weighted Average Nominal Price Indices by Geographic Category

	County					Zip Code			
year	All	Asian	Black	Hispanic		All	Asian	Black	Hispanic
2007	258661	384755	237843	292220		276739	444970	216584	280182
2008	238495	356546	218997	258469		257195	408382	199421	244512
2009	219186	323321	200889	230497		238785	376405	183156	215532
2010	216777	328279	196570	224639		242808	397832	179751	212151
2011	204569	308166	186534	213760		233322	379054	173550	206428
2012	202647	303997	181562	208865		228121	357041	173005	200275
2013	218125	332690	195487	226428		246072	391117	186415	217984
2014	229198	354439	205902	242805		254942	413675	194121	231744
2015	237483	367011	214355	252457		262164	426428	202452	240773
2016	248196	382565	223278	265442		271027	440906	210555	252527
2017	260951	406533	233334	276076		283362	465946	219143	262966

The units are nominal dollars.

Table Four

Zip Code Shift Share Annual Nominal Rate of Return Estimates

Buy	Sell	All	Asian	Black	Hispanic
2007	2010	-0.052	-0.061	-0.071	-0.085
2007	2011	-0.050	-0.055	-0.068	-0.076
2007	2012	-0.042	-0.045	-0.059	-0.063
2007	2013	-0.026	-0.026	-0.042	-0.042
2007	2014	-0.013	-0.010	-0.026	-0.025
2007	2015	-0.005	0.000	-0.016	-0.014
2007	2016	0.003	0.007	-0.007	-0.004
2007	2017	0.009	0.013	0.002	0.003
2007	2018	0.015	0.022	0.010	0.011
2007	2019	0.019	0.024	0.017	0.016
2007	2020	0.023	0.026	0.023	0.021
2007	2021	0.034	0.035	0.036	0.032
2007	2022	0.044	0.044	0.048	0.043
2008	2011	-0.053	-0.057	-0.073	-0.078
2008	2012	-0.042	-0.044	-0.061	-0.061
2008	2013	-0.022	-0.018	-0.039	-0.034
2008	2014	-0.007	0.000	-0.021	-0.013
2008	2015	0.002	0.011	-0.009	-0.001
2008	2016	0.010	0.018	0.001	0.009
2008	2017	0.017	0.025	0.010	0.017
2008	2018	0.023	0.034	0.019	0.025
2008	2019	0.026	0.035	0.025	0.029
2008	2020	0.031	0.037	0.032	0.034
2008	2021	0.043	0.047	0.046	0.047
2008	2022	0.053	0.057	0.042	0.059
2009	2012	-0.029	-0.024	-0.047	-0.036
2009	2013	-0.005	0.008	-0.021	-0.001
2009	2014	0.012	0.029	0.000	0.024
2009	2015	0.021	0.038	0.011	0.035
2009	2016	0.028	0.044	0.021	0.043
2009	2017	0.034	0.050	0.029	0.051
2009	2018	0.040	0.059	0.038	0.059
2009	2019	0.043	0.058	0.044	0.062
2009	2020	0.047	0.059	0.050	0.066
2009	2021	0.060	0.071	0.065	0.080
2009	2022	0.072	0.082	0.078	0.094
2010	2013	0.004	0.018	-0.011	0.013
2010	2014	0.024	0.042	0.015	0.042

2010	2015	0.033	0.051	0.026	0.053
2010	2016	0.040	0.056	0.036	0.061
2010	2017	0.045	0.061	0.045	0.068
2010	2018	0.052	0.070	0.054	0.076
2010	2019	0.053	0.068	0.059	0.077
2010	2020	0.057	0.068	0.065	0.081
2010	2021	0.071	0.080	0.082	0.097
2010	2022	0.083	0.092	0.096	0.112
2011	2014	0.052	0.075	0.048	0.080
2011	2015	0.057	0.080	0.056	0.085
2011	2016	0.062	0.081	0.063	0.089
2011	2017	0.065	0.083	0.069	0.093
2011	2018	0.070	0.092	0.078	0.100
2011	2019	0.070	0.086	0.081	0.099
2011	2020	0.073	0.085	0.086	0.102
2011	2021	0.088	0.097	0.104	0.118
2011	2022	0.101	0.110	0.119	0.134
2012	2015	0.080	0.103	0.084	0.112
2012	2016	0.080	0.098	0.086	0.109
2012	2017	0.080	0.096	0.087	0.108
2012	2018	0.082	0.101	0.092	0.112
2012	2019	0.080	0.093	0.093	0.108
2012	2020	0.082	0.091	0.096	0.109
2012	2021	0.099	0.105	0.114	0.126
2012	2022	0.114	0.118	0.131	0.143
2013	2016	0.073	0.083	0.081	0.095
2013	2017	0.073	0.081	0.082	0.095
2013	2019	0.074	0.080	0.087	0.095
2013	2020	0.076	0.078	0.090	0.095
2013	2021	0.093	0.092	0.109	0.113
2013	2022	0.108	0.106	0.125	0.131
2014	2017	0.066	0.069	0.073	0.081
2014	2018	0.070	0.076	0.079	0.086
2014	2019	0.068	0.069	0.079	0.083
2014	2020	0.071	0.067	0.083	0.084
2014	2021	0.089	0.083	0.102	0.103
2014	2022	0.105	0.098	0.120	0.121
2015	2018	0.069	0.072	0.077	0.082
2015	2019	0.066	0.064	0.077	0.078
2015	2020	0.069	0.063	0.080	0.080
2015	2021	0.089	0.112	0.101	0.100
2015	2022	0.106	0.096	0.119	0.119
2016	2019	0.063	0.061	0.074	0.073
2016	2020	0.066	0.059	0.076	0.075

2016	2021	0.088	0.079	0.100	0.097
2016	2022	0.106	0.095	0.119	0.117
2017	2020	0.064	0.055	0.075	0.070
2017	2021	0.090	0.078	0.056	0.097
2017	2022	0.109	0.096	0.045	0.118

This table reports 87 year of purchase and year of sale entries. Each entry represents the average of the annual percent change in the home's nominal value. The mean and standard deviation for All home buyers is .047 and .041. The mean and standard deviation for Asian home buyers is .054 and .042. The mean and standard deviation for Black home buyers is .048 and .051. The mean and standard deviation for Hispanic home buyers is .059 and .054.

Table Five

The Risk and Return to Home Ownership Over a Five Year Holding Period

	Average Annual Nominal Rate of Return (S.D) Over a Five Year Holding Period			
Geography	All	Asian Buyers	Black Buyers	Hispanic Buyers
Nation	.045 (.049)	.050 (.048)	.038 (.055)	.055 (.061)
Northeast	.033 (.040)	.042 (.040)	.032 (.050)	.035 (.054)
Midwest	.038 (.045)	.033 (.043)	.039 (.066)	.038 (.056)
South	.045 (.048)	.042 (.042)	.036 (.052)	.051 (.055)
West	.062 (.063)	.062 (.059)	.059 (.070)	.068 (.074)
California	.062 (.065)	.063 (.059)	.061 (.075)	.068 (.076)
Los Angeles	.057 (.060)	.052 (.053)	.060 (.071)	.063 (.070)

This table reports the average annual rate of return and standard deviation across ten data points for each cell based on equation (2) in the text for home buyers who purchased between the years 2007 and 2017. The values are calculated assuming a five year holding period. For example, a buyer in 2012 sells in 2017.

Table Six

Loan Size Regressions

2017 Data	Y=log(Loan Size)				
	(1)	(2)	(3)	(4)	(5)
Hispanic	-0.0347***	-0.169***	-0.181***	-0.0663***	-0.0295***
	(0.00106)	(0.000978)	(0.000896)	(0.000836)	(0.000786)
Asian	0.405***	0.203***	0.0283***	0.00635***	0.00569***
	(0.00134)	(0.00122)	(0.00111)	(0.00102)	(0.000962)
Black	-0.0902***	-0.0961***	-0.127***	0.0123***	0.0478***
	(0.00129)	(0.00117)	(0.00106)	(0.000995)	(0.000940)
Constant	5.369***	5.396***	5.411***	5.391***	5.384***
	(0.000367)	(0.000329)	(0.000292)	(0.000263)	(0.000244)
N	3585380	3581508	3580544	3583432	3585380
Fixed Effects	None	State	County	Zip Code	Tract

Standard errors in parentheses
* $p<0.05$ ** $p<0.01$ *** $p<0.001$

The omitted category is white home buyers.

Table Seven

Home Buyer Exposure to College Graduates in the Zip Code

	Zip Code	All	Asian	Black	Hispanic
1%	0.031	0.065	0.083	0.062	0.039
5%	0.065	0.103	0.130	0.094	0.065
10%	0.085	0.127	0.161	0.114	0.087
25%	0.123	0.177	0.245	0.156	0.131
50%	0.181	0.265	0.362	0.225	0.197
75%	0.289	0.392	0.514	0.312	0.295
90%	0.441	0.524	0.620	0.423	0.411
95%	0.539	0.599	0.671	0.496	0.491
99%	0.691	0.728	0.764	0.628	0.641

Using the HMDA loan data's zip code identifier from 2007 to 2017 and year 2010 zip code level data on the share of adults who are college graduates, I report the empirical distribution of neighborhood college graduate by home buyer race and ethnicity. The "Zip Code" column reports the unweighted empirical distribution of the share of college graduates across zip codes in the year 2010.

Table Eight

Home Buyer Exposure to Zip Code Poverty

	Zip Code	All	Asian	Black	Hispanic
1%	0.003	0.018	0.015	0.023	0.022
5%	0.028	0.029	0.026	0.036	0.038
10%	0.041	0.038	0.032	0.047	0.05
25%	0.07	0.058	0.047	0.074	0.079
50%	0.116	0.095	0.075	0.116	0.123
75%	0.178	0.147	0.126	0.172	0.184
90%	0.251	0.203	0.183	0.244	0.243
95%	0.304	0.245	0.221	0.288	0.281
99%	0.438	0.342	0.323	0.369	0.355

Using the HMDA loan data's zip code identifier from 2007 to 2017 and year 2010 zip code level data on the share of people living in poverty, I report the empirical distribution of neighborhood poverty exposure by home buyer race and ethnicity. The "Zip Code" column reports the unweighted empirical distribution of the share of people in poverty across zip codes in the year 2010.