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RACIAL AND ETHNIC DIFFERENCES IN THE FINANCIAL RETURNS TO HOME  
PURCHASES FROM 2007 TO 2020

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Racial and Ethnic Differences in the Financial Returns to Home Purchases from 2007 to 2020  
Matthew E. Kahn  
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## **ABSTRACT**

The racial and ethnic composition of home buyers varies across geographic locations. For example, Asians and Hispanics are much more likely to buy homes in California than Blacks and Blacks are more likely to buy homes in Georgia than other demographic groups. Home prices grow at different rates across geographic units such as counties or zip codes. Hedonic bundling inhibits buyers from purchasing shares of different homes and forming a spatially diversified housing portfolio. Spatial variation in purchases suggests that the average rate of return to housing varies across racial and ethnic groups. To test this claim, I construct a geographic shift-share index by combining Zillow geographic specific home price index data with HMDA micro data. The shift share calculations yield the average rate of return to home ownership by purchase year, and sale year for different demographic groups. Over the years 2007 to 2020, Blacks earned a lower rate of return on home purchases than Asians and Hispanics and the sample average. Within geographic areas, average loan differences across racial and ethnic groups are very small.

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## **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).<sup>1</sup> 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 home owners are less likely to hold as diversified a portfolio as they would have had they rented. Much of their 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 and limited housing supply in productive and beautiful cities, there are large differences in price appreciation across U.S local housing markets. Based on Zillow price index data, U.S real estate increased in nominal terms by 154% from February 1996 to March 2021. Over that same time period, residential real estate prices increased by 368% in San Francisco, 260% in Seattle but only by 60% in Chicago and 62% in Cleveland. Who has disproportionately gained from the spatially concentrated housing boom in high amenity areas and in the Superstar tech cities (Gyourko, Mayer and Sinai 2013)? Who has gained from the increased foreign demand for U.S real estate (Gorback and Keys 2020)?

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. If each geographic community were a microcosm of the nation as a whole and if home ownership rates were the same across groups, then the shift share would yield the same average returns for each group. Given that there are demographic differences in home ownership rates and the spatial distribution of where people choose to live, the “uniform distribution” assumption does not hold.

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<sup>1</sup> 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.

Hispanics are more likely to locate in Texas than Blacks. Asians are more likely to locate in more expensive housing markets. These facts motivate the shift-share analysis.

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. To simplify the presentation, I assume that people hold the asset for at least three years, so I calculate the annual rate of return on housing by demographic group for buyers in each year from 2007 to 2017 who then sell the home in a year between 2010 to 2020.

Over the last decade there has been a real estate boom in California, coastal cities and in tech cities such as Seattle, Asians and Hispanics have been more likely than Blacks to purchase homes in these areas. The shift-share approach yields the finding that Blacks have earned a lower rate of financial return on their housing investments in recent years than the average home buyer and Asians and Hispanics have earned a higher rate of return on housing than the average buyer. Previous research using a different methodology has documented that Blacks have earned a lower rate of return than Whites (see Zonta 2019). She does not also compare the housing returns earned by Asians and Hispanics. She focuses on the role of residential segregation in explaining her facts. It is important to note that I find roughly similar results when I conduct the shift-share analysis at the county level or the zip code level. This spatial aggregate finding suggests that there are multiple mechanisms that are generating the facts. In the last section of the paper I discuss the multiple possible mechanisms.

## Some Descriptive Facts

Throughout this paper, I rely on Zillow's Home Value Index (ZHVI).<sup>2</sup> 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.<sup>3</sup> Over the years 1996 to 2020, the correlation between 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.

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<sup>2</sup> 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.

<sup>3</sup> The data are available here

[https://www.fhfa.gov/DataTools/Downloads/Documents/HPI/HPI\\_AT\\_state.txt](https://www.fhfa.gov/DataTools/Downloads/Documents/HPI/HPI_AT_state.txt)

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. Indiana, Ohio and Iowa are at the other end featuring low returns and a low standard deviation.

Figure Three repeats this exercise but changes the unit of analysis to metropolitan areas. California's metro areas stand out such that San Francisco and San Jose feature the highest average returns and relatively low risk. Baltimore, Chicago and Detroit feature low rates of return and relatively high risk.

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.<sup>4</sup> For a discussion of why the HMDA data were created see Munnell, Tootell, Browne and McEneaney (1996). 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.<sup>5</sup>

The HMDA data set includes all home purchase loans for 1-4 family dwellings. 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. 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. This fact combined with the results reported in Figures foreshadow the findings that I report below. Contrast California with

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<sup>4</sup> The data are posted at <https://www.consumerfinance.gov/data-research/hmda/historic-data/>.

<sup>5</sup> See [https://www.washingtonpost.com/realestate/wealthy-chinese-buyers-are-a-growing-force-in-us-real-estate-markets/2016/10/13/15ab3cba-7441-11e6-8149-b8d05321db62\\_story.html](https://www.washingtonpost.com/realestate/wealthy-chinese-buyers-are-a-growing-force-in-us-real-estate-markets/2016/10/13/15ab3cba-7441-11e6-8149-b8d05321db62_story.html)

Georgia. Based on the HMDA data, only 3.37% of all buyers purchase a Georgia home but 10.16% of Blacks purchase a home there. Texas offers another distinctive data point as 9.64% of Asians and 9.57% of Blacks buy a home there. In contrast, 19.13% of Hispanics purchase a home there.<sup>6</sup> 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 Blacks 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.

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

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 least expensive counties and zip codes. Based on the zip code level data, the average

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<sup>6</sup> 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).

Asian home buyer is spending roughly twice as much on housing than the average Black home buyer.<sup>7</sup>

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  $t$ .

$$\log(\text{loan}_{ijt}) = \mu_{jt} + B_{jt} * X_{jt} + U_{ijt}$$

In Table Four, 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.<sup>8</sup> This fact matters because in the next section I will ignore leverage in calculating the average nominal returns to home ownership.

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<sup>7</sup> 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, 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. Their findings suggest that Black borrowers are more likely to be concentrated among high-risk lenders even among borrowers with good credit scores and low-risk loans.

<sup>8</sup> 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,

## 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 county/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.

$$Average\ Returns_{Dtf} = \sum_{g=1}^G Share_{gtD} * \Delta Zillow_{gtf}$$

The average home price percentage change using the Zillow zipcode/year level data is calculated using this formula.

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

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loan characteristics, housing type, demographics, neighborhood, and lender were about three percentage points more likely to enter foreclosure than similar white households.

In using these formulas, 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 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 (either at the zip code or County level) 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. This assumption rules out differential price discrimination across demographic groups. I am assuming that Blacks 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.<sup>9</sup> 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 Five reports the main results.<sup>10</sup> 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 both the county level shift share and the zip code level shift share. For each of these geographic categories, 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).

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<sup>9</sup> 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.

<sup>10</sup> 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.

The results are similar using the county level or the zip code level share weights. 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. The average buyer earned a .9% annual return while the average Asian earned a 1.4% annual nominal rate of return while the average Black earned .4% return. In contrast, consider buyers who bought in 2012 and sold in 2020. The average buyer in this group earned 7.0% per year while the average Asian buyer in this group earned 8.2% and the average Black earned 6.7% per year. This gap in the rate of returns between Asians and Blacks is found across almost all of the entries. For the zip code shift share, there is a greater than 3% gap between Asian and Black returns for those who bought in 2011 and sold in 2014, 2015 or 2016. Given that the table reports many entries, in Figures Four and Five I graph the average annual rate of return by year of purchase for All buyers, Asian Buyers, Black Buyers and Hispanic Buyers. Figure Four presents the results for those who sell after five years of ownership and Figure Five presents the same graph for those who sell after seven 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.

To summarize the information reported in Table Five, I take the estimates of the annual nominal returns for Asians, Blacks and Hispanics and I pool the observations into a panel regression. I then regress these entries on a year of purchase dummy, and a year of sale dummy. Controlling for these variables, Asians earn a higher rate of return each year relative to Blacks. In a regression with 195 data points using the zip code shift share column data reported in Table Four, where the omitted category is the rate of return for Asian home buyers, the Black coefficient equals -.017 with a t-statistic of 12. The Hispanic coefficient is -.0006 and is not statistically significant. It is important to note that throughout this paper, my focus has been on the annual flow of recent home buyers. I am not examining the financial returns to long term home owners who purchased before 2007 and held onto the asset.

As a final step in studying home price dynamics, I return to the Zillow County sample and focus on the percentage change in a county's ZHVI from 2009 to 2020. In Table Six, I report results where I regress this on a California dummy and the county's percentage college graduate and percentage Black in the year 2000. Across the regressions, I include state fixed effects and

in the right columns I weight by county population in the year 2000. There is a clear California effect. Home prices in California increased by 30% over the rest of the nation. Surprisingly, the human capital effect is small. Across the specifications (with the exception of column 4), a county's percent Black in 2000 is negatively correlated with home price growth from 2009 to 2020. A ten percentage point increase in a county's Black share is associated with a reduction in home price growth by 3.7%

## Open Questions About Mechanisms

I have presented a descriptive conditional analysis. Given where different groups purchase housing, I report their respective realized rates of return on these lumpy investments. I have not modeled why they chose these locations and what tradeoffs they faced in making this choice. The demand and supply for real estate offers some insights into understanding the empirical patterns.

## Demand

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.<sup>11</sup>

A local labor market's industrial structure plays a key role in determining who moves and remains in an area. Basic demographic data indicate that few Blacks live in high tech cities ranging from Boston to San Francisco, Seattle, and Portland. The under-representation of

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<sup>11</sup> 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 homeownership 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.

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

Past reduced form research has studied within metro area locational choice. Using Census data from 1990 Los Angeles, in past work I have documented that controlling for the household head’s age and income that Blacks are less likely to own and move to communities (the census PUMA categories) that feature worse schools, higher crime and worse air quality (DiPasquale and Kahn 1999).<sup>12</sup> Gabriel and Painter (1998) estimate within city discrete choice models of locational choice within Chicago, Los Angeles and Washington DC and document that even controlling for household income that Black homebuyers are much more likely to purchase in Black neighborhoods. Using the methods of Bajari and Benkard (2005), Bajari and Kahn (2005) document that Blacks reveal a greater willingness to pay to live in Black areas. White migrants are willing to pay more to live in areas with a larger share of college graduates. Deng, Ross and Wachter (2003) use data from Philadelphia from the 1985 American Housing Survey and document that the Black home ownership gap persists even when accounting for residential locational choice.<sup>13</sup>

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<sup>12</sup> Using survey data from 1,000 households in Columbus, Ohio in 2005, Haurin and Morrow-Jones (2006) study differences in real estate market tenure decisions between white and Black households. They find that the parents of Black renters are less likely to have been homeowners than white renters and that the parents of white renters were more likely to have had a mortgage. They also find significant racial differences among three additional measures of homeownership knowledge gaps that act as barriers: how to buy a home, how to get a real estate agent, and how to get a mortgage. They estimate a model that suggests that these information gaps in real estate and mortgage markets explain the racial difference in homeownership rates.

<sup>13</sup> Markley et al study how racial and income characteristics structured home price appreciation in Fulton and DeKalb Counties in Atlanta, Georgia from the 2000 to 2003 period before the housing boom to the period after the recovery in 2014 to 2016. They find that after controlling for the foreclosure rate and other variables associated with foreclosure, a block group’s racial composition has more of an impact on home price appreciation than income. They find that homes in majority white high-income neighborhoods in the two Atlanta counties appreciated by over \$91,000 between 2000-3 and 2014-16 while majority Black high-income neighborhoods depreciated by over \$22,000.

All home buyers must confront the hedonic bundling constraint that I discuss below. It represents a supply side constraint such that a large 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). In the aftermath of the financial crisis of 2008, lower loan to value ratios would limit the ability of those who have not accumulated wealth to bid for housing in expensive markets.

During the recent real estate boom, foreign buyers have been purchasing U.S real estate and have focused their investments in Superstar Areas. Gorback and Keys (2020) present intriguing evidence that the rise in Chinese investor purchases of U.S real estate in California and other desirable areas combined with inelastic housing supply has driven up real estate prices over the last decade. This theory suggests that the rise of foreign investment in U.S real estate has accentuated the Superstar Cities effect documented by Gyourko, Mayer and Sinai (2013). If such foreign investors choose to have their families live in these properties or if they visit during vacations, then they will seek out high quality of life areas because they do not directly gain a utility flow from highly productive places (Kahn 2006).

Gorback and Keys use data from 2011 to assign each zip code to a dummy variable treatment status where a zip code is treated if its percent of the population is greater than 5% born in China. Only 1% of the nation's zip codes fall into this category. Across the nation there are 231 zip codes in this category. These treated zipcodes are clustered in many coastal cities such as New York City, Seattle, San Francisco, Los Angeles, Washington, D.C., and Boston. After 2011, they document that home prices grow more in their treated (high foreign born Chinese) areas in a regression that includes geographic fixed effects.

Research on the supply of endogenous local amenities (i.e fancy restaurants) has emphasized a latent production function such that areas with a larger share of college graduates have better "consumer city" amenities (Diamond 2016). Waldfogel (2008) adds a horizontal differentiation element to the consumer city as he emphasizes that there are scale economies of living with your own group because tailored varieties are more likely to be offered.

If Asians have a preference for Asian restaurants and shopping markets and religious opportunities that cater to them, then there are local scale economies that are enhanced when rich, educated members of the same group live close to each other. In this sense, foreign Asian buyers and U.S Asian buyers are complements in producing a “consumer city” that caters to this group. If foreign buyers anticipate this dynamic, then they will be more likely to buy real estate in places where U.S Asian buyers are clustering.

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.

## Supply

I conjecture that a central factor in determining the patterns I have documented is the classic hedonic bundling issue. The indivisibility of housing creates a type of binding hedonic bundling constraint. If a 4,500 square foot home could be easily subdivided into three housing units of 1,500 feet each, then the wealth constraint of purchasing housing in Superstar markets would be weakened. In a case of perfectly divisible housing, people with less wealth could purchase a smaller stake in a local market at the same price per square foot that people with more wealth face. In this sense, the hedonic bundling issue (that a large home cannot be divided up) (Rosen 2002). Home buyers cannot purchase a “share” of a house and they thus cannot create a portfolio of housing. If home buyers could buy a Baltimore home and then sell half of it and use the proceeds to purchase 8% of a Portland house and 4% of a San Francisco house, then I would these weights in my shift share analysis. Hedonic bundling means that such households cannot build a spatially diversified housing portfolio. While REITS offer such diversification possibilities, there would be even greater convergence in average rates of return across groups if

people invested more of their wealth in such assets and/or also participated in new markets such as a shared equity contract (Caplin, Tracy, Chan and Freeman 1997).

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).

In the 1990s, the rate of homeownership in the US increased, but the white and Black gap remained at 26 percentage points. Tighter government oversight and new mortgage products were introduced in the 1990s to increase minority homeownership rates. Gabriel and Rosenthal (2005) use household level data from the Federal Reserve Board's Survey of Consumer Finances from 1983 to 2001 to examine homeownership dynamics. They find that most of the increase in homeownership rates in the 1990s can be attributed to demographic and economic changes and that in the late 1990s, all but 8 percentage points of the 26 percentage point Black-white homeownership gap can be explained by population attributes. They estimate that credit barriers can account for just five percentage points of the minority-white gap. This suggests that government programs and innovations in the mortgage industry had little impact on the increase in homeownership rates.

Ongoing research in urban and real estate economics has focused on the role of regulations in local housing markets as a determinant of inelastic housing supply. Incumbent home owners have an incentive to enact policies that limit new housing supply in order to preserve their own asset's value (Fischel 1999, Glaeser, Gyourko and Saks 2005). Kahn (2011) reports evidence that progressive areas permit the construction of less new housing. Thus, the combination of progressive home owners creates a local inelastic housing supply combined with a local tech boom contributes to soaring home prices and this prices out many minority buyers.

## Conclusion

A home purchase represents a place based bet that both local economic growth and local quality of life will flourish. As time passes, both the buyer and the analyst observe the realized investment returns on the asset. By combining Zillow data and HMDA micro data, I have constructed a shift-share analysis of these realized rates of housing returns. Over the years 2010 to 2020, 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. Future work could incorporate tax considerations, leverage and loan terms into refining these calculations. Given that I found that loan amounts are comparable across demographic groups within narrow geographic areas such as census tracts, it appears that the Loan to Value ratios at purchase are roughly equal across groups.

This paper's simple calculations highlight the importance of bridging ideas from urban economics focused on residential locational choice with themes from real estate finance related to mortgage credit access. Blacks are less likely to buy housing in Superstar Cities that feature few high tech industries and an inelastic housing supply (Gyourko, Mayer and Sinai 2013). Is this due to supply or demand forces? Using the available data, I have not calculated the total portfolio returns for different demographic groups. Future research could study the correlation structure between one's housing portfolio, one's labor income dynamics and the rest of one's finance portfolio.<sup>14</sup>

The rise in real estate prices in productive local labor markets means that nominal wage growth overstates real local wage growth (Moretti 2013). The distributional consequences of the wealth effect induced by rising local real estate prices in specific markets merits more research.

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<sup>14</sup> In the 1990s, Blacks were more likely than whites to invest in housing than in riskier assets such as equities. To examine these differences, Gutter and Fontes (2006) create a two-stage investment decision model that separates the determinants for the acquisition decision from the decision of how to allocate the portfolio. They find that once structural access and awareness barriers are overcome, there are no racial differences between portfolio allocations, implying that while a disparity in the ownership of risky assets exists, it is not due to portfolio allocation decisions. They suggest that a voluntary savings initiative with a graduated investment component could help reduce this gap.

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Figure One  
Nominal Home Price Index Dynamics

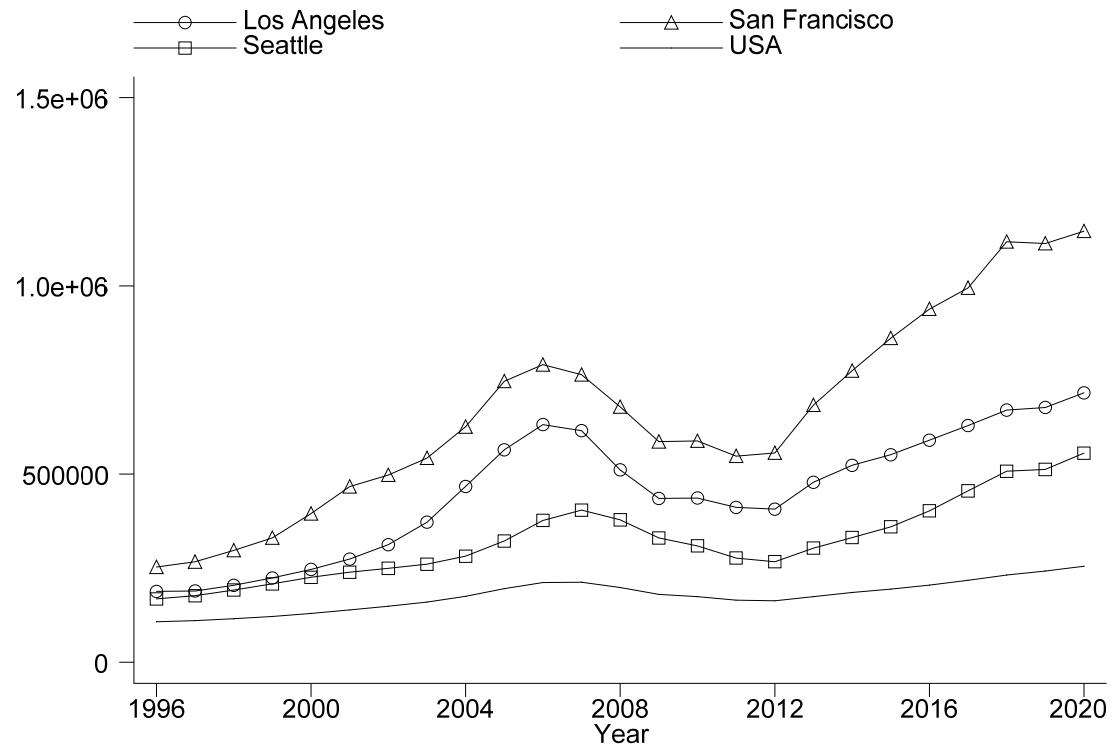


Figure Two

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

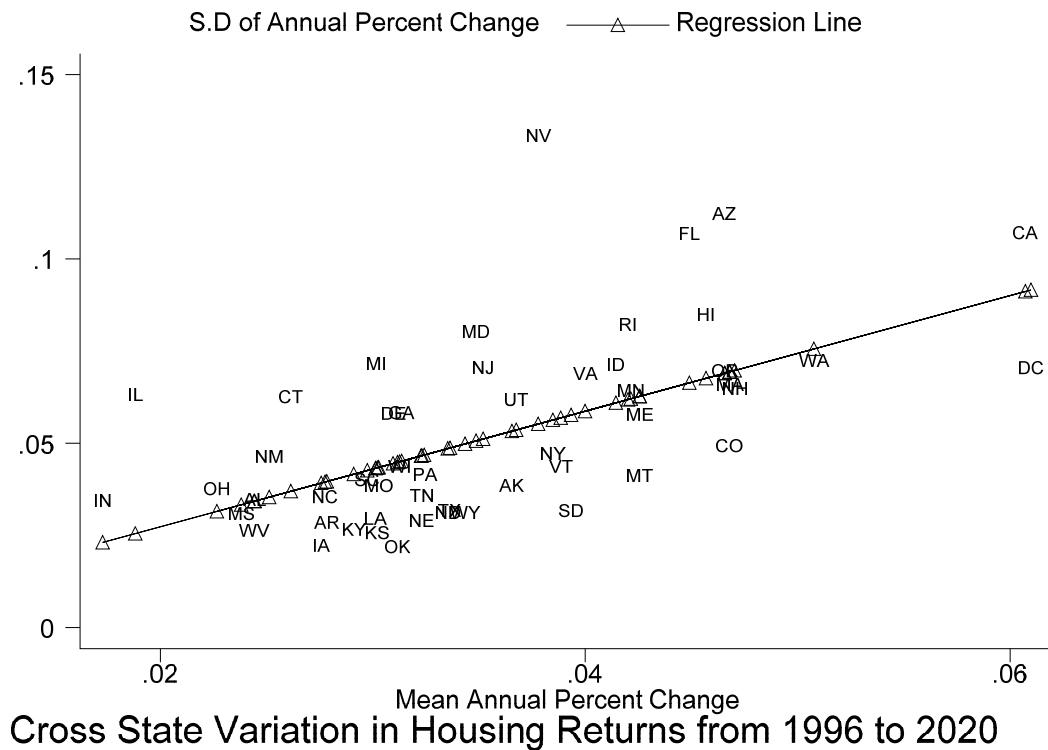


Figure Three

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

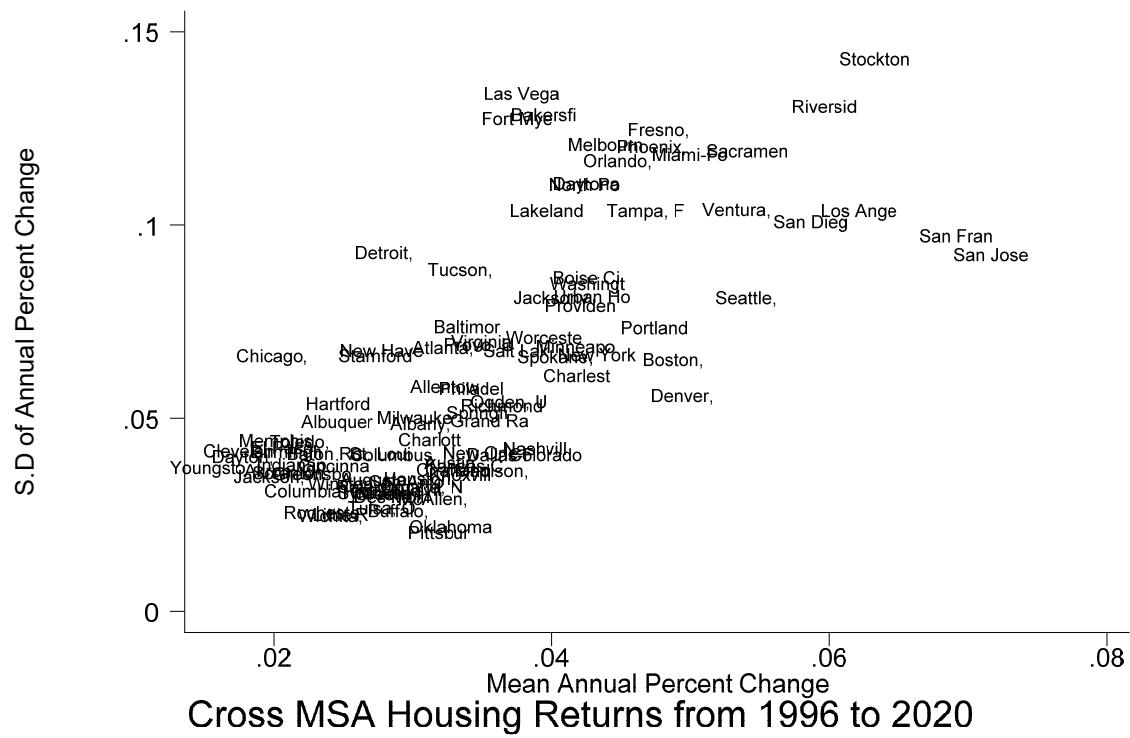


Figure Four

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

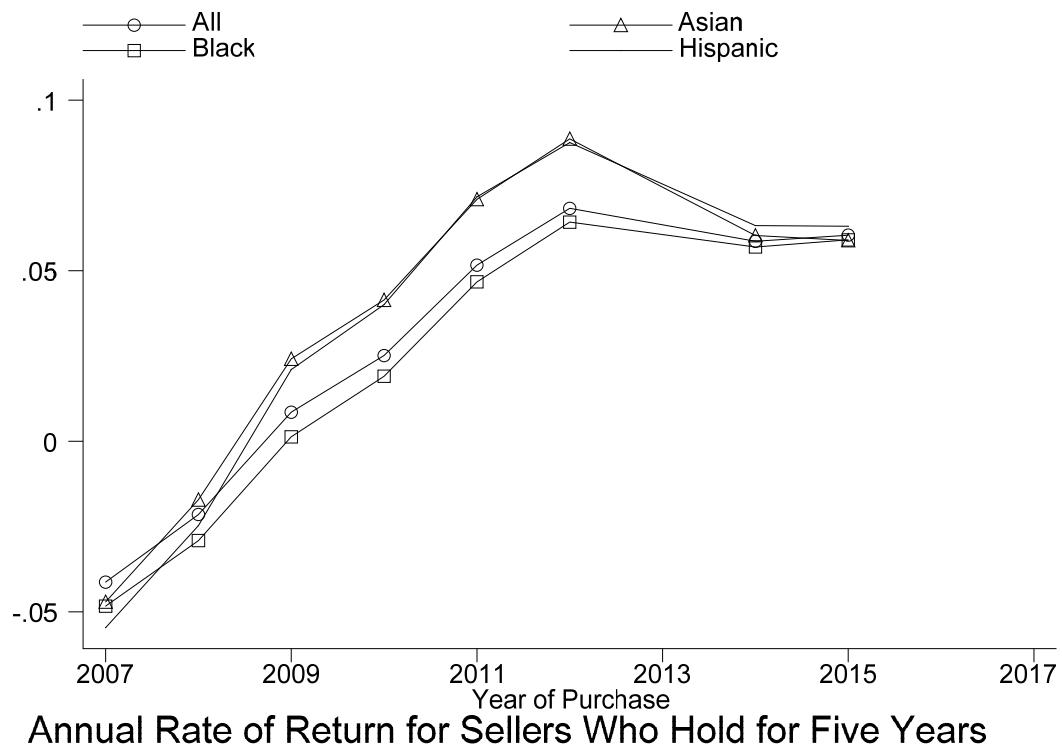


Figure Five

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

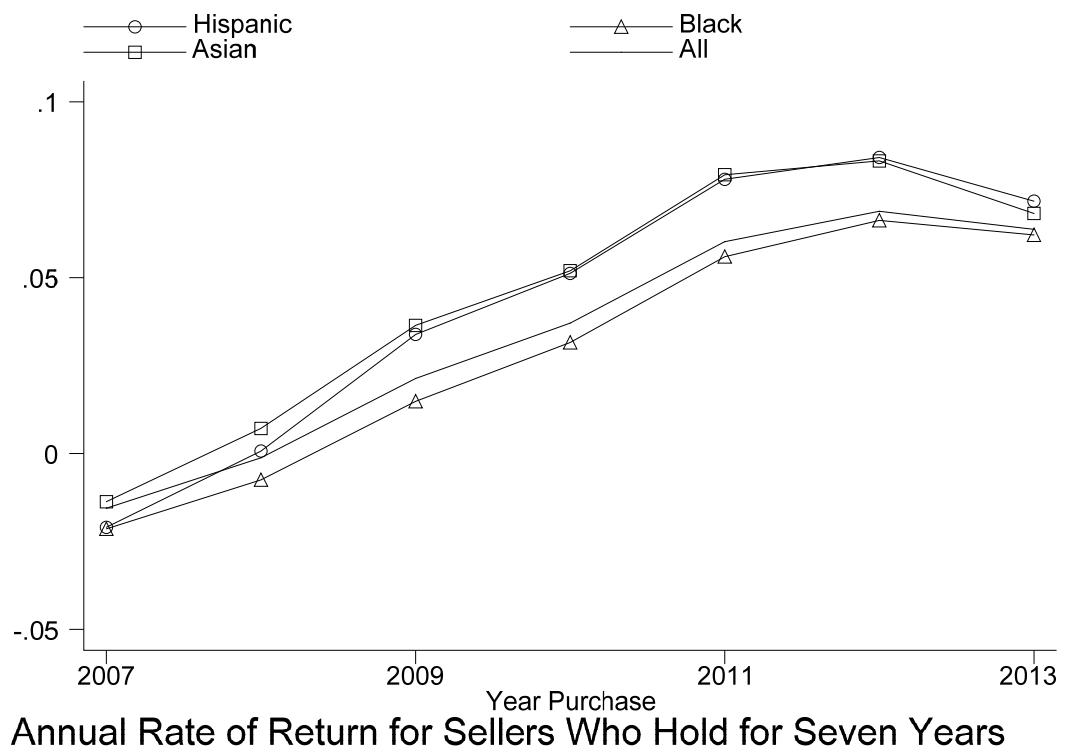


Table One  
The Distribution of Home Buyers Across States

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

year	County				Zip Code			
	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  
Loan Size Regressions

2017 Data	Y=log(Loan Size)				
	(1)	(2)	(3)	(4)	(5)
Hispanic	-0.0347*** (0.00106)	-0.169*** (0.000978)	-0.181*** (0.000896)	-0.0663*** (0.000836)	-0.0295*** (0.000786)
Asian	0.405*** (0.00134)	0.203*** (0.00122)	0.0283*** (0.00111)	0.00635*** (0.00102)	0.00569*** (0.000962)
Black	-0.0902*** (0.00129)	-0.0961*** (0.00117)	-0.127*** (0.00106)	0.0123*** (0.000995)	0.0478*** (0.000940)
Constant	5.369*** (0.000367)	5.396*** (0.000329)	5.411*** (0.000292)	5.391*** (0.000263)	5.384*** (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 Five  
Shift Share Annual Nominal Rate of Return Estimates

		County Level				Zip Code			
Buy	Sell	All	Asian	Black	Hispanic	All	Asian	Black	Hispanic
2007	2010	-0.051	-0.062	-0.059	-0.075	-0.046	-0.054	-0.062	-0.073
2007	2011	-0.050	-0.057	-0.057	-0.067	-0.045	-0.051	-0.061	-0.067
2007	2012	-0.041	-0.047	-0.048	-0.055	-0.038	-0.041	-0.053	-0.055
2007	2013	-0.026	-0.027	-0.033	-0.035	-0.024	-0.022	-0.039	-0.036
2007	2014	-0.016	-0.014	-0.021	-0.021	-0.014	-0.009	-0.027	-0.023
2007	2015	-0.009	-0.006	-0.014	-0.013	-0.007	0.000	-0.019	-0.014
2007	2016	-0.002	0.001	-0.008	-0.005	-0.001	0.006	-0.012	-0.005
2007	2017	0.004	0.007	-0.001	0.001	0.005	0.013	-0.005	0.002
2007	2018	0.009	0.014	0.004	0.007	0.011	0.020	0.002	0.009
2007	2019	0.012	0.015	0.008	0.010	0.014	0.019	0.007	0.012
2007	2020	0.016	0.018	0.012	0.014	0.017	0.022	0.011	0.016
2008	2011	-0.051	-0.056	-0.059	-0.066	-0.047	-0.049	-0.065	-0.065
2008	2012	-0.040	-0.043	-0.048	-0.050	-0.038	-0.038	-0.054	-0.051
2008	2013	-0.021	-0.017	-0.029	-0.025	-0.020	-0.012	-0.036	-0.026
2008	2014	-0.009	-0.001	-0.015	-0.008	-0.007	0.004	-0.022	-0.008
2008	2015	-0.001	0.007	-0.008	0.001	0.000	0.012	-0.013	0.001
2008	2016	0.005	0.014	-0.001	0.008	0.006	0.019	-0.006	0.010
2008	2017	0.012	0.020	0.006	0.015	0.013	0.025	0.002	0.017
2008	2018	0.018	0.027	0.012	0.021	0.019	0.033	0.009	0.024
2008	2019	0.020	0.027	0.015	0.023	0.021	0.031	0.014	0.027
2008	2020	0.024	0.030	0.019	0.027	0.025	0.034	0.019	0.031
2009	2012	-0.029	-0.026	-0.037	-0.031	-0.028	-0.021	-0.045	-0.032
2009	2013	-0.006	0.007	-0.014	0.002	-0.005	0.012	-0.022	0.001
2009	2014	0.009	0.024	0.001	0.021	0.009	0.028	-0.006	0.022
2009	2015	0.015	0.031	0.008	0.027	0.015	0.035	0.002	0.029
2009	2016	0.021	0.036	0.015	0.034	0.021	0.041	0.010	0.037
2009	2017	0.027	0.042	0.021	0.040	0.028	0.047	0.018	0.045
2009	2018	0.033	0.049	0.027	0.045	0.033	0.054	0.025	0.051
2009	2019	0.035	0.047	0.030	0.046	0.035	0.051	0.029	0.053
2009	2020	0.038	0.049	0.033	0.049	0.038	0.053	0.034	0.056
2010	2013	0.003	0.016	-0.006	0.013	0.002	0.020	-0.015	0.013
2010	2014	0.019	0.036	0.012	0.035	0.018	0.039	0.005	0.036
2010	2015	0.025	0.041	0.019	0.040	0.025	0.045	0.013	0.043
2010	2016	0.031	0.047	0.025	0.046	0.031	0.051	0.021	0.051
2010	2017	0.037	0.052	0.032	0.051	0.037	0.056	0.029	0.057
2010	2018	0.043	0.059	0.037	0.056	0.043	0.063	0.037	0.064
2010	2019	0.043	0.055	0.039	0.056	0.043	0.058	0.040	0.064
2010	2020	0.046	0.056	0.042	0.058	0.046	0.059	0.045	0.067

2011	2014	0.046	0.070	0.041	0.071	0.044	0.071	0.034	0.072
2011	2015	0.048	0.069	0.043	0.070	0.047	0.072	0.038	0.073
2011	2016	0.052	0.071	0.047	0.072	0.050	0.074	0.044	0.077
2011	2017	0.056	0.074	0.051	0.075	0.055	0.077	0.050	0.081
2011	2018	0.060	0.079	0.056	0.078	0.059	0.083	0.057	0.086
2011	2019	0.060	0.073	0.056	0.075	0.059	0.075	0.059	0.084
2011	2020	0.061	0.073	0.058	0.076	0.061	0.075	0.062	0.086
2012	2015	0.066	0.092	0.062	0.090	0.067	0.093	0.062	0.096
2012	2016	0.066	0.089	0.062	0.087	0.066	0.089	0.063	0.094
2012	2017	0.068	0.089	0.064	0.088	0.069	0.089	0.067	0.095
2012	2018	0.071	0.092	0.067	0.089	0.071	0.092	0.072	0.097
2012	2019	0.069	0.083	0.066	0.084	0.069	0.083	0.072	0.093
2012	2020	0.070	0.082	0.067	0.084	0.070	0.081	0.074	0.093
2013	2015	0.162	0.191	0.156	0.188	0.161	0.189	0.168	0.207
2013	2016	0.058	0.070	0.056	0.072	0.058	0.070	0.058	0.078
2013	2017	0.061	0.072	0.059	0.073	0.061	0.072	0.062	0.080
2013	2019	0.063	0.069	0.061	0.072	0.062	0.067	0.067	0.079
2013	2020	0.064	0.068	0.062	0.072	0.063	0.066	0.069	0.080
2014	2017	0.057	0.063	0.054	0.063	0.057	0.062	0.058	0.070
2014	2018	0.061	0.068	0.058	0.067	0.061	0.067	0.064	0.074
2014	2019	0.059	0.060	0.057	0.063	0.059	0.059	0.063	0.071
2014	2020	0.060	0.060	0.058	0.064	0.060	0.058	0.066	0.072
2015	2018	0.063	0.069	0.061	0.067	0.063	0.067	0.066	0.075
2015	2019	0.059	0.059	0.058	0.063	0.059	0.057	0.065	0.070
2015	2020	0.060	0.059	0.059	0.063	0.060	0.056	0.066	0.070
2016	2019	0.058	0.056	0.058	0.060	0.058	0.054	0.065	0.066
2016	2020	0.059	0.056	0.058	0.060	0.059	0.053	0.066	0.067
2017	2020	0.055	0.050	0.055	0.055	0.055	0.047	0.063	0.061

Table Six  
The Percent Change in County Home Prices from 2009 to 2020

	(1)	(2)	(3)	(4)
California Dummy	0.281*** (0.0260)		0.368*** (0.0136)	
% College Graduate in 2000	-0.0632 (0.0463)	-0.00888 (0.0375)	0.134** (0.0470)	0.223*** (0.0340)
% Black in 2000	-0.359*** (0.0272)	-0.163*** (0.0281)	-0.147*** (0.0340)	0.172*** (0.0280)
Constant	0.371*** (0.00935)	0.349*** (0.00752)	0.332*** (0.0132)	0.314*** (0.00948)
N	2484	2484	2484	2484
R2	0.11	0.54	0.25	0.67
State Fixed Effects	No	Yes	No	Yes
Weighted by Population	No	No	Yes	Yes

Standard errors in parentheses