

# Returns to owner-occupied Housing and Wealth Inequality \*

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## **Abstract**

How much of the recent increase in wealth inequality is due to returns on owner-occupied housing? In this paper, we analyze how the returns to owner-occupied housing affect the returns on wealth across households with differing wealth levels. Using household portfolio data we show that richer households are typically more exposed to housing, and that some of the recent increase in wealth inequality can be attributed to the high returns on housing. We show that increasing housing supply elasticity to the 90<sup>th</sup> percentile reduces the dispersion in wealth by about 2%. Preliminary results show that the sorting of households of different wealth levels to different regions further increases the disparity in returns between households.

**Preliminary and incomplete - may contain errors.**

## Introduction

Recent research, by [Piketty \(2015\)](#) and others, has shown that there has been a large increase in wealth inequality in western nations since the 1980s and particularly in the United States. In this paper we quantify the extent to which changes in house prices have contributed to this increase in wealth inequality.

The value of a home can be decomposed into the value or replacement cost of the structure and the value of the land on which the home is built. As a durable good the supply of structures is relatively elastic. This is because as [Glaeser \(2011\)](#) points out, the construction industry has a approximately constant returns to scale. This means that in the long run the supply of structures is perfectly elastic. In contrast the supply of land that is suitable for development is not perfectly elastic. While technological changes, such as better transportation, can increase the area of a region where households can commute to and from, there are many barriers that limit the supply of land that's suitable for development.

Regulations that prevent the construction of new housing, including height and density limits, prohibitions on converting land that is currently being used for single family housing to multifamily housing, and regulations that prevent construction in certain areas, reduce the supply of land that is suitable for development. This increases the price of existing land, and hence causes the price of housing to rise. This increases the wealth of existing homeowners, and thus increases inequality between homeowners and renters, as homeowners experience larger capital gains on their home.

Moreover, the topography of the undeveloped land of an area, as well as planning and zoning regulations, affect the elasticity of housing supply in a region. Since the existing housing stock is fixed, if home prices fall below the cost of construction the supply of housing will remain equal to the existing supply and no new construction will take place. Thus, when prices are below the marginal cost of construction the elasticity of supply is zero.<sup>1</sup> As prices rise above the marginal cost of construction, the housing stock will increase. When there are geographical constraints such as large bodies of water that limit the land available for construction, developers have to construct denser, more costly housing, reducing the housing supply elasticity Glaeser (2011).

Government regulations can also reduce the housing supply elasticity. Set-back mandates on new construction, minimum unit size requirements, and parking minimums all increase the marginal cost of construction. Together these regulations as well as height limits and lot size minimums place an upper bound on the number of units that can be legally constructed within a given parcel of land. As with the natural barriers these regulations limit how responsive housing supply is to changes in prices.

The reduction in supply elasticity caused by these regulations and geographical constraints increases the sensitivity of house prices to demand shocks. A positive demand shock caused by increased population growth, looser monetary policy, or easier access to mortgages will increase house prices more in regions that have low elasticity compared to those that have a high supply elasticity.

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<sup>1</sup>In reality the elasticity will not exactly equal zero as the depreciation of the existing housing stock will cause the total supply of housing to fall over time.

Land also represents a large and increasing fraction of total national wealth. [Piketty and Zucman \(2014\)](#) finds that housing represents approximately half of all wealth in developed countries. Moreover, the value of housing stock relative to GDP has increased over time. They find that as of 2010 that the value of the housing stock is greater than 200% of GDP. Since housing represents such a large fraction of total national wealth, factors that affect house prices can potentially have a large quantitative impact on wealth inequality.

This paper connects several strands of literature. Papers such as [Gabaix and Landier \(2008\)](#) and [Gomez et al. \(2019\)](#) explore how inequality has increased at the upper end of the distribution. The former of these papers explores how small shifts in the distribution of talent among top income earners can generate the large increase in incomes among the wealthy. [Gomez et al. \(2019\)](#) creates an accounting framework to decompose the change in wealth among the upper end of the distribution into displacement (entry), returns on wealth, and demographics. He finds that the first two terms explain the entire rise in wealth among the wealthiest.

Following [Gomez et al. \(2019\)](#), our paper uses an accounting framework to decompose the return on wealth among different wealth groups. We decompose the return on wealth for each group into a term returns that is due to owner-occupied housing and another term that is due to the returns on all other assets. Using Census Bureau portfolio data, we can find the makeup each wealth groups portfolio. Then, using actual historical returns, we can calculate the contribution of owner-occupied housing to the return on wealth.

Our research is also related to the recent debate as to whether labor's share of national income has decreased. Within the macroeconomics literature, papers such as [Karabarbounis and Neiman \(2013\)](#) argue that the share of national income that is attributed to labor has decreased over the past 35 years. Papers such as [Dorn et al. \(2017\)](#) attribute this fall in labor share to increased concentration, while [Karabarbounis and Neiman \(2013\)](#) find that changes in the relative price of capital goods can explain much of the fall in labor's share.

While this paper does not explicitly model labor's share of national income, an extension of our framework allows us to compute the rents on housing. Assuming that rents are an increasing function of house prices, the increase in house prices that we document would translate into higher rents. Since rents represent a large fraction of national income even modest rise could explain some of the fall in labor's share of national income over time.

Our paper not only documents that there has been an increase in house prices over the past 30 years, but that this has also been accompanied by rising house price dispersion. This is similar to the results of [Van Nieuwerburgh and Weill \(2010\)](#) who show that house price dispersion has increased at the MSA level. We further extend the results of [Van Nieuwerburgh and Weill \(2010\)](#) using ZIP code level data on house prices as well as incorporating data from the past decade. We find that house price dispersion has continued to increase since their paper was published.

Increased house price dispersion indicates that there has been a large dispersion

in returns across ZIP codes. This creates another potential channel for house prices to affect inequality. If there was positive assortative matching (PAM) between the wealth of a household and the subsequent returns on the housing in that ZIP, this would further increase the dispersion in returns among wealth groups and hence increase inequality between them. While our data does not allow us to see how household portfolios vary at the ZIP code level, we provide bounds on returns given an assumption about the matching between households and ZIPs.

More recently the literature the literature that explores the intersection of macroeconomics and housing has greatly expanded, see [Piazzesi and Schneider \(2016\)](#) for an overview. While our paper only explores how the returns to housing affect wealth inequality, land use restriction can also affect the allocation of labor in the economy. Since the regions with relatively expensive housing tend also to be regions with relatively high labor productivity, increased home prices limits mobility into these regions, particularly for lower income individuals. This induces these low-income households to live in less productive regions and hence to earn lower incomes, potentially increasing inequality between those that can afford to live in the region and those that cannot.

[Herkenhoff et al. \(2018\)](#) explores how land use regulations in high productivity coastal states have reduced aggregate productivity. They find that reducing these land use restrictions would lead to a substantial increase in aggregate US incomes.

For most households, purchasing a home involves taking out a mortgage. Hous-

ing debt, in fact, represents over 70% of total household debt <sup>2</sup>. Therefore, factors that affect the availability or cost of mortgage debt are likely to influence house prices. [Favilukis et al. \(2017\)](#) show that looser mortgage origination standards can generate large housing booms such as the one in the early 2000s. [Krishnamurthy and Vissing-Jorgensen \(2011\)](#) find that unconventional monetary policy decreased interest rates across the entire yield curve. Moreover, their paper finds that unconventional monetary policy that involved large scale purchased of mortgage backed securities, lead to a substantial fall in the yields on these instruments as well as their risk premia. This provides one possible channel for the increase in house prices that we document.

Since the accounting framework that we use takes returns as given, we cannot precisely trace out the implications of unconventional monetary policy on housing returns here. However, given that monetary policy may affect the returns to housing, we could view the large returns to housing, particularly after the 2009 as in part due to the actions of the Federal reserve. One paper that explores how monetary policy can affect house prices is [Kiyotaki et al. \(2011\)](#). In this paper, the authors construct a life-cycle model of the household and show that a change in interest rates have large effects on house prices, particularly when land represents a large fraction of the value of a structure.

In our paper, we focus exclusively on the role that supply elasticity has on house prices. Using supply elasticities developed by [Saiz \(2010\)](#), we show that less elastic regions witnessed smaller increases in house prices over the last 23 years. Using our

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<sup>2</sup>New York Federal Reserve Household Debt and Credit Report (Q2 2019)



accounting framework, we then develop a counterfactual world that is equivalent to increasing the house price elasticity to the 90<sup>th</sup> percentile of MSA's by elasticity. We show that this causes the returns on wealth to fall and that the decrease is greater for richer households. We then compare the dispersion in wealth in our counterfactual world to what we see in the data. The counterfactual scenario has a dispersion in wealth that is approximately 2% smaller than what we see in the data.

As mentioned before, a limitation of our results is that we only have highly aggregated household portfolio composition data. This forces US to use a national average return to housing. In order to see how relaxing this assumption would affect returns we examine cases where there is positive and negative assortative matching of household wealth and the returns on housing within the MSA. We compare these returns to the baseline and show that positive assortative matching substantially increases the returns for the wealthiest households. Lastly, we discuss how to extend our framework to the ZIP code level.

The remainder of the paper is organized as follows. Section two describes the data sources. Section three presents the baseline accounting model that we use to compute the returns on wealth of each group. Section four presents our results. Section five discusses the possibility of extending our results to ZIP code level data. Lastly, section six concludes.

## 2 Data Sources

We obtain Metropolitan Statistical Area (MSA) housing supply elasticities from [Saiz \(2010\)](#). The topography of an area affects the marginal cost of constructing new housing units. MSA with steeper topography will be relatively more expensive to construct new housing on. Furthermore, if a region is bounded by a large body of water such as a lake or a sea, this will reduce the supply of land that is available for development. [Saiz \(2010\)](#) estimates how these geographical constraints affect the housing supply elasticities of MSAs.

The Census Bureau Wealth and Asset Ownership Data Tables, 2015 edition, provides data on the net worth of US households as well as the dollar value of each asset class that households own. The Wealth and Asset Ownership Data Tables also provide this data conditional on the household meeting a certain characteristic, such as race, income level, or wealth levels. For wealth levels there are nine groups. Membership of each group is defined by the individual's total net worth being in an interval. See table 6 in the appendix for further details.

For each of these groups, the Census Bureau data provides us with the mean dollar value of asset owned by members of each group, conditional on them reporting ownership of that asset class. Using the proportion of each group that owned that asset, we compute the unconditional mean dollar value of each asset owned by that group by multiplying the proportion who report ownership, by the conditional mean dollar value. Here, we are implicitly assuming that failure to report is equivalent to not owning the asset. For the analysis in the paper, we exclude the group with a zero or negative reported net worth as we have limited data on household liabilities.

We use data from Zillow to get the ZIP code level mean home price. Zillow constructs the monthly mean house price in each ZIP code based on quality-adjusted repeat transactions within the ZIP code. We aggregate this ZIP code level house price to the MSA level using a linking table between ZIP codes and CBSAs from the Department of Housing and Development. Since the MSAs used in the Saiz paper are no longer used we then link these CBSAs to MSAs using a linking table provided by the NBER. We aggregate the ZIP code level house price to the MSAs data by taking a population weighted mean across all ZIP codes in the MSA. Aggregating the data is necessary as [Saiz \(2010\)](#) only provides an MSA level elasticity.

In the fifth section we discuss how to extend these results to the ZIP code level. Specifically, we explain how to calculate the elasticities of [Saiz \(2010\)](#) at the ZIP code level, as well as how to deal with the increased ability of households to substitute between such small regions.

Data on equity returns comes from The Center for Research in Security Prices (CRSP). We use the return on the value-weighted S&P 500 index, including all dividends and other distributions. Furthermore, we assume that all dividends are reinvested in the equity portfolio. Furthermore, we assume that privately, whether it's held in a mutual fund or via direct ownership of a firm has the same return as public equity. While there is some debate as to the return on private equity, see [Phalippou and Gottschalg \(2008\)](#) for example. Since we largely care about changes in returns due to housing our simplification doesn't affect the results of our paper. For pension assets, we follow [Andonov et al. \(2017\)](#) and allocate 75% of

pension assets into equities and the remainder into interest-earning assets, which we described below.

Since the Census Bureau's Wealth and Asset Ownership Data Tables do not provide the term structure of fixed income asset, we impute a single interest rate for all interest-earning assets at financial institutions. We use the effective Federal funds rate from the Federal Reserve of St. Louis as this interest rate. The class denominated deposit assets is comprised of interest-earning assets at financial institutions, educational savings accounts, annuities, cash value of life insurance, and 25% of the value of retirement accounts.

Cash assets of households are computed as the sum of non-interest-earning deposits at financial institutions and other assets. In practice, other assets represent less than 0.5% of all household assets and so it makes little difference where we include them. We assume that these cash assets have zero percent nominal rate of return.

We compute other property assets of the household as the sum of all rental property and other real estate equity. Following [Eisfeldt and Demers \(2018\)](#) real returns on invest property are computed as 4% per annum. Since the [Eisfeldt and Demers \(2018\)](#) argues that actual returns on investment property is similar across MSAs our assumption of a constant return is relatively reasonable. They find that this is because the rent-to-price ratio tends be larger in regions that had lower house price growth.

Table 1: This table present summary statistics for the MSA level housing elasticities and population.

Statistic	Mean	St. Dev.	10 <sup>th</sup> percentile	90 <sup>th</sup> percentile
Elasticity	2.537	1.433	1.065	4.368
Population	773,579	1,266,825	123,847	1,716,841

Lastly, the share of assets in motor vehicles is computed as total equity in motor vehicles divided by total net worth. We compute a depreciation rate of 12%. All data is deflated using the Bureau of Economic Analysis Personal Consumption Expenditures (PCE) price index. We also obtain some stylized facts on asset shares from [Piketty \(2015\)](#). Table 1 provides an overview of our MSA data. From the table it is easy to see that MSAs are highly heterogeneous in terms of population and elasticities.

### 3 Accounting Model

Here we develop an accounting framework that allows us to compute the mean returns on a household's wealth, conditional on their portfolio composition. Since our data gives us portfolio choices for each group we group households into groups  $g \in \{0, 1, \dots, G\}$ . Where membership of group  $g$  means that the household's wealth is within a certain interval.

Each household has a stock of wealth composed of different assets such as cash, deposits, stocks, real estate, and durable goods. A household's share of wealth in asset  $i$  is denoted  $s_{g,i}$ , where  $i \in \{1, 2, \dots, I\}$ . We compute the share of wealth in asset  $i$  by households in group  $g$  as the mean value of equity in as-

set  $i$  owned by group  $g$  divided by the total mean net-worth of households in group  $g$ .

Since assets differ in both returns and taxes, we need to take this into account when computing the return on a household's wealth. For instance, housing is subject to numerous tax exemptions which increase the after-tax return of this type of investment relative to, say, investing in the stock market. We compute the return on each asset  $R_i$  using the nominal net return,  $r_i$ , the tax rate on returns to the asset,  $\tau_i$ , and the rate of inflation,  $\pi$ . We then compute the household's after-tax real return as

$$R_i = \frac{1 + r_i(1 - \tau_i)}{1 + \pi} - 1$$

This means that, for instance, that the return on cash for the household approximately equals one minus the inflation rate.

Data limitations prevent us from accounting for the effect leverage would have on the returns across wealth groups. Since we do not have data to jointly match household wealth and the composition of their liabilities, all returns are computed on an unlevered basis. Leverage will increase the returns on an asset when the return is positive, as we document with owner-occupied housing. Homeowners, due to tax considerations and financial constraints, typically borrow large fraction of the cost of a property. This means that the return on their equity can be far greater than the unlevered return on housing. Thus, the results in this paper on the effect of housing are rather conservative.

For a given household  $g$ , we can compute the expected return on its wealth,  $R^g$ . The expected return on wealth is a weighted average of the expected return

on each asset class, where the weights are given by the share of wealth invested in that asset. That is,

$$R^g = \sum_{i \in I} s_{g,i} R_i.$$

Naturally, the portfolio composition will vary across groups. For instance, wealthier households have a larger portion of their wealth on stocks and real estate compared to poorer households. This leads to differences in the returns to wealth across households and that households. Furthermore, this implies that households are *heterogeneously exposed* to shocks to the assets' returns. Hence, a sequence of positive shocks to an asset's return, such as a housing or a stock-market boom, would affect the *distribution* of wealth.

We can use this simple structure to calculate counterfactual expected returns on wealth under the assumption that portfolios' composition remains constant. For instance, we can calculate new returns on wealth under the assumption that all households had the same fraction of their wealth invested in housing. The difference between this counterfactual and the actual returns will give us a sense of how much of the change in the distribution is driven by the realization of housing returns. A counterfactual exercise of the paper consists of calculating the returns on wealth if the return on housing had been lower, which would have been the case if there were less housing regulations or more land availability for construction and housing prices were less responsive to shocks.

Importantly, this type of counterfactual calculation is not meant to capture a *causal* relationship. If we wanted to calculate what the distribution of wealth

would have been under a different realization of asset returns, we would need to account for the households' adjusting their portfolios to the new asset prices and beliefs about future asset returns. Since the purpose of our exercise is to get a sense of the magnitude of the contribution of housing returns to the increase in wealth inequality, we will proceed with a simple accounting exercise that does not take into account equilibrium effects.

## 4 Results

We divide our results into purely empirical results, the results of our accounting framework, and a counterfactual analysis using the accounting framework.

### 4.1 Elasticity and Home Price Dispersion.

As a preliminary exercise, we examine how the coefficient of variation changed over time. The coefficient of variation is a scale-free measure of dispersion of a distribution. Our results build on those of [Van Nieuwerburgh and Weill \(2010\)](#). Our contribution is to include the post-financial-crisis period as well as the use of a finer unit of observation, namely we use ZIP code level as opposed to MSA level house price data.

Figure 1 plots the time series of the coefficient of variation for ZIP code level house prices in the US from 1996 to 2019. The figure shows that there has been a large increase in house prices dispersion across ZIP codes over time. This increased dispersion also implies a large variation in returns to owner-occupied housing across regions, during this time.



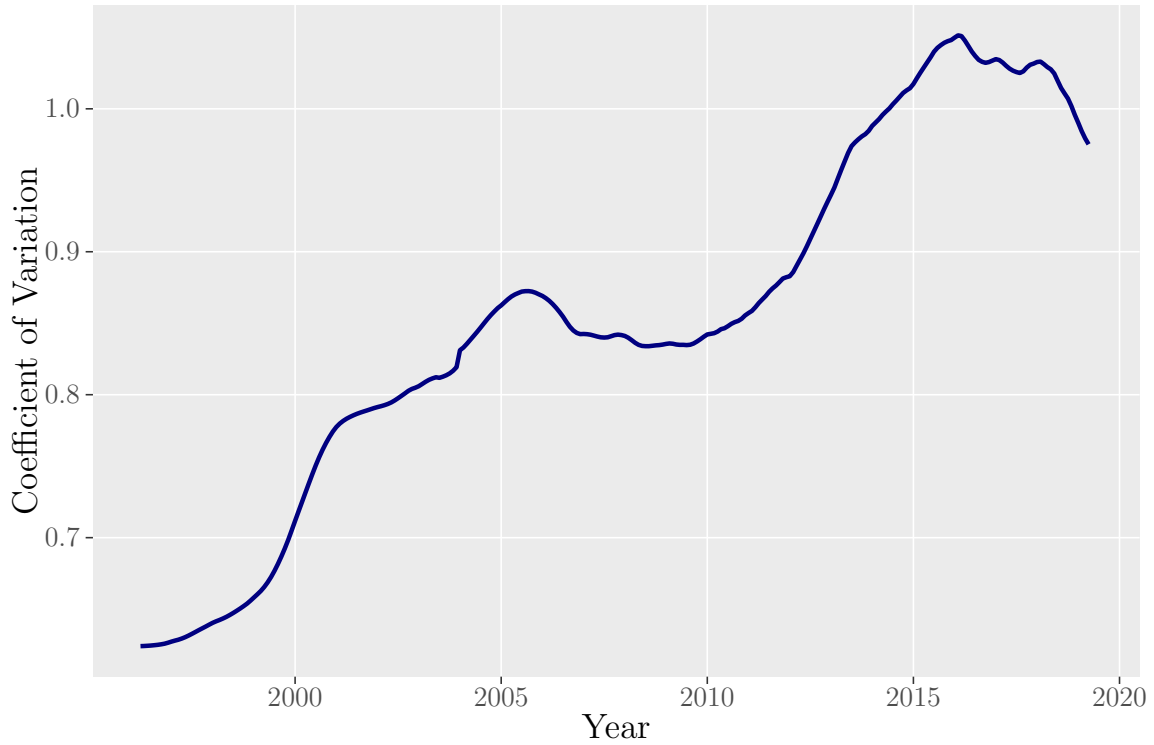


Figure 1: This series plots the coefficient of variation for US ZIP code level house prices over time. Source: Zillow monthly repeat sales house prices.

Since households are only exposed to owner-occupied housing in their region these differences in housing returns across regions naturally lead to increased inequality between households. Homeowners who happen to live in regions where prices increased the most, such as coastal California, will have had much higher returns than homeowners living in regions where there was little growth in real home prices, such as in the rust belt states. These differences in returns across groups will naturally lead to increased wealth inequality.

Moreover, since real after-tax returns on owner-occupied housing are higher

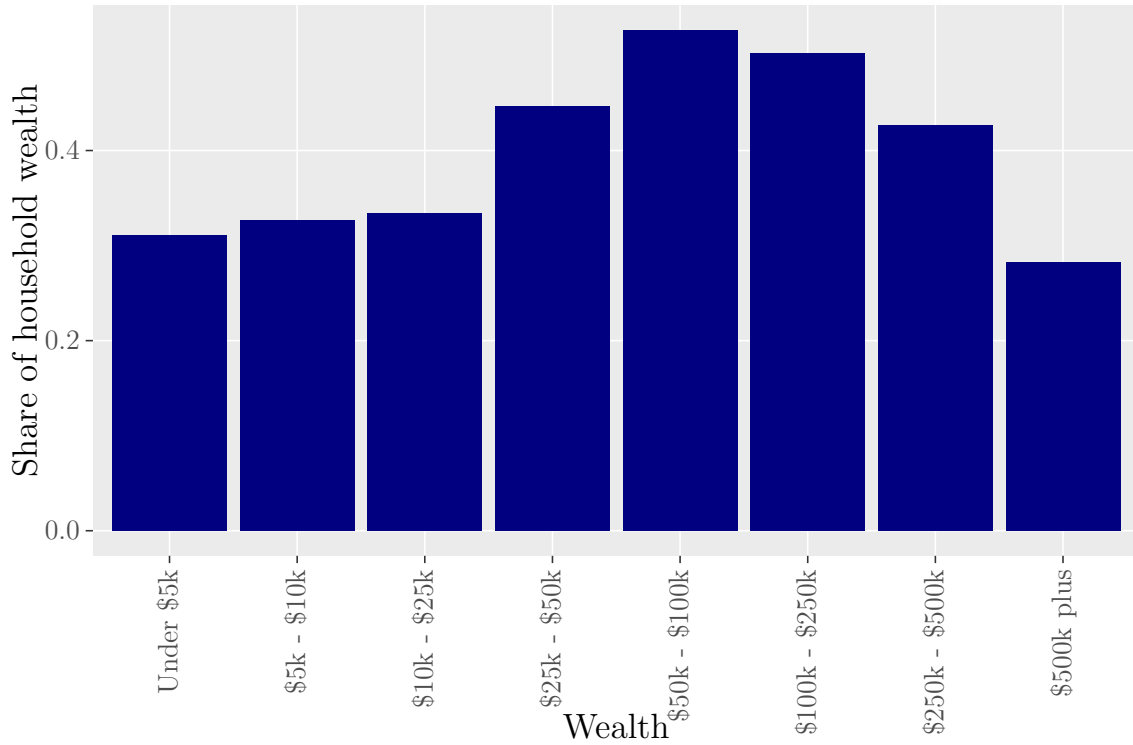


Figure 2: This figure plots the housing share of household wealth for different wealth levels. Wealth groups are in 2015 \$. Source: Census Bureau.

than most other asset classes and approximately equal to that of equity, see table 4 and [Jordà et al. \(2019\)](#), differences in the exposure of households of different wealth levels to housing will lead to differences in the returns that individuals with different wealth levels receive. Figure 2 shows that housing wealth as a share of total wealth tends to increase as wealth increases until wealth reaches \$100,000, after which it declines. This means that, on average, households with more wealth are more exposed owner-occupied housing.

The increase in the coefficient of variation not only entails that there has been a large amount of heterogeneity in returns to housing across ZIP codes, but also

that the ZIP codes that experienced large increases in returns were regions that were already (in 1996) more expensive. If returns were larger in regions that were relatively inexpensive then coefficient of variation would have declined.

While there are many reasons why the dispersion in home prices may have increased, such as divergent in regional productivity, see [Van Nieuwerburgh and Weill \(2010\)](#), our paper focuses on supply constraints. Planning and zoning regulations, geographic land constraints, and taxation of housing construction, all reduce the supply of housing. Furthermore, regulation and geographic constraints will reduce the supply elasticity, [Glaeser and Gyourko \(2018\)](#). Regulations such as high limits and set back requirements increase the marginal cost of producing new housing units. Natural barriers such as bodies of water have similar effects.

Due to the endogenous nature of regulation, in this paper we confine our analysis to differences in housing supply elasticity that [Saiz \(2010\)](#) attributes to natural constraints on the construction of new housing. These natural barriers to housing construction are likely to be exogenous to other factors in an area that could affect the price of housing, making a causal interpretation of the regression more plausible.

Using the estimated elasticities of [Saiz \(2010\)](#), [Figure 3](#) plots the mean log change in real house prices between April 1996 and April 2019 in each MSA against its elasticity. The size of each point in the plot represents the MSAs population. The figure illustrates that there is a negative relationship between an MSA's elasticity and the appreciation in house prices over this time. MSAs with larger elasticities, that is regions where there are fewer natural barriers to housing construction, saw

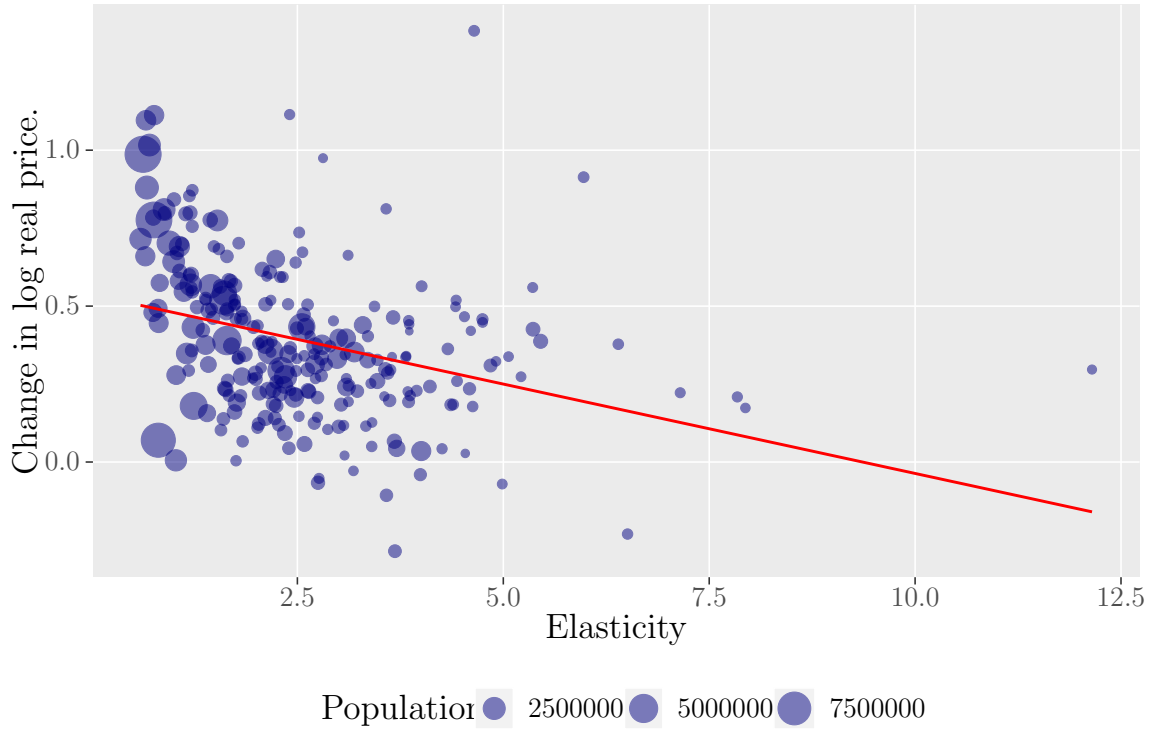


Figure 3: This figure plots the MSA level elasticity against the mean change in the real log house price between April 2019 and April 1996. The red line is fitted using OLS. Sources: Zillow, [Saiz \(2010\)](#), the BEA, and authors' calculations.

smaller increases in real house prices.

In order to formalize the results of [3](#), we regress the log change in real home prices between 2019 and 1996 for each MSA on the MSA's elasticity. [Table 2](#) contains the results. All standard errors are clustered at the state level. We find that the coefficient on the MSA's elasticity is negative and significant at the 5% level. This implies that MSA's with more elastic housing supply saw smaller appreciation in real house prices over the period. The coefficient of -0.003 implies that increasing the MSA's supply elasticity from the 10<sup>th</sup> to the 90<sup>th</sup> percentile will reduce the

average real returns on housing by 1% per annum.

Table 2: Regression of the log change in mean home prices across MSAs between April 1996 and April 2019 on the housing supply elasticity. Standard errors are clustered at the state level.

<i>Dependent variable:</i>	
Annualized change in mean log real price	
Elasticity	−0.003** (0.001)
Constant	0.024*** (0.004)
Observations	110
R <sup>2</sup>	0.099
Adjusted R <sup>2</sup>	0.091
Residual Std. Error	0.010 (df = 108)
<i>Note:</i>	*p<0.1; **p<0.05; ***p<0.01

An extension of Table 2 is to regress the monthly change in the annualized mean real log price across MSAs on the MSA elasticities plus fixed effects. That is, to estimate the following equation

$$\Delta p_{m,t+1} = \beta \text{Elasticity}_m + F.E. + \varepsilon_{m,t+1}, \quad (1)$$

where  $\Delta p_{m,t+1}$  is the change in the mean real log house price in MSA  $m$  in date (year, month)  $t + 1$ .  $\text{Elasticity}_m$  is the elasticity in MSA  $m$ , F.E. stands for fixed effects, and  $\varepsilon_{m,t+1}$  is an error term.

Table 3 contains the results of regression 1. We cluster the standard errors at

the date level. In all specifications  $\beta$ , the coefficient on elasticity, is negative and significant at the 5% level. Depending on the specification  $\beta$  is between -0.003 and -0.001. This implies that moving from the 10<sup>th</sup> to the 90<sup>th</sup> percentile reduces the mean annualized real return on owner-occupied housing by between 0.33% and 1%.

Table 3: Regression of the monthly log change in mean home prices across MSAs between April 1996 and April 2019 on the housing supply elasticity. Standard errors are clustered at the date level.

	<i>Dependent variable:</i>		
	Mean change in MSA price		
	(1)	(2)	(3)
Elasticity	-0.002*** (0.0003)	-0.003*** (0.001)	-0.001** (0.0003)
State F.E.	Yes	No	Yes
Date F.E.	No	Yes	Yes
Observations	49,457	49,457	49,457
R <sup>2</sup>	0.025	0.403	0.420
Adjusted R <sup>2</sup>	0.024	0.399	0.416
Residual Std. Error	0.076 (df = 49414)	0.060 (df = 49180)	0.059 (df = 49139)

*Note:*

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

## 4.2 Accounting Framework Results

The baseline values we use to estimate the returns for each asset class are in [4](#). Using these values and the portfolio weights for different households wealth groups (see appendix [7](#)), we first compute the mean real returns for each wealth group. Figure [4](#) contains the returns for each wealth group as well as our counterfactual exercise described latter.

Table 4: Baseline average after-tax real rates of return on assets.

Asset Class	Gross Rate of Return
owner-occupied housing	1.025
Cash and equivalents	0.983
Interest Earning	1.001
Equities	1.031
Vehicles	0.880
Other Property	1.034

Furthermore, Figure 4 also plots counterfactual returns for each wealth group. For the counterfactual, we assume that the mean housing elasticity equals the 90<sup>th</sup> percentile value. We use the baseline regression in table 2 to estimate the counterfactual return on owner-occupied housing. All other real returns remain are held fixed.

Figure 4 illustrates how returns are an increasing function of the household's net worth. The negative after-tax real returns for poorer households are due to the large share of vehicle equity in their portfolios. Households with higher levels of wealth tend to skew their portfolios towards asset classes such as equity and housing, both of which have positive after-tax real returns over the period.

The values of the counterfactual plot in Figure 4 also illustrates the importance of housing for upper-middle and rich households. It is these households that see the largest decrease in the average return of their portfolio when we increase the housing supply elasticity. The portfolios of households with little net worth consist largely of safe assets and vehicles and are thus largely unaffected by changes in the

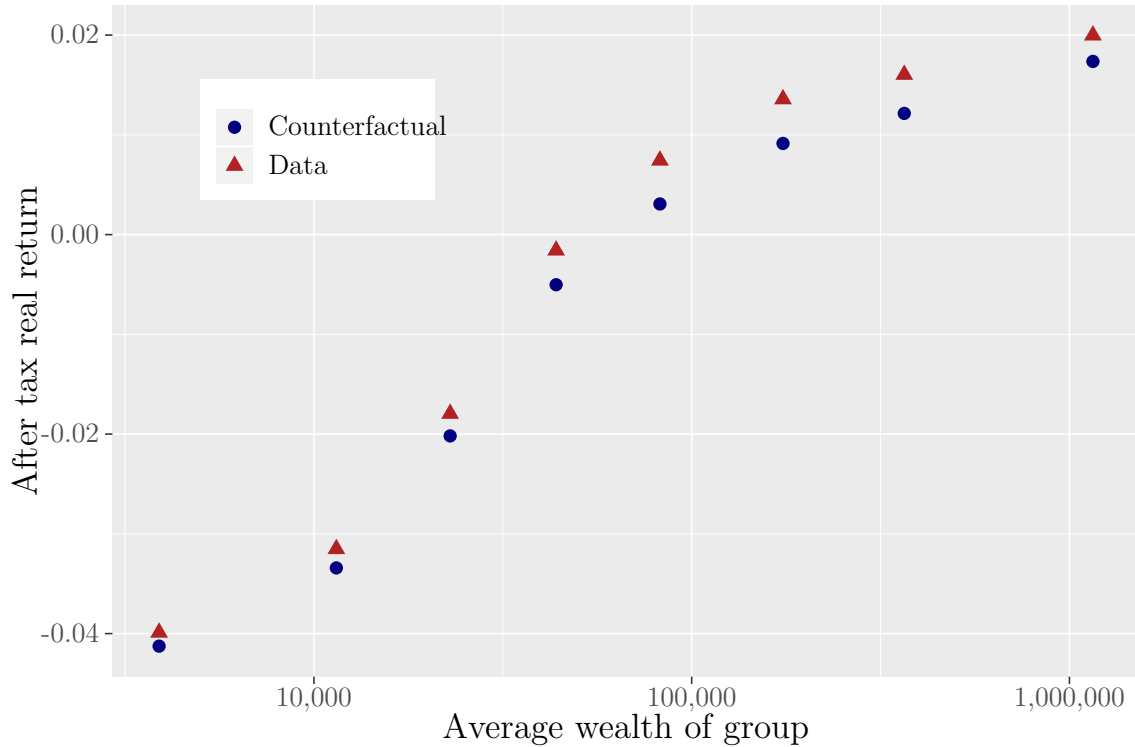


Figure 4: This figure plots average real return on each wealth group’s portfolio against the average wealth of that wealth group. The counterfactual returns are constructed assuming that the elasticity of housing supply had been that of the 90<sup>th</sup> percentile. Sources: Census Bureau, Zillow, [Saiz \(2010\)](#), the BEA, and authors’ calculations.

returns to owner-occupied housing.

A crucial limitation of our counterfactual analysis is that the returns on all other asset classes are assumed to be unaffected by the change in housing supply elasticity. While this may be a reasonable approximation for assets such as vehicles, cash and equivalents, this is obviously less reasonable in the case of the returns to other property. An increase in housing elasticity would likely also affect the capital gains on other property, such as rental properties. Furthermore, an increase in



supply elasticity may also cause renters to substitute to owner-occupied housing, potentially reducing rental yields as well.

Given the data limitations we described above, we proceed to place confidence bounds on the returns to wealth across different households. Depending on the matching between the household's wealth levels and the housing market they select, we can create upper and lower bounds for the returns to wealth of different households. If wealthier households tend to match with MSAs that experienced larger appreciation, then this will increase the wealth inequality. The reverse is true if richer households lived in regions that experienced little growth in house prices.

Since we do not have data on how households of different wealth levels match to MSAs, we instead explore what would happen to returns across wealth groups if there was positive assortative matching (PAM) of household wealth and subsequent returns or if there was negative assortative matching (NAM) between wealth and the subsequent return on housing in the MSA. Figure 5 plots what the returns across different wealth groups would look like if there was PAM, NAM, as well as the baseline returns from our accounting model.

In Figure 5, we first calculated the quantiles of returns from 1996 to 2019 across all MSAs. We then calculate a weighted mean return across all MSAs in that quantile, weighting by the population of the MSA. For PAM, we assumed that wealthiest household group matched to the quantile with the largest return and for NAM we assumed the opposite.

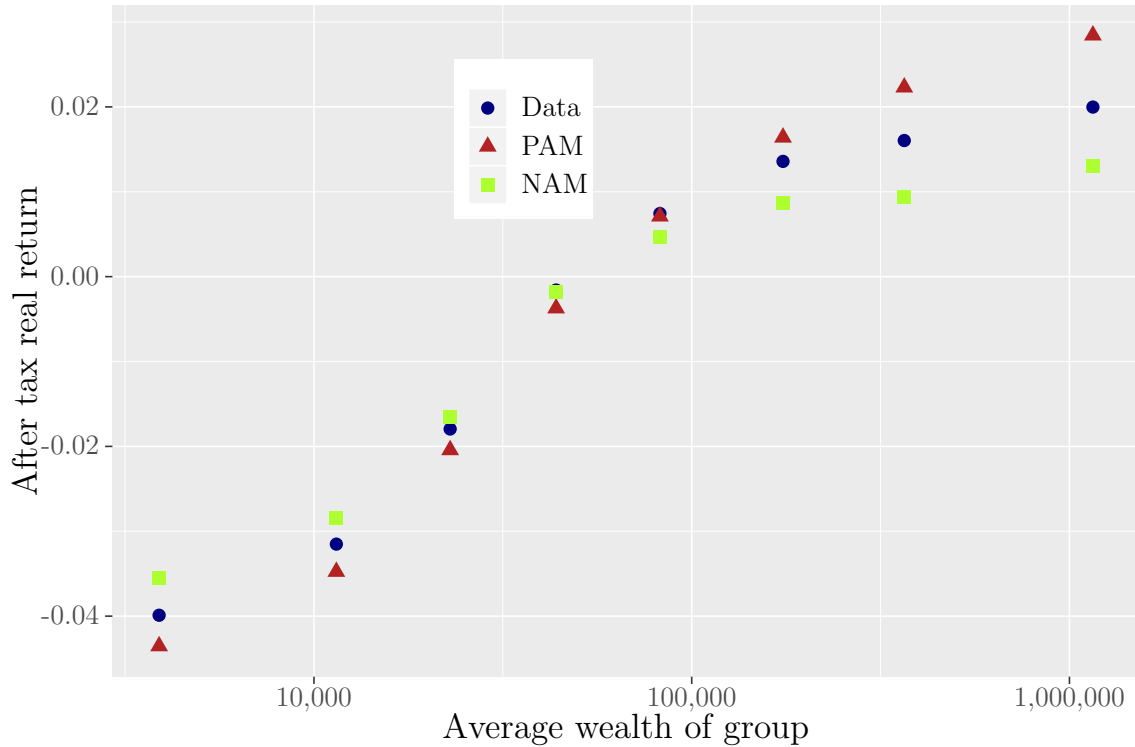


Figure 5: This figure plots average real return on each wealth group’s portfolio against the average wealth of that wealth group. PAM signifies that there was positive assortative matching between household wealth levels and subsequent returns to owner-occupied housing. NAM signifies that there was negative assortative matching between household wealth levels and subsequent returns to owner-occupied housing. All returns are average real after-tax returns. Sources: Census Bureau, Zillow, [Saiz \(2010\)](#), the BEA, and authors’ calculations.

Our data does not allow us to definitively say whether we have PAM or NAM or random matching. Still, the increased house price dispersion we document indicates that areas that were initially more expensive had higher subsequent returns. Mechanically, owning a home (ignoring mortgage debt for the moment) in a more expensive area leads to more increases of the wealth of the household. Since mortgage underwriting standards typically specify minimum down-payments as well as maximum loan-to-income limits, it is typically richer households that

live in more expensive areas. This would lead to PAM between household wealth and subsequent returns on housing, further magnifying inequality.

In Figure 8, in Appendix A, we plot the mean real average house price appreciation in each MSA against its initial price in 1996. The plot shows that more expensive MSA on average have had faster house price appreciation than cheaper MSAs. Once again, this observation would support our view that there was PAM between a household's wealth and the returns in their ZIP.

### 4.3 Counterfactual Wealth Distribution

We now use our results to produce a counterfactual wealth distribution. We use the terminal Census Bureau values of wealth in 2015 and the data values of returns to project what the actual values wealth for each group would have been in 1996. By dividing the total wealth of each group our estimated compounded return, we obtain the mean wealth of each group in 1996. We calculate automobiles by assuming that their real value remains constant due to the significance of inflows and outflows for this asset class. We then use the counterfactual returns that we calculated assuming that the house price elasticity equaled the 90<sup>th</sup> percentile value, to project what the counterfactual wealth of each group in 2015 would be.

In Figure 6, we plot the change in total wealth for each wealth group in our counterfactual. As one would expect the change in wealth approximately follows a U-shaped curve. Housing is an important part of wealth for upper-middle wealth households. Thus, it is these households that see the largest decreases in their wealth when the returns to housing decrease. The portfolios of the wealthiest

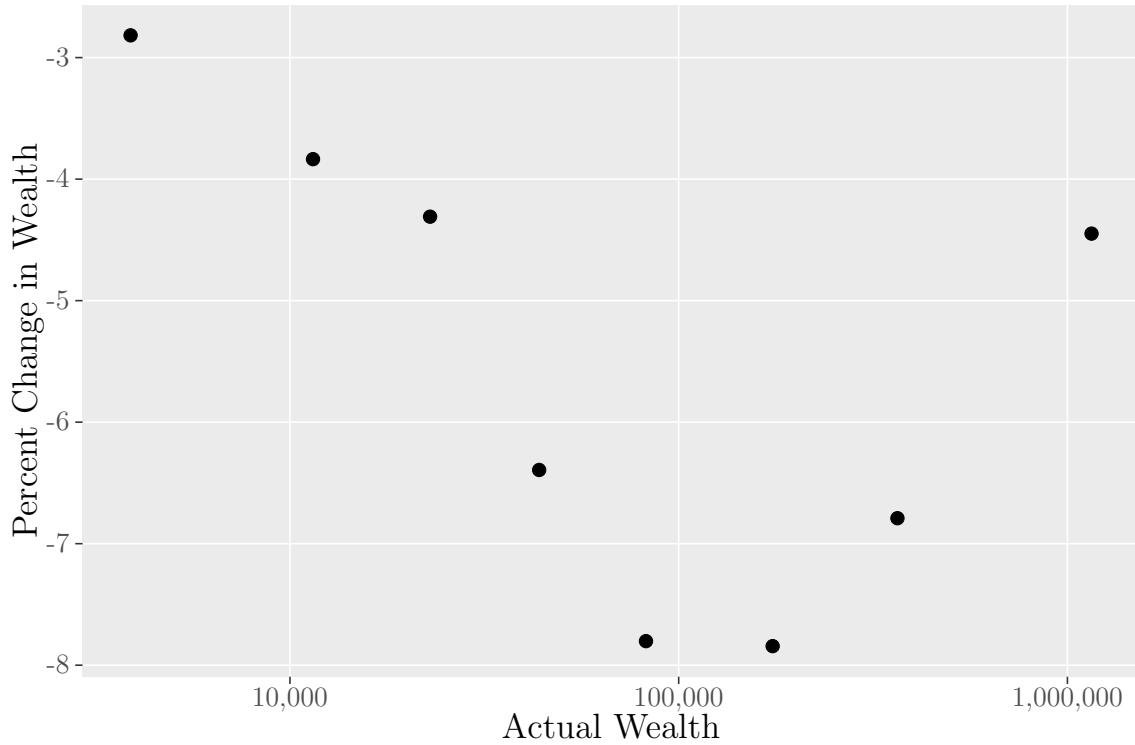


Figure 6: This figure plots percentage change in wealth when we compare the counterfactual wealth level to the wealth level in the data. The counterfactual wealth level is determined by calculating the 1996 wealth level using the 2015 census data and the returns we calibrated and working back to 1996. We the project forward using our counterfactual return to housing holding other asset’s returns constant. See text for details.

households by contrast, contain much more equity, and are thus less affected by this change. What little net worth the poorest households have, tends to be concentrated in durable goods and liquid assets such as cash.

Table 5 contains the coefficient of variation for wealth according to the data and according to the counterfactual scenario. According to our simple counterfactual exercise increasing the in the house price elasticity to the 90<sup>th</sup> percentile would

reduce the dispersion in wealth across cohorts by approximately 2%. Thus, we can see that at the aggregate level returns on owner-occupied housing have modestly contributed to wealth inequality over the period of study.

Table 5: This table shows the coefficient of variation in wealth between our eight groups in the data as well as in the counterfactual scenario we created.

Coefficient of Variation of Wealth	
Data	Counterfactual
0.593	0.587

## 5 Extension to ZIP code level

In the counterfactual exercise of this paper, we considered housing returns at a national level only. This is because, as discussed earlier, data limitations mean we only have national portfolio data. While we explored how matching of households to MSAs would affect our results, in this section, we discuss how we can further extend our results to account for matching of households at the ZIP code level. MSA are often large heterogeneous regions, so even using MSA level data masks much of the heterogeneity in returns to housing that can occur at a ZIP code level. For example, if richer neighborhoods had higher returns than poorer ones, this would increase the contribution of owner-occupied housing to wealth inequality.

To get a sense of the heterogeneity in housing returns across ZIP codes in Figure 7, we plot the difference in the average real return of housing in each ZIP code and the average real return of housing for the relevant MSA. If there was no hetero-

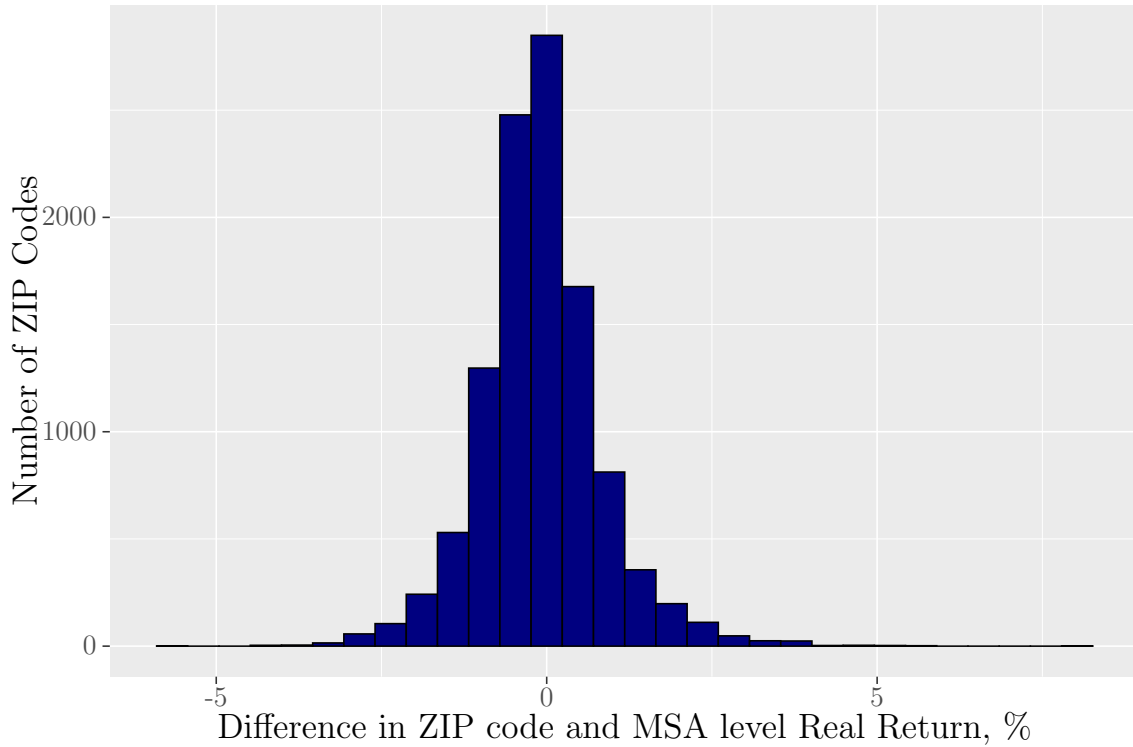


Figure 7: This figure plots difference in the average real return on housing for each ZIP code and the real return on housing in MSA in which the ZIP code is located. Sources: Census Bureau, Zillow, the BEA, and authors' calculations.

ogeneity in returns across the MSA, this would be a degenerate distribution equal to zero. It is clear from [7](#) that this is not the case. There is substantial heterogeneity in returns within an MSA. The 10<sup>th</sup> and 90<sup>th</sup> percentile of the difference are -1.12% and 0.96% respectively. Compounded over several decades, a 2% difference can lead to an enormous dispersion in the wealth levels across different wealth groups.

To extend the analysis to the ZIP code level, we would first need to estimate the ZIP code level housing supply elasticity that is due to geographical constraints. To obtain these elasticities, we extend the framework of [Saiz \(2010\)](#) to the ZIP

code level. First, using satellite data available at a very fine level (30 by 30 meters cells), we calculate land availability and topography of a region. Secondly, we use data on house prices which is also highly disaggregated, (we can get the individual house prices from the data that underlines the Zillow ZIP code house price data). Then, if we can identify demand shocks, we can estimate supply elasticities for narrowly defined regions.

This gives us an extremely local level supply elasticity. However, there will be substitution between adjacent areas. Consider a ZIP code where there is no development land available, but that is next to a ZIP which is completely undeveloped. While the elasticity within that ZIP might be very small, since people can easily substitute to the adjacent ZIP, prices will behave more like those in a ZIP code with a high elasticity. Thus, we would also need to consider how easily households can substitute to nearby ZIPs. How close of a substitute one ZIP code is for another is likely to be a decreasing function of commute times between ZIPs, a decreasing function of differences in the distance to amenities of a region, and an increasing function of the similarity of the ZIP across characteristics, such as the proportion of the ZIP that is covered by trees, amount of pollution, and crime.

Extending the elasticity to the ZIP code level is potentially important. For some MSAs, it is not particularly reasonable to assign one elasticity because of the differences in topography across the city. This will mean that prices in certain ZIP codes within a city will respond differently to a common shock, increasing the dispersion in returns. Moreover, it may be the case that within an MSA that the wealth of each household may be correlated with the elasticity of the area the

homeowner lives in. This is because natural barriers to construction such as water are also highly valuable amenities.

Consider the case of the Los Angeles MSA. Within this MSA, the annualized average real house price appreciation from 1996 to 2019 was 4.3% across all ZIPs, equally weighting each ZIP. However, the 10<sup>th</sup> percentile of house price appreciation is just 3.4%, while the 90<sup>th</sup> percentile is over 5.8%. Thus, we can see that not only is there a large amount of heterogeneity between MSAs but also within them. The more disaggregated the level we examine returns to owner-occupied housing the larger the potential heterogeneity in returns. This increases the potential for housing to create wealth inequality.

## 6 Conclusion

In this paper, we evaluated how returns to owner-occupied housing affect wealth inequality in the United States. We document that the after-tax real returns to owner-occupied housing approximately equals that of equity. Our paper shows that owner-occupied housing represents a large fraction of household net worth. Moreover, we find that richer households typically have a larger fraction of their net worth in housing. Thus, high returns to housing not only increase average household wealth but also increase wealth inequality between households. Using an accounting framework, we decompose the returns of each wealth group into housing and non-housing returns. Furthermore, we construct a counterfactual analysis where we increase the house price elasticity to the 90<sup>th</sup> percentile. We find that



this reduces the coefficient of variation in wealth by approximately 2%.

While data limitations mean we cannot exactly determine the matching of households to MSA, we consider a cases where there is positive assortative matching (PAM) or negative assortative matching (NAM) between household wealth and housing returns. We document that whether matching is PAM or NAM matters a great deal for the returns on household wealth. Compared with NAM after tax annualized returns on wealth are about 2% higher if one assumes PAM.

Finally, this paper discusses how to extend our results to the ZIP code level. We describe how to compute the local level housing elasticities in this case and the difficulty that using such local level elasticities brings, namely the ability of households to substitute between these local regions.

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## A Figures and Data

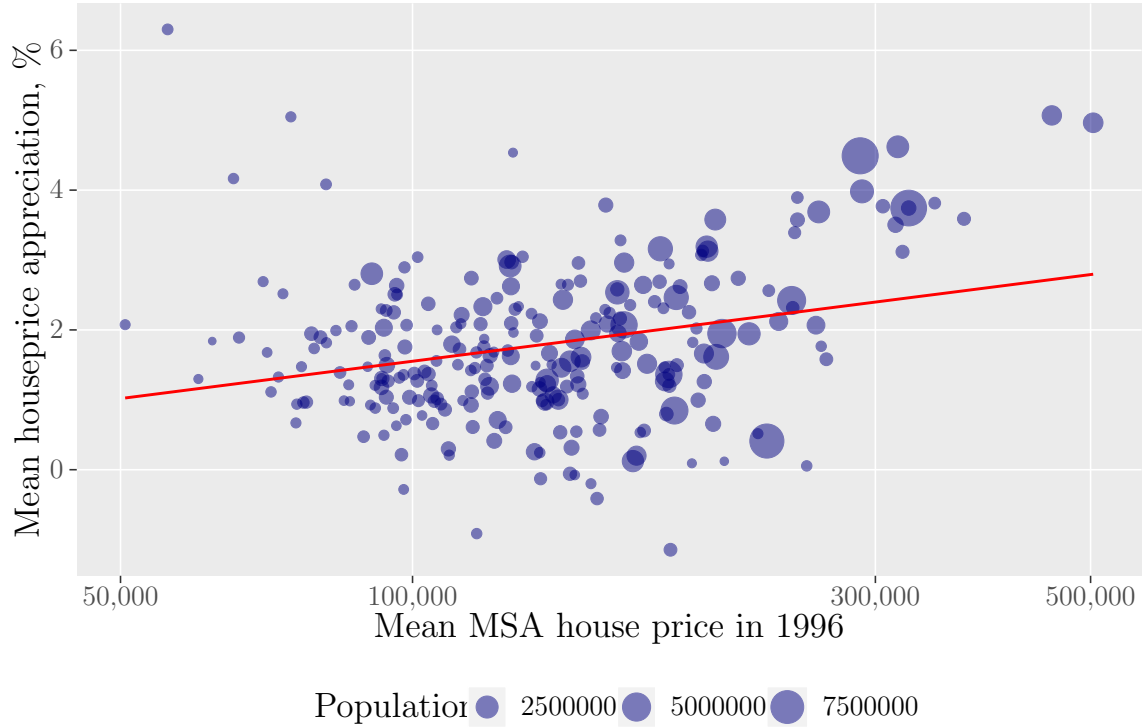


Figure 8: This figure plots average annual real house price appreciation in each MSA against the average price of a home in the MSA in 1996. The size of each bubble indicates the population of the MSA, and the line is the line of best fit, fitted using OLS regression. Source: Zillow and authors' calculations.

Table 6: Average total wealth within each wealth group.

Net Worth	Average Total wealth
\$1 to \$4,999	3,890.996
\$5,000 to \$9,999	11,463.160
\$10,000 to \$24,999	22,936.020
\$25,000 to \$49,999	43,757.860
\$50,000 to \$99,999	82,393.310
\$100,000 to \$249,999	174,472.300
\$250,000 to \$499,999	365,375.000
\$500,000 and over	1,153,769.000

Table 7: Portfolio weights for different wealth groups.

Net Worth	Own home	Cash	Deposits	Equity	Cars	Other R.E.
\$1 to \$4,999	0.147	0.106	0.211	0.150	0.386	0
\$5,000 to \$9,999	0.205	0.085	0.231	0.149	0.330	0
\$10,000 to \$24,999	0.240	0.061	0.250	0.206	0.242	0
\$25,000 to \$49,999	0.370	0.043	0.229	0.220	0.137	0
\$50,000 to \$99,999	0.469	0.025	0.185	0.215	0.087	0.018
\$100,000 to \$249,999	0.477	0.018	0.187	0.241	0.048	0.028
\$250,000 to \$499,999	0.418	0.013	0.201	0.286	0.034	0.047
\$500,000 and over	0.281	0.011	0.208	0.387	0.016	0.097