

Falling Behind: Has Rising Inequality Fueled the American Debt Boom

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Abstract

This paper studies whether the interplay of social comparisons in housing and rising income inequality contributed to the household debt boom in the United States between 1980 and 2007. We develop a tractable macroeconomic model with general social comparisons in housing to show that changes in the distribution of income affect aggregate housing demand, aggregate debt, and house prices if (and only if) social comparisons are asymmetric. In the empirically relevant case of upward-looking comparisons, rising inequality can rationalize a substantial share of the observed housing and debt boom. (*JEL* D14, D31, E21, E44, E70, R21)

Social comparisons matter for economic decision-making. People buy bigger cars when their neighbors win the lottery (Kuhn et al. 2011), the nonrich move their spending to visible goods (like housing) when top incomes rise in their state (Bertrand and Morse 2016), and people spend more on home improvements when very big houses are built in their neighborhood (Bellet 2024). While the importance of social comparisons is well-documented in empirical work, the vast majority of macroeconomic models abstract from social interactions (Kuchler and Stroebel 2021).

This paper studies whether the interplay of social comparisons in housing and rising income inequality contributed to the household debt boom in the United States

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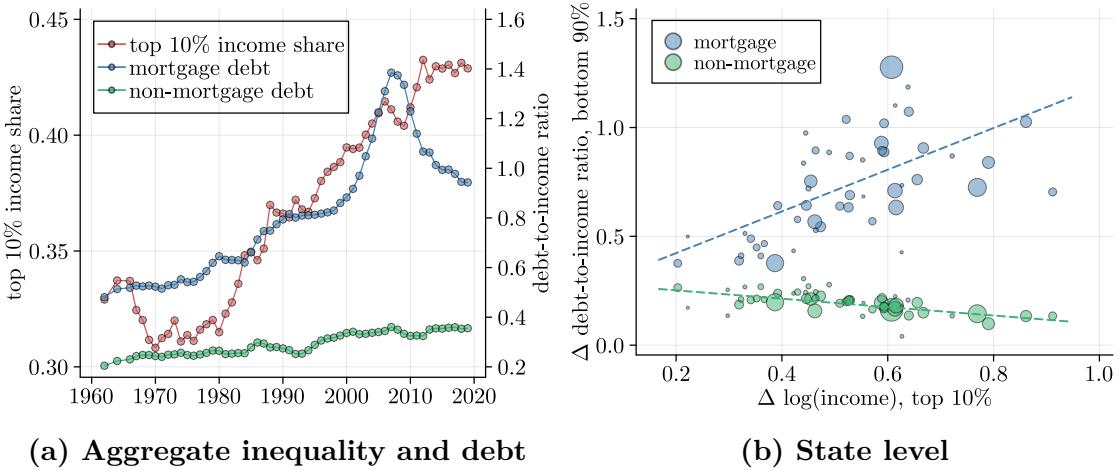


Figure 1: Income inequality and household debt

Panel (a) shows the evolution of the debt-to-income ratio and the top 10% income share in the United States. Panel (b) plots the change in the mortgage-to-income ratio and the non-mortgage-to-income ratio of the bottom 90% of the income distribution in each state against the change in the log of average incomes of the state's top 10% between 1980–1982 and 2005–2007. The size of the markers corresponds to the state's population size in the base period.

Alt text: Line graph labeled (a) and scatterplot with linear fits labeled (b). (a) Evolution of inequality, and the debt-to-income ratio from 1960 to 2020 for mortgage and nonmortgage debt; (b) Correlation between the change in log-income of the top 10% and the change in debt-to-income ratio of the bottom 90% for mortgage and nonmortgage debt.

prior to the Great Recession. Between 1980 and 2007, both household indebtedness (mostly mortgages) and income inequality increased substantially (panel (a) of Figure 1). Panel (b) shows that this aggregate relationship is also present at the state level: states that experienced a stronger increase in average top incomes also experienced a stronger increase in the mortgage-to-income ratio of nonrich households.¹ While several authors have alluded to social comparisons (keeping up with the Joneses) to link the rise in inequality and debt (e.g., Rajan 2011; Stiglitz 2009; Frank 2013) we lack a framework to study how distributional changes affect aggregate indebtedness in the presence of social comparisons. Previous models of social comparisons either abstract from durable goods and intertemporal decisions (Ballester, Calvó-Armengol, and Zenou 2006; Ghigino and Goyal 2010), or cannot accommodate the empirically relevant case where agents compare themselves to rich(er) agents (Badarinza 2019; Grossmann et al. 2021).

¹No such relationship exists for nonmortgage debt. See Appendix A for a detailed descriptive analysis of the relationship between top incomes and nonrich debt. In particular, we show that rising income inequality in a region is associated with rising mortgage-to-income ratios, home ownership rates, and house price. Notably, this also holds across commuting zones after controlling for unobserved heterogeneity across states.

This paper develops a dynamic macroeconomic model with nondurable consumption and durable housing, heterogeneity in permanent income, and an arbitrary network of social comparisons in housing, that enables us to characterize the effect of distributional changes on macroeconomic aggregates in closed form.² Our main theoretical result is that an increase in income inequality raises house prices and aggregate debt if and only if social comparisons are upward-looking. Our quantitative analysis is based on distributional national accounts ([DINA](#)) and Census/ACS data and recent micro evidence on housing comparisons by Bellet ([2024](#)). We show that the rise in U.S. income inequality and upward-looking housing comparisons can explain a sizeable share of the increase in the aggregate mortgage-to-income ratio, the housing expenditure share, and house prices. In line with the data, the aggregate effects are driven by a disproportionate increase in housing and mortgage demand of nonrich households. As nonrich households increase housing relative to income, they also increase their wealth-to-income ratio, which helps explain the decoupling of income and wealth inequality documented by Kuhn, Schularick, and Steins ([2020](#)).

In our model, households' utility depends on status-neutral consumption and their housing status, which measures how their own house compares to those of their reference group (the Joneses). To illustrate our mechanism, consider an increase in the incomes of the rich. Equipped with more resources, rich households will improve (or upsize) their houses and thereby reduce the housing status for all other households that compare themselves to the rich. Each of these nonrich households will shift expenditures away from status-neutral consumption towards status-enhancing housing in an effort to keep up with the housing benchmark set by the rich. Importantly, since housing is a durable good (and consumption is nondurable), all households affected by the social housing externality find it optimal to purchase the entire house upfront by taking on (mortgage) debt. Note that households that do not care directly about the houses of the rich still experience a status externality if their reference group cares about the rich. Formally, we show that the network of social comparisons gives rise to a matrix of social externalities that encodes to what extent each household's income affects consumption, housing, and mortgage demand of all other households.

The closed-form characterization of households' optimal choices allows us to study the effects of changes in the income distribution on aggregate housing and

²This captures the notion that housing is arguably the most important conspicuous good—both in terms of visibility and expenditure share (e.g., Solnick and Hemenway [2005](#); Bertrand and Morse [2016](#)).

debt. We show that the consequences of rising income inequality crucially depend on the structure of social comparisons. In the special case where social comparisons are homogeneous and symmetric—each household’s reference measure is the average house in the population—changes in the distribution of incomes do not affect aggregates. Incidentally, this is the case studied in the macro-finance literature on “keeping up with the Joneses” (e.g., Abel 1990; Gali 1994; Campbell and Cochrane 1999; Ljungqvist and Uhlig 2000; Badarinza 2019; Grossmann et al. 2021). However, when the network of social comparisons is asymmetric such that households differ in their “popularity,” aggregate demand for housing and debt increases if (and only if) income is redistributed towards more popular households. In the empirically relevant case of upward-looking comparisons (where households compare themselves to the rich), rising income inequality drives up house prices and aggregate debt.

The theoretical results extend those of Ballester, Calvó-Armengol, and Zenou (2006) and Ghiglino and Goyal (2010), who show that, in a static model, economic choices are proportional to the household’s centrality in the network of social comparisons. Furthermore, like in Ghiglino and Goyal (2010), redistribution towards more popular agents raises the equilibrium price of the status good. In contrast to these papers, we study the role of social comparisons in a dynamic setting and show that observed changes in income inequality can have quantitatively important effects on macroeconomic aggregates in the presence of social comparisons.

In particular, we use our tractable framework to analyze whether the shift in the U.S. income distribution and social comparisons in housing can generate quantitatively significant effects that contribute to our understanding of the U.S. housing and debt boom between 1980 and 2007 documented by Jordà, Schularick, and Taylor (2016). We calibrate the model to match the aggregate mortgage-to-income ratio and housing expenditure share in 1980, and feed in the observed shift in the U.S. income distribution between 1980 and 2007. Note that we focus on changes in permanent income inequality rather than changes in income volatility, as the former was the main driver of the increase in cross-sectional inequality in the United States (see, e.g., Kopczuk, Saez, and Song 2010; Guvenen et al. 2022).³ In order to discipline the structure and strength of the comparison motive, we calibrate the model to match recent evidence on the relative importance of own and reference house size among U.S. home owners by Bellet (2024). In line with this evidence, we assume

³In fact, Sabelhaus and Song (2010) and Guvenen, Ozkan, and Song (2014) find that the variance of both transitory and persistent income shocks has declined in the decades prior to the Great Recession. Note that persistent shocks increase idiosyncratic income risk while changes in permanent income do not.

that all households compare themselves (only) with the rich, defined as the top 10% of the income distribution.⁴

We find that rising inequality and keeping up with rich Joneses can rationalize roughly 75% of the increase in the housing expenditure share (3 p.p.), 15% of the increase in mortgage-to-income ratio (12 p.p.), and 10% of the increase in house prices (7.1%). As comparisons are arguably constrained by geographic proximity, we use both state-level administrative DINA data and commuting-zone-level Census/ACS data to distinguish between nationwide and within-region changes in income inequality. However, as around 90% of the nationwide increase in income inequality took place within regions, we find very similar quantitative results whether or not we add spatial heterogeneity and restrict households' reference groups to the local rich who live in the same state, labor market area, or commuting zone.

We also find that the aggregate effects are driven by nonrich households. Our mechanism can thus explain why the increase in mortgage-to-income ratios and housing expenditure shares in the data was larger for nonrich households. In addition, the model helps rationalize why wealth inequality increased less than income inequality in the four decades prior to the Great Recession (as first documented by Kuhn, Schularick, and Steins [2020]). Intuitively, the shift towards housing expenditures induced by nonrich households' desire to keep up with the houses of the rich funnels income into a consumption good that is also an asset. And since this is only done by nonrich households, wealth inequality decreases relative to the case without (upward-looking) social comparisons in housing.

We also show that our quantitative results are robust to changes in the structure of comparison networks that give rise to trickle-down effects of rising income inequality. In particular, when each household's reference house is the average house of all households above them in the income distribution, 90% of the baseline effect remains. And even in the case where households only compare themselves to those in the income decile just above them, over 60% of the effects survive as housing externalities trickle down the income distribution. In addition, the effects are robust (or even weakly stronger) when we limit the scope of social comparisons to households in the same age group or assume alternative values of the intratemporal substitution elasticity between consumption and housing. Finally, we analyze how the economy transitions from the initial to the new steady state. While social com-

⁴This is also in line with other micro evidence showing that comparisons are upward-looking (Ferrer-i-Carbonell 2005; Clark and Senik 2010; Card et al. 2012; Bertrand and Morse 2016).

parisons affect long-run outcomes, they do not change the transition dynamics for a given increase in steady state house prices.

In sum, we find that the secular rise in U.S. permanent income inequality can jointly rationalize a significant part of three long-run trends, namely (i) the increase in housing demand captured by the increase in the expenditure share of housing (Bertrand and Morse 2016) and the house price, (ii) the mortgage-driven increase in household indebtedness that was particularly strong for nonrich households, and (iii) the disproportionate rise in wealth-to-income ratios of nonrich households (Kuhn, Schularick, and Steins 2020). In addition, Appendix A shows that the core prediction of our mechanism, that is, a positive relationship between top income inequality and nonrich housing and mortgage demand, holds not only in the aggregate but also across states or commuting zones. Specifically, states and commuting zones where local income inequality increased more strongly also experienced a stronger increase in house prices and mortgage debt (but not non-mortgage debt) of nonrich households.

Our quantitative findings contribute to a large quantitative literature that studies the drivers of house prices and debt in the United States.⁵ Badarinza (2019) and Grossmann et al. (2021) show that the presence of status externalities inefficiently increases the level of housing demand and, in the former case, mortgage demand. In contrast to our paper, they assume comparisons with the mean, and do not study the role of changes in income inequality. Kumhof, Rancière, and Winant (2015) and Mian, Straub, and Sufi (2021) do study the effects of increasing (permanent) income inequality and find that rising income inequality can drive up debt-to-income ratios of nonrich households due to an increase in the supply of credit driven by higher saving rates of the rich. In contrast to our paper, they do not study the role of social comparisons and do not differentiate between nondurable consumption

⁵The literature also studies the determinants of homeownership. However, as we abstract from an extensive margin housing decision to maintain tractability in the presence of asymmetric housing comparisons, our model cannot speak directly to this issue. We discuss potential implications for home ownership in the conclusion. Empirically, variation in the change in income inequality across commuting zones is also positively related to changes in local home ownership rates (see Appendix A.4).

and housing.⁶ Another strand of the literature studies the role of credit conditions (e.g., Favilukis, Ludvigson, and Nieuwerburgh 2017; Garriga, Manuelli, and Peralta-Alva 2019; Justiniano, Primiceri, and Tambalotti 2019) and expectations (Adam, Kuang, and Marcet 2012; Kaplan, Mitman, and Violante 2020) for house prices and borrowing in the 2000s. While these papers analyze short-run fluctuations, our paper studies long-run trends due to permanent changes in the income distribution. We discuss potential complementarities in the conclusion.

1 Model

We consider a world that is populated by a unit mass of atomistic households that differ by their income type $i \in \{1, \dots, N\}$. Types are ordered by their permanent income \mathcal{Y}_i from poor to rich,

$$\mathcal{Y}_1 < \mathcal{Y}_2 < \dots < \mathcal{Y}_N.$$

Permanent incomes are exogenous and are the sum of a household's time-invariant flow income y_i and interest income from initial wealth: $\mathcal{Y}_i = y_i + r a_0^i$. Population shares are denoted by ω_i .

Households' flow utility $u(c, s)$ depends on consumption c and housing status, $s(h_i, \tilde{h}_i)$, which is increasing in their own house h_i , but decreasing in the reference measure \tilde{h}_i , which is a weighted sum of houses of other households to whom the household compares herself:

$$\tilde{h}_i = \sum_{j=1}^n g_{ij} h_j, \quad \text{where } g_{ij} \geq 0.$$

This gives rise to a network of social comparisons where the weights $(g_{ij})_{ij}$ form the network's adjacency matrix, $G = (g_{ij})_{ij}$.⁷ If an edge g_{ij} is positive, then we say that

⁶There is also a large literature studying how changes in income risk affect precautionary saving and borrowing in incomplete market economies (e.g., Carroll 1997; Gourinchas and Parker 2002). Nakajima (2005) finds that the increased demand for precautionary savings due to higher income volatility can increase house prices through a general equilibrium effect that lowers the return on financial assets due to increasing demand. However, using large administrative data, Sabelhaus and Song (2010) and Guvenen, Ozkan, and Song (2014) find that the variance of both transitory and persistent income shocks has declined in the decades prior to the Great Recession and hence does not contribute to the rise in cross-sectional income inequality.

⁷The adjacency matrix allows us to write the reference measure in vector form $\tilde{\mathbf{h}} = G\mathbf{h}$.

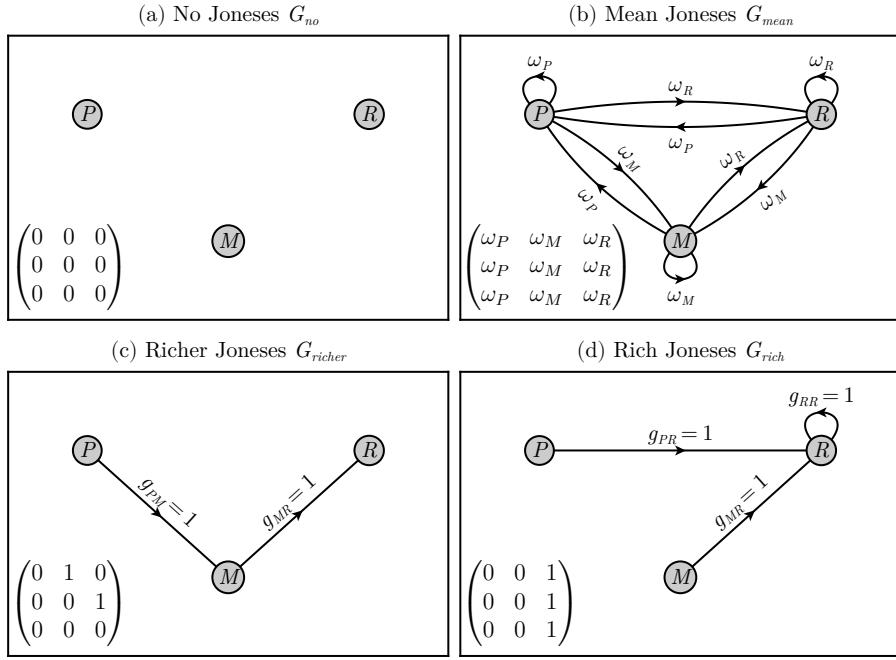


Figure 2: Four network structures

Different network structures (and corresponding adjacency matrices) for three household types: poor P , middle-class M , and rich R .

Alt text: Four panels showing different network structures and corresponding adjacency matrices labeled (a), (b), (c), and (d).

household i 's housing status is affected by household j 's house or that household j exerts a negative externality on household i .

Figure 2 shows four simple networks that will be used to illustrate the analytical results. For ease of exposition, these examples have three types: poor P , middle-class M , and rich R with population weights $\omega = (\omega_P, \omega_M, \omega_R)$.

In panel (a), there are no links, that is, no social comparisons. Households' housing status does not depend on others' houses. This is implicitly assumed in the vast majority of macroeconomic models that abstract from social comparisons. In panel (b), all households care equally about all types according to their population share ω_j . This means that the reference house $\tilde{h}_i = \bar{h}$ is simply the average house in the economy. This case is studied in a classic macro-finance literature (e.g., Abel 1990; Gali 1994; Campbell and Cochrane 1999; Ljungqvist and Uhlig 2000) on keeping up with the Joneses in models without income heterogeneity.

The remaining two networks in panels (c) and (d) capture the empirical finding that social comparisons are not symmetric, but mostly upward-looking (e.g., Ferrer-i-Carbonell 2005; Clark and Senik 2010; Card et al. 2012; Bellet 2024). In panel (c),

households compare themselves to those just above them in the income distribution. And in panel (d), all households, including the rich, compare themselves only to the rich. As we will show below, asymmetric comparisons are key for changes in the distribution of income to affect macro-financial aggregates such as the aggregate debt-to-income ratio.

The remaining parts of the model are standard, following the “canonical macroeconomic model with housing” in Piazzesi and Schneider (2016). Households’ expected discounted lifetime utility of streams of consumption $c_t > 0$, housing $h_t > 0$, and assets $a_t \in \mathbb{R}$ is given by

$$\sum_{t=0}^{\infty} ((1-m)\beta)^t \frac{\left((1-\xi)c_t^\varepsilon + \xi s(h_t, \tilde{h}_t)^\varepsilon\right)^{\frac{1-\gamma}{\varepsilon}}}{1-\gamma},$$

where m is the constant mortality rate, $\beta = \frac{1}{1+\rho}$ and $\rho \geq 0$ is the discount rate, $1/\gamma > 0$ is the intertemporal elasticity of substitution (IES), $1/(1-\varepsilon) > 0$ is the intratemporal elasticity of substitution between consumption and housing status, and $\xi \in (0, 1)$ is the relative utility weight for housing status.⁸

Housing is both a consumption good and an asset. It is modeled as a homogeneous, divisible good. As such, h represents a one-dimensional composite measure of housing quality (including size, location, and amenities). A household’s housing stock depreciates at rate $\delta \in (0, 1)$ and can be adjusted frictionlessly.⁹ Home improvements and maintenance expenditures x_t have the same price as housing (p) and go into the value of the housing stock one for one.

Households can save ($a > 0$) and borrow ($a < 0$) at the exogenous interest rate r . The flow budget constraints are

$$\begin{aligned} a_{t+1} &= y_t + (1+r)a_t - c_t - px_t, \\ x_t &= h_t - (1-\delta)h_{t-1}, \end{aligned}$$

subject to the nonnegativity constraint for housing, $h_t > 0$, and given initial wealth $a_0 \in \mathbb{R}$ and $h_{-1} = 0$. Debt is limited by a collateral constraint, $a_t > -ph_t$, which will never bind in equilibrium.

⁸The simple demographic structure (perpetual youth) matters only quantitatively, and ensures that there is a transition path between any two steady states. The IES does not matter in the analysis of steady states, but it is relevant for transition paths in Section 4.3.

⁹Frictionless adjustment is justified because we are interested in comparing long-run changes.

We assume that households choose streams of consumption $c_t > 0$, housing $h_t > 0$, and assets $a_t \in \mathbb{R}$ to maximize their discounted lifetime utility subject to a lifetime budget constraint, and the laws of motion for assets and housing.

2 Analytical Results

In this section, we first characterize households' optimal choices in the presence of social comparisons, and then derive necessary and sufficient conditions for rising income inequality to affect the aggregate debt-to-income ratio. We start by keeping house prices fixed before introducing a construction sector and requiring market clearing on the housing market.

We need two assumptions in order to obtain tractability. First, the interest rate equals the discount rate. Second, the social status function s is linear.

Assumption 1. $r = \rho$.

Assumption 2. The status function is linear, $s(h, \tilde{h}) = h - \varphi_i \tilde{h}$, where $\varphi_i \in [0, 1]$ can vary by income type i .

We further require the network of social comparisons to satisfy the following regularity condition.

Assumption 3. The Leontief inverse $(I - \Phi G)^{-1}$ exists and is equal to $\sum_{k=0}^{\infty} \Phi^k G^k$ for Φ being a diagonal matrix with $\varphi_i \equiv \Phi_{ii}$ from Assumption 2.

Assumption 3 is satisfied whenever the power of the matrix converges, $G^k \rightarrow G^\infty$. For example, if G represents a Markov chain with a stationary distribution or if G is nilpotent.

2.1 Characterization of households' optimal choices

We first analyze a partial equilibrium where the references measures are consistent with households' choices. We show that, given prices, household i 's optimal housing and debt are increasing in the permanent income of another type j as long as there is a (direct or indirect) path from i to j in the comparison network. This condition holds whenever i compares herself to j , or whenever i compares herself to somebody that compares herself to j , and so on.

Households' optimal decisions are summarized in the following proposition.

Proposition 1. Under assumptions 1, 2, and 3, the optimal choices $\mathbf{h} = (h_1, \dots, h_N)^T$ and $\mathbf{a} = (a_1, \dots, a_N)^T$ are given by

$$\begin{aligned}\mathbf{h} &= \kappa_2(I + L)\mathbf{Y}, \\ -\mathbf{a} &= \kappa_3(I + L)\mathbf{Y} - \mathbf{a}_0,\end{aligned}$$

where $L = \sum_{i=1}^{\infty} (\kappa_1 \Phi G)^i$ is the social externality matrix (weighted matrix of direct and indirect paths in the network of comparisons), and the constants $\kappa_1 \in (0, 1)$ and $\kappa_2, \kappa_3 > 0$ depend on model parameters and the house price.

Proof. See Appendix C.1. \square

Proposition 1 states that households' policy functions for housing, consumption and debt are linear combinations of their own permanent income and other types' permanent incomes. The extent to which others' incomes matter is encoded in the social externality matrix $L = \sum_{i=1}^{\infty} (\kappa_1 \Phi G)^i$.¹⁰

Table 1: Social externality matrices for four example networks

(a) L_{no}	(b) L_{mean}	(c) L_{richer}	(d) L_{rich}
$\begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix}$	$\frac{\tilde{\varphi}}{1-\tilde{\varphi}} \begin{pmatrix} \omega_P & \omega_M & \omega_R \\ \omega_P & \omega_M & \omega_R \\ \omega_P & \omega_M & \omega_R \end{pmatrix}$	$\begin{pmatrix} 0 & \tilde{\varphi} & \tilde{\varphi}^2 \\ 0 & 0 & \tilde{\varphi} \\ 0 & 0 & 0 \end{pmatrix}$	$\frac{\tilde{\varphi}}{1-\tilde{\varphi}} \begin{pmatrix} 0 & 0 & 1 \\ 0 & 0 & 1 \\ 0 & 0 & 1 \end{pmatrix}$

Social externality matrices for the networks shown in Figure 2. For better readability, we assume $\varphi_i = \varphi$ for all types i and define $\tilde{\varphi} := \kappa_1 \varphi$.

Table 1 shows the social externality matrices for the four simple networks shown in Figure 2 (for simplicity, we set $\varphi_i = \varphi$ constant across types in these examples). In the case of *No Joneses* (a), L_{no} is a zero matrix because there are no social comparisons. In the case of *Mean Joneses* (b), there are infinitely many paths from each type to each other type. The externality of any type on households from all other types is proportional to the respective population share. In the case of *Richer Joneses* (c), there are two paths of length 1, from P to M and from M to R , and one

¹⁰The social externality matrix L is the Leontief inverse of G minus the identity matrix. Recall that each power G^k represents (weighted) walks of length k in the network of comparisons. Also note that optimal choices are proportional to $(I + L)\mathbf{Y}$, the (income-weighted) Bonacich-Katz out-centralities of the comparison network. This result is reminiscent of that in Ballester, Calvó-Armengol, and Zenou (2006), where the unique Nash equilibrium in a large class of network games is proportional to the (unweighted) Bonacich-Katz centrality.

path of length 2 from P to R via M . This example illustrates the general result that types need not be directly linked for a social externality to emerge: Even though the poor do not compare themselves to the rich ($g_{PR} = 0$), incomes of the rich will still affect choices of the poor because the poor compare themselves to the middle-class who compare themselves to the rich. In other words, the externality trickles down the income distribution.

To better see how social comparisons affect households' optimal consumption and housing choices, we rewrite optimal housing choices of type- i households:

$$h_i = \kappa_2 \left((1 + L_{ii}) \mathcal{Y}_i + \sum_{j \neq i} L_{ij} \mathcal{Y}_j \right).$$

Without social comparisons, the housing policy function only depends on own permanent income as $L_{ij} = 0$ for all $i \neq j$. In contrast, whenever type- i households care directly or indirectly about type- j households, $L_{ij} > 0$, type- i households' housing increases in type j 's permanent income. The strength of the externality, L_{ij} , depends on (i) the number and strength of all direct and indirect comparison links from i to j encoded in G , and (ii) deep model parameters such as the utility weight of housing or the intratemporal elasticity of substitution between housing and consumption.¹¹

Intuitively, as \mathcal{Y}_j rises, type- j households will improve (or upsize) their housing stock h_j , which increases the reference measure \tilde{h}_i for all types i that care about type j , directly or indirectly. Each of these households will optimally shift expenditures away from status-neutral consumption and towards status-enhancing housing.

As houses are durable, households take on debt to pay for the entire house ph upfront and only replace the depreciation δph at each future point in time. By taking on debt, households shift some of their lifetime income forward to finance their house and are able to keep the stock of housing constant over time. Hence, when households scale up their house following an increase in others' incomes, they also take on a bigger mortgage.

If housing were nondurable, it would not be debt-financed and changes in optimal housing would have no effect on optimal debt. To see this, consider the case of perfectly nondurable housing ($\delta \rightarrow 1$). As the depreciation rate approaches 100%, the social externality matrix disappears from the formula for optimal debt. Note that

¹¹The higher the utility weight on housing and the more substitutable are housing and consumption, the stronger will be the externality.

the optimal housing decision remains positive and dependent on social externalities, it is just not relevant for debt anymore.

2.2 Effect on aggregates depends on popularity

Knowing each households' policy functions, we now derive expressions for the aggregate demand for housing and debt. To this end, we first define a household's popularity and then show that aggregate housing and debt are weighted sums of households' permanent incomes, where the weights depend on households' popularities.

Proposition 1 reveals that the j^{th} column of the social externality matrix L captures how strongly type j 's income influences the choices of all other types. We define the popularity of type j as the population-weighted j^{th} column sum of L .

Definition 1 (Popularity). We define the vector of popularities $\mathbf{b}^T = (b_1, \dots, b_N)^T$ as

$$\mathbf{b}^T = \boldsymbol{\omega}^T \sum_{i=1}^{\infty} (\kappa_1 \Phi G)^i = \boldsymbol{\omega}^T L,$$

and type j 's popularity $b_j = \sum_{i=1}^N \omega_i L_{ij}$ as the j^{th} component of \mathbf{b} .

Popularity measures how many other households are affected by j 's permanent income (directly and indirectly) and how strongly they are affected. It is the weighted sum of all pairwise externalities from j onto other types. The weights $\boldsymbol{\omega}$ are the types' population shares.

Table 2: Popularities for four example networks

(a) \mathbf{b}^{no}	(b) \mathbf{b}^{mean}	(c) \mathbf{b}^{richer}	(d) \mathbf{b}^{rich}
$\begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}$	$\frac{\tilde{\varphi}}{1-\tilde{\varphi}} \begin{pmatrix} \omega_P \\ \omega_M \\ \omega_R \end{pmatrix}$	$\begin{pmatrix} 0 \\ \omega_P \tilde{\varphi} \\ \omega_P \tilde{\varphi}^2 + \omega_M \tilde{\varphi} \end{pmatrix}$	$\frac{\tilde{\varphi}}{1-\tilde{\varphi}} \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix}$

Popularity vectors for the networks shown in Figure 2. For better readability, we define $\tilde{\varphi} := \kappa_1 \varphi$.

Table 2 shows the vector of popularities for the four social comparison networks in Figure 2. In the case of *No Joneses* (a), all types have a popularity of 0. In the case of *Mean Joneses* (b), the popularity is proportional to the population weights. In cases (c) and (d), the poor type P is not popular (no type cares about them),

whereas the rich type R has a strictly positive popularity because the other types care about R .

Proposition 2 shows that aggregate housing, consumption, and debt can be written as a weighted sum of lifetime incomes where the weights consist of households' popularities and population weights.

Proposition 2. *Aggregate housing and debt are given by*

$$H := \boldsymbol{\omega}^T \mathbf{h} = \kappa_2(\boldsymbol{\omega} + \mathbf{b})^T \mathbf{y} \quad (1)$$

$$-A := -\boldsymbol{\omega}^T \mathbf{a} = \kappa_3(\boldsymbol{\omega} + \mathbf{b})^T \mathbf{y} - \boldsymbol{\omega}^T \mathbf{a}_0. \quad (2)$$

Proof. See Appendix C.2. □

Intuitively, Proposition 2 shows that the more popular a type, the bigger will be its influence on macroeconomic aggregates through the social externalities exerted upon other households. This is reminiscent of the result of Acemoglu et al. (2012), where the influence of an industry's productivity on aggregate output is determined by the industry's centrality in the input-output network.¹²

2.3 Consequences of rising income inequality

Next, we show how aggregate housing-to-income and debt-to-income react to changes in the income distribution. We will compare two steady states that differ only in the distribution of labor incomes \mathbf{y} .

We consider mean-preserving redistribution of (labor) income from type- i to type- j households. We show that the aggregate housing-to-income ratio and the aggregate debt-to-income ratio increase if the relative difference in popularities between j and i exceeds the relative difference in population weights.

Proposition 3 (Redistribution). *Compare two steady states that differ only in disposable incomes. Let the difference in disposable incomes be $\Delta \mathbf{y} = \mathbf{y}' - \mathbf{y}$, where*

$$\underbrace{\omega_j}_{>0} \underbrace{\Delta y_j}_{<0} + \underbrace{\omega_i}_{<0} \underbrace{\Delta y_i}_{<0} = 0, \quad \text{and } \Delta y_k = 0 \text{ for all } k \notin \{i, j\}.$$

¹²Popularity is the population-weighted Bonacich-Katz in-centrality. It measures the externality of a given type on all other types.

Then the difference in aggregate housing-to-income and aggregate debt-to-income is positive if and only if type- j households are more popular than type- i households, that is:

$$\Delta \frac{\omega^T h}{\omega^T y} > 0 \iff \frac{b_j}{\omega_j} > \frac{b_i}{\omega_i} \quad \text{and} \quad \Delta \frac{-\omega^T a}{\omega^T y} > 0 \iff \frac{b_j}{\omega_j} > \frac{b_i}{\omega_i}.$$

Proof. See Appendix C.3. □

Why do we have to rescale the popularities of types i and j by the types' respective population weights? This is because we consider mean-preserving redistribution of a group of households to another group of households instead of from one individual to another. If all households have the same population weight, only the difference in popularities matters. In general, however, if we redistribute a total of one dollar from type i to type j , every type- i household loses $1/\omega_i$ dollars and every type- j household receives $1/\omega_j$ dollars. The fewer type- j households there are, the higher is the additional income each of these households receives, and the stronger is the increase in their average house. Hence, we require a lower popularity of type- j households in order to get the same increase in others' housing and debt. Hence, aggregate housing-to-income and debt-to-income ratios increase if the ratio of popularities, b_j/b_i , is larger than the ratio of the absolute values of the average changes in incomes, ω_j/ω_i .¹³

Proposition 3 shows that asymmetric comparisons are needed in order for changes in the income distribution to generate aggregate effects. According to the classic macroeconomic interpretation of keeping up with the (mean) Joneses, example (b) in Figure 2 and Table 2, all types are equally popular, $b_j = b_i$ for all i, j . Under upward comparisons, however, rising income inequality can drive up aggregate housing-to-income and debt-to-income as long as the rich are sufficiently popular. In example (d), where the rich are everyone's comparison group and hence the only type that exerts a social externality, redistribution from the nonrich to the rich increases the aggregate housing-to-income and debt-to-income ratios. In example (c), these ratios increase whenever the rich are sufficiently popular relative to the middle class.

Note that in the special case of Cobb-Douglas aggregation the optimal choice of debt is independent of prices.

Corollary 1. *Under Cobb-Douglas aggregation, $\varepsilon \rightarrow 0$, the results for debt ($-a$) in Propositions 1 and 3 are independent of house prices.*

¹³The fact that households' policies are linear in incomes explains why we simply have to rescale with the population weight instead of a function thereof.

Proof. See Appendix C.4. □

Intuitively, households want to keep housing expenditures (price times quantity) constant when prices change. As debt is a function of expenditures, it is unaffected by changes in the house price. Hence, Propositions 1 and 3 also hold in general equilibrium in this special case. In the next section, we show that house prices react to redistribution in a similar way.

2.4 Housing market equilibrium

We now introduce a construction sector to the model and study how rising income inequality and social comparisons affect the housing market equilibrium. There are two competitive production sectors producing the nondurable consumption good c , and new housing investment I_h , respectively. Total labor supply is normalized to one and we denote $N_h \in (0, 1)$ as the fraction of labor supplied to the housing construction sector. Following Kaplan, Mitman, and Violante (2020), there is no productive capital in this economy.

Nondurable consumption sector. The final consumption good is produced using a linear production function

$$Y_c = \Theta(1 - N_h),$$

where $1 - N_h \in (0, 1)$ is the share of labor supplied to the consumption good sector and Θ is labor productivity. The equilibrium wage per unit of labor is pinned down at $w = \Theta$.¹⁴

Construction sector. We model the housing sector following Kaplan, Mitman, and Violante (2020) and Favilukis, Ludvigson, and Nieuwerburgh (2017). Developers produce housing investment I_h from labor N_h and buildable land, \bar{L} , with a Cobb-Douglas production function

$$I_h = (\Theta N_h)^\alpha (\bar{L})^{1-\alpha}.$$

¹⁴Neither labor supply nor the wage appear in the earnings process because there is no aggregate risk, households inelastically supply one unit of labor, and the wage is equal to 1.

with $\alpha \in (0, 1)$. Each period, the government issues new permits equivalent to \bar{L} units of land, and these are sold at a competitive market price to developers. A developer solves

$$\max_{N_h} p_t I_h - w N_h \quad \text{s.t. } I_h = (\Theta N_h)^\alpha \bar{L}^{1-\alpha}.$$

In equilibrium, this yields the following expression for optimal housing investment

$$I_h(p) = (\alpha p)^{\frac{\alpha}{1-\alpha}} \bar{L}$$

which implies a price elasticity of aggregate housing supply of $\frac{\alpha}{1-\alpha} > 0$.

Equilibrium. We showed in Proposition 1 that the total demand for housing is

$$H_d(p) = \kappa_2(p) (\omega + \mathbf{b}(p))^T \mathbf{y}.$$

We now make the dependence on p explicit.¹⁵ In equilibrium, housing demand must equal housing supply, $H_d(p) = H_s(p)$. In a stationary equilibrium, the stock of housing must be constant such that housing investment equals the depreciated share of the housing stock, $I_h(p) = \delta H_d(p)$. The equilibrium house price thus solves the following equation:

$$(\alpha p)^{\frac{\alpha}{1-\alpha}} \bar{L} = \delta \kappa_2(p) (\omega + \mathbf{b}(p))^T \mathbf{y}.$$

Proposition 4 (Redistribution and House Prices). *Assume that house prices adjust to clear the housing market. Compare two steady states that differ only in disposable incomes. Let the difference in disposable incomes be $\Delta \mathbf{y} = \mathbf{y}' - \mathbf{y}$, where*

$$\underbrace{\omega_j \Delta y_j}_{>0} + \underbrace{\omega_i \Delta y_i}_{<0} = 0, \quad \text{and } \Delta y_k = 0 \text{ for all } k \notin \{i, j\}.$$

Then, there exists $\bar{e} > 1$ such that for all ε that satisfy $\frac{1}{1-\varepsilon} < \bar{e}$, house prices increase if and only if

$$\frac{b_i}{\omega_i} < \frac{b_j}{\omega_j}.$$

Proof. See Appendix C.5 \square

¹⁵The vector of popularities is a function of the house price as $\mathbf{b}(p) = \sum_{i=1}^{\infty} \kappa_1(p) \Phi G^i$.

The restriction that the intratemporal elasticity of substitution between housing and consumption, $e = 1/(1 - \varepsilon)$, cannot be arbitrarily high reflects the fact that we are not able to prove that housing demand is monotonically decreasing in the house price for high levels of e in the presence of social comparisons. Intuitively, it may happen that an increase in the house price raises households' popularity enough to undo the initial drop in housing demand. Note, however, that Proposition 4 covers the empirically relevant case where housing and consumption are complements ($e < 1$), as well as the frequently studied case of Cobb-Douglas preferences ($e = 1$).

As Cobb-Douglas aggregation is the most common assumption in macroeconomic models with housing, we study this case in more detail. Lemma 5 in Appendix C.6 shows that Cobb-Douglas preferences allow for a closed-form expression for the house price, which, just like the aggregates H and $-A$, is a monotone transformation of $(\omega + b)^T \gamma$. Hence, the relationship between income inequality and housing and mortgage demand extends to house prices.

3 Calibration

In this section, we discuss how we calibrate the model to match the distribution of incomes, the aggregate housing expenditure share, and the debt-to-income ratio in 1980, as well as recent causal micro estimates of the strength of social comparisons in housing.

3.1 Housing comparisons

The most important part of the calibration concerns the housing comparison motive. The calibration has three aspects: the structure of the comparison network, the strength of the comparison motive, and the spatial scope of comparisons.

Structure. Our theoretical analysis showed that the structure of the comparison network is crucial in order to understand the relationship between distributional shifts and aggregate indebtedness and house prices. That is, it is crucial to know whether households' reference groups simply contain all other households independent of their income or whether households care more about the housing decisions of households at the top of the income distribution.

While evidence on the structure of households' comparison networks is still somewhat scarce, empirical studies consistently find that comparisons are indeed upward-looking (as presumed by Duesenberry 1949).¹⁶

In order to discipline the structure and strength of housing comparisons in our model, we draw on the recent analysis of housing comparisons among U.S. homeowners by Bellet (2024). The study shows that homeowners exposed to the construction of large houses in their county report significantly lower satisfaction with their own homes, while their neighborhood satisfaction remains unaffected.¹⁷ Importantly, both low and middle class households respond to the top but not to the bottom of the local housing distribution, implying that the rich are the reference group for the rest of society.

Our baseline calibration uses three income groups: the bottom 50%, the middle 40%, and the top 10% of the income distribution. In line with the empirical evidence, we assume that the top 10% are the reference group for all three groups of households (*rich Joneses*). In the robustness analysis, we will investigate how the results change under alternative forms of upward-looking comparisons, specifically trickle-down comparisons where each income group compares itself to all households above them or only to the income group just above them. In that context, we will also analyze a more granular split of the income distribution, that is, deciles instead of the split into bottom 50%, middle 40%, and top 10%.

Strength. Having pinned down the structure of housing comparisons, we still need to calibrate the strength of the comparison motive. Following Bellet (2024), we capture this idea using a sensitivity measure defined as the ratio of the elasticity of utility with respect to reference housing, to the elasticity of utility with respect to own housing,

$$\text{sensitivity} := -\frac{\partial \log(u)/\partial \log(\tilde{h})}{\partial \log(u)/\partial \log(h)}.$$

This statistic measures by how much a household's own house has to improve in order to balance out the loss in utility from a 1% increase in reference housing.

¹⁶For example, Ferrer-i-Carbonell (2005), Clark and Senik (2010), and Card et al. (2012) find that relative income comparisons are upward-looking, that is, that households' self-reported well-being or job satisfaction decreases in comparison to the income of richer households. Bertrand and Morse (2016) show that nonrich households increase expenditures on visible goods, in particular housing, when incomes of the rich increase, but not when average incomes increase.

¹⁷The causal effect of housing-induced status externalities is identified using variation in the visibility of large homes induced by the counties' road network and differences in when large comparison houses are built relative to households' location decisions.

Bellet (2024) estimates a value of 0.8. This means that a 0.8% increase in own house size is needed to offset the utility loss from a 1% increase in the size of top (visible) houses.¹⁸

In our model, the comparison-sensitivity is given by

$$\text{sensitivity} = \varphi \frac{\tilde{h}}{h},$$

so it is not a structural parameter, but depends on the parameter φ and the ratio of reference and own housing. This implies that, for a given φ , the comparison-sensitivity decreases in own housing and thus in own income, which is counterfactual according to Bellet (2024).¹⁹ Instead we allow φ_i to vary across income groups and match a constant type-specific sensitivity of 0.8.

Scope. The third important question for the quantitative analysis is which income distribution to use in order to form these income groups. As a first benchmark, we use the nationwide income distribution, implicitly assuming that households are equally exposed to all other households in the United States. While households learn about housing trends in other parts of the country through widespread media coverage of housing trends and high mobility rates, social comparisons are most likely constrained by geographic proximity. In other words, the local rich are arguably more important in shaping households' housing demand through social status externalities because their houses are more visible than those of other rich households living in another part of the United States.²⁰

We thus exploit the tractability of our model and add a spatial dimension that allows us to analyze locally constrained comparisons where a household's reference group is restricted to other households living in the same region. Regions are either the 51 states, 394 labor market areas (LMAs), or 741 commuting zones (CZs), where commuting zones are the smallest geographic partition of the United States

¹⁸Specifically, he estimates how the log of households' self-reported housing satisfaction relates to the logs of own and reference house size using only reference houses built during the household's tenure period. The ratio of the two coefficients in the log-log model gives the sensitivity.

¹⁹Using a ratio-specification as in Abel (1990), $s(h, \tilde{h}) = h/\tilde{h}^\varphi$, would imply that the sensitivity equals φ . We cannot use this specification without losing tractability (Assumption 2).

²⁰Bellet (2024) shows that visibility is a prerequisite for such externalities as mansions built away from public road networks do not affect others' housing demand. However, this does not imply that the houses of the rich in other parts of the country are unobservable. The tightness of spatial limits to housing comparisons is thus unclear.

with consistent identifiers in the Census/ACS data.²¹ State-level comparisons imply that households in Texas do not care about houses in Oklahoma or Massachusetts and sub-state-level comparisons imply that households in the Dallas metro area do not compare themselves to households from other states or from other parts of Texas. In these scenarios, regional instead of nationwide changes in income inequality matter. If the increase in U.S. income inequality is largely driven by growing income differentials between relatively rich and poor regions, inequality within each region may increase significantly less than nationwide inequality. With locally constrained comparisons, this will reduce the aggregate effects of rising inequality through social comparisons.

The key advantage of the nationwide and state-level analyses is that we can use administrative data on disposable income based on the distributional national accounts data of Piketty, Saez, and Zucman (2018), which do not suffer from underreporting of top incomes.²² In order to study comparisons within LMAs or CZs, we have to use income data from the 1980 Census and the 2005–2007 ACS. As the Census/ACS data do not contain information on disposable income, we use household pretax income, which includes money income from all sources, including Social Security income and welfare income. Note, however, that, due to underreporting of top incomes in survey data, the top 10% of income shares in the Census/ACS data are actually slightly lower than those for disposable income in the administrative DINA data.

3.2 Parameters and model fit

Externally calibrated parameters. The housing supply elasticity $\frac{\alpha}{1-\alpha}$ is taken from Saiz (2010). As far as the elasticity of substitution between consumption and housing $1/(1 - \varepsilon)$ is concerned, the literature has yet to converge to a common value. Estimates range from around 0.15 (from structural models; e.g., Flavin and Nakagawa [2008] and Bajari et al. [2013]) up to 1.25 (Ogaki and Reinhart [1998] and Piazzesi, Schneider, and Tuzel [2007]; using estimates from aggregate data). Many papers have picked parameters out of this range, with a significant number

²¹We use the 1990 definition of LMAs and CZs following Autor and Dorn (2013), who provide a time-consistent mapping between commuting zones and county groups in the 1980 Census and Public Use Micro Areas in the 2005–2007 ACS data, respectively.

²²The state-level DINA micro files, based on Piketty, Saez, and Zucman (2018), are provided by Mian, Straub, and Sufi (2020), who use state-level data from the Internal Revenue Service (IRS) in order to impute state identifiers for observations with adjusted gross income above 200,000 dollars.

assuming an elasticity of 1.0 (Cobb-Douglas aggregation).²³ In line with most of the literature, our baseline calibration thus assumes an intratemporal elasticity of substitution of 1.0. In the robustness section, we show how the results change when we vary this parameter. The flow of land permits \bar{L} is set to 1.0.

Internally calibrated parameters. Besides the comparison parameters φ_i , this leaves three parameters for internal calibration: the discount rate ρ , the utility weight of housing status ξ , and the depreciation rate of housing δ . We calibrate these parameters to match the aggregate mortgage-to-income ratio of 0.646, the aggregate expenditure share of housing (shelter) of 0.162, and the employment share in the construction sector of 0.05.²⁴ As aforementioned, the group-specific strength of the comparison motive φ_i is set to match a comparison-sensitivity of 0.8 for all groups.

For analyses using subnational comparison networks, we recalibrate the model using the joint distribution of incomes and regions and allow house prices to vary across regions. As we do not have data on mortgage-to-income ratios and housing expenditure shares by geographic units, we use the same targets for all regions. In order to match those targets, the internally estimated parameters are allowed to vary across regions. This approach allows us to focus on the question of how the aggregate effects change for different distributions of within-region changes in income inequality. The calibration results are shown in Figure D.3.²⁵

Parameters and model fit. Table 3 shows the externally and internally calibrated parameters. The calibrated comparison parameters φ_i are equal to 0.105, 0.278, and 0.8 for households in the bottom 50%, middle 40%, and top 10% of the income distribution, respectively. The discount factor ρ is just below 0.1, the utility weight of housing status equals 0.037, and the annual depreciation rate is just above 0.1.

²³Garriga and Hedlund (2020) use 0.13, Garriga, Manuelli, and Peralta-Alva (2019) use 0.5, many papers use Cobb-Douglas (that is, an elasticity of 1.0; for example, Berger et al. [2018] and Landvoigt [2017]) and Kaplan, Mitman, and Violante (2020) use 1.25.

²⁴Note that throughout the analysis we refer to the aggregate mortgage-to-income ratio as aggregate mortgage debt over aggregate income, and to the aggregate expenditure share of housing as aggregate housing expenditures over aggregate total expenditures.

²⁵As ρ , ξ , and δ are perfectly pinned down by the mortgage-to-income ratio, the housing expenditure share, and the employment share of construction sector, they do not vary across regions. The only parameters that vary across regions are the φ_i . In order to ensure that the comparison-sensitivity is constant across regions, regional differences in the income distribution require different values of φ_i .

Table 3: Baseline calibration

Parameter description	Value	Source
<i>Preferences</i>		
$\frac{1}{m}$	average life-time	45.0 working age 20–65
ρ	discount factor	0.0989 internally calibrated
ξ	utility weight of housing	0.0371 internally calibrated
$\frac{1}{1-\varepsilon}$	elasticity of substitution (s vs c)	1.0 literature, see text
φ_P	strength of comparison motive	0.105 internally calibrated
φ_M	strength of comparison motive	0.278 internally calibrated
φ_R	strength of comparison motive	0.8 internally calibrated
<i>Technology</i>		
$\frac{\alpha}{1-\alpha}$	housing supply elasticity	1.5 Saiz (2010)
δ	depreciation rate of housing	0.103 internally calibrated
\bar{L}	flow of land permits	1.0 ad hoc

Calibrated model parameters. The internally calibrated parameters are chosen to match targeted moments in Table 4.

Table 4 shows the model fit. The model matches the empirical target moments perfectly. While we only target aggregate statistics in our calibration, our calibration also captures the lack of significant variation in debt-to-income ratios and housing expenditure shares across the income distribution, as shown in Figure 3.

Note that the aggregate loan-to-value (LTV) ratio is pinned down by our calibration targets: we can match only two moments out of mortgage-to-income, loan-to-value, and expenditure share of housing. Assuming zero initial assets a_{-1} , it turns out that the LTV is given by

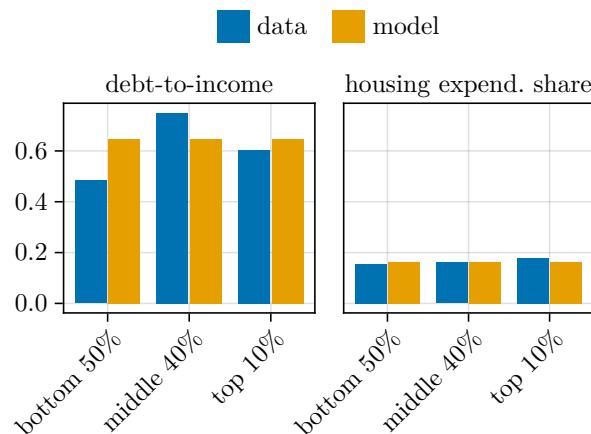
$$\frac{-a}{ph} = \frac{\kappa_3}{p\kappa_2} = \frac{1 - \delta}{1 + r} = 79.81\%.$$

In our model, the LTV is constant over the life cycle since debt is rolled over indefinitely. Thus, the model captures the high LTV ratio of first-time home buyers. In the data, the LTV decreases with age, as the debt gets repaid; in the model, the LTV is fixed at the high initial value.

Table 4: Model fit (targets)

Moment	Model	Target	Source
mortgage-to-income	0.646	0.646	DINA (1980)
expenditure share of housing	0.162	0.162	CEX (1982)
sensitivity to reference housing	(0.8, 0.8, 0.8)	0.8	Bellet (2024)
empl. share in construction sector	0.05	0.05	Kaplan, Mitman, and Violante (2020)

Targeted moments and model fit of the baseline calibration; see Table 3.

**Figure 3: Model fit by income groups (validation)**

Comparison of debt-to-income ratios and housing expenditure shares by income groups between model (baseline calibration) and data (DINA/CEX).

Alt text: Two bar plots showing the baseline calibration's model fit of the debt-to-income ratio and the housing expenditure share relative to the data by income groups.

4 Quantitative Results

Having calibrated the model to match key aggregates in 1980, we now study whether increasing income inequality and housing comparisons can rationalize a meaningful part of the U.S. housing and mortgage boom between 1980 and 2007. Over this period, the top 10% income share increased from 33% to 41% at the expense of nonrich households above and below the median. At the same time, the housing expenditure share increased by almost 25%, the mortgage-to-income ratio more than doubled, and house prices increased by almost 60% (Table 5).

Throughout the analysis, we exogenously redistribute incomes in line with the observed shift in the distribution of disposable income. As our mechanism operates in the long run, the core of our quantitative analysis is a comparison of steady states with different levels of income inequality. Nevertheless, in Section 4.3, we discuss the transition dynamics in the model.

4.1 Baseline results

Table 6 presents the effects of rising income inequality for nationwide and state-level comparisons. For the nationwide benchmark where housing comparisons are not constrained by spatial proximity, column 2 shows that our mechanism explains an increase in the housing expenditure share of 3 percentage points (p.p.), an increase in the mortgage-to-income ratio of 12 p.p. and an increase in house prices of 7.1%. Relative to the observed changes in the data, the model can thus rationalize 79% of the shift towards housing expenditures, 16% of the increase in indebtedness, and 12% of the increase in house prices.

The next step in the analysis is to study scenarios where housing comparisons are spatially constrained. As it is unclear what the true spatial scope of comparisons is, we analyze different geographic partitions of the United States. The smallest possible partition in the administrative DINA data is the 50 + 1 states. Column 3 of Table 6 shows the results for state-level comparisons taking into account the joint distribution of incomes and states. As some of the increase in nationwide income inequality is driven by growing income disparities across states, the effect of our mechanism is attenuated. Quantitatively, however, the difference between the nationwide benchmark and the state-level analysis is small. Our mechanism still explains 74% of the increase in housing expenditure shares, 15% of the mortgage boom, and 11% of the house price boom.

Table 5: Rising income inequality and the housing and mortgage booms

Moment	1980	2007	Source
<i>Rising Income Inequality</i>			
bottom 50% income share	0.21	0.17	DINA
middle 40% income share	0.46	0.42	DINA
top 10% income share	0.33	0.41	DINA
<i>Housing and mortgage booms</i>			
expenditure share of housing	0.162	0.2	CEX
mortgage-to-income	0.646	1.39	DINA
real house price index	100.0	158.6	Case-Shiller

Observed income inequality and housing and mortgage statistics in 1980 and 2007.

Table 6: The consequences of rising inequality (DINA)

Variable	1980		2007	
	all scopes (1)	nation (2)	state (3)	
expenditure share of housing	0.162	0.192	0.19	
mortgage-to-income	0.646	0.766	0.758	
real house price index	100.0	107.1	106.5	
Δ top 10% income share (p.p.)		7.98	7.54	
Δ middle 40% income share (p.p.)		-3.67	-3.37	
Δ bottom 50% income share (p.p.)		-4.31	-4.17	
number of regions		1	51	

Model-generated housing and mortgage statistics for 1980 and 2007 using the baseline calibration for different scopes of social comparisons. Income inequality measures from DINA data.

Table 7: The consequences of rising inequality (Census/ACS)

Variable	1980		2007		
	all scopes (1)	nation (2)	state (3)	LMA (4)	CZ (5)
expenditure share of housing	0.162	0.192	0.19	0.189	0.189
mortgage-to-income	0.646	0.768	0.761	0.755	0.755
real house price index	100.0	107.2	106.8	106.4	106.4
Δ top 10% income share (p.p.)		6.54	6.14	5.78	5.77
Δ middle 40% income share (p.p.)		-3.37	-3.12	-2.87	-2.85
Δ bottom 50% income share (p.p.)		-3.16	-3.02	-2.92	-2.91
number of regions		1	51	394	741

Model-generated housing and mortgage statistics for 1980 and 2007 using the baseline-calibration for different scopes of social comparisons. Income inequality measures from Census/ACS data.

Columns 1 and 2 of Table 7 repeat the analysis of Table 6 and show that the results are virtually unchanged when using Census/ACS rather than DINA data.²⁶

But what happens when we look at more granular partitions of the United States (which are only available in the Census/ACS data)? Columns 4 and 5 reveal that our mechanism still generates sizeable increases in the aggregate housing expenditure share and mortgage-to-income ratio even when the scope of housing comparisons is confined to the household's labor market area or commuting zone. The reason why our results are largely invariant to the scope of housing comparisons is that the bulk of the nationwide increase in income inequality took place within regions. For example, the nationwide top 10% income share in the Census/ACS data increased by 6.54 p.p. (column 1). The average increase in the within-commuting-zone top 10% income share across all commuting zones is equal to 5.77 p.p. or 88.2% of the nationwide figure. Figure 4 plots the entire distribution of the change in within-region top 10% income shares between 1980 and 2007 across states and commuting zones. Strikingly, income inequality increased not only nationwide, or within the 51

²⁶This is the case despite the fact that the p.p. change in income shares is smaller in the Census/ACS data. As the baseline level of income inequality is also smaller, the relative change in income inequality is very similar. In particular, the 1980 Census/ACS income shares of the top 10%, middle 40%, and bottom 50% are 0.27, 0.51, and 0.22, respectively.

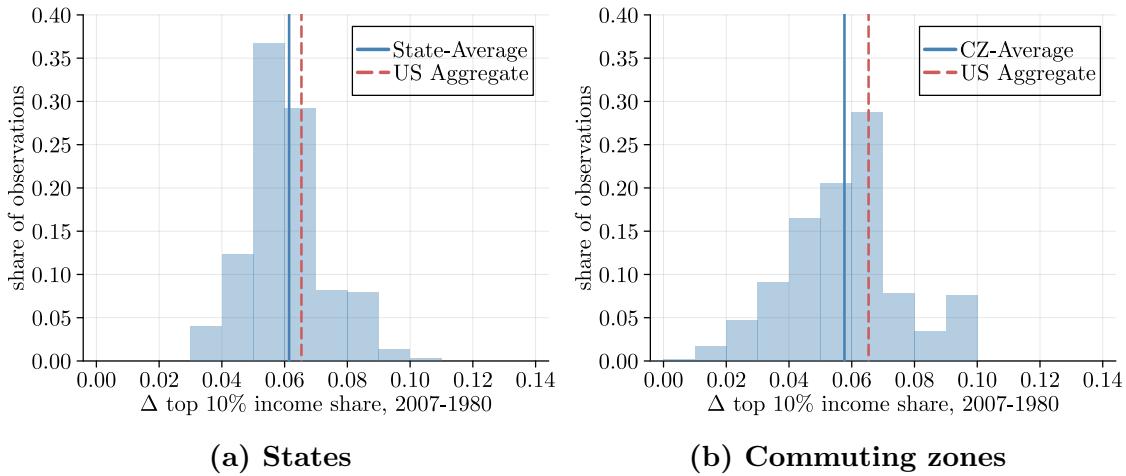


Figure 4: Change in within-region top 10% income shares (Census/ACS)

This figure shows the distribution of the 2007–1980 change in within-region top 10% income shares across states and commuting zones. Population weights from 1980 are used. The vertical lines depict the average across the within-region changes (blue, solid) and the change in the nationwide top 10% income share (red, dashed). Data: Census/ACS.

Alt text: Two histograms showing the distribution of the change in within-region top 10% income shares between 1980 and 2007 across states and commuting zones.

states (panel (a)), but also within all of the United States' 741 commuting zones (panel (b)).

Note that these results do not imply that the scope of housing comparisons is particularly broad. Instead, the fact that spatial income disparities contribute only little to the overall increase in income inequality implies that heterogeneity in the scope of housing comparisons matters only if between-region income differences drive the evolution of overall inequality. While one could in principle argue that this aspect becomes more relevant for even narrower comparison scopes, we do not think that it is particularly plausible that households only see houses in their immediate neighborhood, but not in the rest of their commuting zone. In addition, our spatially segregated analysis assumes that there are no connections between regions. In reality, even very narrowly defined reference groups will overlap and thereby induce indirect housing externalities that effectively broaden the scope of comparisons.

We thus conclude that our mechanism can explain a substantial share of the U.S. housing and mortgage boom between 1980 and 2007. As the spatial scope of housing comparisons does not significantly change the aggregate effects, the following analyses use the benchmark scenario without spatial limits to housing comparisons.

Table 8: Heterogeneity by income groups

Income group	Δ mortgage-to-income		Δ expenditure share of housing	
	data	model	data	model
top 10%	54.7 p.p.	0.0 p.p.	2.35 p.p.	0.0 p.p.
middle 40%	87.4 p.p.	17.5 p.p.	3.81 p.p.	4.37 p.p.
bottom 50%	88.4 p.p.	27.6 p.p.	4.36 p.p.	6.9 p.p.

Observed and model-generated changes in the mortgage-to-income ratio and the expenditure share of housing by income groups. Data: DINA/CEX.

Heterogeneity by income. Table 8 shows how housing expenditure shares and mortgage-to-income ratios changed across the income distribution in the model and the data. In the data, both measures increased more for nonrich households than for rich households. Our mechanism replicates this heterogeneity. The rich do not react at all because they are not affected by status externalities (they only compare themselves to their own type). Absent status externalities, Cobb-Douglas aggregation implies that expenditure shares are constant—even in general equilibrium. Hence, housing expenditures of the rich do not change relative to other consumption expenditures.

In contrast, both the bottom 50% and middle 40% experience a drop in housing status as their reference group (the rich) scales up their housing in proportion to their incomes. In particular, the model predicts that households in the middle 40% increase their housing expenditure share by 4.37 p.p. and their mortgage-to-income ratio by 17.5 p.p. The response for the bottom 50% is even stronger.²⁷ This implies that the change in the aggregate housing expenditure share and mortgage-to-income ratio induced by our mechanism is entirely driven by nonrich households who compare themselves to the rich.

Wealth inequality. Rising income inequality and upward-looking social comparisons raise the aggregate level of housing and mortgage debt in the economy. But what about net wealth (the value of housing net of debt)? While our model is not

²⁷The somewhat stronger effect for the bottom 50% is consistent with our empirical finding that the relationship between changes in top incomes and changes in nonrich mortgage-to-income ratios is stronger for the bottom 50% (see Appendix Figure A.5).

designed to capture static differences in income and wealth inequality, we can still ask how a change in income inequality affects wealth inequality.²⁸

It turns out that wealth inequality does increase as a result of the increase in income inequality. However, our model predicts that the increase in wealth inequality is weaker than the increase in income inequality. Intuitively, when nonrich households shift expenditures from the consumption good to housing, they build up net worth because housing is not only a consumption good but also an asset. This implies that net-worth-to-income increases for the nonrich. As housing expenditure shares of the rich are unaffected (Table 8), their wealth-to-income ratio stays constant. This, in turn, implies that wealth inequality does not rise as strongly as income inequality due to upward-looking social comparisons in housing.

Table 9 shows that, while the top 10% of income share increases by 8.0 p.p., the top 10% of wealth share in the model increases by only 1.5 p.p. from a baseline level of 33%. Conversely, the wealth shares of the bottom 50% and middle 40% of the income distribution decline less than their income shares. The pattern is the same in the data where the wealth share of households in the top 10% of the income distribution increases by only 3.8 p.p. from a baseline value of 57.5%.²⁹ Note that Kuhn, Schularick, and Steins (2020) first documented the decoupling of U.S. income and wealth inequality in the four decades leading up to the Great Recession. In line with our model, they also find that the decoupling was driven by increases in housing wealth relative to income of nonrich households.

4.2 Robustness analysis

We turn to several robustness checks in order to see how the results change when we deviate from certain assumptions made in the baseline calibration of the model.

Structure of comparisons. As we have shown in Section 2, the effect of redistribution on house prices and debt depends on the structure of social comparisons. That is, we showed analytically that redistribution has no effect on aggregate housing and mortgage demand when social comparisons are absent (*No Joneses*) or symmet-

²⁸In our analysis, the initial wealth distribution and the initial income distribution are identical by construction. Cobb-Douglas aggregation implies that net wealth is proportional to the house value. Since our calibration pins down the initial housing value relative to income for each type, initial net-worth-to-income is the same for all types.

²⁹In the model, households in the top 10% of the income distribution are also in the top 10% of the wealth distribution. While income and wealth are highly correlated, this is not the case in the data. For consistency, Table 9 shows the wealth share of each income group in the data.

Table 9: Changes in income and wealth inequality

Income group	Δ income share		Δ wealth share	
	data	model	data	model
top 10%	8.0 p.p.	8.0 p.p.	3.8 p.p.	1.5 p.p.
middle 40%	-3.7 p.p.	-3.7 p.p.	-2.3 p.p.	-0.7 p.p.
bottom 50%	-4.3 p.p.	-4.3 p.p.	-1.5 p.p.	-0.8 p.p.

Observed and model-generated changes in income and wealth shares by income groups. Data: DINA.

ric (*Mean Joneses*), while there are effects for upward-looking social comparisons. Below we vary the specific nature of upward-looking comparisons.

In the baseline calibration, we assume that all households compare themselves to the rich (*Rich Joneses*). While this appears to be the empirically relevant case (Bellet 2024), we now study how the results change under two weaker forms of upward-looking comparisons. Specifically, we assume that nonrich households compare themselves either only to households in the income group directly above them (*Richer Joneses*) or to all richer households (*All Richer Joneses*). In the case of *Richer Joneses*, the social status externality of the rich trickles down the distribution: While the bottom 50% do not care about the houses of the rich, they do care about the houses of the middle 40%, who, in turn, react to the bigger houses of the rich.

The case of *All Richer Joneses* is a mix of the baseline (*Rich Joneses*) and *All Richer Joneses* such that the reference house is equal to the average house size of all households above the median.

Table 10 shows that the effects weaken only marginally for both alternative network structures. Note, however, that with only three income groups, nothing changes for households in the middle 40% of the income distribution. Only the reference group of the bottom 50% changes. And, as their contribution to aggregate debt is relatively small, it is not surprising that the results do not change dramatically.

We therefore split the population into deciles instead of the three income groups and repeat the analysis with this more granular split of the income distribution. Table 11 shows the results. For the intermediate case of *All Richer Joneses*, the results are still close to the baseline effects. That is, 90% of the baseline effects remains for all three variables. As expected, however, the effects are significantly weaker for the

Table 10: Different forms of upward-looking comparison networks

Variable	1980		2007	
	all structures (1)	rich Jon. (2)	all richer Jon. (3)	richer Jon. (4)
expend. share of housing	0.162	0.192	0.191	0.19
mortgage-to-income	0.646	0.766	0.764	0.759
real house price index	100.0	107.1	107.0	106.7

Model-generated housing and mortgage statistics for 1980 and 2007 using the baseline calibration for different structures of social comparisons using DINA income inequality measures.

case of *Richer Joneses*. Comparing columns 2 and 4 shows that just over 60% of the baseline effect survives under this extreme version of trickle-down comparisons, which, given the empirical evidence, is not the empirically relevant case. Hence, we conclude that plausible deviations from the baseline network structure do not substantially reduce the explanatory power of our mechanism.

Age-specific comparisons. Another possible limit to households' reference groups is age. In other words, households may not compare themselves to all rich households, but only to rich households within their own age group. Like spatial limits to comparisons, age-specific comparisons require us to analyze the effects of changing the joint distribution of incomes and age.

Table 12 compares the baseline results (for the Census/ACS data) to those for two different splits of the age distribution. In column 3, we split households into young and old depending on whether the household head is older than 45. In column 4, we use eight 5-year age bins.³⁰ In both cases, we group households into the standard three income groups with age-group-specific cutoffs. As income inequality increased within all age groups (see Appendix Figure D.2), the effects of our mechanism are virtually unchanged.

While this is reassuring, we do not think that age-specific comparison networks are particularly plausible as the age of a (rich) homeowner is much harder to observe than the house itself. Rather than operating within a household's group of personal

³⁰More precisely, the age groups are under 35, 35–39, …, 60–64, and 65 and over.

Table 11: Robustness: Different forms of upward-looking comparison networks with income deciles

Variable	1980		2007	
	all structures (1)	rich Jon. (2)	all richer Jon. (3)	richer Jon. (4)
expenditure share of housing	0.162	0.192	0.189	0.18
mortgage-to-income	0.646	0.766	0.756	0.72
real house price index	100.0	107.1	106.5	104.5

Model-generated housing and mortgage statistics for 1980 and 2007 for different structures of social comparisons using DINA income inequality measures.

contacts, our mechanism emphasizes that nonrich households compare their houses to those of all rich households in the same area.

Sensitivity analyses. Finally, we conduct a sensitivity analysis of two key parameters: the intratemporal elasticity of substitution and the comparison sensitivity (which measures the strength of the comparison motive).

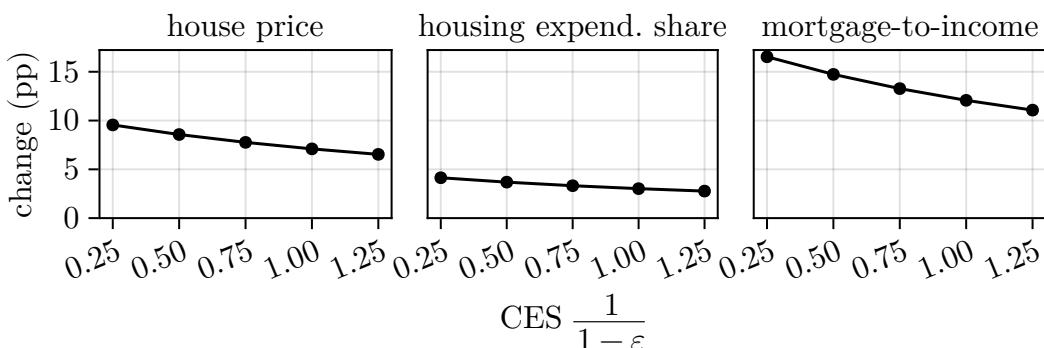
The first analysis verifies that the assumption of Cobb-Douglas aggregation is not crucial for the quantitative results. In the knifeedge case of Cobb-Douglas aggregation, expenditure shares, and hence debt, are not affected by the house price. However, when consumption and housing are complements and the price of housing rises because of increasing housing demand, households will increase the expenditure share of housing and take on more mortgage debt. If the intratemporal elasticity exceeds unity, a rise in house prices will dampen the shift from consumption to housing.

To test the sensitivity of our results, we vary the intratemporal elasticity of substitution between consumption and housing between 0.25 and 1.25, that is, the range of values used in other studies. We then recalibrate the model in order to start from the same baseline in 1980. Figure 5 confirms the above intuition. The aggregate effects of rising income inequality become stronger when the intratemporal elasticity of substitution between status-neutral consumption and housing status decreases. For the lowest elasticity of 0.25, as suggested by micro estimates, our mechanism explains over 20% of the observed increase in mortgage-to-income and just over

Table 12: Robustness: Age-Specific Comparison Networks

Variable	1980		2007	
	all scopes		above/below 45	5-year age bins
	(1)	(2)	(3)	
expenditure share of housing	0.162	0.191	0.193	
mortgage-to-income	0.646	0.764	0.772	
real house price index	100.0	106.9	107.4	
Δ top 10% income share (p.p.)		6.47	6.44	
Δ middle 40% income share (p.p.)		-3.22	-2.43	
Δ bottom 50% income share (p.p.)		-3.25	-4.01	
number of age groups		2	8	

Model-generated housing and mortgage statistics for 1980 and 2007 assuming social comparisons within age groups, and using Census/ACS income inequality measures.

**Figure 5: Robustness: Different intratemporal substitution elasticities between consumption and housing**

This figure shows the effects of rising income inequality on the house price, the housing expenditure share, and the mortgage-to-income ratio for different levels of the intratemporal elasticity of substitution between consumption and housing, $1/(1 - \varepsilon)$. For each value of the elasticity, we recalibrate the model. The internally calibrated parameters are shown in Figure D.4.

Alt text: Three line graphs showing the change in house prices, the housing expenditure share, and the mortgage-to-income ratio for different values of the intratemporal elasticity of substitution ranging from 0.25 to 1.25.

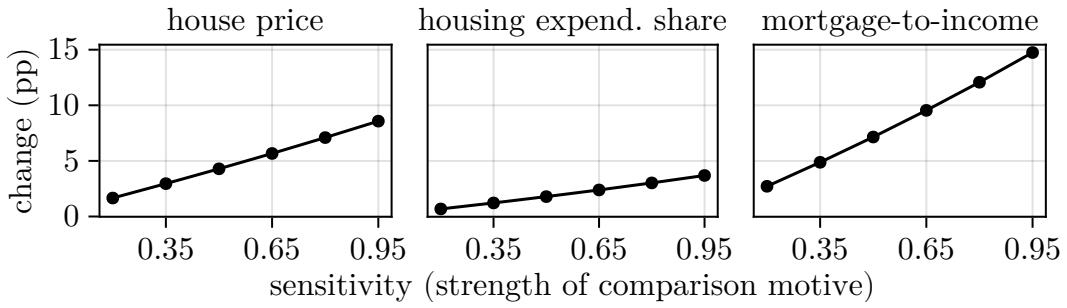


Figure 6: Robustness: Varying the strength of the comparison motive

This figure shows the effects of rising income inequality on mortgage-to-income, the house price, and the housing expenditure share for different levels of the comparison sensitivity. For each value of the sensitivity, we recalibrate the model. The internally calibrated parameters are shown in Figure D.5.

Alt text: Three line graphs showing the change in house prices, the housing expenditure share, and the mortgage-to-income ratio for different values of the sensitivity parameter ranging from 0.2 to 0.95.

15% of the increase in house prices. Increasing the elasticity from 1 to 1.25, the upper end of the spectrum of empirical estimates based on macro data, does not reduce the effects substantially. Hence, if anything, the assumption of Cobb-Douglas aggregation is conservative.

Next, we study how the effect of inequality on our aggregates of interest (house prices, housing expenditures and aggregate debt) depends on the strength of the comparison motive, that is, the comparison-sensitivity we target in the calibration. As we do not allow for comparisons in nonhousing consumption, our baseline target of 0.8 may overstate effects of rising inequality on the shift towards housing expenditures and the increase in indebtedness triggered by the increase in housing demand.³¹ While we cannot introduce a second status good, we can investigate how lowering the comparison-sensitivity for housing affects the results. Figure 6 shows that, as expected, the effects become smaller as we reduce the sensitivity towards zero (the atomistic case of *no Joneses*).³² However, as the relationship is linear, our mechanism still generates sizeable effects even if the sensitivity is slightly overstated.

³¹Some nondurable consumption goods such as jewelry and clothes are also very visible and may serve as a signal of social status (e.g., Heffetz 2011; Solnick and Hemenway 2005; Bertrand and Morse 2016).

³²For our baseline network structure, the relationship is exactly linear. The sensitivity pins down the parameter φ , which appears in the social externality matrix. Depending on the structure of social comparisons, the social externality matrix may contain φ^i for any power i (e.g., Table 1). Since there are no indirect externalities of the top 10% onto the non rich in the baseline specification, only φ^1 shows up in the social externality matrix. Hence the linear relationship. For network structures with indirect externalities, the relationship becomes slightly convex but is very similar.

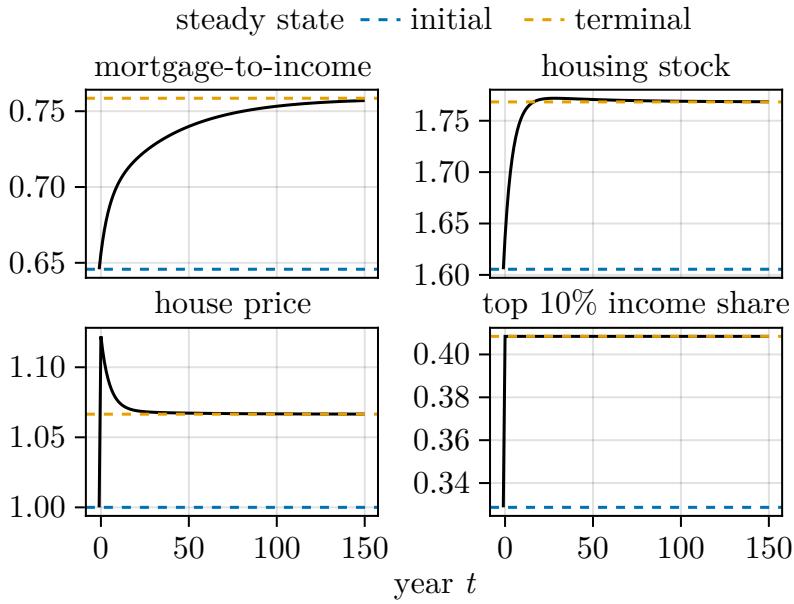


Figure 7: Transition after change in income inequality

Evolution of aggregate mortgage-to-income, housing stock and the house price after an unexpected change in income inequality from 1980 to 2007 levels (“MIT shock”), starting from the baseline steady state (1980).

Alt text: Four line graphs showing the simulated development of the mortgage-to-income ratio, the housing stock, the house price, and the top 10% income share over time in reaction to a instantaneous increase in income inequality.

4.3 Transition between steady states

While we think of our mechanism as a long-run force due to adjustment frictions in housing markets, it is worth asking whether the comparison of steady states is justified in the sense that the economy actually converges to the new long-run steady state when starting out in the initial steady state.

In this section, we thus analyze the economy’s transition path from the old steady state (before redistribution) to the new steady state (after redistribution). In particular, we assume that for $t \leq -1$ the economy is in its initial steady state with the U.S. income distribution of 1980. At $t = 0$, the income distribution changes unexpectedly and permanently. Figure 7 shows the perfect-foresight transition paths (solid lines) as well as the steady-state levels from Table 6 (dashed lines).³³

First, observe that the economy indeed converges to the new steady state. Second, observe that the nature of the transition looks very different for the mortgage-

³³ Appendix E provides computational details. The inverse IES parameter γ is irrelevant for the baseline results, as it drops from all steady state expressions. For the analysis of the transition path, we set it to the standard value $\gamma = 2$.

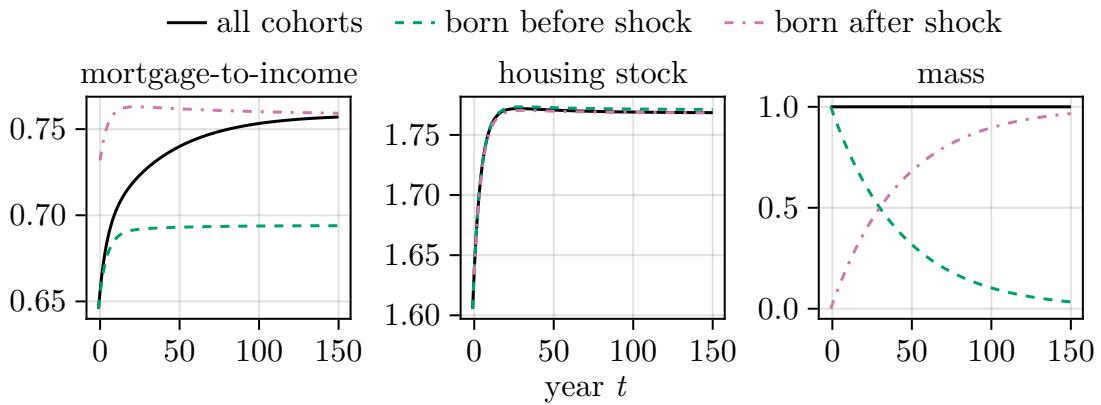


Figure 8: Transition dynamics for different cohorts

Decomposition of the paths of aggregate mortgage-to-income and the housing stock by (groups of) cohorts (born before vs. after the shock) after an unexpected change in income inequality from 1980 to 2007 levels (“MIT shock”), starting from the baseline steady state (1980).

Alt text: Three line graphs showing, for cohorts born before and after the shock, the simulated development of the mortgage-to-income ratio, the housing stock, and the cohorts mass over time in reaction to a instantaneous increase in income inequality.

to-income ratio, house prices, and the stock of housing. While the mortgage-to-income ratio converges monotonically and quite slowly, the house price initially jumps above the new steady state value and then converges much faster.

Convergence of house prices. Why does the house price overshoot? While the construction sector only needs to replace depreciated housing when the economy is in a steady state, it now additionally needs to fill the gap between the old and the new steady state housing stock, which we denote by H and H' , respectively. Due to the sudden change in the income distribution, the demand for housing investment jumps from δH to $H' - H + \delta H$, which is greater than the new steady state housing investment demand of $\delta H'$. Hence, the price jumps above the new steady state level to induce this strong supply response in the housing sector. As the housing stock approaches the new optimum, the house price decreases to reach its new steady state.

Convergence of debt. Debt, on the other hand, converges more slowly. While the majority of the increase happens relatively quickly within the first 10 years after the shock, the final 20% of the transition takes a very long time even after the aggregate housing stock has reached its new steady state level. This is driven by cohort-specific differences in debt-to-income ratios and the perpetual youth assumption.

tion which implies that a substantial share of households survives for an implausibly long time.

In particular, cohorts born before the shock have different optimal choices from cohorts born after the shock because of a shock-induced wealth effect for existing households. That is, the old cohorts who owned a house before the shock experience a positive housing wealth effect because the unexpected increase in house prices increases their housing wealth. In contrast, cohorts born after the shock enter with zero initial wealth. Hence, households born before the shock can tap into their newfound housing wealth in order to finance the increase in housing demand. This attenuates the increase in the demand for mortgage debt. This is shown in Figure 8. While both groups of cohorts converge to very similar housing stocks, the new steady state debt level is lower for the households born before the shock relative to those born after the shock. While the group-specific debt levels converge quite fast, average debt converges much more slowly as the old cohort dies with a constant mortality rate.

However, note that this pattern is not specific to a model with social comparisons. As shown in Figure 9, the transition paths of debt, the housing stock, and house prices in response to a 5% permanent productivity shock have a very similar shape independent of whether social comparisons are present: The house prices jumps on impact, overshoots, and converges quite fast. Debt, in contrast, takes longer to converge because of the aforementioned wealth effect and the assumption of constant mortality rates.

Gradual increase in inequality. The fact that house prices overshoot so strongly is due to the assumption that inequality changes all the way from the 1980 to the 2007 level in period 0. If, instead, inequality changes in, say, 20 small and unexpected steps, the shape of the transition becomes much less extreme; see Figure 10. The maximal increase in house price (relative to the initial steady state) is less than 10% (3 p.p. overshooting), while it was 14% (7 p.p. overshooting) in the baseline transition path. At the same time, mortgage-to-income converges much faster in the initial years because the wealth effects are smaller.

In sum, the transition analysis shows that (i) steady state comparisons are not misleading, and (ii) social comparisons, while affecting steady state outcomes, do not affect the transitional dynamics for a given change in long run steady states. Perhaps more interestingly, the different patterns for house prices and mortgage debt are consistent with the dynamic relationship among top incomes and house

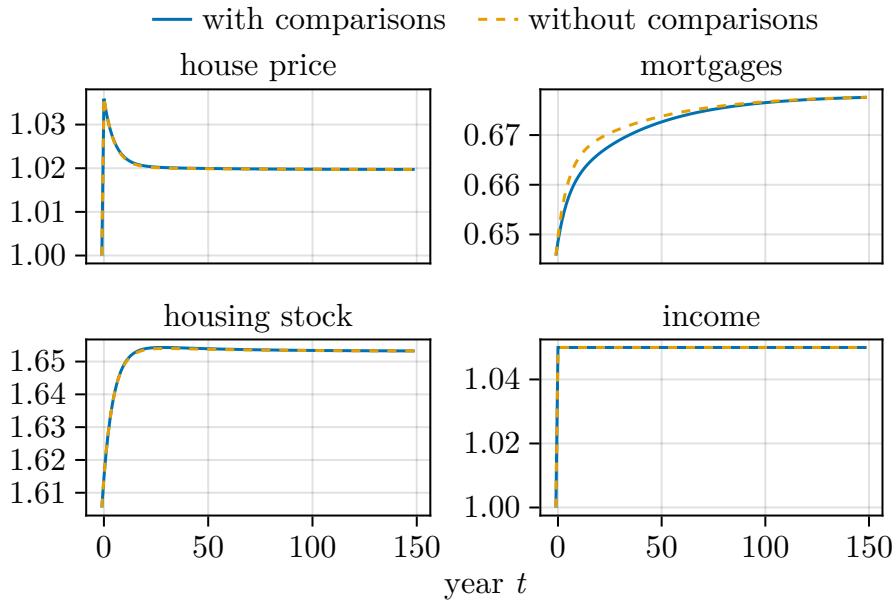


Figure 9: Transition after a permanent productivity shock with and without comparisons

Evolution of aggregate mortgages and the housing stock after an unexpected change in the productivity level (“MIT shock”), starting from the baseline steady state (1980). The solid lines show the baseline calibration; the dotted lines show a calibration without social comparison.

Alt text: Four line graphs showing, for the cases with and without comparisons, the simulated development of aggregate mortgage, the housing stock, the house price, and the aggregate income over time in reaction to a permanent productivity shock.



Figure 10: Transition for step-wise change in inequality

Evolution of aggregate mortgage-to-income, housing stock, and the house price in response to a sequence of 20 unexpected shocks to income inequality (“MIT shocks”) that result in the level of income inequality from 2007.

Alt text: Two line graphs showing the simulated development of the house price and the mortgage-to-income ratio over time in reaction to a step-wise change in income inequality.

prices and mortgage debt that we document in Appendix Tables A.2 and A.3. In particular, we find that nonrich debt reacts to changes in top incomes with a lag of 5 years while house prices react almost immediately.

5 Conclusion

This paper develops a tractable framework to study the effects of general social comparisons among heterogeneous agents on aggregate consumption and borrowing behavior. We show that the nature of social comparisons critically determines the link between inequality and debt. Whenever income is redistributed from a less to a more popular agent, demand for housing and debt rises. This link only breaks down when all agents have the same popularity. This (counterfactual) knife edge case occurs when agents compare themselves with the population average, which is the standard specification in previous studies of social comparisons in a macro-finance context.

Using this framework, we can rigorously analyze the idea that income inequality drives up household debt due to upward-looking social comparisons (e.g., Rajan 2011; Stiglitz 2009; Frank 2013). In fact, the quantitative analysis shows that this link can rationalize up to 15% of the U.S. mortgage debt boom prior to the Great Recession. The model not only captures aggregate trends, but also the heterogeneous debt responses across the income distribution. In addition, the model helps rationalize the decoupling of income and wealth inequality driven by a disproportionate increase in housing wealth of nonrich households (Kuhn, Schularick, and Steins 2020).

The first limitation is the lack of an extensive margin that is the focus of a large literature in macro-finance.³⁴ We omitted this margin from the model for two reasons. First, it would compromise tractability. Second, there is no evidence on social comparisons in the setting of rented housing. While it is plausible to assume that ownership increases housing status independent of the house itself, ownership status is much less visible (Veblen 1899). It is thus unclear how rising income inequality affects homeownership. On the one hand, a status premium of ownership can generate a positive link between long-run changes in income inequality and

³⁴For example, Chambers, Garriga, and Schlagenhauf (2009), and Fisher and Gervais (2011) study how homeownership is related to idiosyncratic income risk, and Favilukis, Ludvigson, and Nieuwerburgh (2017), Kaplan, Mitman, and Violante (2020), Garriga, Manuelli, and Peralta-Alva (2019), and Garriga and Hedlund (2020) study the effects of business cycle swings in house prices, constraints, or idiosyncratic income risk.

nonrich home ownership. In Appendix A.4, we indeed find that commuting zones that experienced a stronger increase in income inequality between 1980 and 2007 also saw an increase in home ownership among nonrich households. On the other hand, in times when prices substantially exceed rents because of expectation-driven house price booms, as was the case in the years just before the Great Recession (e.g., Adam, Kuang, and Marcket 2012; Kaplan, Mitman, and Violante 2020), households may prefer to rent a relatively large house rather than own a relatively small one because the status effect of house size dominates that of ownership.

The second limitation of our tractable framework is that no agents are borrowing-constrained in equilibrium. In a setting where constraints matter, the effects of our mechanism could be dampened because rising inequality pushes nonrich households, particularly those in the bottom 50%, against the borrowing constraint such that housing and mortgage debt react less strongly. Our demand-side mechanism should be considered as complementary to the multitude of studies that provide explanations for a surge in the supply of credit, which often work via looser borrowing constraints (e.g., Kumhof, Rancière, and Winant 2015; Favilukis, Ludvigson, and Nieuwerburgh 2017). Our mechanism can be an important amplifier of these channels. With more people close to the constraint, a relaxation of borrowing constraints will have bigger aggregate effects on house prices and debt. Hence, our mechanism might have contributed to the surge in subprime mortgage debt when borrowing constraints were relaxed ahead of the Great Recession.

Unlike supply-side mechanisms, and to the extent that social comparisons have a strong spatial dimension, our channel also helps to rationalize the link between rising top incomes and nonrich debt-to-income ratios at the state level as the local rich exert a social externality on nonrich households in the same area. In contrast, rising top incomes arguably have only small effects on local credit supply if financial markets are integrated across U.S. states.

Another question is whether other adjustment margins exist that allow households to deal with a loss in relative housing status due to rising inequality. For example, households may purposefully move into regions where income inequality is lower so that their relative housing status is higher. In the extreme case where households are perfectly segregated and only care about their immediate neighbors, status externalities disappear as income differences disappear. However, for reasonably small regions such as commuting zones, we show that within-region changes in income inequality are still large enough to generate sizeable effects. And while spatial income disparities have increased, they still only explain a small part of overall

income inequality, even at the county level (Gaubert et al. 2021). Another margin of adjustment is labor supply. Intuitively, nonrich households may increase labor supply in order to keep up with the rich. This may be especially important for poor households that would otherwise be borrowing constrained and is an interesting avenue for future research.

In order to seriously quantify the effect of rising inequality on macro-financial outcomes, it is essential to have a good estimate of popularities across the income distribution, or even better, to have an estimate of the comparison network. Future research should thus investigate to whom households compare themselves. The exact asymmetries in the network of comparisons shapes the degree to which agents differ in their popularity and hence in how much their choices affect others (social externality), and thereby macrofinancial aggregates.

The replication code and data are available in the Harvard Dataverse at <https://doi.org/10.7910/DVN/GFCSRE>

Appendix

A Empirical Analysis: Top Incomes and Nonrich Debt

In this appendix, we use state-level DINA data (Piketty, Saez, and Zucman 2018) and IPUMS Census/ACS data to document that the key prediction of our mechanism is borne out in state- and sub-state level U.S. data between 1980 and 2007: rising top incomes are associated with rising mortgage-to-income ratios, but constant or falling nonmortgage-debt-to-income ratios of nonrich households.

Figure A.1 documents the positive relationship between the long-run change in debt-to-income ratios of the bottom 90% and the corresponding change in average log top 10% incomes between the years 1980–1982 and 2005–2007.³⁵ Panel (a) shows that states that experienced a stronger increase in average top incomes also experienced a stronger increase in the debt-to-income ratio of nonrich households. Panel (b) shows that this positive relationship is entirely driven by mortgage debt whereas nonmortgage debt is, if anything, negatively related to top incomes. This is consistent with a shift towards housing expenditures due to social status externalities in housing, upward-looking comparisons and rising top income inequality.

In the following, we document that this relationship (i) also holds in richer fixed effects regressions, (ii) takes time to materialize, and (iii) holds not only across the 51 states, but also across the 741 U.S. commuting zones. However, let us emphasize at the outset that we do not have an explicit source of quasi-experimental variation in top incomes.³⁶ Hence, we do not claim that the relationships documented below can be interpreted causally. Nevertheless, we find that the link between top income inequality and nonrich indebtedness is a robust feature of the data and consistent with the large literature on social comparisons that motivates our theoretical and quantitative analysis (Kuchler and Stroebel 2021).

³⁵We take 3-year averages to limit the importance of temporary shocks in 1980 and 2007. However, the relationship is virtually unchanged without the averaging.

³⁶We follow Mian, Straub, and Sufi (2020) and argue that plenty of evidence in the literature supports the view that the rise in top inequality was triggered by shifts in technology and globalization that took place at the outset of the rise in inequality around 1980 (e.g., Katz and Murphy 1992; Autor, Katz, and Kearney 2008; Smith et al. 2019).

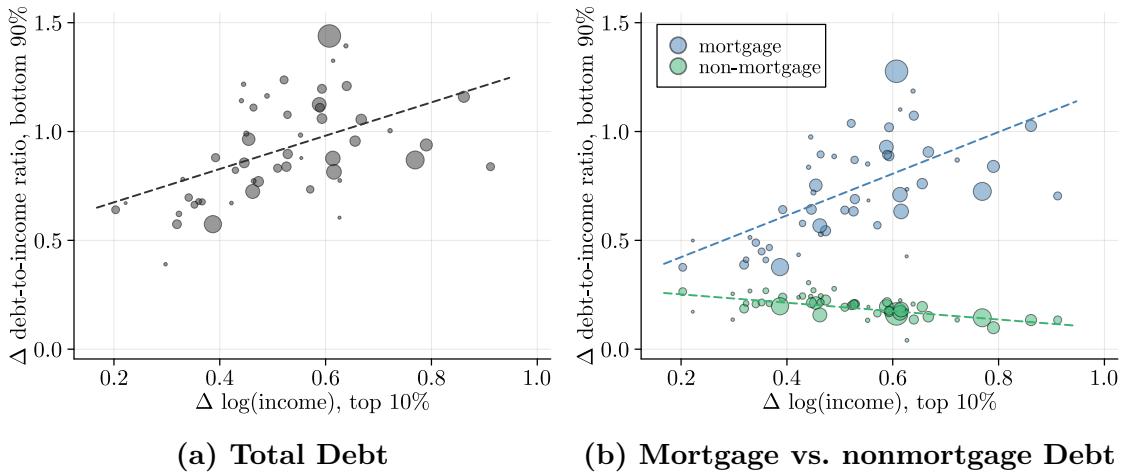


Figure A.1: Nonrich debt and top incomes: 1980–2007

Panel (a) plots the change in the debt-to-income ratio of the bottom 90% against the change in the log of average top 10% of incomes for each state between 1980–1982 and 2005–2007. Panel (b) shows the change in the ratio of mortgage debt to income and nonmortgage debt to income. The size of the markers corresponds to the state's population size in the base period. Data: DINA.
Alt text: Two scatterplots with linear fits labeled (a) and (b) showing the correlation between the change in log income of the top 10% and the change in debt-to-income ratio of the bottom 90% in (a) for total debt, and in (b) for mortgage and nonmortgage debt.

A.1 Data

We use two different data sets, both of which have their advantages and disadvantages. First, we use state-level data on incomes and debt between 1980 and 2007 adapted from the data provided by Mian, Straub, and Sufi (2020).³⁷ These data are based on DINA data from Piketty, Saez, and Zucman (2018). As state-level identifiers in the DINA data are suppressed for incomes above 200,000 U.S. dollars, state identifiers are imputed using state-level data from the Internal Revenue Service (IRS), which include information on how many tax returns above 200,000 dollars (adjusted gross income) come from each state.³⁸ While the imputation is based on adjusted gross income, we use disposable cash income as our measure of income.³⁹

³⁷The data are part of the replication kit for Mian, Straub, and Sufi (2020) (<http://scholar.harvard.edu/straub/MSSavingglutreplication>).

³⁸The imputation is based on the assumption that incomes above 200,000 dollars follow a state-specific Pareto distribution with density $f_s(y) = \frac{\alpha_s 200,000^{\alpha_s}}{y^{\alpha_s+1}}$, where α_s can be computed from the state-level mean income of units with gross income above 200,000 dollars. The ratio of the state-specific and aggregate income density gives the relative likelihood that an observation comes from that state. This is then used to weight all observations when computing state averages.

³⁹The results are very similar when using adjusted gross incomes.

The advantages of this administrative data set is that it does not suffer from underreporting of top incomes, is available for all years between 1980 and 2007 and includes information on both mortgage and nonmortgage debt levels. The main downside of the DINA data is that we cannot use more granular spatial variation, which is desirable to the extent that housing comparisons are spatially constrained and income distributions within smaller geographic areas drive social status externalities.

We thus use the 1980 Census and 2005–2007 ACS data to check whether the relationship between top incomes and nonrich debt holds up when using variation across commuting zones, as defined by Autor and Dorn (2013). In contrast to the DINA data, the Census/ACS data only contain information on mortgage debt-service payments, but no information on the stock of debt or nonmortgage debt. As the Census/ACS data do not contain information on disposable income, we use household pretax income (*HHINCOME*), which includes money income from all sources including Social Security income and welfare income. Note, however, that due to underreporting of top incomes in survey data, the top 10% of income shares in the Census/ACS data are actually slightly lower than those for disposable income in the administrative DINA data.

A.2 Fixed effect regressions: Nonrich debt and top incomes

To complement the graphical analysis of long-differences in Figure A.1, we use the annual state-level DINA data to estimate whether rising top incomes are associated with rising nonrich debt after controlling for time-invariant nonrich incomes, state-level heterogeneity, aggregate shocks, and state-specific time trends. As in Bertrand and Morse (2016), we use lagged top incomes, as any causal effect of social comparisons would realistically occur with a delay.

We estimate regression equations of the following form:

$$\begin{aligned} \log(debt_{s,t}^{bot90}) = & \beta \log(income_{s,t-k}^{top10}) + \gamma \log(income_{s,t}^{bot90}) + \delta \log(income_{s,t-k}^{bot90}) \\ & + state_s + year_t + state_s \times trend_t + \varepsilon_{s,t}, \end{aligned} \quad (\text{A.1})$$

where s indexes states and t indexes years. The dependent variable is the log of total debt, mortgage debt, or debt of nonrich households defined as the bottom 90% of a state's income distribution. The main explanatory variable is the log of lagged top incomes measured as the average income in the top 10% of a state's

Table A.1: Fixed effect regressions: Mortgage and nonmortgage debt

	log(total debt _t ^{bot90})			log(mortgage debt _t ^{bot90})			log(non-mortgage debt _t ^{bot90})		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
log(<i>income</i> _{t-k} ^{top10})	0.317*** (0.116)	0.272*** (0.087)	0.300*** (0.087)	0.468*** (0.167)	0.418*** (0.131)	0.453*** (0.131)	-0.075* (0.041)	-0.121*** (0.041)	-0.103** (0.042)
log(<i>income</i> _t ^{bot90})	0.539*** (0.173)	0.804*** (0.214)	0.432* (0.243)	0.561** (0.247)	1.001*** (0.308)	0.562 (0.358)	0.498*** (0.061)	0.530*** (0.057)	0.242*** (0.073)
log(<i>income</i> _{t-k} ⁹⁰)	0.120 (0.172)	0.324** (0.132)	0.260** (0.126)	0.172 (0.238)	0.488** (0.203)	0.405** (0.197)	-0.048 (0.070)	-0.029 (0.063)	-0.069 (0.063)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State time trends		Yes	Yes		Yes	Yes		Yes	Yes
Demographic controls			Yes			Yes			Yes
R ²	0.975	0.981	0.982	0.965	0.973	0.975	0.977	0.982	0.985
Observations	1,173	1,173	1,173	1,173	1,173	1,173	1,173	1,173	1,173
Clusters	51	51	51	51	51	51	51	51	51

Estimation results corresponding to Equation (A.1) for $k = 5$ and different types of debt. Robust standard errors, clustered at the state level, are in parentheses. * $p < .1$; ** $p < .05$; *** $p < .01$.

income distribution. If β is positive, higher top income levels are associated with higher future indebtedness of nonrich households as we control for current and past nonrich income.

Table A.1 shows the estimation results for Equation (A.1) with $k = 5$ for different types of nonrich debt on the left hand side.⁴⁰ Columns 2, 5, and 8 show the results of our preferred specification (Equation A.1). In columns 1, 4, and 7, we omit state-specific linear time trends and in columns 3, 6, and 9 we add demographic controls to capture time-varying heterogeneity in age, gender, marital status, and the number of kids among nonrich households. Reassuringly, all specifications yield very similar results.

For our preferred specification, an increase in top incomes by 1% is associated with an increase in the nonrich debt by about 0.27%. While the same increase in top incomes translates into a 0.42% increase in nonrich mortgage debt, nonmortgage debt decreases by 0.12%. On average, top incomes increased by 57% and nonrich mortgage debt increased by 113% between 1980 and 2007. A coefficient of $\beta = 0.42$ thus suggests that increasing top incomes can rationalize an increase in mortgage debt by 24% or roughly one fifth of the overall increase.

Why do we not see a positive relationship between top incomes and nonmortgage debt? Our theoretical analysis shows that we only expect top incomes to increase nonrich debt for goods that are both (more) status relevant (relative to other goods)

⁴⁰When estimating Equation (A.1), we weight observations by population size to obtain nationally representative coefficients and cluster standard errors at the state level.

and durable such that higher expenditures today do not prevent higher expenditures in the future. The findings are thus in line with our assumption that housing is more status-relevant than nonhousing consumption inducing households to substitute towards housing. Bertrand and Morse (2016) also find that expenditures on more visible consumption goods, and in particular housing, increase in lagged top incomes while households spend less on utilities or health and education.⁴¹

Table A.2 presents estimation results of Equation A.1 for mortgage debt and $k = 1, \dots, 8$. The results show that it takes time for rising top incomes to translate into higher nonrich debt. It takes 3 years for the effects to become significant at the 5% significance level and the effect builds up over the first 5 years. This delay is to be expected if the results are driven by the housing externalities as improving housing takes time. Both the rich and the nonrich take time to react to higher top incomes and improved top housing, respectively. Interestingly, while the effect of top incomes steadily increases in the lag order, the effect of own income kicks in right away. Again, this is in line with a trickle-down type pattern where top incomes impact a nonrich household's housing and mortgage decisions with a greater delay than own incomes.

A.3 Top incomes and nonrich debt across commuting zones

Using Census/ACS survey data, we can test whether the relationship between top incomes and nonrich debt also holds at finer geographic levels such as commuting zones. We follow Autor and Dorn (2013) to map the Census/ACS geographic identifiers into 1 of 741 commuting zones and assign a unique state identifier to each commuting zone.⁴² Recall that we have to use households' mortgage-debt-service payments as a proxy for the stock of debt. Figure A.2 shows how the within-region change in the mortgage-debt-service-to-income ratio of the bottom 90% relates to the change in average top incomes in the region. Panel (a) documents that states with higher growth in top incomes between 1980 and 2007 experienced significantly higher increases in nonrich indebtedness. Reassuringly, panel (b) shows that this

⁴¹While it would be worthwhile to study nonrich debt on other status-relevant durables such as cars, we cannot distinguish between different types of nonmortgage debt. Hence, we only capture the net effect on all types of nonmortgage debt; many of them are either less status relevant and/or nondurable. Moreover, the evidence on cars is surprisingly mixed. On the one hand, Kuhn et al. (2011) find significant conspicuous consumption patterns for cars among neighbors of lottery winners. On the other hand, Bertrand and Morse (2016) do not find that nonrich expenditures on cars respond to top incomes.

⁴²In particular, we use map county groups in the 1980 Census and PUMA codes in the 2005–2007 ACS.

Table A.2: Fixed effect regressions: Dynamic effects

	log(mortgage debt _t ^{bot90})							
	<i>k</i> = 1	<i>k</i> = 2	<i>k</i> = 3	<i>k</i> = 4	<i>k</i> = 5	<i>k</i> = 6	<i>k</i> = 7	<i>k</i> = 8
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(income _{t-k} ^{top10})	0.065 (0.134)	0.211* (0.124)	0.329*** (0.120)	0.373*** (0.124)	0.418*** (0.131)	0.423*** (0.119)	0.471*** (0.122)	0.316*** (0.111)
log(income _t ^{bot90})	0.993*** (0.207)	0.994*** (0.247)	1.072*** (0.298)	1.072*** (0.316)	1.001*** (0.308)	0.921*** (0.279)	0.805*** (0.254)	0.731*** (0.225)
log(income _{t-k} ^{bot90})	0.590*** (0.204)	0.686*** (0.205)	0.714*** (0.196)	0.663*** (0.199)	0.488** (0.203)	0.473** (0.187)	0.189 (0.173)	0.172 (0.168)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State time trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>R</i> ²	0.971	0.972	0.973	0.973	0.973	0.974	0.978	0.979
Observations	1,377	1,326	1,275	1,224	1,173	1,122	1,071	1,020
Clusters	51	51	51	51	51	51	51	51

This table shows the estimation results corresponding to Equation A.1 for $k = 1, \dots, 8$. The dependent variable is the log of mortgage debt of the bottom 90%. Robust standard errors, clustered at the state level, are in parentheses. * $p < .1$; ** $p < .05$; *** $p < .01$.

relationship also extends both qualitatively and quantitatively to the level of commuting zones after controlling for state fixed effects.⁴³ This shows that unobserved time-varying heterogeneity across states cannot rationalize the link between top incomes and non-rich mortgage debt across states.⁴⁴

A.4 Top incomes and nonrich home ownership

While our model abstracts from extensive margin housing decisions, it is worthwhile to ask whether extensive margin housing demand, that is, home ownership, is also related to top income inequality. Using Census/ACS data, Figure A.3 shows that rising top incomes of the local rich are also positively associated with homeownership rates among nonrich households. Again, the relationship holds across states and across commuting zones after controlling for cross-state heterogeneity. Hence, rising top incomes seem to increase housing demand of nonrich households not only at the intensive, but also at the extensive, margin.

⁴³For commuting zones, we first residualize the changes in mortgage-debt-service-to-income ratios and top incomes by regressing each variable on state fixed effects and then plot the relationship between the residuals (plus the respective mean).

⁴⁴Note that the relationship between top incomes and nonrich debt also holds when using the change in the top income share as the explanatory variable and/or when controlling for the change in nonrich incomes.

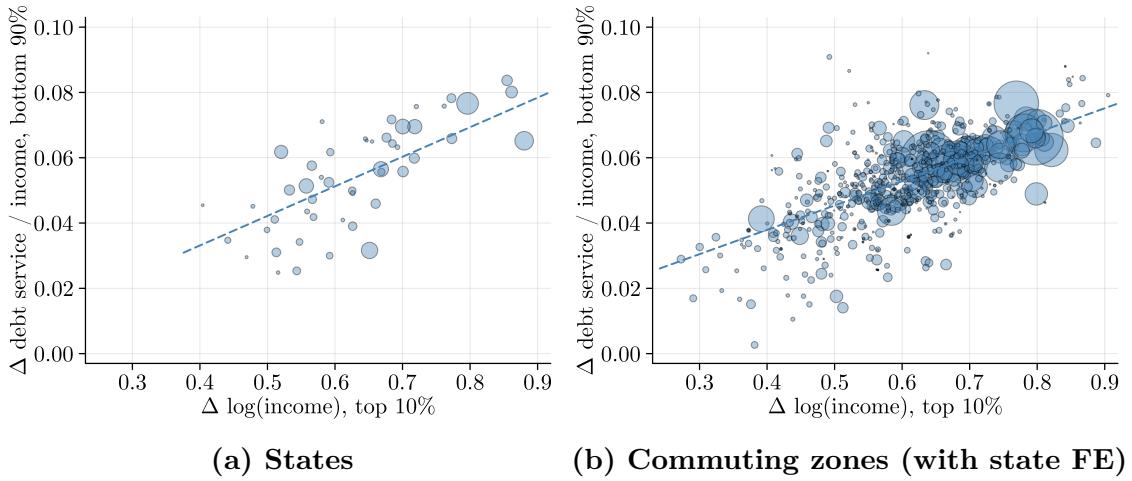


Figure A.2: Nonrich mortgage-debt-service and top incomes: 1980–2007, Census/ACS

Panel (a) plots the change in the mortgage-service-to-income ratio of the bottom 90% against the change in the log of average top 10% of incomes for each state between 1980 and 2005–2007 using data from the 1980 Census and the 5-year ACS 2005–2007. Panel (b) shows the same relationship at the level of commuting zones after controlling for state fixed effects (standard errors are clustered at the state level). Commuting zones are defined as in Autor and Dorn (2013). The size of the markers corresponds to the square root of the region’s population size in the base period.

Alt text: Two scatterplots with linear fits labeled (a) and (b) showing the correlation between the change in log income of the top 10% and the change in debt-service-to-income ratio of the bottom 90% in (a) at the state level and in (b) at the commuting zone level.

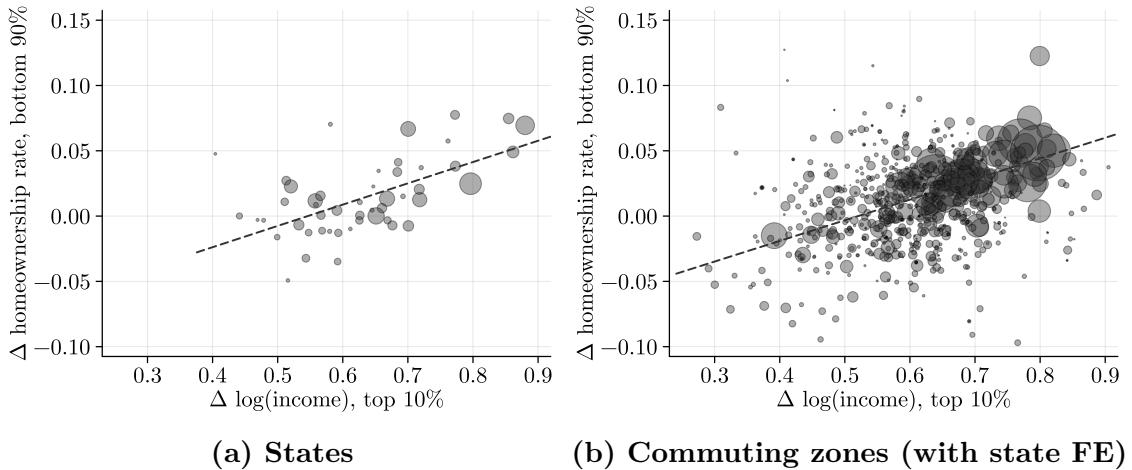


Figure A.3: Nonrich home ownership and top incomes: 1980–2007, Census/ACS

Panel (a) plots the change in the share of homeowners among the bottom 90% of a region's income distribution against the change in the log of average top 10% incomes for each state between 1980 and 2005–2009 using data from the 1980 Census and the 5-year ACS 2005–2009. Panel (b) shows the same relationship at the level of commuting zones after controlling for state fixed effects (standard errors are clustered at the state level). Commuting zones are defined as in Autor and Dorn (2013). The size of the markers corresponds to the square root of the region's population size in the base period.

Alt text: Two scatterplots with linear fits labeled (a) and (b) showing the correlation between the change in log income of the top 10% and the change in homeownership rate of the bottom 90% in (a) at the state level and in (b) at the commuting zone level.

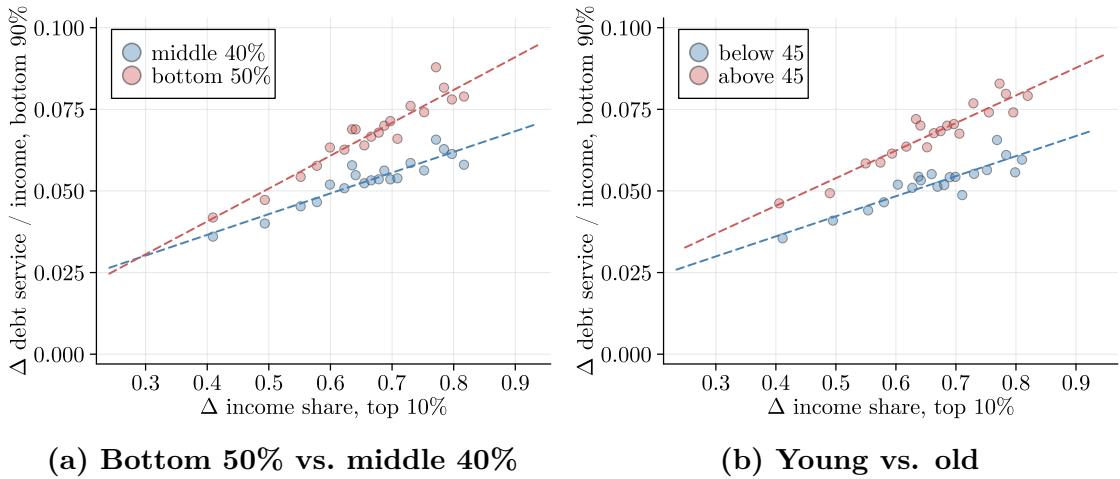


Figure A.4: Nonrich debt and top incomes across commuting zones: Heterogeneity

Panel (a) plots the change in the mortgage-service-to-income ratio of the bottom 50% and middle 40% of the income distribution against the change in the log of average top 10% of incomes for each commuting zone and controlling for state fixed effects between 1980 and 2005–2007. Panel (b) shows the same relationship for households in the bottom 90% of the income distribution with heads above 45 (old) and below 45 (young) years of age. Commuting zones are defined as in Autor and Dorn (2013). The size of the markers corresponds to the square root of the regions population size in the base period. Data: Census 1980, ACS 2005–07.

Alt text: Two scatterplots with linear fits labeled (a) and (b) showing the correlation between the change in the income share of the top 10% and the change in debt-service-to-income ratio of the bottom 90% in (a) for the bottom 50% and middle 40% and in (b) for households aged above and below 45 years.

A.5 Heterogeneity by Income and Age

Figure A.4 shows the relationship between top incomes and debt across commuting zones (within states) for subgroups of nonrich households. Panel (a) shows that, consistent with the results of our quantitative analysis, the relationship is slightly stronger for households below the median than for nonrich households above the median of the income distribution. Panel (b) shows that differences across age are even less pronounced.

Figure A.5 shows the same splits when using home ownership as the dependent variable. Overall, the lack of substantial heterogeneity is not surprising given that we analyze long-run changes over a period of almost 30 years.

A.6 Top Incomes and House Prices

Using state-level house price data and state-level DINA data, Figure A.6 shows that the positive relationship between rising income inequality and housing demand is

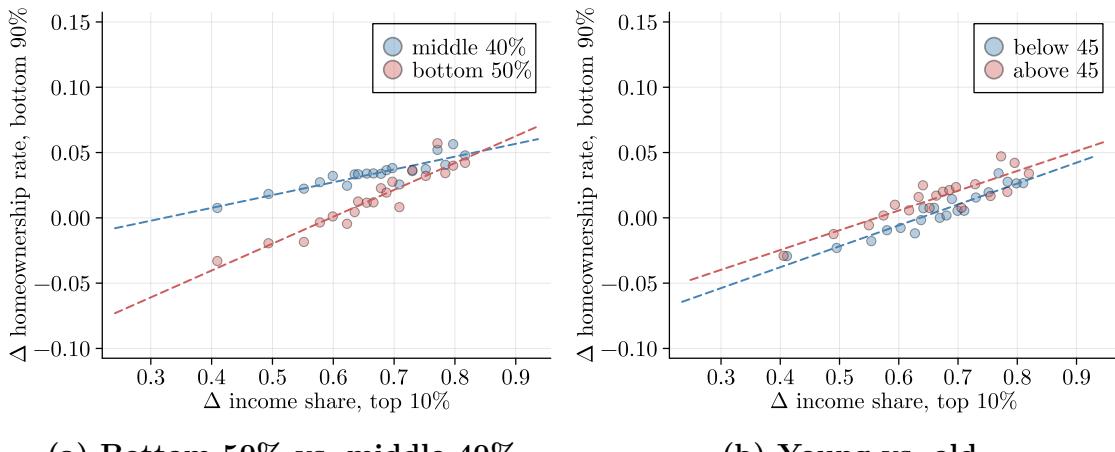


Figure A.5: Nonrich homeownership and top incomes across commuting zones: Heterogeneity

Panel (a) plots the change in the mortgage-service-to-income ratio of the bottom 50% and middle 40% against the change in the log of average top 10% of incomes for each commuting zone and controlling for state fixed effects between 1980 and 2005–2007. Panel (b) shows the same relationship for households in the bottom 90% of the income distribution with heads above 45 (old) and below 45 (young) years of age. Commuting zones are defined as in Autor and Dorn (2013). The size of the markers corresponds to the square root of the regions population size in the base period. Data: Census 1980, ACS 2005–07.

Alt text: Two scatterplots with linear fits labeled (a) and (b) showing the correlation between the change in the income share of the top 10% and the change in home-ownership rate of the bottom 90% in (a) for the bottom 50% and middle 40% and in (b) for households aged above and below 45.

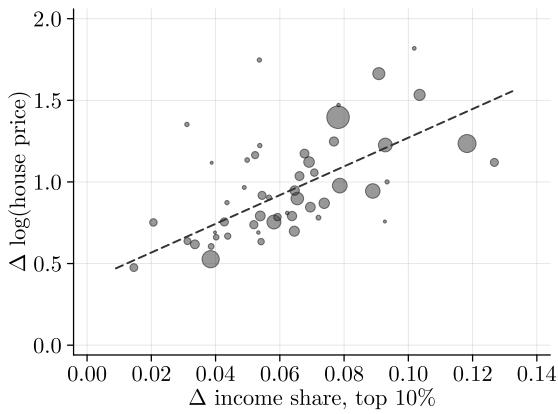


Figure A.6: Top incomes and house prices, 1980–2007

This figure plots the change in the state-level real house price index between 1980 and 2007 against the corresponding change in the top 10% of income share. Data: DINA and Shiller (2015).

Alt text: Scatterplot with linear fit showing the correlation between the change in the income share of the top 10% and the change in the log house price.

also visible when using state-level house prices as the dependent variable. Note that this relationship is robust to controlling for the change in nonrich incomes.

Table A.3 shows the results of fixed effect regressions that estimate the effect of lagged top incomes on house prices when controlling for contemporaneous average incomes of all households in the state. Consistent with the results of our transition analysis in Section 4.3, the effect of top incomes on house prices is more immediate than on nonrich mortgage debt. In contrast, lagged incomes of the bottom 90% do not have a significant effect on house prices. This is again consistent with upward-looking comparisons.

Table A.3: Fixed effect regressions: Dynamic effects on state-level house prices

	$\log(\text{house price}_t)$							
	$k = 1$	$k = 2$	$k = 3$	$k = 4$	$k = 5$	$k = 6$	$k = 7$	$k = 8$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\log(\text{income}_{t-k}^{\text{top10}})$	0.819*** (0.140)	0.883*** (0.152)	0.827*** (0.165)	0.743*** (0.195)	0.588** (0.229)	0.327 (0.252)	-0.020 (0.244)	-0.350* (0.190)
$\log(\text{income}_t^{\text{all}})$	0.697** (0.283)	0.946*** (0.311)	1.111*** (0.318)	1.139*** (0.295)	1.084*** (0.256)	0.997*** (0.254)	0.932*** (0.267)	0.936*** (0.256)
$\log(\text{income}_{t-k}^{\text{bot90}})$	0.282 (0.226)	0.143 (0.221)	0.070 (0.232)	-0.128 (0.266)	-0.338 (0.313)	-0.526* (0.302)	-0.542* (0.280)	-0.475* (0.269)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State time trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.944	0.945	0.943	0.942	0.940	0.938	0.938	0.940
Observations	1,377	1,326	1,275	1,224	1,173	1,122	1,071	1,020
Clusters	51	51	51	51	51	51	51	51

This table shows the estimation results corresponding to a version of Equation A.1 for $k = 1, \dots, 8$, where, instead of controlling for contemporaneous nonrich incomes, we control for average contemporaneous income in the state. The dependent variable is the log of the state-level house price index. Robust standard errors, clustered at the state level, are in parentheses. * $p < .1$; ** $p < .05$; *** $p < .01$.

B The Consequences of Uneven Income Growth

Between 1980 and 2007, real pretax incomes of the top 10% doubled, while those of the bottom 50% stagnated, according to DINA data by Piketty, Saez, and Zucman (2018). This is shown in Figure B.1. The bottom 50% did not participate in the growth of aggregate income.

In this appendix we analyze the aggregate consequences of this uneven income growth. Under what circumstances will aggregate housing demand and aggregate debt rise if only one type experiences income growth?

We show that the aggregate housing-to-income ratio and the aggregate debt-to-income ratio increase whenever a household j 's popularity is higher than the average popularity of the other types (weighted by income and corrected for population weights). In absolute terms, aggregate housing and aggregate debt always increase in this case.

Proposition 5 (Uneven growth). *Compare two steady states that differ only in disposable incomes. Let the difference in disposable incomes be $\Delta \mathbf{y} = \mathbf{y}' - \mathbf{y}$, where*

$$\Delta y_j > 0, \quad \text{and } \Delta y_i = 0 \text{ for all } i \neq j.$$

The aggregate housing-to-income ratio increases if and only if type j 's popularity is higher than the average popularity of the other types (weighted by incomes, corrected by population share):

$$\Delta \frac{\omega^T \mathbf{h}}{\omega^T \mathbf{y}} > 0 \iff \frac{b_j}{\omega_j} > \sum_{i \neq j} \lambda_i \frac{b_i}{\omega_i},$$

with weights given by $\lambda_i = \frac{\omega_i y_i}{\omega^T \mathbf{y} - \omega_j y_j}$, and $\sum_{i \neq j} \lambda_i = 1$. The same condition holds for the debt-to-income ratio if aggregate initial wealth is zero, $\omega^T a_0 = 0$. If aggregate initial wealth is positive, this condition is sufficient, but not necessary.

Proof. See Appendix C.3. □

Let us consider the effect of uneven growth of top incomes y_R on aggregate debt-to-income or aggregate housing-to-income for the four simple networks from Figure 2. In the cases of *No Joneses* (a) and *Mean Joneses* (b), the ω -corrected popularity $\frac{b_i}{\omega_i}$ is the same for all types. That is, there will be no effect on aggregate housing-to-income or aggregate debt-to-income. In the case of *Rich Joneses* (d), there will be a positive effect if the rich R gain because the rich are more popular

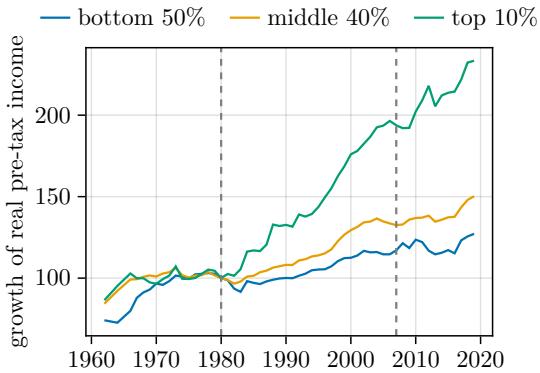


Figure B.1: Growth of pretax real incomes by income groups in the United States

The base year is 1980. Data: [DINA](#).

Alt text: Line graph showing the percentage change of real pretax income over the years 1960 to 2020 relative to the reference year 1980 for the bottom 50%, middle 40%, and top 10%.

than the other types. In the case of *Richer Joneses* (c), one cannot generally say if the rich are sufficiently popular for a positive effect on aggregate housing-to-income and debt-to-income. Figure B.2 shows the parameter regions in which the rich R are more popular than the income weighted average of types P and M ,

$$\underbrace{\lambda_P \frac{b_P}{\omega_P} + \lambda_M \frac{b_M}{\omega_M}}_{=0} > \frac{b_R}{\omega_R}.$$

Only if the population share of the rich ω_R gets very large will the popularity of the rich R get low enough that uneven income growth of the rich will not drive up aggregate debt-to-income. The region where redistribution from M to R will drive up aggregate debt levels,

$$\frac{b_M}{\omega_M} > \frac{b_R}{\omega_R},$$

is the same as in the right-most panel of Figure B.2 ($\lambda_M = 1$).

The lessons of this example hold more generally. According to the classic macroeconomic interpretation of keeping up with the Joneses, rising top income inequality will have no effect on aggregate housing-to-income and aggregate debt-to-income. This is because all types have the same corrected popularity. Under upward comparisons, however, rising top income inequality will drive up aggregate housing-to-income and debt-to-income as long as the rich are sufficiently popular.

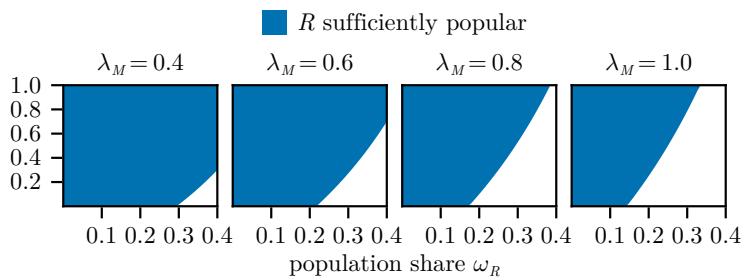


Figure B.2: Are the rich sufficiently popular in the case of *Richer Joneses* (c)?

The figure shows the parameter regions for which unequal growth causes increases in aggregate debt-to-income and housing-to-income ratios. λ_M is the income share of the middle 40% out of the incomes of the bottom 90%. For relevant population shares of the rich R (10% or less), uneven growth always increase aggregate debt-to-income and housing-to-income ratios.

Alt text: The figure shows the parameter regions for which unequal growth causes increases in aggregate debt-to-income and housing-to-income ratios for four different income shares of the middle class.

C Proofs and Additional Analytic Results

C.1 Proof of Proposition 1

Proof. The constants are given by

$$\begin{aligned} \mathbf{c} &= \kappa_1(I + L)\mathbf{y} - \frac{p}{1+r}L\mathbf{y} \\ \kappa_0 &= \left(p\frac{\delta+r}{1+r}\frac{1-\xi}{\xi}\right)^{\frac{1}{1-\varepsilon}} > 0 \\ \kappa_1 &= \frac{\kappa_0}{p\frac{\delta+r}{1+r} + \kappa_0} \in (0, 1) \\ \kappa_2 &= \frac{1}{p\frac{\delta+r}{1+r} + \kappa_0} > 0 \\ \kappa_3 &= \frac{p(1-\delta)}{1+r}\kappa_2 > 0. \end{aligned}$$

From Lemmas 1 and 2, we get that

$$c = \kappa_0 s(h, \tilde{h}) = \kappa_0 h - \kappa_0 \varphi \tilde{h}. \quad (\text{C.1})$$

Choices are constant over time because $(1+r)\beta = 1$. The lifetime budget constraint is

$$\begin{aligned} (1+r)a_0 + \frac{1+r}{r}y &= \frac{1+r}{r}(c + \delta ph) + (1-\delta)ph \\ \implies \mathbf{y} := ra_0 + y &= c + \delta ph + \frac{r}{1+r}(1-\delta)ph. \\ &= c + ph \frac{\delta+r}{1+r} \end{aligned}$$

Using Equation (C.6)

$$\begin{aligned} &= h \left(p \frac{\delta+r}{1+r} + \kappa_0 \right) - \kappa_0 \varphi \tilde{h} \\ \implies h &= \frac{\mathbf{y} + \kappa_0 \varphi \tilde{h}}{p \frac{\delta+r}{1+r} + \kappa_0} = \underbrace{\frac{1}{p \frac{\delta+r}{1+r} + \kappa_0} \mathbf{y}}_{\kappa_2} + \underbrace{\frac{\kappa_0}{p \frac{\delta+r}{1+r} + \kappa_0} \varphi \tilde{h}}_{\kappa_1} = \kappa_2 \mathbf{y} + \kappa_1 \varphi \tilde{h}, \quad (\text{C.2}) \end{aligned}$$

where $\kappa_1 \in (0, 1)$ since $\kappa_0 > 0$ and $p \frac{\delta+r}{1+r} > 0$. Stacking Equations (C.2) for and using $\tilde{\mathbf{h}} = G\mathbf{h}$,

$$\begin{aligned}\mathbf{h} &= \kappa_2 \mathbf{y} + \kappa_1 \varphi G \mathbf{h} \\ \mathbf{h} &= (I - \kappa_1 \varphi G)^{-1} \kappa_2 \mathbf{y}.\end{aligned}$$

$(I - \kappa_1 \varphi G)^{-1}$ is a Leontief inverse. It exists if the matrix power series $\sum_{i=0}^{\infty} (\kappa_1 \varphi G)^i$ converges.⁴⁵ In that case,

$$(I - \kappa_1 \varphi G)^{-1} = \sum_{i=0}^{\infty} (\kappa_1 \varphi G)^i = \underbrace{(\kappa_1 \varphi G)^0}_I + \underbrace{\sum_{i=1}^{\infty} (\kappa_1 \varphi G)^i}_{=:L}.$$

Thus,

$$\mathbf{h} = \kappa_2 (I + L) \mathbf{y}.$$

Moreover,

$$\begin{aligned}\tilde{\mathbf{h}} &= G\mathbf{h} = \frac{\kappa_1 \varphi}{\kappa_1 \varphi} G \left(\sum_{i=0}^{\infty} (\kappa_1 \varphi G)^i \right) \kappa_2 \mathbf{y} \\ &= \frac{1}{\kappa_1 \varphi} \left(\sum_{i=1}^{\infty} (\kappa_1 \varphi G)^i \right) \kappa_2 \mathbf{y} \\ &= \frac{1}{\kappa_0 \varphi} \left(\sum_{i=1}^{\infty} (\kappa_1 \varphi G)^i \right) \mathbf{y} \\ &= \frac{1}{\kappa_0 \varphi} L \mathbf{y}.\end{aligned}$$

⁴⁵This is the case for all nilpotent matrices (there exists a power p such that $G^p = 0I$) (there are no infinitely long paths in the network) or if all eigenvalues of $\kappa_1 \varphi G$ are between 0 and 1. This holds whenever G can be interpreted as a Markov Chain.

Now, we use Equation (C.1) to arrive at the expression for debt.

$$\begin{aligned}
-ra &= y - \delta ph - c \\
&= y - \delta ph - \kappa_0 h + \kappa_0 \varphi \tilde{h} \\
&= y - (\delta p + \kappa_0)h + \kappa_0 \varphi \tilde{h} \\
-r\mathbf{a} &= \mathbf{y} - \underbrace{(\delta p + \kappa_0)\kappa_2(I + L)\mathbf{y} + L\mathbf{y}}_{=: \kappa_6} \\
&= (\mathbf{y} - r\mathbf{a}_0) - \kappa_6(I + L)\mathbf{y} + L\mathbf{y} \\
&= (1 - \kappa_6)(I + L)\mathbf{y} - r\mathbf{a}_0 \\
\implies -\mathbf{a} &= \underbrace{\frac{1 - \kappa_6}{r}(I + L)\mathbf{y} - \mathbf{a}_0}_{=: \kappa_3}.
\end{aligned}$$

Note that

$$\begin{aligned}
1 - \kappa_6 &= 1 - \frac{\delta p + \kappa_0}{p \frac{\delta+r}{1+r} + \kappa_0} \\
&= \frac{p \frac{\delta+r}{1+r} + \kappa_0}{p \frac{\delta+r}{1+r} + \kappa_0} - \frac{\delta p + \kappa_0}{p \frac{\delta+r}{1+r} + \kappa_0} \\
&= \left(p \frac{\delta+r}{1+r} - \delta p \right) \kappa_2 \\
&= p \frac{r(1-\delta)}{1+r} \kappa_2 \\
\implies \kappa_3 &= \frac{p(1-\delta)}{1+r} \kappa_2.
\end{aligned}$$

This completes the proof of Proposition 1. □

Lemma 1. *The necessary conditions for an optimum of the households' problem are*

$$\beta^t u_c(c_t, s(h_t, \tilde{h}_t)) = \lambda_t \quad (\text{C.3})$$

$$\beta^t u_s(c_t, s(h_t, \tilde{h}_t)) s_h(h_t, \tilde{h}_t) = \lambda_t p \frac{\delta+r}{1+r} \quad (\text{C.4})$$

$$\lambda_{t+1}(1+r) = \lambda_t, \quad (\text{C.5})$$

where λ_t are the Lagrange multipliers of the constraint optimization problem.

Proof. The Lagrangian is

$$\begin{aligned}\mathcal{L} = & \sum_{t=0}^{\infty} \beta^t u(c_t, s(h_t, \tilde{h}_t)) \\ & + \lambda_t \left(y_t + (1+r)a_t - c_t - p(h_t - (1-\delta)h_{t-1}) - a_{t+1} \right).\end{aligned}$$

First and second conditions are the first order conditions for c_t and a_t . The first order condition with respect to h_t is

$$\beta^t u_{s_t} s_{h_t} = p(\lambda_t - \lambda_{t+1}(1-\delta)).$$

Using Equation (C.5),

$$\beta^t u_{s_t} s_{h_t} = \lambda_t p \left(1 - \frac{1-\delta}{1+r} \right).$$

Rearranging delivers Equation (C.4). \square

Lemma 2. *Under our assumption of CRRA-CES preferences, the optimal relation of c_t and h_t is given by*

$$\frac{\xi}{1-\xi} \left(\frac{s(h_t, \tilde{h}_t)}{c_t} \right)^{\varepsilon-1} s_h(h_t, \tilde{h}_t) = (r+\delta)p.$$

Further, Assumption 2 yields

$$c_t = \kappa_0(h_t - \varphi \tilde{h}_t), \quad \text{where } \kappa_0 := \left(p \frac{\delta+r}{1+r} \frac{1-\xi}{\xi} \right)^{\frac{1}{1-\varepsilon}}. \quad (\text{C.6})$$

Proof. Combining Equations (C.3) and (C.4) yields

$$\frac{u_s(c_t, s_t)}{u_c(c_t, s_t)} s_h(h_t, \tilde{h}_t) \stackrel{!}{=} p \frac{\delta+r}{1+r}.$$

For the given CRRA-CES preferences, the marginal utilites are given by

$$\begin{aligned}u_c(c_t, s_t) &= ((1-\xi)c_t^\varepsilon + \xi s_t^\varepsilon)^{\frac{1-\gamma}{\varepsilon}-1} (1-\xi)c_t^{\varepsilon-1} \\ u_s(c_t, s_t) &= ((1-\xi)c_t^\varepsilon + \xi s_t^\varepsilon)^{\frac{1-\gamma}{\varepsilon}-1} \xi s_t^{\varepsilon-1}.\end{aligned}$$

Thus,

$$\frac{u_s(c_t, s_t)}{u_c(c_t, s_t)} = \frac{\xi}{1 - \xi} \left(\frac{s_t}{c_t} \right)^{\varepsilon-1}.$$

Plugging in above yields the first statement. Using Assumption 2, we get

$$\begin{aligned} \frac{\xi}{1 - \xi} \left(\frac{h_t - \varphi \tilde{h}}{c_t} \right)^{\varepsilon-1} &= p \frac{\delta + r}{1 + r}. \\ \left(\frac{c_t}{h_t - \varphi \tilde{h}} \right) &= \left(p \frac{\delta + r}{1 + r} \frac{1 - \xi}{\xi} \right)^{\frac{1}{1-\varepsilon}} =: \kappa_0 \\ c_t &= \kappa_0 h_t - \kappa_0 \varphi \tilde{h}_t. \end{aligned}$$

□

C.2 Proof of Proposition 2

Proof. $\omega^T \mathbf{h} = \omega^T (\kappa_2(I + L)\mathbf{y}) = \kappa_2(\omega^T + \omega^T L)\mathbf{y} = \kappa_2(\omega + \mathbf{b})^T \mathbf{y}$, where the first equality follows from Proposition 1 and the final equality from Definition 1. The argument for debt is similar. □

C.3 Proof of Proposition 3 (and Proposition 5 in Appendix B)

Proof. The expressions for aggregate housing and debt as a function of population weights and popularities are given in Proposition 2.

$$\omega^T \mathbf{h} = \kappa_2(\omega + \mathbf{b})^T \mathbf{y} \tag{C.7}$$

$$-\omega^T \mathbf{a} = \kappa_3(\omega + \mathbf{b})^T \mathbf{y} - \omega^T \mathbf{a}_0. \tag{C.8}$$

The difference between aggregate housing and aggregate debt across two steady states depends on differences in permanent incomes $\Delta \mathbf{y} = \Delta \mathbf{y}' - \mathbf{y}$:

$$\begin{aligned} \Delta \omega^T \mathbf{h} &= \omega^T (\mathbf{h}' - \mathbf{h}) = \kappa_2(\omega + \mathbf{b})^T \Delta \mathbf{y} \\ \Delta(-\omega^T \mathbf{a}) &= \omega^T (-\mathbf{a}' - (-\mathbf{a})) = \kappa_3(\omega + \mathbf{b})^T \Delta \mathbf{y}. \end{aligned}$$

Hence, a change in the income distribution $\Delta \mathbf{y}$ increases steady state aggregate housing and debt, if and only if $(\omega + \mathbf{b})^T \Delta \mathbf{y} > 0$.

Concerning the case of mean-preserving redistribution, we get

$$\begin{aligned} (\boldsymbol{\omega} + \mathbf{b})^T \Delta \mathbf{y} &= (\omega_i + b_i) \Delta y_i + (\omega_j + b_j) \Delta y_j \\ &= b_i \Delta y_i + b_j \Delta y_j \\ &= \left(b_j - \frac{\omega_j}{\omega_i} b_i \right) \Delta y_j. \end{aligned}$$

Since $\Delta y_j > 0$ by assumption, the expression is positive whenever $(b_j - \frac{\omega_j}{\omega_i} b_i) > 0$, which is equivalent to $\frac{b_j}{\omega_j} > \frac{b_i}{\omega_i}$. As aggregate income is constant, the housing-to-income and debt-to-income ratios increase if and only if aggregate housing and debt increase, respectively. This completes the proof of Proposition 3.

For the case of unequal growth, we get

$$(\boldsymbol{\omega} + \mathbf{b})^T \Delta \mathbf{y} = (\omega_j + b_j) \Delta y_j > 0,$$

independent of the distribution of population weights or popularities because $\Delta y_i = 0$ for all $i \neq j$. This proves that aggregate housing and debt increase in the case of uneven growth.

We are left to show that the housing-to-income and debt-to-income ratios increase if and only if

$$\frac{b_j}{\omega_j} > \sum_{i \neq j} \lambda_i \frac{b_i}{\omega_i},$$

with weights given by $\lambda_i = \frac{\omega_i y_i}{\omega^T \mathbf{y} - \omega_j y_j}$. Note that $\sum_{i \neq j} \lambda_i = 1$.

Dividing Equations (C.7) and (C.8) by $\boldsymbol{\omega}^T \mathbf{y}$ gives the aggregate housing-to-income and debt-to-income ratios:

$$\begin{aligned} \frac{\boldsymbol{\omega}^T \mathbf{h}}{\boldsymbol{\omega}^T \mathbf{y}} &= \kappa_2 \left(1 + \frac{\mathbf{b}^T \mathbf{y}}{\boldsymbol{\omega}^T \mathbf{y}} \right) \\ -\frac{\boldsymbol{\omega}^T \mathbf{a}}{\boldsymbol{\omega}^T \mathbf{y}} &= \kappa_3 \left(1 + \frac{\mathbf{b}^T \mathbf{y}}{\boldsymbol{\omega}^T \mathbf{y}} \right) - \frac{\boldsymbol{\omega}^T \mathbf{a}_0}{\boldsymbol{\omega}^T \mathbf{y}}. \end{aligned}$$

The housing-to-income ratio is increasing if and only if $\frac{\mathbf{b}^T \mathbf{y}}{\boldsymbol{\omega}^T \mathbf{y}}$ increases in y_j . Hence, Lemma 3 completes this part of the proof. For the debt-to-income ratio, this is a sufficient, but not a necessary condition as the increase in aggregate income leads to an increase in the debt-to-income ratio because initial wealth is constant. Hence, a larger share of lifetime permanent income is received in the future, which induces agents to take on more debt, $\frac{\partial}{\partial y_j} \frac{\boldsymbol{\omega}^T \mathbf{a}_0}{\boldsymbol{\omega}^T \mathbf{y}} < 0$. This completes the proof of Proposition 5. \square

Lemma 3. Let $b_i, \omega_i, \mathcal{Y}_i \geq 0$ and $\frac{\partial \mathcal{Y}_i}{\partial y_i} = 1$ for all i . Then,

$$\frac{\partial}{\partial y_j} \frac{\mathbf{b}^T \mathbf{y}}{\boldsymbol{\omega}^T \mathbf{y}} > 0 \iff \frac{b_j}{\omega_j} > \sum_{i \neq j} \lambda_i \frac{b_i}{\omega_i},$$

with $\sum_{i \neq j} \lambda_i = 1$. The weights given by $\lambda_i = \frac{\omega_i \mathcal{Y}_i}{\boldsymbol{\omega}^T \mathbf{y} - \omega_j \mathcal{Y}_j}$, that is the income share of type i of the incomes not earned by j .

Proof. Using the quotient rule and rearranging gives

$$\begin{aligned} \frac{\partial}{\partial y_j} \frac{\mathbf{b}^T \mathbf{y}}{\boldsymbol{\omega}^T \mathbf{y}} &= \frac{b_j \boldsymbol{\omega}^T \mathbf{y} - \omega_j \mathbf{b}^T \mathbf{y}}{(\boldsymbol{\omega}^T \mathbf{y})^2} \frac{\partial \mathcal{Y}_j}{\partial y_j} > 0 \\ \iff \boldsymbol{\omega}^T \mathbf{y} b_j &> \omega_j \mathbf{b}^T \mathbf{y} \\ &= \omega_j \sum_{i=1}^n b_i \mathcal{Y}_i = \omega_j b_j \mathcal{Y}_j + \omega_j \sum_{i \neq j} b_i \mathcal{Y}_i \\ \iff b_j (\boldsymbol{\omega}^T \mathbf{y} - \omega_j \mathcal{Y}_j) &> \omega_j \sum_{i \neq j} b_i \mathcal{Y}_i \\ \iff \frac{b_j}{\omega_j} (\boldsymbol{\omega}^T \mathbf{y} - \omega_j \mathcal{Y}_j) &> \sum_{i \neq j} \frac{b_i}{\omega_i} \omega_i \mathcal{Y}_i. \end{aligned}$$

Rearranging completes the proof. □

C.4 Proof of Corollary 1

Proof. Consider agents' policy functions in Proposition 1. As $\varepsilon \rightarrow 0$, $\kappa_0 \rightarrow p(r + \delta) \frac{1-\xi}{\xi}$ and is hence proportional to p . This implies that κ_3 and hence also agents' optimal choice of debt, $-a$, are independent of p . Consequently, p does not show up in the respective expressions in Propositions 1 and 3. □

C.5 Proof of Proposition 4

Proof. Define the implicit function

$$F(p; y_1, \dots, y_N) = \delta \kappa_2(p) (\boldsymbol{\omega} + \mathbf{b}(p))^T \mathbf{y} - (\alpha p)^{\frac{\alpha}{1-\alpha}} \bar{L},$$

which in equilibrium equals zero, $F(p, y) = 0$. Now consider the total differential of the house price function $p(y)$:

$$dp = \sum_{k=1}^N \frac{\partial p}{\partial y_k} dy_k,$$

By the implicit function theorem, we have

$$dp = \sum_{k=1}^N -\frac{\frac{\partial F}{\partial y_k}}{\frac{\partial F}{\partial p}} dy_k = -\frac{\frac{\partial F}{\partial y_i}}{\frac{\partial F}{\partial p}} dy_i - \frac{\frac{\partial F}{\partial y_j}}{\frac{\partial F}{\partial p}} dy_j = \frac{\frac{\partial F}{\partial y_j}}{\frac{\partial F}{\partial p}} \frac{\omega_j}{\omega_i} dy_j - \frac{\frac{\partial F}{\partial y_j}}{\frac{\partial F}{\partial p}} dy_j,$$

where the second equality follows from $dy_k = 0$ for all $k \notin \{i, j\}$ and the last equality uses $dy_j = -\frac{\omega_i}{\omega_j} dy_i$. Lemma 4 shows that there exists a $\bar{e} > 1$ such that $\frac{\partial F}{\partial p} \Big|_y < 0$ whenever $e \equiv 1/(1 - \varepsilon) < \bar{e}$. Hence, for all $e < \bar{e}$, we have

$$\begin{aligned} dp > 0 &\iff \frac{\frac{\partial F}{\partial y_j}}{\frac{\partial F}{\partial p}} \frac{\omega_j}{\omega_i} dy_j - \frac{\frac{\partial F}{\partial y_j}}{\frac{\partial F}{\partial p}} dy_j > 0 \\ &\iff \frac{\partial F}{\partial y_i} \frac{\omega_j}{\omega_i} dy_j - \frac{\partial F}{\partial y_j} dy_j < 0 \\ &\iff \delta\kappa_2(p(y)) (\omega_i + b_i(p(y))) \frac{\omega_j}{\omega_i} - \delta\kappa_2(p(y)) (\omega_j + b_j(p(y))) < 0 \\ &\iff (\omega_i + b_i(p(y))) \frac{\omega_j}{\omega_i} - (\omega_j + b_j(p(y))) < 0 \\ &\iff \omega_j + \frac{\omega_j}{\omega_i} b_i < \omega_j + b_j \\ &\iff 1 + \frac{b_i(p(y))}{\omega_i} < 1 + \frac{b_j(p(y))}{\omega_j} \\ &\iff \frac{b_i(p(y))}{\omega_i} < \frac{b_j(p(y))}{\omega_j}, \end{aligned}$$

which completes the proof of Proposition 4. \square

Lemma 4. Consider the function

$$F(p; y_1, \dots, y_N) = \delta\kappa_2(p) (\boldsymbol{\omega} + \mathbf{b}(\kappa_1(p)))^T \mathcal{Y} - (\alpha p)^{\frac{\alpha}{1-\alpha}} \bar{L},$$

where $\kappa_1(p)$ is defined as in Proposition 1:

$$\kappa_1(p) = \frac{p^e x^e}{p^{\frac{\delta+r}{1+r}} + p^e x^e} \quad \text{with } x = \frac{\delta+r}{1+r} \frac{(1-\xi)}{\xi} > 0, \text{ and } e = \frac{1}{1-\varepsilon} > 0.$$

Then, there exists $\bar{e} > 1$ such that $\partial F/\partial p$ is negative for all $e < \bar{e}$.

Proof. The partial derivative of F with respect to p is given by:

$$\begin{aligned} \frac{\partial F(p, y)}{\partial p} &= \underbrace{\delta \frac{\partial \kappa_2(p)}{\partial p} (\boldsymbol{\omega} + \mathbf{b}(\kappa_1(p)))^T \mathbf{y}}_{\equiv A < 0} \\ &\quad + \underbrace{\frac{\partial \kappa_1}{\partial p} \delta \kappa_2(p) \sum_{i=1}^N \frac{\partial b_i}{\partial \kappa_1} y_i}_{\equiv B > 0} \\ &\quad - \underbrace{\alpha^{\frac{\alpha}{1-\alpha}} \bar{L} \frac{\alpha}{1-\alpha} p^{\frac{2\alpha-1}{1-\alpha}}}_{\equiv C < 0}. \end{aligned}$$

As $\partial \kappa_2/\partial p < 0$, the first term is negative, $A < 0$. Moreover, note that the last term is also negative, $C < 0$. Finally, $B > 0$ because $b_i(\kappa_1) = \sum_{k=1}^{\infty} (\kappa_1 \varphi G)^k$, $\varphi > 0$, and all entries of G are nonnegative such that $\partial b_i/\partial \kappa_1 > 0$.

Hence, for $\partial F/\partial p$ to be negative, we need to show that:

$$\frac{\partial \kappa_1}{\partial p} \leq -\underbrace{\frac{(A+C)}{B}}_{>0}.$$

The partial derivative of κ_1 with respect to p is given by:

$$\frac{\partial \kappa_1}{\partial p} = \frac{ep^{e-1}x^e(p^{\frac{\delta+r}{1+r}} + p^e x^e) - p^e x^e(p^{\frac{\delta+r}{1+r}} + ep^{e-1}x^e)}{(p^{\frac{\delta+r}{1+r}} + p^e x^e)^2} = \frac{(e-1)p^e x^e \frac{\delta+r}{1+r}}{(p^{\frac{\delta+r}{1+r}} + p^e x^e)^2}.$$

From here, we first find that

$$\frac{\partial \kappa_1}{\partial p} < 0 \iff e \leq 1,$$

which is a sufficient condition for $\partial F/\partial p < 0$ because $0 < -\frac{(A+C)}{B}$. Note that $\partial \kappa_1/\partial p$ is continuously differentiable in e . The partial derivative with respect to e evaluated at $e = 1$ is positive:

$$\begin{aligned}\frac{\partial}{\partial e} \left(\frac{\partial \kappa_1}{\partial p} \right) &= \frac{\frac{\delta+r}{1+r}(xp)^e(\frac{\delta+r}{1+r}p + (xp)^e) - ((xp)^e - \frac{\delta+r}{1+r}p)(e-1)\log(xp))}{(\frac{\delta+r}{1+r}p + (xp)^e)^3} \\ \frac{\partial}{\partial e} \left(\frac{\partial \kappa_1}{\partial p} \right) \Big|_{e=1} &= \frac{\frac{\delta+r}{1+r}xp(\frac{\delta+r}{1+r}p + xp)}{(\frac{\delta+r}{1+r}p + xp)^3} > 0.\end{aligned}$$

Hence, there exists a $\bar{e} > 1$ such that $\frac{\partial F}{\partial p} < 0$ for all $e < \bar{e}$. \square

C.6 Lemma 5

Lemma 5. *Under Cobb-Douglas aggregation, $\varepsilon \rightarrow 0$, the equilibrium house price is*

$$p = \alpha^{-\alpha} \left(\frac{\delta\xi}{\bar{L}} \frac{1+r}{\delta+r} (\boldsymbol{\omega} + \mathbf{b})^T \mathbf{y} \right)^{1-\alpha}.$$

Proof. The market clearing condition is $I_h = \delta H$, where aggregate housing demand is $H = \boldsymbol{\omega}^T \mathbf{h} = \kappa_2(p)(\boldsymbol{\omega} + \mathbf{b}(p))^T \mathbf{y}$ and optimal housing investment is $I_h = (\alpha p)^{\frac{\alpha}{1-\alpha}} \bar{L}$. The equilibrium price is implicitly given by

$$(\alpha p)^{\frac{\alpha}{1-\alpha}} \bar{L} = \delta \kappa_2(p)(\boldsymbol{\omega} + \mathbf{b}(p))^T \mathbf{y}.$$

As $\varepsilon \rightarrow 0$, κ_1 simplifies to $1 - \xi$ (hence \mathbf{b} is independent of p), and $\kappa_2(p)$ to $\frac{\xi(1+r)}{p(\delta+r)}$. Thus, the equilibrium condition simplifies to

$$(\alpha p)^{\frac{\alpha}{1-\alpha}} p \bar{L} = \delta \xi \frac{1+r}{\delta+r} (\boldsymbol{\omega} + \mathbf{b})^T \mathbf{y}.$$

Rearranging completes the proof. \square

D Additional Tables and Figures

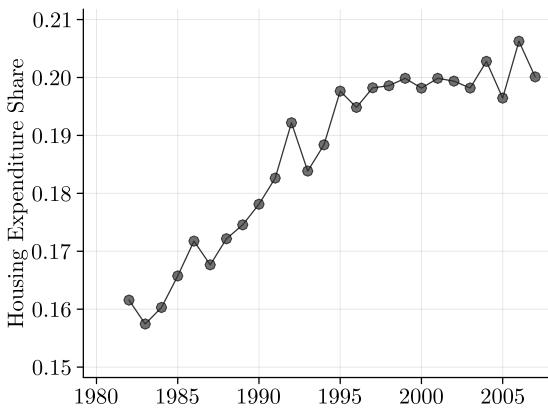


Figure D.1: Housing expenditure share

This figure shows the housing expenditure share between 1982 and 2007. Data: CEX (Bertrand and Morse 2016).

Alt text: Line graph showing the rise of the housing expenditure share from 1982 to 2007.

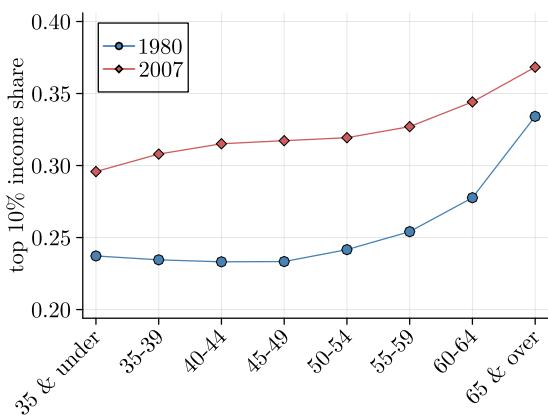


Figure D.2: Within-age-group income inequality

This figure shows the income share of the top 10% of households within different age groups in 1980 and 2007. The age of the household is measured by the age of the household head. Data: Census/ACS.

Alt text: Line graph showing the income share of the top 10% in 1980 and 2007 for eight different age groups by year: 35 and under, 35-39, 40-44, 45-49, 50-54, 55-59, 60-64, and 65 and over.

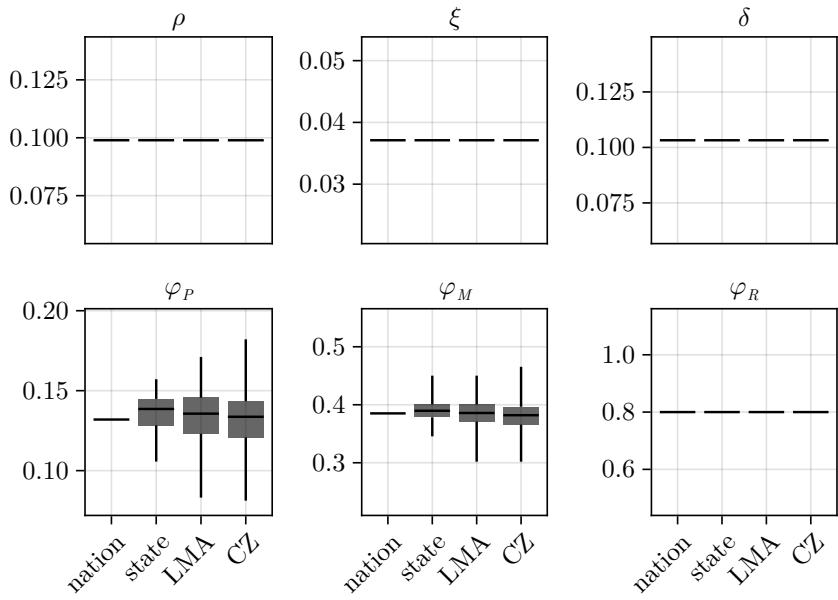


Figure D.3: Calibrated values of φ for within-region comparisons

This figure shows the range of calibrated parameters by region; we match the housing expenditure share, debt-to-income, and comparison sensitivities in each individual region. Note that only φ_P and φ_M do vary across regions. Conditional on a given comparison sensitivity, the other parameters are independent of the income distribution.

Alt text: Six box-and-whisker plots, one for each calibrated parameter, showing the calibrated parameters ρ , ξ , δ , φ_P , φ_M , and φ_R with four boxes in each plot corresponding to the four different comparison levels: nation, state, labor market area, and commuting zone.

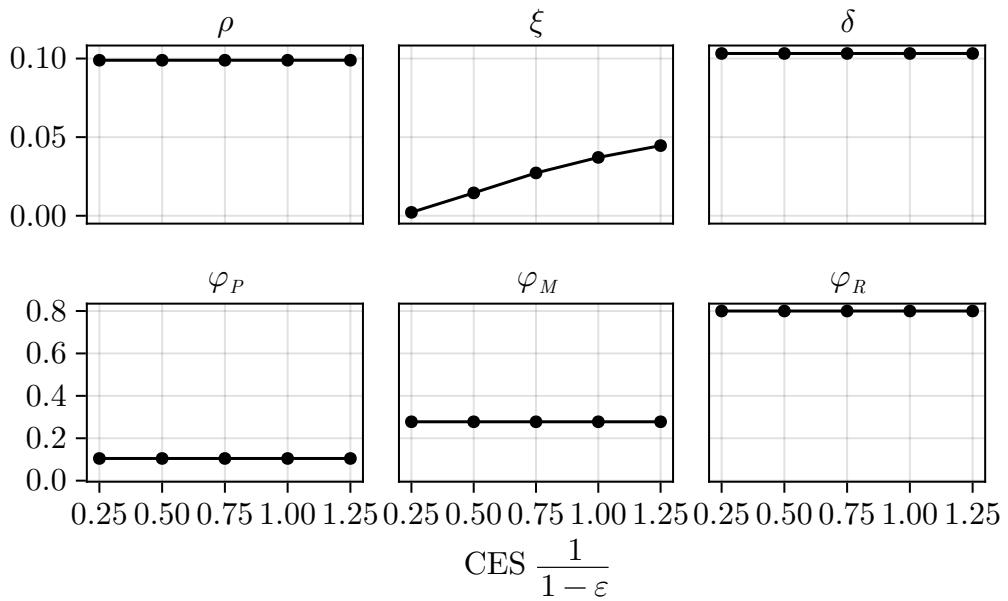


Figure D.4: Sensitivity analysis: Calibrated parameters for different values of the intratemporal elasticity of substitution

This figure shows the internally calibrated parameters corresponding to the results shown in Figure 5.

Alt text: Six line graphs, one for each calibrated parameter, showing the calibrated parameters $\rho, \xi, \delta, \varphi_P, \varphi_M$, and φ_R for different values of the intertemporal elasticity of substitution ranging from 0.25 to 1.25.

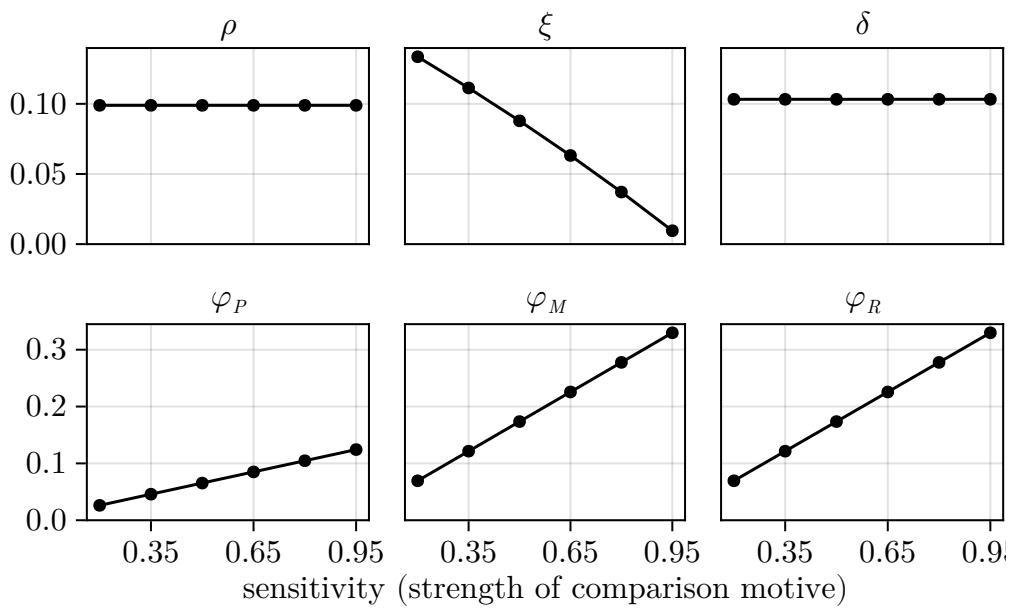


Figure D.5: Sensitivity analysis: Calibrated parameters for different values of the comparison sensitivity

This figure shows the internally calibrated parameters corresponding to the results shown in Figure 6.

Alt text: Six line graphs, one for each calibrated parameter, showing the calibrated parameters $\rho, \xi, \delta, \varphi_P, \varphi_M$, and φ_R for different values of the sensitivity parameter ranging from 0.2 to 0.95.

E Computational Details for Transition Analysis

E.1 Optimality Conditions

Let us focus on a given group of households, that is, a combination of income group and cohort. To simplify notation, we do not index variables by s and g . However, note that reference housing of income group g at time t is the same for all cohorts.

Auxiliary functions. The functions κ_0 and Γ are functions of the current and future house price:

$$\begin{aligned}\kappa_0(p_t, p_{t+1}) &= \left(\frac{(1-\xi)}{\xi} \left(p_t - \beta(1-\delta)p_{t+1} \right) \right)^{\frac{1}{1-\varepsilon}} \\ \Gamma(p_t, p_{t+1}) &= \left((1-\xi) + \xi \left(1/\kappa_0(p_t, p_{t+1}) \right)^\varepsilon \right)^{\frac{1-\sigma-\varepsilon}{\varepsilon}} \quad \text{for } \varepsilon \neq 0.\end{aligned}$$

In the special case of Cobb-Douglas ($\varepsilon = 0$), we have

$$\Gamma(p_t, p_{t+1}) = \kappa_0^{-\xi(1-\sigma)}.$$

Consumption over time.

$$c_t = \underbrace{\left(\frac{\Gamma(p_{t+1}, p_{t+2})}{\Gamma(p_t, p_{t+1})} \right)^{-1/\sigma}}_{\equiv \Theta_t} c_{t+1} = \Theta_t c_{t+1}.$$

Consumption vs. housing (status).

$$\begin{aligned}h_t - \varphi \tilde{h}_t &= \underbrace{\frac{1}{\kappa_0(p_t, p_{t+1})}}_{\equiv \Psi_t} c_t = \Psi_t c_t \\ h_t &= \Psi_t c_t + \varphi \tilde{h}_t.\end{aligned}$$

Note on corner cases. If $p_t < \beta(1-\delta)p_{t+1}$, κ_0 (and, hence, Θ_t) is not defined. In such corner cases, Θ_t should be such that a minimal consumption level c_{min} is reached.

$$\Theta_t := \frac{c_{min}}{c_{t+1}}.$$

Similarly, Ψ_t should be such that the status level is minimal.

$$\begin{aligned}\Psi_t c_t &= h_t - \varphi \tilde{h}_t =: s_{min} \\ \implies \Psi_t c_{min} &= s_{min} \\ \implies \Psi_t &= \frac{s_{min}}{c_{min}}\end{aligned}$$

Consumption and housing status as a function of terminal consumption.

$$c_t = \underbrace{\left(\prod_{s=t}^{T-1} \Theta_s \right)}_{\equiv \Omega_t^T} c_T = \Omega_t^T c_T \quad (\text{E.1})$$

$$h_t = \Psi_t c_t + \varphi \tilde{h}_t = \underbrace{\Psi_t \Omega_t^T}_{\equiv \Xi_t^T} c_T + \varphi \tilde{h}_t = \Xi_t^T c_T + \varphi \tilde{h}_t \quad (\text{E.2})$$

E.2 Lifetime Budget Constraint

Let's write the lifetime budget constraint of a cohort of income group g born in $t = s$. To simplify notation, we again do not index variables by s and g . However, recall that reference housing of income group g at time t is the same for all cohorts.

$$\begin{aligned}\sum_{t=s}^{\infty} R^{t-s} (c_t + p_t x_t) &= \sum_{t=s}^{\infty} R^{t-s} y_t + (1+r)a_{s-1} + \underbrace{p_s(1-\delta)h_{s-1}}_{\text{initial house (given)}} \\ \underbrace{\sum_{t=s}^{\infty} R^{t-s} (c_t + p_t h_t) - \sum_{t=s+1}^{\infty} R^{t-s} (p_t(1-\delta)h_{t-1})}_{\text{LHS: expenditures (endogenous)}} &= \underbrace{\sum_{t=s}^{\infty} R^{t-s} y_t + (1+r)a_{s-1} + p_s(1-\delta)h_{s-1}}_{\text{RHS: resources (exogenous)}},\end{aligned}$$

where $R \equiv 1/(1+r)$ and $x_t = h_t - (1-\delta)h_{t-1}$. As h_{s-1} is predetermined, the second sum on the LHS starts at $t = s+1$.

Expenditures (LHS). Note that h_{t-1} is given for $t = s$ such that Equation E.2 does not apply in a cohort's initial period $t = s$.

$$\begin{aligned}
\text{LHS} &= \sum_{t=s}^{\infty} R^{t-s} (c_t + p_t h_t) - \sum_{t=s+1}^{\infty} R^{t-s} (p_t(1-\delta)h_{t-1}) \\
&= \sum_{t=s}^{\infty} R^{t-s} \left(\underbrace{\Omega_t c_T}_{c_t} + p_t \left(\underbrace{\Xi_t c_T + \varphi \tilde{h}_t}_{h_t} \right) \right) - \sum_{t=s+1}^{\infty} R^{t-s} p_t(1-\delta) \left(\underbrace{\Xi_{t-1} c_T + \varphi \tilde{h}_{t-1}}_{h_{t-1}} \right) \\
&= c_T \left[\sum_{t=s}^{\infty} R^{t-s} (\Omega_t + p_t \Xi_t) - \sum_{t=s+1}^{\infty} R^{t-s} p_t(1-\delta) \Xi_{t-1} \right] \\
&\quad + \sum_{t=s}^{\infty} R^{t-s} (\varphi p_t \tilde{h}_t) - \sum_{t=s+1}^{\infty} R^{t-s} (\varphi p_t(1-\delta) \tilde{h}_{t-1}) \\
&= c_T Z_s + W_s
\end{aligned}$$

Since $\Omega_t = 1$, $\Xi_t = \Xi_T = \Psi_T$, and $\tilde{h}_t = \tilde{h}_T$ for $t \geq T$, where house prices are constant, we can rewrite the infinite sums as follows:

$$\begin{aligned}
Z_s &= \sum_{t=s}^{\infty} R^{t-s} (\Omega_t + p_t \Xi_t) - \sum_{t=s+1}^{\infty} R^{t-s} p_t(1-\delta) \Xi_{t-1} \\
&= \sum_{t=s}^T R^{t-s} (\Omega_t + p_t \Xi_t) + \frac{1}{r} R^{T-s} (1 + p_T \Psi_T) \\
&\quad - \sum_{t=s+1}^T R^{t-s} (p_t(1-\delta) \Xi_{t-1}) - \frac{1}{r} R^{T-s} p_T(1-\delta) \Psi_T \\
&= \sum_{t=s}^T R^{t-s} (\Omega_t + p_t \Xi_t) - \sum_{t=s+1}^T R^{t-s} (p_t(1-\delta) \Xi_{t-1}) + \frac{1}{r} R^{T-s} (1 + \delta p_T \Psi_T)
\end{aligned}$$

and

$$\begin{aligned}
W_s &= \sum_{t=s}^{\infty} R^{t-s} (\varphi p_t \tilde{h}_t) - \sum_{t=s+1}^{\infty} R^{t-s} (\varphi p_t (1-\delta) \tilde{h}_{t-1}) \\
&= \sum_{t=s}^T R^{t-s} (\varphi p_t \tilde{h}_t) + \frac{1}{r} R^{T-s} (\varphi p_T \tilde{h}_T) \\
&\quad - \sum_{t=s+1}^T R^{t-s} (\varphi p_t (1-\delta) \tilde{h}_{t-1}) - \frac{1}{r} R^{T-s} (\varphi p_T (1-\delta) \tilde{h}_T) \\
&= \sum_{t=s}^T R^{t-s} (\varphi p_t \tilde{h}_t) - \sum_{t=s+1}^T R^{t-s} (\varphi p_t (1-\delta) \tilde{h}_{t-1}) + \frac{1}{r} R^{T-s} (\varphi \delta p_T \tilde{h}_T).
\end{aligned}$$

Lifetime income (RHS).

$$\text{RHS} \equiv Y(s) = \sum_{t=s}^T R^{t-s} y_t + \frac{1}{r} R^{T-s} y_T + p_s (1-\delta) h_{s-1} + (1+r) a_{s-1}.$$

E.3 Algorithm to Find Equilibrium House Price Sequence

1. Exogenously given: lifetime income $Y(s)$ for each cohort s and initial assets and housing for each income group.
2. Guess sequence of housing $h(g, t)$ for each income group g and time t (but averaged across cohorts).
3. Use the comparison network to compute reference housing $\tilde{h}(g, t)$ for each income group g and time t .
4. Compute aggregate housing $H(t)$ for each t by aggregating over income groups.
5. Compute aggregate housing investment $X(t)$ and the sequence of house prices $p(t)$ implied by $X(t)$ and the firm optimality condition.
6. Compute terminal consumption $c(s, g, T)$ for each cohort s and income group g .

$$c(s, g, T) = \frac{Y(s, g) - W(s, g)}{Z(s)} \tag{E.3}$$

7. Use $c(s, g, T)$ and Equations (E.1) and (E.2) to compute $c(s, g, t)$ and $h(s, g, t)$ for each s , g , and t .

8. Compute $h'(g, t)$ by averaging over cohorts for each t and g and compare $h'(g, t)$ to the guess $h(g, t)$.
9. Update guess and repeat the above steps until convergence.

References

- Abel, A. B. 1990. Asset prices under habit formation and catching up with the Joneses. *American Economic Review* 80:38–42.
- Acemoglu, D., V. Carvalho, A. Ozdaglar, and A. Tahbaz-Salehi. 2012. The network origins of aggregate fluctuations. *Econometrica* 80:1977–2016.
- Adam, K., P. Kuang, and A. Marcet. 2012. House price booms and the current account. *NBER Macroeconomics Annual* 26:77–122.
- Autor, D. H., and D. Dorn. 2013. The growth of low-skill service jobs and the polarization of the United States labor market. *American Economic Review* 103:1553–97.
- Autor, D. H., L. F. Katz, and M. S. Kearney. 2008. Trends in United States wage inequality: Revising the revisionists. *Review of Economics and Statistics* 90:300–23.
- Badarinza, C. 2019. Mortgage debt and social externalities. *Review of Economic Dynamics* 34:43–60.
- Bajari, P., P. Chan, D. Krueger, and D. Miller. 2013. A dynamic model of housing demand: Estimation and policy implications. *International Economic Review* 54:409–42.
- Ballester, C., A. Calvó-Armengol, and Y. Zenou. 2006. Who's who in networks. Wanted: The key player. *Econometrica* 74:1403–17.
- Bellet, C. S. 2024. The McMansion effect: Positional externalities in United States suburbs. *Journal of Public Economics* 238:105–74.
- Berger, D., V. Guerrieri, G. Lorenzoni, and J. Vavra. 2018. House prices and consumer spending. *Review of Economic Studies* 85:1502–42.
- Bertrand, M., and A. Morse. 2016. Trickle-down consumption. *Review of Economics and Statistics* 98:863–79.
- Campbell, J. Y., and J. H. Cochrane. 1999. By force of habit: A consumption-based explanation of aggregate stock market behavior. *Journal of Political Economy* 107:205–51.
- Card, D., A. Mas, E. Moretti, and E. Saez. 2012. Inequality at work: The effect of peer salaries on job satisfaction. *American Economic Review* 102:2981–3003.
- Carroll, C. D. 1997. Buffer-stock saving and the life cycle/permanent income hypothesis. *Quarterly Journal of Economics* 112:1–55.
- Chambers, M., C. Garriga, and D. E. Schlagenhauf. 2009. Housing policy and the progressivity of income taxation. *Journal of Monetary Economics* 56:1116–34.

- Clark, A. E., and C. Senik. 2010. Who compares to whom? The anatomy of income comparisons in Europe. *Economic Journal* 120:573–94.
- Duesenberry, J. 1949. *Income, saving and the theory of consumer behavior*. Cambridge, Massachusetts: Harvard University Press.
- Favilukis, J., S. C. Ludvigson, and S. van Nieuwerburgh. 2017. The macroeconomic effects of housing wealth, housing finance, and limited risk sharing in general equilibrium. *Journal of Political Economy* 125:140–223.
- Ferrer-i-Carbonell, A. 2005. Income and well-being: An empirical analysis of the comparison income effect. *Journal of Public Economics* 89:997–1019.
- Fisher, J. D., and M. Gervais. 2011. Why has home ownership fallen among the young? *International Economic Review* 52:883–912.
- Flavin, M., and S. Nakagawa. 2008. A model of housing in the presence of adjustment costs: A structural interpretation of habit persistence. *American Economic Review* 98:474–95.
- Frank, R. 2013. *Falling behind: How rising inequality harms the middle class*. Oakland, California: University of California Press.
- Gali, J. 1994. Keeping up with the Joneses: Consumption externalities, portfolio choice, and asset prices. *Journal of Money, Credit and Banking* 26:1–8.
- Garriga, C., and A. Hedlund. 2020. Mortgage debt, consumption, and illiquid housing markets in the Great Recession. *American Economic Review* 110:1603–34.
- Garriga, C., R. Manuelli, and A. Peralta-Alva. 2019. A macroeconomic model of price swings in the housing market. *American Economic Review* 109:2036–72.
- Gaubert, C., P. Kline, D. Vergara, and D. Yagan. 2021. Trends in United States spatial inequality: Concentrating affluence and a democratization of poverty. *AEA Papers and Proceedings* 111:520–25.
- Ghiglino, C., and S. Goyal. 2010. Keeping up with the neighbors: Social interaction in a market economy. *Journal of the European Economic Association* 8:90–119.
- Gourinchas, P.-O., and J. A. Parker. 2002. Consumption over the life cycle. *Econometrica* 70:47–89.
- Grossmann, V., B. Larin, H. T. Löfflad, and T. Steger. 2021. Distributional consequences of surging housing rents. *Journal of Economic Theory* 196:105–275.
- Guvenen, F., G. Kaplan, J. Song, and J. Weidner. 2022. Lifetime earnings in the United States over six decades. *American Economic Journal: Applied Economics* 14:446–79.
- Guvenen, F., S. Ozkan, and J. Song. 2014. The nature of countercyclical income risk. *Journal of Political Economy* 122:621–60.

- Heffetz, O. 2011. A test of conspicuous consumption: visibility and income elasticities. *Review of Economics and Statistics* 93:1101–17.
- Jordà, Ò., M. Schularick, and A. M. Taylor. 2016. Sovereigns versus banks: Credit, crises, and consequences. *Journal of the European Economic Association* 14:45–79.
- Justiniano, A., G. E. Primiceri, and A. Tambalotti. 2019. Credit supply and the housing boom. *Journal of Political Economy* 127:1317–50.
- Kaplan, G., K. Mitman, and G. L. Violante. 2020. The housing boom and bust: Model meets evidence. *Journal of Political Economy* 128:3285–345.
- Katz, L. F., and K. M. Murphy. 1992. Changes in relative wages, 1963–1987: Supply and demand factors. *Quarterly Journal of Economics* 107:35–78.
- Kopczuk, W., E. Saez, and J. Song. 2010. Earnings inequality and mobility in the United States: Evidence from Social Security data since 1937. *Quarterly Journal of Economics* 125:91–128.
- Kuchler, T., and J. Stroebel. 2021. Social Finance. *Annual Review of Financial Economics* 13:37–55.
- Kuhn, M., M. Schularick, and U. I. Steins. 2020. Income and wealth inequality in America, 1949–2016. *Journal of Political Economy* 128:3469–519.
- Kuhn, P., P. Kooreman, A. Soeteveent, and A. Kapteyn. 2011. The effects of lottery prizes on winners and their neighbors: Evidence from the Dutch postcode lottery. *American Economic Review* 101:2226–47.
- Kumhof, M., R. Rancière, and P. Winant. 2015. Inequality, leverage, and crises. *American Economic Review* 105:1217–45.
- Landvoigt, T. 2017. Housing demand during the boom: The role of expectations and credit constraints. *Review of Financial Studies* 30:1865–902.
- Ljungqvist, L., and H. Uhlig. 2000. Tax policy and aggregate demand management under catching up with the Joneses. *American Economic Review* 90:356–66.
- Mian, A., L. Straub, and A. Sufi. 2020. *The saving glut of the rich and the rise in household debt*. Working Paper, National Bureau of Economic Research.
- 2021. Indebted demand. *Quarterly Journal of Economics* 136:2243–307.
- Nakajima, M. 2005. *Rising earnings instability, portfolio choice, and housing prices*. Unpublished Manuscript.
- Ogaki, M., and C. M. Reinhart. 1998. Measuring intertemporal substitution: The role of durable goods. *Journal of Political Economy* 106:1078–98.
- Piazzesi, M., and M. Schneider. 2016. Housing and macroeconomics. *Handbook of Macroeconomics* 2:1547–640.

- Piazzesi, M., M. Schneider, and S. Tuzel. 2007. Housing, consumption and asset pricing. *Journal of Financial Economics* 83:531–69.
- Piketty, T., E. Saez, and G. Zucman. 2018. Distributional national accounts: Methods and estimates for the United States. *Quarterly Journal of Economics* 133:553–609.
- Rajan, R. G. 2011. *Fault lines: How hidden fractures still threaten the world economy*. Princeton, New Jersey: Princeton University Press.
- Sabelhaus, J., and J. Song. 2010. The Great Moderation in micro labor earnings. *Journal of Monetary Economics* 57:391–403.
- Saiz, A. 2010. The geographic determinants of housing supply. *Quarterly Journal of Economics* 125:1253–96.
- Shiller, R. J. 2015. *Irrational exuberance: Revised and expanded third edition*. Princeton, New Jersey: Princeton University Press.
- Smith, M., D. Yagan, O. Zidar, and E. Zwick. 2019. Capitalists in the twenty-first century. *Quarterly Journal of Economics* 134:1675–745.
- Solnick, S., and D. Hemenway. 2005. Are positional concerns stronger in some domains than in others? *American Economic Review* 95:147–51.
- Stiglitz, J. 2009. The global crisis, social protection and jobs. *International Labour Review* 148:1–13.
- Veblen, T. 1899. *The theory of the leisure class*. New York: Macmillan.