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Cross-Sectional Patterns of Mortgage Debt During the Housing Boom: Evidence and Implications

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Abstract:
In this paper, we use two comprehensive microdata sets to study how the distribution of mortgage debt evolved during the 2000s housing boom. We show that the allocation of mortgage debt across the income distribution remained stable, as did the allocation of real estate assets. Any theory of the boom must replicate these facts, and a general equilibrium model shows that doing so requires two elements: (1) an exogenous shock that increases expected house price growth or, alternatively, reduces interest rates and (2) financial markets that endogenously relax borrowing constraints in response to the shock. Empirically, the endogenous relaxation of constraints was largely accomplished with subprime lending, which allowed the mortgage debt of low-income households to increase at the same rate as that of high-income households.

JEL Classifications: D12, D14, E03, G21, R21
Keywords: housing boom, mortgage debt, foreclosure crisis, real estate

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1. INTRODUCTION

In this paper, we use two comprehensive micro data sets to study how the distribution of mortgage debt evolved during the 2000s housing boom. We are motivated by two themes in the literature.

First, many researchers argue that the growth of debt in the United States during the 2000s is central to understanding the foreclosure and financial crisis that followed. According to the Federal Reserve's Flow of Funds,[1] the aggregate stock of mortgage debt on the liability side of household balance sheets doubled from \$5.3 trillion in 2001 to \$10.6 trillion in 2007. Mortgage debt grew much faster than income, so there was a substantial increase in the debt-to-income ratio, as seen in Figure 1. The debt boom was, of course, followed by a wave of defaults on that mortgage debt and associated losses at financial institutions.

Second, the emergence of the subprime mortgage market in the 2000s and its disproportionate role in the foreclosure and financial crisis has led many to believe that the growth of subprime was the key driver of the increase in debt.[2] Subprime lenders, as their name suggests, provided financing to borrowers who were ineligible for so-called prime loans. Reasons for ineligibility included insufficient income relative to mortgage payments, previous defaults, and low levels of liquid wealth, and often some combination of all three. Between 2001 and 2007, subprime lending grew by over 550 percent, or more than five times as fast as the market as a whole, and went from less than 2.5 percent of outstanding mortgage debt to almost 8.4 percent.[3] Subprime loans also drew attention because they accounted for a hugely disproportionate share of defaults in the crisis.[4] Finally, losses on debt backed by subprime loans played a key role in the financial crisis.

The simultaneous increase in debt and the growth in subprime lending led many to argue that the reason for the growth in debt was the expansion of credit to marginal subgroups of the population. Our analysis of the data, however, uncovers striking evidence against this theory. The distribution of debt shows remarkable cross-sectional stability throughout the boom. If we look at the bottom quintile of the income distribution in the Survey of Consumer Finances (SCF) in 2001 and 2007, we see debt growth of about 73 percent. For the top quintile, the figure is 85 percent. Put differently, the bottom and top quintiles of the income distribution accounted for 5.6 percent and 48 percent, respectively, of outstanding

[1] Now officially called the Financial Accounts of the United States.

[2] See, for example, Chapters 5 and 6 of Financial Crisis Inquiry Commission (2011) or Mian and Sufi (2009), who write, "The sharp increase in mortgage defaults in 2007 is significantly amplified in subprime ZIP codes, or ZIP codes with a disproportionately large share of subprime borrowers as of 1996. Prior to the default crisis, these subprime ZIP codes experience an unprecedented relative growth in mortgage credit."

[3] The figure for growth in subprime is based on growth in the outstanding stock of subprime mortgage debt in the CoreLogic ABS database. Total outstanding mortgage debt is from the Flow of Funds.

[4] According to the Mortgage Bankers Association, over the period 2007–2010, subprime loans accounted for 37.9 percent of all foreclosure starts and 11.2 percent of all mortgages serviced.

debt in 2001 and 5 percent and 46 percent in 2007.

The stability of the distribution of mortgage debt is robust to the use of alternative data sets and definitions of marginal borrowers. In addition to the SCF, we follow Mian and Sufi (2009) and analyze a combination of credit bureau data and IRS income data. The credit bureau/IRS sample has two big advantages over the SCF. First, it has millions of observations as opposed to the thousands in the SCF, and second, it has detailed geographic information, which is absent from the SCF. Despite these differences, we find essentially the same results using the credit bureau/IRS data. This holds whether we look at the whole country or within metro areas, again following Mian and Sufi (2009), who argue that cross-regional effects can confound estimates of microeconomic changes in debt.

In addition to income, we rank households by credit score, by net worth, and by whether they were previously denied credit. We confirm earlier work that shows that while default rates were higher in low-income areas, the cross-sectional behavior of defaults did not change during the foreclosure crisis. If we rank zip codes using the share of the population that was subprime in 1999, we find that in 2001, the riskiest zip codes accounted for 13 percent of all defaults. In 2009 their share declined to 10.5 percent of defaults.[5]

Earlier work shows that there was a relative increase in the number of loan originations in low-income areas, which was widely believed to imply a shift in the distribution of debt. We show that this relative increase in originations was exactly offset by a relative increase in loan terminations. For example, buyers took out new loans to buy houses, but the sellers used the money to pay off existing loans, so the overall number of loans did not change. These two offsetting forces mean that low-income households were no more likely to have a mortgage relative to high-income households in 2007 versus 2001.

Our findings have significant implications for our understanding of the housing boom and bust of the 2000s. We propose that any theory of the boom must replicate two basic facts: an increase in the level of house prices and no change in the distribution of housing wealth and debt. Using a general equilibrium model, we show that an explanation of these facts requires two elements: (1) an exogenous shock to the economy that increases expected house price growth or, alternatively, reduces interest rates, and (2) financial markets that endogenously relax borrowing constraints in response to the shock. The combination of these two elements is essential. An exogenous relaxation of credit constraints per se can generate an increase in house prices, but it forces a redistribution of housing wealth and debt *toward* constrained households, as unconstrained households reduce their consumption of housing in response to a higher user cost. A shock to expected house price growth or interest rates without a relaxation in constraints has the opposite effect. It reduces the user cost of housing, raising desired consumption of housing for everyone. As prices rise, constraints tighten, resulting in

[5]We define someone as subprime if they have an Equifax Risk Score less than 660.

a reallocation of housing wealth and debt *away from* constrained households.

Our theory reconciles what appear to be contradictory claims about the boom. On one hand, there is both empirical and institutional evidence of a significant relaxation of credit standards in which subprime played a key role.[6] Yet our data show that debt grew for all households, including those least likely to benefit from a relaxation of credit constraints. To illustrate how our theory reconciles these facts, we conduct a counterfactual exercise in which we construct zip-code-level debt histories. According to our calculations, subprime led to an increase in debt growth in low-income areas over what would otherwise have been attained. This is evidence of a relaxation of credit constraints. But debt growth in low-income areas did not outpace growth in high-income areas, consistent with our theoretical argument that the effect of subprime was to allow low-income households to keep pace with high-income households. In other words, everyone wanted to spend more on housing; high-income households just did not rely on subprime debt to do so.

Our empirical contribution is most closely related to Mian and Sufi (2009, 2017) and Adelino, Schoar, and Severino (2016). These papers focus on the evolution of new mortgage originations in the boom. Although the authors draw different conclusions, they largely agree that there was a relative increase in originations of new mortgages in areas with high proportions of marginal or low-income borrowers. Mian and Sufi (2017) argue that this increase reflects a reallocation of debt to marginal borrowers, while Adelino, Schoar, and Severino (2016) argue that it is also consistent with a stable debt distribution. Without the evidence on mortgage terminations or the stock of debt that we present below, neither team of researchers could resolve the issue, nor could they relate the patterns they found to a consistent theoretical explanation of the boom.[7]

Our research highlights the importance of looking at both the stocks and flows of debt. Many of the key questions about the crisis—such as predictions about foreclosures or exposure of the financial system—involve the stock. The stock is, of course, a function of inflows and outflows, so the two are not mutually exclusive. However, focusing only on inflows could and did lead researchers and policymakers to the erroneous conclusion that problems in the mortgage market were largely confined to the subprime market. We show that this conclusion is misguided.

In addition, we contribute to the growing theoretical literature on the origins of the housing boom.[8] Our model of the housing market allows us to think about previous contributions in a single unified framework. Using our model, we suggest a narrative of the

[6] See Mayer, Pence, and Sherlund (2009) and Keys et al. (2010), for example.

[7] Section B.1 of the internet appendix contains a detailed discussion of previous papers on mortgage debt.

[8] Papers in this segment of the literature include Greenwald (2016), Kiyotaki, Michaelides, and Nikolov (2011), Sommer, Sullivan, and Verbrugge (2013), Favilukis, Ludvigson, and Van Nieuwerburgh (2017), Justiniano, Primiceri, and Tambalotti (2019), and Kaplan, Mitman, and Violante (2019).

origins of the housing boom—a shock to house prices paired with an *endogenous* relaxation of credit constraints—that is consistent with the empirical facts. We therefore contribute to the large literature that emphasizes aggregate factors affecting both the demand and the supply of credit during the housing boom.[9]

Our work has implications for policy. Limits on subprime lending and other innovations in credit markets would have had mixed effects. On one hand, the effect on the overall growth of leverage in the United States would have been small, as most of the total increase in debt took place among high-income households that were unlikely to be constrained either before or after the boom. Additionally, restricting credit would have led to less debt growth among low-income households and therefore fewer foreclosures. On the other hand, the combination of inflexible borrowing constraints and rising house prices would have closed off the owner-occupied market to many low-income borrowers, reducing their real housing consumption as well as their homeownership rates.

The effect of a restriction in subprime lending on the financial crisis is more complicated. Most of the losses related to subprime lending came not from actual defaults but from losses on a type of AAA-rated derivative security called a synthetic collateralized debt obligation (CDO). As Cordell, Huang, and Williams (2012) show, for every \$1 of credit losses from subprime defaults, investors lost more than \$2 on AAA-rated synthetic CDOs. Limits on subprime lending would have reduced the quantity of subprime loans, but whether they would have dented the market for subprime derivatives is an open question.

We proceed as follows. In Section 2 we discuss our data sources; in Section 3 we detail our empirical findings; in Section 4 we discuss the implication for theories of the origins of the housing boom. In Section 5, we conclude.

2. DATA

2.1. The New York Fed Consumer Credit Panel and the IRS Statistics of Income

Zip-code-level measures of mortgage debt come from the Federal Reserve Bank of New York's Consumer Credit Panel (CCP), a quarterly, longitudinal 5 percent sample of individual credit histories supplied by the Equifax credit bureau. The data set begins in 1999, and because individual-level credit histories are included in the sample based on the last two digits of the individual's Social Security number, the data set is automatically updated to incorporate new entrants over time.

The CCP contains detailed information on mortgage debt, including the amounts and dates associated with the origination of new loans, as well as outstanding balances for first

[9]Other papers in this literature include Bhutta (2015), Albanesi, De Giorgi, and Nosal (2017), Ferreira and Gyourko (2015), Loewenstein (2018), and Ospina and Uhlig (2018).

mortgages, subordinate mortgages, and home equity lines of credit (HELOCs) over the life of the loan. We define the termination of a mortgage in the CCP as occurring in the last quarter that a mortgage appears in the data, and the value of that termination is defined as the last positive balance amount of the loan.

This detail allows us to paint a comprehensive picture of both stocks and flows of mortgage debt. The net change in the stock of mortgage debt is simply gross inflows less gross outflows:

Net Change in Stock of Mortgage Debt =

+ Gross Inflows
  - **Purchase mortgages and other originations,** where other originations include interest-rate and cash-out refinances, home equity loans, and HELOCs. The latter type of mortgage is included only if it is originated with a positive balance.
  - **Increases in existing balances**, which refer mainly to increases in HELOC balances.

− Gross Outflows
  - **Sales and other terminations,** which include mortgages that have been refinanced.
  - **Decreases in existing balances,** which account for standard amortization and existing repayments.

In addition to information on mortgage debt, the CCP contains a small number of borrower-level characteristics, such as age and an end-of-quarter credit score called the Equifax Risk Score. This score, created by Equifax, resembles a FICO score, in that a higher value indicates a lower probability of default over the near term.

The CCP does not contain any information on income, so we follow previous research and construct aggregates of debt at the zip-code level, which we merge with zip-code-level data on income from the IRS. The IRS income data are comprehensive, because they are based on the universe of tax returns. They include adjusted gross income (AGI) and salary and wage income for 1998, 2001, 2002, and 2004 through 2012.[10] We use the number of tax returns in the IRS data set as a measure of the number of households by zip code. In the empirical work below, income is defined as salary and wage income, which is the most important type of income considered by lenders when underwriting mortgage loans.[11]

When using the zip-code-level data, we use 2006 as the ending year of the boom instead of 2007. The number of filers rose sharply in 2007, as people were encouraged to file returns

[10] The IRS income data come from the Statistics of Income Program. See http://www.irs.gov/uac/SOI-Tax-Stats-Individual-Income-Tax-Statistics-zip-Code-Data-%28SOI%29 for details.

[11] A type of income that lenders generally do not consider is capital gains, which is included in AGI. Here again, measurement issues are not a great concern. Figure B.2 in the internet appendix shows that our main results are robust to defining income either as salary and wages or as AGI.

in order to receive economic-stimulus payments.[12] These additional filers have little effect on income aggregates, implying that these filers reported low (or zero) incomes, but they distort our measure of the number of households in each zip code in 2007 relative to other years and therefore have the potential to influence our results.[13]

Summary statistics for the zip-code-level CCP/IRS data set are presented in Table 1. The values are medians within each IRS-return-weighted income quintile at the beginning and end of the mortgage boom: 2001 and 2006. The quintiles are constructed to have similar numbers of households as measured by the number of tax returns, so the negative correlation between zip-code-level population and income means that low-income quintiles tend to include more zip codes than high-income quintiles.

2.2. The Survey of Consumer Finances

We generate a number of results using individual-level data from the Survey of Consumer Finances (SCF), a triennial survey of households conducted by the Federal Reserve. The SCF provides a complete characterization of household-level balance sheets. Fields we use include data on various types of mortgage debt and measures of total household wealth. In addition, we use real estate asset valuations that are self-reported.[14] Information on both mortgage debt and real estate assets is broken down into the household's primary residence along with data related to any other real estate. When studying debt, we consider the sum of all mortgage debt on residential real estate in the SCF, including first mortgages, subordinate mortgages, and HELOCs. When looking at assets, we consider the sum of all residential real estate assets.

Unlike the CCP, the SCF includes information on individual household income, including total income (comparable to AGI) and wage and salary income, along with a host of demographic variables, including the age, marital status, and race of the household head.

Summary statistics for SCF data in 2001 and 2007 appear in Table 2. The second column of figures in the table shows the number of unweighted SCF observations for each quintile.[15] These translate to sample sizes of almost 4,500 in both 2001 and 2007.

[12] See Figure B.3 in the appendix.

[13] Figure B.4 in the appendix confirms that our zip-code-level results hold even when we choose 2007 as the boom's last year.

[14] Gallin et al. (2018) find that self-reported house values (such as those in the SCF) were on average close to values from automated valuation models (AVMs) during the housing boom. Self-reported values were somewhat higher than those from AVMs during the ensuing bust, however, suggesting that some owners were late to recognize house price declines. In unreported work, we verified that accounting for the years since homeowners purchased their primary residences has virtually no effect on the distribution of housing wealth with respect to wage income in 2007, which is just after prices started falling.

[15] The number of unweighted observations is not an integer, because each SCF household is represented by five implicates, and the income fields often differ slightly across implicates for a given household.

2.3. *Other Data Sources*

We use several other data sets to supplement our analysis. These include the CoreLogic Private Label Securities ABS Database, which provides loan-level data only for mortgages that have been packaged into nonagency securities (that is, securities that are not backed by any government-sponsored enterprise, such as Fannie Mae, Freddie Mac, and Ginnie Mae). For this specific group of mortgages, which includes the large majority of subprime loans, the coverage of the CoreLogic data set is excellent, as it contains an expansive set of variables for loans in almost all nonagency securities issued since 1992. We use the CoreLogic data to measure cross-sectional patterns of securitized subprime debt.

3. EMPIRICAL FINDINGS

The main empirical finding of this paper is that there was no reallocation in mortgage debt toward low-income or marginal borrowers during the housing boom. In Figure 2 we present our basic results. Figure 2a is a bar chart of the shares of total outstanding mortgage debt held by households in various quintiles of wage income in the 2001 and 2007 waves of the SCF. Figure 2b is the parallel plot from the CCP/IRS data set, where the quintiles are returns-weighted income per tax return quintiles across zip codes. Neither plot indicates a significant increase in any quintile's share of debt during the housing boom.

Figures 2c and 2d are binned scatter plots of log mortgage debt against log wage income in 2001 and either 2007 (when using the SCF) or 2006 (when using the CCP/IRS data). There is an approximately log-linear relationship between income and debt that shifts upward nearly equally across the income distribution, indicating that debt rose by similar percentages for low-income and high-income households.

Figures 2e and 2f are bar charts of mortgage debt levels for each income quintile at the beginning and end of the boom. In both the SCF and the CCP/IRS data, debt in every income quintile approximately doubled. Because higher-income borrowers on average take out larger mortgages, this pattern implies that the largest dollar increase in mortgage debt was taken out by the relatively wealthy. According to the SCF, the top 20 percent took out \$1.5 trillion in new debt from 2001 to 2006, while mortgage debt for the lowest-income quintile rose by only \$320 billion.

In the remainder of this section we marshal an array of evidence to demonstrate that our claims about the evolution of the distribution of debt are extremely robust and hold across a broad array of specifications. In subsection 3.1, we use a regression specification to conduct a formal test of the proposition that the distribution shifted; this analysis controls for observable characteristics of households that might confound our findings. We then consider the debt-income relationship within cities to control for the wide variation in house price experiences in the boom (subsection 3.1.1), confirm that our results hold when considering the distribution of mortgage debt with respect to net worth as opposed to income (subsection 3.1.2), show that there was no reallocation of mortgage debt to households with low credit scores (subsection 3.1.3), decompose changes in indebtedness into intensive and extensive margins (subsection 3.1.4), and illustrate that the stability of the debt distribution also applies to real estate investors (subsection 3.1.5).[16] Lastly, we show that the proportional increase in debt during the boom was followed by a proportional increase in defaults during the bust (subsection 3.1.6). In section 3.2 we reconcile our main results regarding the *stock* of mortgage debt with data on *flows* of debt. We show that while there were changes in the inflows of debt, they were perfectly offset by changes in outflows, and thus the changes in inflows did not have any effect on the stock of debt. Lastly, in Section 3.3 we show that concurrent with the proportional increase in debt, there was a proportional increase in holdings of real estate assets.

3.1. The Distribution of the Stock of Mortgage Debt

To test whether there was any change in the relationship between debt and income, we estimate the following regression equation of debt on income:

$$E(d_{cit}|y_{cit}) = \alpha_t + \beta_t \cdot y_{cit}, \tag{1}$$

which assigns a debt stock d to unit i in housing market c in year t as a function of income y. Unit i could refer to either a zip code (in the CCP/IRS data) or a household (in the SCF). The parameters of the function, α and β, have time subscripts to allow them to change over time.

If the increase in debt in the 2000s disproportionately flowed to borrowers with low income, then β_t would fall over time. If, on the other hand, the increase in debt was proportional across the whole distribution, then the intercept α_t would increase over time, but we would see no change in the slope coefficient β_t.

Estimated β_ts are presented in Figure 3. Consider first the CCP/IRS estimates in the top panel. The regressions are weighted by the number of households in the zip code, errors are clustered by core-based statistical area (CBSA), and both debt and income are in logs, so parameter estimates can be interpreted as elasticities. These estimates lie in a fairly tight range, between about 1.35 and 1.45, indicating that the β_ts change little over time. If

[16] Amromin and McGranahan (2015) also study the stock of mortgage debt using the CCP. However, their definition of the stock of mortgage debt omits home equity lines of credit (HELOCs). Since HELOCs are more likely to be taken out by high-income borrowers, they find a small reallocation of mortgage debt toward low-income borrowers. As a result, they conclude that "low-income zip codes experienced a more rapid expansion of credit leading up to the Great Recession, especially in mortgage loans" (Amromin and McGranahan 2015, p. 147).

anything, the income effect grows slightly, with the 2006 coefficient about 0.07 higher than the 2001 coefficient, a difference that is statistically significant, but economically small.[17]

The bottom panel of Figure 3 presents household-level estimates using the SCF. Here, the income coefficients are estimated with a Poisson regression of the level (not log) of mortgage debt on the natural log of wage income and other demographic variables, including age.[18] The SCF income coefficients fluctuate modestly over time, as they are somewhat elevated in 1989 and 2004 and lower than average in 2001 and 2010. As was the case with the zip-code-level results, however, there is no evidence of a sustained decline in the slope from 2001 to 2007.[19]

3.1.1. Within Individual Housing Markets

Mian and Sufi (2009) point out that changes across local housing markets can mask a reallocation of mortgage debt to marginal borrowers within those markets. Suppose a financial innovation leads to faster debt growth for marginal borrowers, but house prices are growing faster in markets with higher income growth. The cross-city correlation between debt and income may overwhelm the financial-innovation effect, so that researchers mistakenly conclude that no innovation occurred. In light of the significant variance in how individual cities experienced the housing boom, this is a potential problem for our regressions.[20] To address this, we follow Mian and Sufi (2009) and add a full set of year-specific CBSA fixed effects to equation (1) to control for any market-specific factors that influence demand for mortgage debt besides income:

$$E(d_{cit}|y_{cit}) = \alpha_{ct} + \beta_t \cdot y_{cit}. \tag{2}$$

[17] The standard error on the difference between the 2001 and 2006 income coefficients is 0.02, and the t-statistic on the difference is 3.8. Because the binned scatter plot of Equifax data in Figure 2 suggests that the debt-income relation is not exactly log-linear (specifically, that the slope of the scatter plot is steeper at low incomes), we ran some unreported regressions that also include the square of income-per-household. We found that even though the implied relationship between debt and income is not perfectly linear in logs, the relationship shifts upward uniformly across the income distribution, as the binned scatter plot suggests.

[18] A Poisson regression of y_i on x_i is specified as $y_i = exp(\alpha + \beta x_i + \epsilon_i)$. The Poisson specification is preferred to a log-log specification because the latter would exclude households with zero levels of debt. Households with zero levels of wage income are excluded from the regressions, as are households with heads aged 65 years or older. In addition to the log of household income, the regressions also include dummies for the age group of the household head (younger than 35, 35–44, 45–54, and 55–64), the number of children, and dummies for nonwhite and marital status. Controlling for age in these individual household-level regressions is important because older households have had time to amortize a larger fraction of their mortgages.

[19] It is worth noting that both of these regressions show that not only was there no change in the relationship between debt and income between 2001 and 2007, there was no change in this relationship at any point during the housing boom. In other words, there is no evidence that low-income borrowers initially took on more mortgage debt, leading to higher house prices and more mortgage borrowing by high-income households as described in Landvoigt, Piazzesi, and Schneider (2015).

[20] See Figure B.5 in the appendix for an illustration of the extent to which mortgage debt grew at different rates across CBSAs.

Figure 4a is a binned scatter plot comparing income and debt done with a full set of CBSA fixed effects, which is simply a nonparametric form of the equation above. There was no change in the slope between 2001 and 2006 (that is, $\beta_{2006} = \beta_{2001}$), which implies that the within-city relationship between income and debt is stable over the sample period. Income coefficients from a parametric ordinary least squares regression confirm the results of the binscatter and are reported in Figure B.6 in the appendix.

Throughout the remainder of this section we focus on within-CBSA results when considering data from the CCP/IRS, but results generated without CBSA-year fixed effects are similar. See Figure B.7 in the appendix for details.

3.1.2. Debt and Net Worth

The SCF allows us to look at the distribution of mortgage debt by net worth. This is of interest for two reasons. First, households with low salary and wage income may have high net worth, especially if most of their income is from capital gains.[21] Second, lenders may make exceptions to their standard underwriting guidelines for households with high net worth. Because net worth and income are positively correlated, it would be surprising if debt shifted toward low-net-worth borrowers when no shift occurred toward low-income borrowers. Yet income—particularly salary and wage income—is not perfectly correlated with net worth. Therefore, we may see a reallocation of mortgage debt toward low-net-worth households even if we do not see a similar pattern with respect to income.

The results are depicted in Figure 5a and show that there was no reallocation of mortgage debt toward low-net-worth households. Like income, mortgage debt did increase, but it increased proportionately across the entire distribution.[22]

3.1.3. Debt and Credit Scores, and Creditworthiness

Another variable that lenders care about is the borrower's credit score. Credit scores and income are highly—but not perfectly—correlated, so again it would be surprising if we saw a reallocation to low-credit-score borrowers that did not also result in a reallocation to low-income borrowers. The relationship between credit scores and debt is more nuanced than the relationship between income and debt. As pointed out by Mian and Sufi (2009), there are concerns about endogeneity when considering the relationship between debt and credit scores. Easier access to credit can improve household finances and reduce delinquency,

[21] This is especially relevant to our analysis because our main measure of income is salary and wage income, and we remove households with zero salary and wages in the SCF.

[22] The CCP does not have any information on assets, so it is impossible to replicate this analysis using the CCP/IRS data. One could, in principle, use dividend and interest data from the IRS, which are correlated with asset wealth, but the Statistics of Income from the IRS doesn't begin breaking out dividend income in its zip-code-level data until 2004.

which, in turn, will raise credit scores. We therefore follow Mian and Sufi (2009) in using the percentage of households with an Equifax Risk Score below 660 in a base year.

As shown in Figure 4b, there was no reallocation of mortgage debt toward zip codes where more borrowers had low credit scores. These results are consistent with the results in Mian and Sufi (2009). They find a statistically significant effect of subprime share, but it is economically tiny: A two-standard-deviation increase in the fraction of subprime borrowers in a zip code generates only 1.1 percentage points of additional debt growth each year versus a mean growth rate of 14.5 percent. In addition, they do not control for population growth across zip codes, and when we replicate their regression controlling for population growth, the effect of subprime share is both economically and statistically insignificant.[23] Our results are also consistent with the main thrust of Albanesi, De Giorgi, and Nosal (2017), who analyze the relationship between debt and Equifax Risk Scores in the CCP in more detail.

The SCF can be used to investigate the relationship between debt and creditworthiness using data at the household level. The SCF does not include credit scores, but it does indicate whether the household has ever been denied credit, or has feared that this will occur. The SCF data do not show any change in the relationship between these two variables and mortgage borrowing. Households that answered yes to at least one of those questions accounted for about 17 percent of all mortgage debt in 2001 and the same share in 2007. To get more insight, we turn these two discrete indicators into a continuous variable using a logit model. The dependent variable in this regression indicates whether the household has been turned down for credit, or has feared being turned down, within the past five years. The right-hand-side variables are a collection of household characteristics.[24] We then group households into quintiles using the predicted values of this regression. The results appear in Figure 5b. They make clear that there was little change in the distribution of mortgage debt across households with different predicted probabilities.

3.1.4. The Intensive and Extensive Margins of Debt

So far, our regression analysis has ignored the distinction between the intensive and extensive margins. Specifically, the left-hand side of our regression is debt per household, which could reflect changes in debt per mortgagor (the intensive margin), changes in the share of households with a mortgage (the extensive margin), or some combination of the two. For example, it is possible that mortgage debt increased along the extensive margin in low-income zip codes, while increasing along the intensive margin in high-income zip codes in a manner that left the distribution of mortgage debt per household unchanged.

[23] See Section B.1.1 in the appendix for details.

[24] These characteristics are a quadratic of the age of the head of the household, race interacted with educational attainment of the head, the number of children, and the marital status of the household head.

We separate the within-CBSA binned scatter plot depicted in Figure 4a into the extensive and intensive margins. Figure 4c, the extensive margin plot, shows a binned scatter plot of the ratio of the number of households with a mortgage in the CCP divided by the number of returns in the IRS data regressed on average income for 2001 and 2006.[25] Figure 4d, the intensive margin plot, is a binned scatter plot of mortgage debt per household with a mortgage regressed on average household income. The plots of the intensive and the extensive margins both show essentially no change in the relationship between 2001 and 2006.

The SCF shows no change in the relative shares of households with a mortgage across income groups. In addition, the SCF allows us to look at homeownership rates. Figure 5c confirms that the share of homeowners in each income quintile remained stable over the course of the housing boom.

3.1.5. Debt Held by Investors

Haughwout et al. (2011) show that investors played a disproportionate role in the housing boom and bust. We ask whether there is any evidence of a change in the relationship between debt and income among investors in the CCP/IRS data and the SCF. As before, we find no evidence of a change. We define investors in the CCP as people who have three or more active first liens in their credit file. We choose this definition because credit files can be updated with a lag, and people with just two first liens may simply have refinanced or be in the process of transitioning to a new home. Therefore, if an individual has three active first liens on their credit file, it is highly likely that the person owns property other than their primary residence.

The distribution of mortgage debt among investors in the CCP in 2001 and 2006 is depicted in Figure 4e. Similar to our results for all households, there is no reallocation of mortgage debt toward low-income investors. It is important to note that we have no way of knowing which loans are backed by the borrower's primary residence, so debt in this plot reflects all mortgage debt held by investors in the CCP, not just that backed by investment properties.

Figure 5d is a plot of the distribution of the shares of nonprimary residence mortgage debt across income quintiles from the SCF. Approximately 12 percent (in 2001) to 14 percent (in 2007) of households in the SCF have mortgage debt on a nonprimary residence. The small sample size means the shares of nonprimary real estate held by each income quintile are

[25] As we might expect, this plot of the mortgageship rate indicates a positive relationship between a zip code's income and the share of its residents who have mortgage debt. A large part of the positive correlation flows from higher rates of homeownership in high-income communities. However, a zip code's homeownership rate is also determined by how many residents own their homes free and clear and these households. Indeed, at very high income levels, the share of mortgaged households flattens out, perhaps reflecting the larger propensity of high-income persons to own their homes without any debt.

slightly less stable between 2001 and 2007 than the shares of mortgage debt held by investors in the CCP/IRS. However, there is still no evidence of a reallocation of nonprimary residence mortgage debt toward low-income investors. On the contrary, the share of nonprimary mortgage debt held by the highest income quintile increases slightly, while the share held by the lowest income quintile remains unchanged.

3.1.6. The Distribution of Defaults

Previous research shows that the foreclosure crisis impacted mortgage borrowers throughout the income distribution (Ferreira and Gyourko 2015; Adelino, Schoar, and Severino 2016). The CCP allows a comprehensive analysis of default patterns, due to its wide coverage and its information on when mortgages enter various stages of delinquency. Because the CCP is quarterly, we define a default as the first transition of a mortgage to 90-day delinquency. We then calculate the default rate by zip code as the share of all active first liens in quarter $t-1$ that transition to 90-day delinquency in quarter t, where the denominator is all mortgages at risk of default in quarter $t-1$.

Figure 4f plots the share of defaults for each zip-code-level income decile from 2001 through 2009. The deciles are calculated based on income in 2001 and are weighted by the number of households (as measured by the number of tax returns) in the zip code. Shares of defaults in lower-income zip codes remained effectively constant from 2001 through 2009, implying that the increase in default rates was broad-based across income classes. Had there been a disproportionate increase in risky debt to low-income borrowers, default rates would have increased proportionately more in low-income zip codes, resulting in these zip codes accounting for a higher share of defaults. Instead, the slight increase in the share of defaults for the highest income deciles indicates that there was, if anything, a proportionately higher increase in default rates in high-income zip codes.[26] This analysis confirms the finding of Adelino, Schoar, and Severino (2016) that the share of defaults by high-income and prime borrowers increased during the bust.[27]

[26]Mian and Sufi (2009) focus on *absolute differences* in default rates across income groups. Because low-income and subprime borrowers default at higher rates on average, a proportional increase in default rates for all income groups implies a larger absolute change in default rates for low-income borrowers.

[27]Adelino, Schoar, and Severino (2016) use data from HMDA and the McDash mortgage servicer data set to infer that the share of total delinquency value accounted for by high-income borrowers rose. Although the McDash data set does not become fully representative of the mortgage market until 2005, the more comprehensive CCP data set confirms this result. Other important research on foreclosure patterns comes from Ferreira and Gyourko (2015), who find that twice as many prime as subprime borrowers lost their homes over their full sample period (2009:Q1–2012:Q3).

3.2. *Stocks versus Flows*

The lack of any change in the distribution of the stock of mortgage debt across the income distribution is consistent with changes in the distribution of mortgage flows documented in the earlier literature. Figure 6a is a binned scatter plot of the zip-code-level log of the dollar value of mortgage originations per household, deviated from CBSA-year means, against income per household. This figure clearly illustrates the central finding in the earlier literature: During the boom, total originations in low-income areas rose by relatively more than in high-income areas. That is, in contrast to the results for debt stocks, the relationship between originations and income did decline over time. However, Figure 6c shows that the relationship between mortgage *terminations* and income declined as well.[28]

Figures 6b and 6d show income coefficients from an analogous regression specification to equation 2:

$$E(d_{cit}|y_{cit}) = \alpha_{ct} + \beta_t \cdot y_{cit}. \tag{3}$$

However, in this case, $E(d_{cit}|y_{cit})$ is the dollar value of originations or terminations per household in a given year. The income coefficients decline for both originations and terminations over the course of the boom. But because the relative shifts in the two debt flows are the same, they offset one another, leaving the distribution of the stock of debt unchanged.

This relative increase in churn in low-income zip codes is driven by two factors. One is undoubtedly the disproportionate participation of high-income borrowers in the refinancing boom of 2001 through 2003. The reasons behind this boom are well-known.[29] Due in part to aggressive monetary easing by the Federal Reserve during and after the 2001 recession, the 30-year mortgage rate fell from around 8.5 percent in early 2000 to about 5.5 percent in mid-2003.[30] Higher levels of refinancing generate higher amounts of mortgage churn, and Figure 6 suggests that high-income borrowers were more likely to participate in the 2001–2003 refinancing boom, consistent with previous research on the propensity to refinance.[31] This is most likely why the 2002 coefficient estimate is higher than the 2001 coefficient estimate. We do not have IRS income data for 2003, but it is likely that the 2003 income

[28]Consistent with Mian and Sufi (2009) this analysis is conducted on a within-CBSA basis. See Figure B.8 in the appendix for analogous results without CBSA-year fixed effects.

[29]For a discussion of the refinancing boom with a focus on cash-out refinancing, see Bhutta and Keys (2016).

[30]The interest rate cited is the 30-year contract rate for conventional 30-year mortgages as measured by Freddie Mac.

[31]In his presidential address to the American Finance Association, Campbell (2006) highlights three major financial mistakes often made by US households, one of which is the failure to refinance a fixed-rate mortgage when declining interest rates make it profitable to do so. Using early 2000s data from the American Housing Survey, Campbell finds that "younger, smaller, better educated, better off, white households with more expensive houses were more likely to refinance their mortgages between 2001 and 2003. These patterns suggest that prompt refinancing requires financial sophistication" (Campbell 2006, p. 1581).

effects for both originations and terminations were even larger than the 2002 values. As this wave fell off after 2003, the *relative* amount of churn in low-income communities increased.

However, it is unlikely that the refinancing boom of 2001 through 2003 can explain why the coefficient on income dropped below its 2001 value in 2005 and 2006, years after the refinancing boom ended. This continued drop in the coefficient is most likely driven by a relative increase in purchase mortgages in low-income zip codes. This relative increase in purchase mortgage activity did not have any impact on the distribution of the stock of debt because purchase mortgages typically replace the sellers' mortgages on the homes being transacted.[32]

3.3. The Distribution of Real Estate Assets

Up to now, most research on the housing boom has focused on mortgage debt, but economic models of housing have implications for real estate assets that are more direct. Households' key choice variable in models is the amount of housing to consume; debt is simply the method by which this choice is financed. Because some households own their homes free and clear while others have significant amounts of debt, real estate assets and mortgage debt are not perfectly correlated in the cross section.[33] Consequently, the proportional increase in mortgage debt documented above does not directly imply a parallel increase in real estate assets across income groups.

As it turns out, however, the distribution of real estate assets with respect to income also remained remarkably stable during the boom. The top panel of Figure 7 shows the shares of real estate assets from the SCF for 20 household-weighted quantiles by income. We combine assets on all residential real estate, including both primary homes and vacation or investment properties. As expected, holdings of real estate are positively correlated with income, but during the boom there was no reallocation of real estate assets toward low-income households. This finding is robust to whether we exclude investment properties and second homes, whether we focus on just recent home buyers or all homeowners, whether we divide the sample by income or wealth, and what definition of income we use. In other words, as with debt, the striking fact about the cross-section of housing wealth is how little it changed in the greatest housing boom in American history, not how much.

The bottom panel of Figure 7 shows the shares of outstanding debt in the SCF using

[32]The impact of simultaneous originations and terminations on credit allocation plays an important role in Gerardi and Willen (2009), who study the effect of subprime lending on urban neighborhoods in Massachusetts. The authors find that during the housing boom, African Americans accounted for a disproportionately large share of buyers in the state's urban neighborhoods. But African Americans also accounted for an equally high percentage of sellers. The implication is that subprime lending increased sales turnover without affecting minority homeownership rates.

[33]The correlation between mortgage debt and real estate households in the SCF with positive real estate assets was 0.60 in 2007. The correlation was slightly higher (0.63) in 2001.

20 income categories, and is thus a finer disaggregation of the debt distribution than that provided by the SCF bar charts shown earlier. This higher level of disaggregation shows a slight decline in the share of mortgage debt held by the top 5 percent of the income distribution. This fact does not change our main conclusion, because the lower panel provides no evidence for a reallocation of mortgage debt toward low-income households. What this disaggregation does show is that the top 5 percent of households by income—the group least likely to be constrained by borrowing limits—funded their acquisitions of real estate through means other than debt (for example, by selling other assets).[34] As we will see in the next section, the rapid increase in asset holdings among higher-income, unconstrained households provides a great deal of theoretical leverage for understanding why the US housing boom occurred.

4. IMPLICATIONS FOR THEORIES OF THE BOOM

In the wake of the financial crisis, researchers have built models with the goal of matching basic facts about the housing boom. In general, the focus has been on trying to explain the steep increase in house prices. Many researchers propose an expansion of credit as an explanation;[35] others argue for a decline in interest rates;[36] yet a third group of researchers argue for shocks to beliefs about future house prices.[37]

In this section, we construct a simple model of the housing market that serves two purposes. First, it allows us to think about different explanations for the housing boom in a single unified framework. Second, we focus on the cross-sectional implications of these potential explanations—implications that are typically not explored in the existing literature. We then use the model to reinterpret the growth of subprime lending, a key feature of the boom.

[34] This result elucidates the differences between our analysis and the stylized fact presented in Figure 2, Panel A of Kumhof, Rancière, and Winant (2015). They find that during the housing boom the debt-to-income (DTI) ratio of the bottom 95 percent of the income distribution rose more than the DTI ratio of the top 5 percent. While the top 5 percent of the income distribution took on relatively less debt than the bottom 95 percent, explaining the slower growth in their DTI ratio, the share of real estate assets held by the top 5 percent remained stable, consistent with a broad increase in demand for residential real estate.

[35] Kiyotaki, Michaelides, and Nikolov (2011), Sommer, Sullivan, and Verbrugge (2013), Favilukis, Ludvigson, and Van Nieuwerburgh (2017), and Greenwald (2016) are notable examples.

[36] See Justiniano, Primiceri, and Tambalotti (2019) and Favilukis, Ludvigson, and Van Nieuwerburgh (2017).

[37] See Kaplan, Mitman, and Violante (2019).

4.1. A Model of Housing and Credit

We consider a continuous-time, non-stochastic endowment economy with a fixed stock of housing. Housing should be thought of as land, which does not depreciate. We focus on the user cost in the spirit of Poterba (1984), but our treatment more closely follows Hornstein (2009).[38]

Infinitely lived households receive labor income, can borrow and save, and can allocate their expenditure across a consumption good and housing:

$$\max_{\{c(t),h(t)\}_{t=0}^{\infty}} \int_{t=0}^{\infty} e^{-\rho t} N(t) u(c(t), h(t)) dt.$$

Here, ρ is the subjective discount rate; N is household size, which grows at rate $\dot{N}/N = n$; h is real units of housing; and c is consumption. Household wealth a grows at:

$$\dot{a}(t) = N(t)y(t) + r(t)a(t) - N(t)c(t) - p(t)x_h(t), \tag{4}$$

where y is individual income, p is the price of housing, r is the interest rate, and x_h is additions to h. The evolution of h, the household stock of housing, is given by:

$$\dot{h}(t) = x_h(t).$$

We assume that all households share the same individual income growth rate $\dot{y}/y = g$, discount factor ρ, and household size N, and face a flow limit on how much they can spend on housing relative to income:

$$rph \leq \phi N y. \tag{5}$$

The dynamic budget constraint (equation [4]) and a no-ponzi-game condition yields the lifetime budget constraint:

$$\int_{s=t}^{\infty} e^{-R(t,s)} \big(N(s)c(s) + p(s)\big(r(s) - \dot{p}(s)/p(s)\big)h(s)\big)\, ds = \\ a(t) + p(t)h(t) + \int_{s=t}^{\infty} e^{-R(t,s)} N(s)y(s)ds, \tag{6}$$

which highlights that the relevant price of housing is not $p(t)$ but the user cost $p(s)\big(r(s) - \dot{p}(s)/p(s)\big)$.

A study of two housing-demand equations illustrates the basic intuition for how shocks

[38]The key differences with Hornstein (2009) are that we assume a fixed supply of housing, allow for population growth, and use a constraint on house spending rather than a constraint on borrowing.

reallocate housing, The first equation is the first-order condition

$$\frac{MU_h}{MU_c} = \underbrace{p \cdot (r - \dot{p}/p)}_{\text{user cost}}, \tag{7}$$

which determines demand among unconstrained households (MU_h and MU_c are the marginal utilities of housing and consumption respectively). To get the second equation, we rearrange the spending constraint to obtain housing demand among constrained households:

$$h = \phi \frac{Ny}{rp}. \tag{8}$$

Equations (7) and (8) show in a general setting that relaxing the spending constraint and increasing expected price growth per se lead to reallocations of housing. Relaxing the constraint—increasing ϕ—increases demand among constrained households (equation [8]), but has no effect on demand among unconstrained households (equation [7]). Because demand now exceeds supply, p must rise leading to an equilibrium reallocation toward constrained households. In contrast, an increase in expectations $\dot{p}/p$ reduces the user cost and increases demand among unconstrained households while having no direct effect on demand among constrained households, leading to an opposite reallocation in equilibrium. To generate both rising prices and a stable distribution—consistent with our empirical results—we need a combination of an increase in expectations *and* an offsetting relaxation of constraints.

To illustrate precisely how constraints and expectations interact, we consider the special case where

$$u(c(t), h(t)) = \log\left(c(t)^{1-\theta}(h(t)/N(t))^{\theta}\right).$$

Equation (7) now simplifies to:

$$h = \frac{\theta N y}{p \cdot (r - \dot{p}/p)}. \tag{9}$$

Households can differ in θ, $y(0)$, and their endowments of housing. We follow Greenwald (2016) and Justiniano, Primiceri, and Tambalotti (2019) and assume that there exist lender and borrower households. At time 0, lender households own all the housing. Both lenders and borrowers start with zero financial assets ($a(0) = 0$ for all households). Lenders have no labor income ($y_L = 0$), and they derive no utility from consuming housing services ($\theta_L = 0$).

We assume that there are two types of borrowers. Type $b1$ and $b2$ borrowers differ in income $y_{b2} > y_{b1}$ and preference for housing $\theta_{b1} > \phi(\rho - n)/(\rho + g) > \theta_{b2}$, which, in equilibrium, implies that type $b1$ borrowers are constrained and type $b2$ borrowers are unconstrained. We justify the negative correlation between θ and y by pointing to a large literature on the link between budget shares on housing and income (see Federal Housing Administration 1947 and, more recently, Albouy, Ehrlich, and Liu 2016).

We now turn to equilibrium. Along the balanced growth path:

$$r = \rho + g, \quad \dot{p}/p = g + n \text{ and } r - \dot{p}/p = \rho - n. \tag{10}$$

If α is the share of type $b1$ borrowers in the economy and $\overline{h}$ is the aggregate stock of housing then:

$$p = \frac{N}{\overline{h}}\left((1-\alpha)\frac{\theta_{b2}y_{b2}}{r-\dot{p}/p} + \alpha\frac{\phi y_{b1}}{r}\right) = \frac{N}{\overline{h}}\left((1-\alpha)\frac{\theta_{b2}y_{b2}}{\rho-n} + \alpha\frac{\phi y_{b1}}{\rho+g}\right) \tag{11}$$

where the second equality follows from equation (10). Equation (11) shows that a relaxation of the constraint (an increase in ϕ), a shock to expectations (an increase in n), and a shock to interest rates (a reduction in ρ) all raise the price of housing. In this sense, our model replicates the basic findings of Favilukis, Ludvigson, and Van Nieuwerburgh (2017), Greenwald (2016), and many others that relaxation of a credit constraint can increase the price of housing. It also illustrates that a shock to beliefs (similar to Kaplan, Mitman, and Violante 2019) or a shock to interest rates (similar to Justiniano, Primiceri, and Tambalotti 2019) also raises the price of housing. We show in the appendix that the presence of an unconstrained rental market mitigates the effect of constraints on prices, consistent with the findings of Kaplan, Mitman, and Violante 2019.

Implications for the cross-section of housing assets follow from the substitution of the equilibrium price (equation [11]) into the demand function for constrained households (equation [8]):

$$\frac{h_{b1}}{\overline{h}} = \frac{\alpha\frac{\phi y_{b1}}{\rho+g}}{(1-\alpha)\frac{\theta_{b2}y_{b2}}{\rho-n} + \alpha\frac{\phi y_{b1}}{\rho+g}}. \tag{12}$$

Equation (12) shows that increases in ϕ and n lead to reallocations, respectively, toward and away from constrained households. In addition, a fall in ρ leads to a reallocation away from unconstrained households. Thus, neither a relaxation of credit, a shock to expectations, nor a shock to interest rates alone can match the data. The intuition is simple. An increase in ϕ shifts the demand curve for constrained households (equation [8]) and has no effect on demand for unconstrained households (equation [9]), and vice versa for an increase in n. A reduction in ρ shifts the demand curve more for unconstrained households than for constrained.

To explain the data using the model, one needs a combination of an exogenous shock to n or ρ, in concert with what we call, in a slight abuse of language, an "endogenous constraint."[39] The endogenous constraint replaces equation (5) with a constraint that depends on the user

[39]The constraint is not endogenous in the sense that it does not emerge endogenously from the behavior of optimizing lenders—as we do not explicitly model lenders. As we explain below, we view equation (13) as a reduced form of the behavior of an optimizing lender.

cost of housing rather than just the interest cost:

$$p(r - \dot{p}/p)h \leq \overline{\theta} N y. \tag{13}$$

Among other things, this formalizes the idea that increases in $\dot{p}/p$ lead lenders to relax borrowing constraints. As shown by Gerardi et al. (2008) and Foote, Gerardi, and Willen (2012), lenders explicitly attributed their willingness to expand their credit offerings to optimistic beliefs about the evolution of house prices because, according to their models, rising prices lead to fewer defaults and lower losses conditional on default. One can also view equation (13) as a reduced form for the optimizing lenders in Kaplan, Mitman, and Violante (2019), who relax credit constraints in response to an increase in the probability of high future house prices. [40]

The equilibrium price with the endogenous constraint is

$$p = \frac{N}{\overline{h}} \frac{(1-\alpha)\theta_{b2} y_{b2} + \alpha \overline{\theta} y_{b1}}{r - \dot{p}/p} = \frac{N}{\overline{h}} \frac{(1-\alpha)\theta_{b2} y_{b2} + \alpha \overline{\theta} y_{b1}}{\rho - n}, \tag{14}$$

meaning that the equilibrium share of constrained households is:

$$\frac{h_{b1}}{\overline{h}} = \frac{\alpha \overline{\theta} y_{b1}}{(1-\alpha)\theta_{b2} y_{b2} + \alpha \overline{\theta} y_{b1}}. \tag{15}$$

Equation (15) shows that with the endogenous constraint, shocks to n or ρ have no effect on the allocation of housing across the population. In other words, an increase in n or ρ can generate an increase in house prices without any cross-sectional reallocation of house spending.[41]

We note that the endogenous constraint described in equation (13) ensures a stable distribution only for the specific functional forms we study here. For example, if the elasticity of substitution between housing and consumption is less than one, then a price increase leads households to want to increase the share of their budget devoted to housing. With equation (13) and low elasticity, a price increase would thus lead to a reallocation toward unconstrained households. However, one can adapt equation (13) to ensure that there is

[40] Kaplan, Mitman, and Violante (2019) stress the importance of a rental market. In the appendix, we show what happens with the addition of a rental market in which no households are constrained. In this case, an increase in ϕ has no effect on prices, but it can lead to an increase in homeownership.

[41] One seemingly plausible alternative explanation would be an exogenous relaxation of constraints that leads to an endogenous increase in $\dot{p}/p$. This explanation would not work in this model because relaxing the constraint affects the *level* of house prices but it has no effect on the expected growth rate. None of the models discussed above features a causal link between constraints and expectations either. More generally, in a model with adjustment costs, an increase in demand leads to an immediate increase in the price level followed by a *reduction* in $\dot{p}/p$.

no reallocation with other functional forms. While changing the constraint repeatedly may seem ad hoc, it is consistent with our general idea that lenders adapt constraints to changing economic circumstances and the alternative —lenders who do not adapt—seems both a priori unrealistic and at odds with what we find in the data.

4.2. The Demand for Housing and the Demand for Debt

In the model, we focus on the predictions for the share of housing rather than the predictions for the share of debt. The predictions for debt are identical: A shock to $\dot{p}/p$ combined with an endogenous relaxation of constraints affects neither the share of mortgage debt nor the share of housing held by constrained households. Both of these predictions match the data; however, for a couple reasons, we view the results on real estate assets as more informative for understanding the boom.

First, in the data, mortgage debt and housing demand are not equivalent. As shown in Figure 7, the share of mortgage debt held by the top 5 percent of the income distribution declined slightly, while their share of real estate assets remained almost the same. Households in the top 5 percent reallocated other assets to increase spending on housing, whereas households elsewhere in the distribution relied on debt. The actions of the top 5 percent of the income distribution are important because they imply that the increase in house prices was married to a broad-based increase in demand for housing, and that this increase in demand did not hinge on the use of mortgage debt.

Second, mortgage debt is different from the general debt usually included in macroeconomic models because it allows a household to extract a flow of housing services (with associated flow cost $p(r - \dot{p}/p)$ from a long-lived asset (with associated price p). Mortgage debt allows an optimizing household that wants to spend $p(r - \dot{p}/p) \cdot h$ on a flow of housing services, but cannot afford $p \cdot h$, to buy a house. Rearranging equation (14) illustrates how, with an endogenous constraint, there can be large variations in price (and therefore large variations in debt) without any change in the user cost:

$$p(r - \dot{p}/p) = p(\rho - n) = \tfrac{N}{\overline{h}} \left[(1-\alpha)\theta_{b2} y_{b2} + \alpha \overline{\theta} y_{b1} \right]. \tag{16}$$

A reduction in the interest rates (a change in ρ) or an increase in house price growth (a change in n) leads to an increase in p but has no effect on the user cost.[42] Because houses are more expensive, but the flow cost is unchanged, households take on more debt to purchase the same home. In our perfect-foresight model, there are no negative consequences of this increase in debt because households are reacting to a true reduction in the flow costs of housing. In reality, the increase in debt can cause problems if price gains do not in fact

[42]A shock to interest rates driven by a reduction in g leads to perfectly offsetting reductions in r and $\dot{p}/p$.

materialize.

4.3. Reinterpreting Subprime

During the US housing boom of the 2000s, lending constraints were relaxed in large part through the growth of subprime lending. Our model allows us to interpret subprime as an endogenous response to the inflexibility of traditional sources of credit for marginal borrowers. Without subprime, as price expectations—$\dot{p}/p$—and thus prices—p—rose in the 2000s, rigid rules among traditional lenders would have driven marginal borrowers into smaller and smaller homes or out of homeownership altogether, reallocating housing to the wealthy.

To understand this in the context of the model, we start by rewriting the flow constraint—equation (13)—as a maximum monthly payment-to-income (PTI) ratio constraint:

$$PTI = \frac{rph}{yN} \leq \frac{r}{r - \dot{p}/p}\overline{\theta}.$$

A policymaker or researcher observing an increase in the maximum market PTI in the subprime market would not know if it was driven by an increase in $\overline{\theta}$ or an increase in $\dot{p}/p$. But as equation (15) shows, an increase in $\overline{\theta}$ would have led to counterfactual shifts in debt and housing wealth toward constrained households. The more plausible interpretation is that the growth of subprime was an endogenous response to an increase in $\dot{p}/p$.

Before 2001, the main alternative source of funds for marginal borrowers was the Federal Housing Administration (FHA). FHA loans were risky, typically defaulting at rates three to five times higher than prime loans.[43] Although the FHA lent to marginal borrowers, the program was notoriously inflexible.[44] For example, FHA prohibited interest-only mortgages and loans with low or no documentation, and hybrid adjustable-rate mortgages (ARMs) did not become available through FHA until 2004.[45]

In the context of the model, we can think of the FHA as using fixed beliefs $\overline{\pi} = \dot{p}/p$ to set its constraint:

$$\frac{rph}{yN} \leq PTI_{FHA} = \frac{r}{r - \overline{\pi}}\overline{\theta}.$$

As long as population beliefs $\dot{p}/p$ are in line with $\overline{\pi}$, the FHA represents a viable source of funds. But as $\dot{p}/p$ and thus p go up, as they did during the boom, the maximum level of

[43] According to the Mortgage Bankers Association, in 2004, lenders initiated foreclosure proceedings on 0.98 percent of all FHA loans, 1.49 percent of subprime loans, and 0.19 percent of all prime loans.

[44] See, for example, the discussion in Jaffee and Quigley (2008).

[45] Hybrid ARMs offer a fixed rate for a specified period of time and adjust as a function of an index such as LIBOR after that. The typical subprime hybrid ARM was known as a 2/28 because it was fixed for 2 years and adjusted for the 28 remaining years of the contract.

housing consumption available through the FHA will fall:

$$h_{FHA} = \frac{\overline{\theta} y N}{p(r - \overline{\pi})}.$$

In contrast, private subprime lenders could and did adjust their lending standards to allow much bigger effective PTI ratios. They did this by allowing borrowers to include unverified income in their loan applications—in 2005, 41 percent of subprime mortgages were low- or no-documentation—or by reducing the noninterest portion of the mortgage payment using alternative products (in 2005, 29 percent of subprime mortgages were interest only).[46]

We interpret the explosion of subprime lending as an endogenous market response to the rigidness of the FHA. The top panel of Figure 8 shows that the growth of subprime coincided with and almost perfectly offset a decline in FHA lending. The Government Accountability Office (2007) documents that industry participants generally believed that subprime growth came at the FHA's expense and presents geographic evidence that confirms that view.

Without subprime, there would have been a reallocation of mortgage debt towards unconstrained borrowers. We can see this directly. The bottom panel of Figure 8 shows two counterfactual exercises. The figure starts with a replication of Figure 2d that reprises our main point that the slope of the overall relationship between debt and income did not change during the boom. Our first counterfactual exercise is to assume that the only increase in debt was the addition of subprime (the line labeled "2001 Debt+Net Subprime"). If that were the case, then we would have seen a reallocation of debt toward low-income households. The second counterfactual is to imagine a world in which there had been no subprime (the line labeled "2001 Debt+Net Prime"). If there had been no subprime, then we would have seen an *increase* in the slope of the relationship between debt and income and a reallocation of mortgage debt toward high-income households.

While subprime lending was an endogenous response to the 2000s housing market, it is important to note that subprime loans did play a role in the financial crisis. Synthetic collateralized debt obligations (CDOs), which are securities issued by a trust that invests mainly in derivatives tied to the performance of mortgage-backed securities (MBS), were heavily invested in derivatives on BBB-rated subprime MBS. While comprising only a small portion of the overall market for subprime MBS, the loss rates on these BBB-rated MBS were high (Ospina and Uhlig 2018). Figure 9 illustrates the power of CDOs focusing on a comparison of the issuance of BBB-subprime MBS and the issuance of CDOs backed by these securities. From 2003 to 2005, issuance of BBB-subprime MBS grew by about \$10 billion, but total exposure of the financial system grew by almost \$50 billion.[47] When these

[46] See Government Accountability Office (2007) for details.

[47] About 80 percent of all MBS were rated AAA. As pointed out in the Financial Crisis Inquiry Commission

loans defaulted, investors in these synthetic CDOs lost multiples of the amount these loans were actually worth.

5. CONCLUSION

During the 2000s housing boom, the cross-sectional distribution of both debt and housing wealth was stable over time. Any successful theory of the boom must match this fact, just as it must predict a big increase in housing prices. We use a simple general equilibrium model to show that one exogenous shock often featured in housing models—a relaxation of borrowing constraints—cannot fit this fact, because it predicts a reallocation of debt and assets toward previously constrained households.

The factor that reduced user costs and raised demand for housing across the population is most likely optimistic expectations for future house prices. Existing research has focused on the two elements of the user cost that our model highlights—a decline in interest rates and an increase in future price expectations.[48] We lean toward the price-expectations view primarily for empirical reasons. Nominal interest rates drifted lower for many years after the Volcker disinflation without setting off a national housing boom, and the period when prices were rising fastest (2003 through 2006) experienced flat or rising interest rates, not falling rates. An even bigger timing problem for the interest-rate theory is that after the boom, housing prices declined sharply even as nominal rates moved lower.

Price expectations are harder to measure than interest rates, but there is substantial evidence that the early 2000s was a period of intense optimism about housing. Gerardi et al. (2008) find that major banks held a rosy view about future price growth during the boom and that this view influenced lending decisions. Borrowers were also optimistic, according to the survey evidence in Case, Shiller, and Thompson (2012). For their part, professional economists may have been skeptical that the price boom was fully justified by fundamentals, but they generally kept those views to themselves. In a survey of economists' research during this period, Gerardi, Foote, and Willen (2011) find that few were willing to state on the record that the price boom was destined to end badly.

For economists, a big problem with labelling the boom a bubble is that the profession has yet to reach consensus on how expectations can become disconnected from fundamentals; we have yet to find a workhorse alternative to the rational-expectations paradigm. In the model of this paper, we tie price expectations to future population growth in a perfect-foresight framework. But we also believe that price expectations would exert a positive influence on

(2011), most AAA-rated MBS did not suffer any impairments during the crisis. Ospina and Uhlig (2018) put the losses on AAA-rated MBS backed by subprime loans at only $4.3 billion, or about 0.4 percent of the amount issued. Losses on lower-rated subprime MBS were much higher.

[48]Justiniano, Primiceri, and Tambalotti (2019) argue for the interest-rate explanation; Glaeser, Gottlieb, and Gyourko (2013) argue against it.

housing demand even if expectations were set nonrationally. Some of the most interesting work on the housing boom asks how expectations can be affected by cognitive costs, social interactions between optimists and pessimists, and psychological biases.[49] We believe that the ultimate explanation of the housing boom will incorporate one or more of these new ideas, coupled with an endogenous relaxation of borrowing constraints that keeps the distribution of mortgage debt and assets stable over time.

[49] Gennaioli and Shleifer (2018) stress the role of expectations in the crisis. Fuster, Laibson, and Mendel (2010), Fuster, Hebert, and Laibson (2012), Burnside, Eichenbaum, and Rebelo (2016), and Glaeser and Nathanson (2015) explore the formation and/or consequences of nonstandard expectations.

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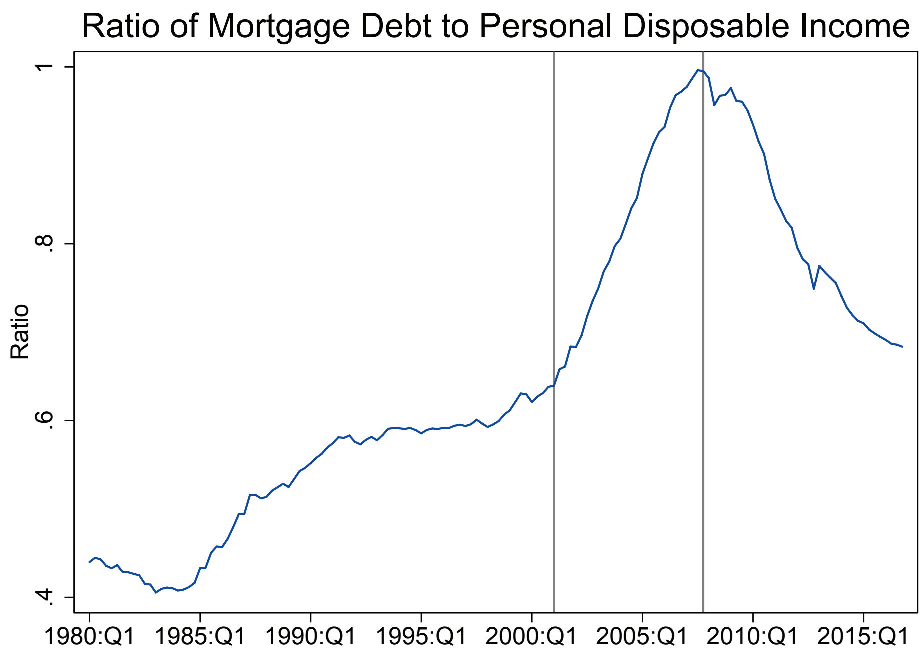


Figure 1. US Mortgage Debt-to-Income Ratio: 1980:Q1 to 2015:Q4. *Note:* The mortgage debt ratio is defined as total home mortgage liabilities in the household sector divided by total personal disposable income for the household and nonprofit sectors. The income variable is seasonally adjusted at an annual rate. *Source:* Federal Reserve, Financial Accounts of the United States (Flow of Funds).

	Income per Return Quintile				
	1	2	3	4	5
2001					
Zip Codes (#,000)	17	9	6	4	4
S&W per Return ($,000)	22	26	31	38	52
AGI per Return ($,000)	28	34	39	49	71
Avg. Mortgage Debt ($,000)	51	60	74	92	130
Avg. 1st Mortgage ($,000)	41	47	57	70	94
Avg. 2nd Mortgage ($,000)	6	5	4	4	4
Avg. HELOC ($,000)	2	2	3	3	4
Mortgaged Households (%)	27	34	39	44	51
Median Age	45	45	44	44	45
Median Equifax Risk Score	657	684	700	721	742
Median House Price ($,000)	79	97	119	156	243
2006					
Zip Codes (#,000)	16	8	6	4	4
S&W per Return ($,000)	24	30	35	42	59
AGI per Return ($,000)	32	39	46	57	87
Avg. Mortgage Debt ($,000)	73	88	112	147	215
Avg. 1st Mortgage ($,000)	57	66	81	100	137
Avg. 2nd Mortgage ($,000)	9	8	9	11	13
Avg. HELOC ($,000)	6	8	9	12	18
Mortgaged Households (%)	32	40	45	52	58
Median Age	47	47	47	46	47
Median Equifax Risk Score	656	689	707	729	754
Median House Price ($,000)	133	148	189	249	390
House Price Apprec. 2001–2006	51	41	42	43	44

Table 1. Summary Statistics for Zip Codes in the CCP/IRS Data Set. *Note:* Values at the zip-code level are summarized by return-weighted salary and wages per return quintiles from the IRS, so there are approximately the same number of returns in each quintile. The reported values are return-weighted medians within each quintile. Average mortgage debt is the total stock of mortgage debt divided by the number of people in the zip code holding a mortgage, after correcting for joint mortgages. The average value of each type of mortgage is the total stock of debt for that mortgage type divided by the number of outstanding mortgages of that type in each zip code. The percentage of mortgaged households is the number of couples or individuals holding a mortgage divided by the number of returns from the IRS. The median house price is from Zillow, and house price appreciation at the zip-code level is calculated from the CoreLogic zip-code-level house price index. *Sources:* NY Fed Consumer Credit Panel/Equifax, IRS Statistics of Income, and CoreLogic. Median house price levels are freely available from Zillow.com for non-commercial use.

Year	Income Quintile	No. of Unweighted Obs.	Mortgaged Households (% of Hholds)	Total Mortgage Debt	Debt on Primary Residence	Other Mortgage Debt	Wage & Salary Income	Home Ownership Rate (%)	Value of Primary Residence	Value of All Resid. Real Estate	Median Debt-Service Ratio
2001	1	555.2	24	15,373	14,540	833	12,030	36	40,560	46,163	48
	2	545.2	36	23,170	21,118	2,051	29,057	48	48,595	54,741	24
	3	487.6	59	40,370	38,198	2,172	45,183	70	84,423	92,476	18
	4	528.0	71	64,680	61,065	3,616	68,840	81	128,077	141,449	14
	5	985.4	85	130,324	120,524	9,801	169,382	93	292,495	345,387	12
2007	1	502.6	24	25,583	23,239	2,344	13,202	35	56,360	63,844	55
	2	495.4	41	44,315	3,9654	4,662	32,777	52	89,257	10,1780	25
	3	458.2	62	74,954	70,901	4,054	51,843	72	15,6287	179,481	22
	4	496.6	79	126,786	114,192	12,594	79,424	83	230,873	265,318	18
	5	966.2	87	231,872	202,267	29,605	19,8981	94	489,184	632,831	14

Table 2. Summary Statistics for Households in the Survey of Consumer Finances. *Note:* All variables except the debt-service ratio are calculated as simple means of weighted averages from the five multiple implicates of the public-use summary data of the SCF. The debt-service ratio is the simple mean of the weighted median over all households with mortgage debt. Quintiles are based on wage and salary income. Figures are nominal dollar values unless otherwise noted. *Source:* Federal Reserve, Survey of Consumer Finances.

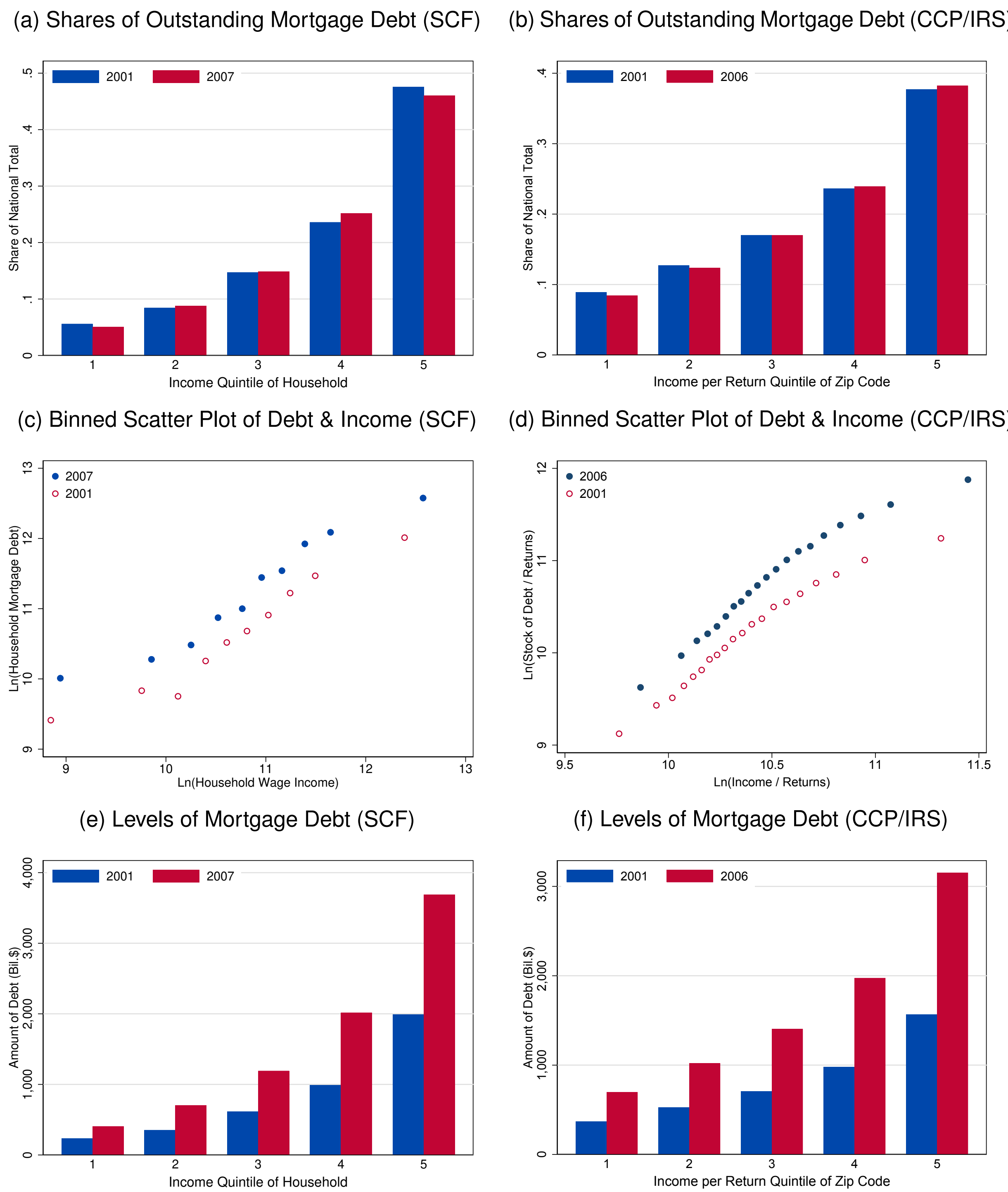


Figure 2. The Relationship between Mortgage Debt and Income among US Households (Left Panels) and Zip Codes (Right Panels). *Note:* The panels at left use data from the Survey of Consumer Finances to depict the household-level relationship between wage income and mortgage debt in 2001 and 2007. The panels at right use debt data from the CCP and income data from the Internal Revenue Service to show the zip-code-level relationship in these variables in 2001 and 2006. Households with no wage income in the SCF and zip codes with no reported wage and salary income from the IRS are not included. *Sources:* NY Fed Consumer Credit Panel/Equifax, IRS Statistics of Income, and Federal Reserve, Survey of Consumer Finances.

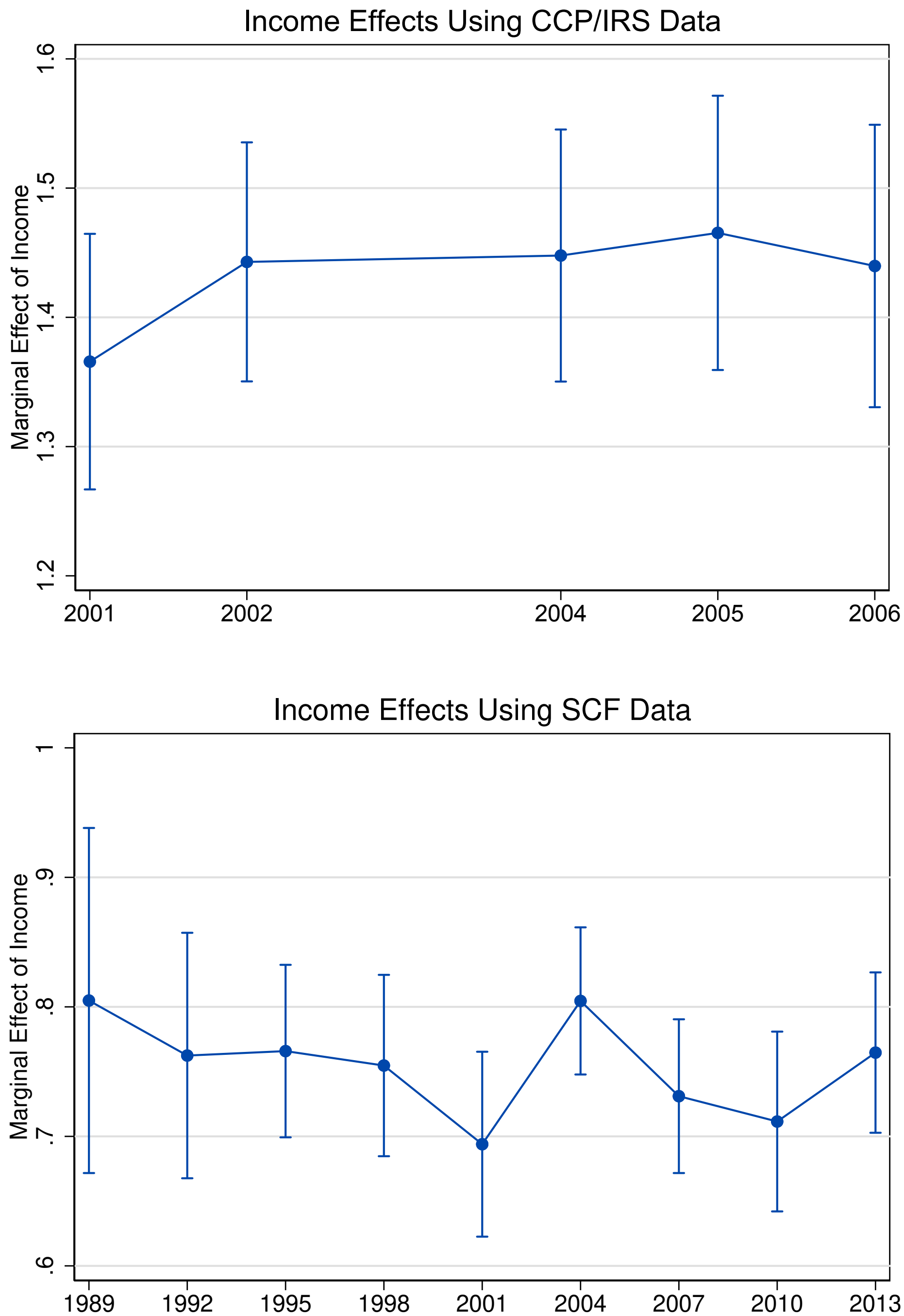


Figure 3. Regression Evidence on the Relationship between Mortgage Debt and Income among US Zip Codes and Households. *Note:* The top panel graphs income coefficients (and 95 percent confidence intervals) from a returns-weighted regression of zip-code-level mortgage debt on income for all years from 2001 through 2006, save for 2003 (when IRS income data are not available). Standard errors are clustered by CBSA (not CBSA-year). The bottom panel depicts income coefficients from a pooled Poisson regression for household debt in the SCF, in which the log of wage and salary income, dummies for the age of the household head (younger than 35, 35–44, 45–54, and 55–64), the number of children, and dummies for nonwhite and marital status are each interacted with yearly dummies. Households with heads 65 and older and households with no wage income are excluded. Standard errors are calculated as in Rubin (1987), but with no degrees-of-freedom adjustment. *Sources:* NY Fed Consumer Credit Panel/Equifax, IRS Statistics of Income, and the Federal Reserve, Survey of Consumer Finances.

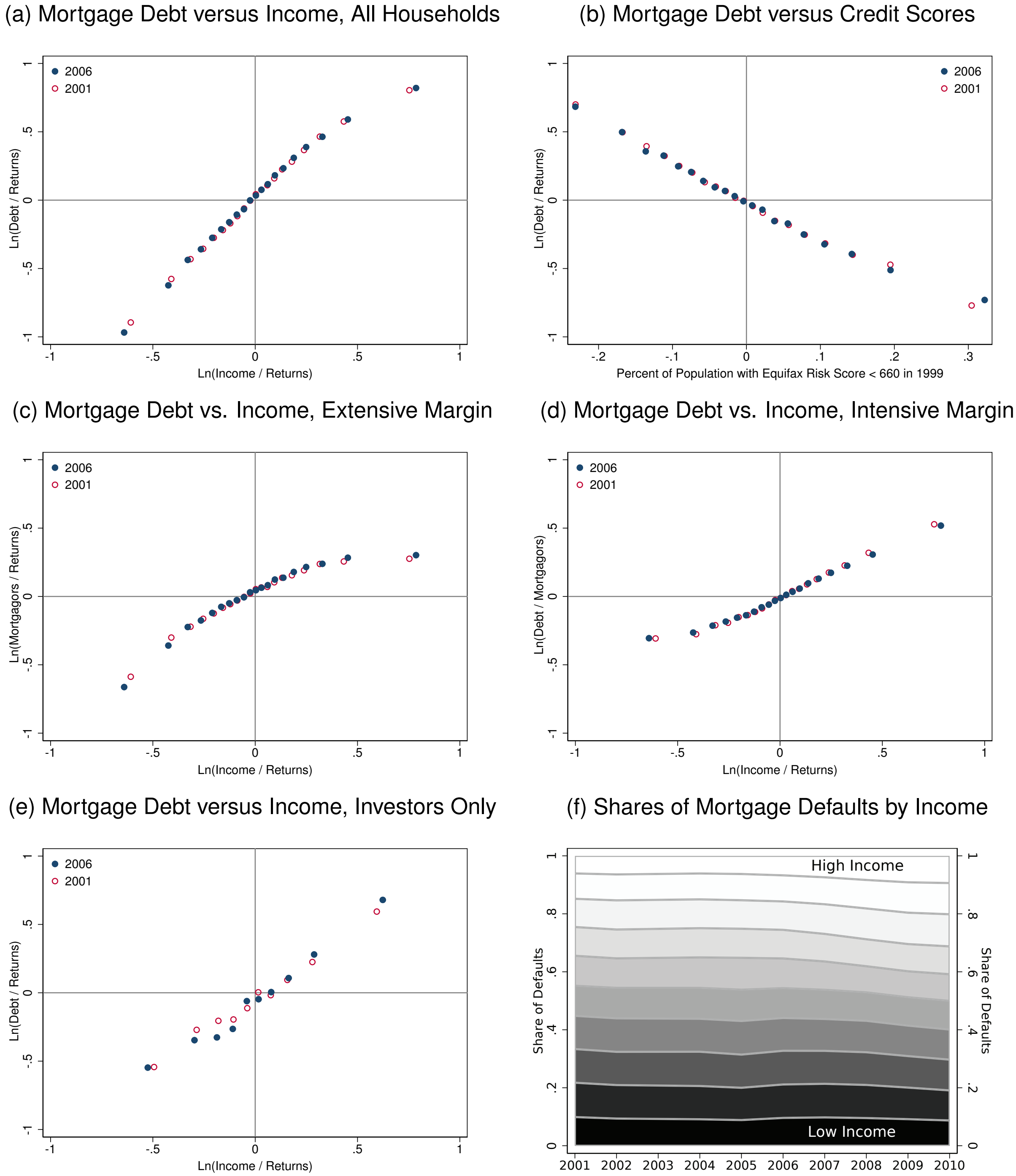


Figure 4. Evolution of Various Indicators. *Note:* All panels except for panel 4f are binned scatter plots of zip-code-level measures in the New York Fed Consumer Credit Panel. We compare 2001 and 2006 in all panels except panel 4f, where we plot shares of defaults by within-CBSA household-weighted deciles of salary and wage income per household. All binscatters are constructed by deviating both the debt and income variables from CBSA means, separately in 2001 and 2006, and then averaging these deviations into 10 or 20 household-weight quantiles for each year. *Sources:* NY Fed Consumer Credit Panel/Equifax and IRS Statistics of Income.

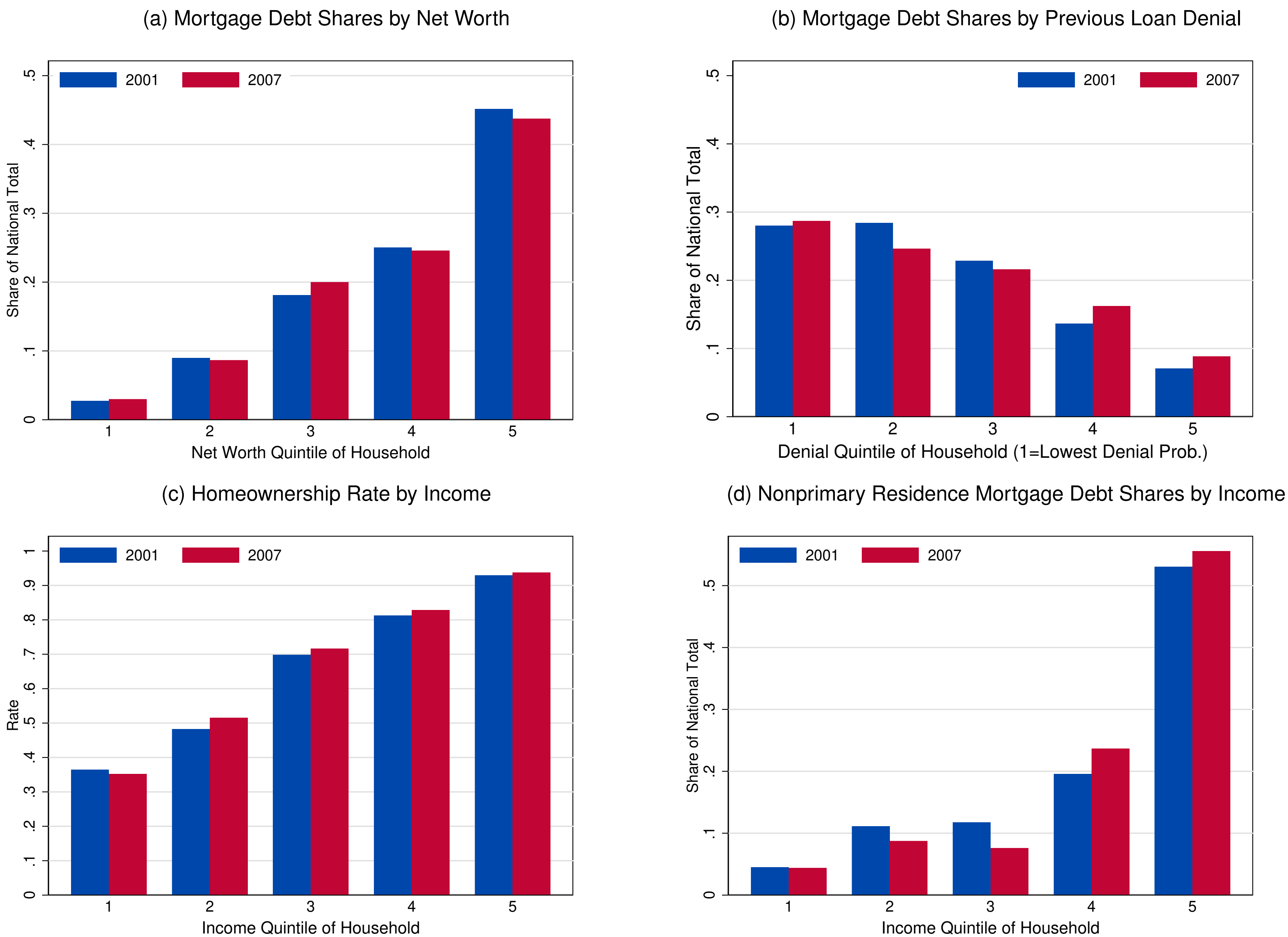


Figure 5. The Distribution of Mortgage Debt in the SCF. *Note:* Each panel shows the share of mortgage debt held in 2001 and 2007 by quintiles of households in the SCF. The probability of denial is the predicted value from a logit regression of an indicator of whether a household was denied credit or feared being denied credit over the last five years. *Source:* Federal Reserve, Survey of Consumer Finances.

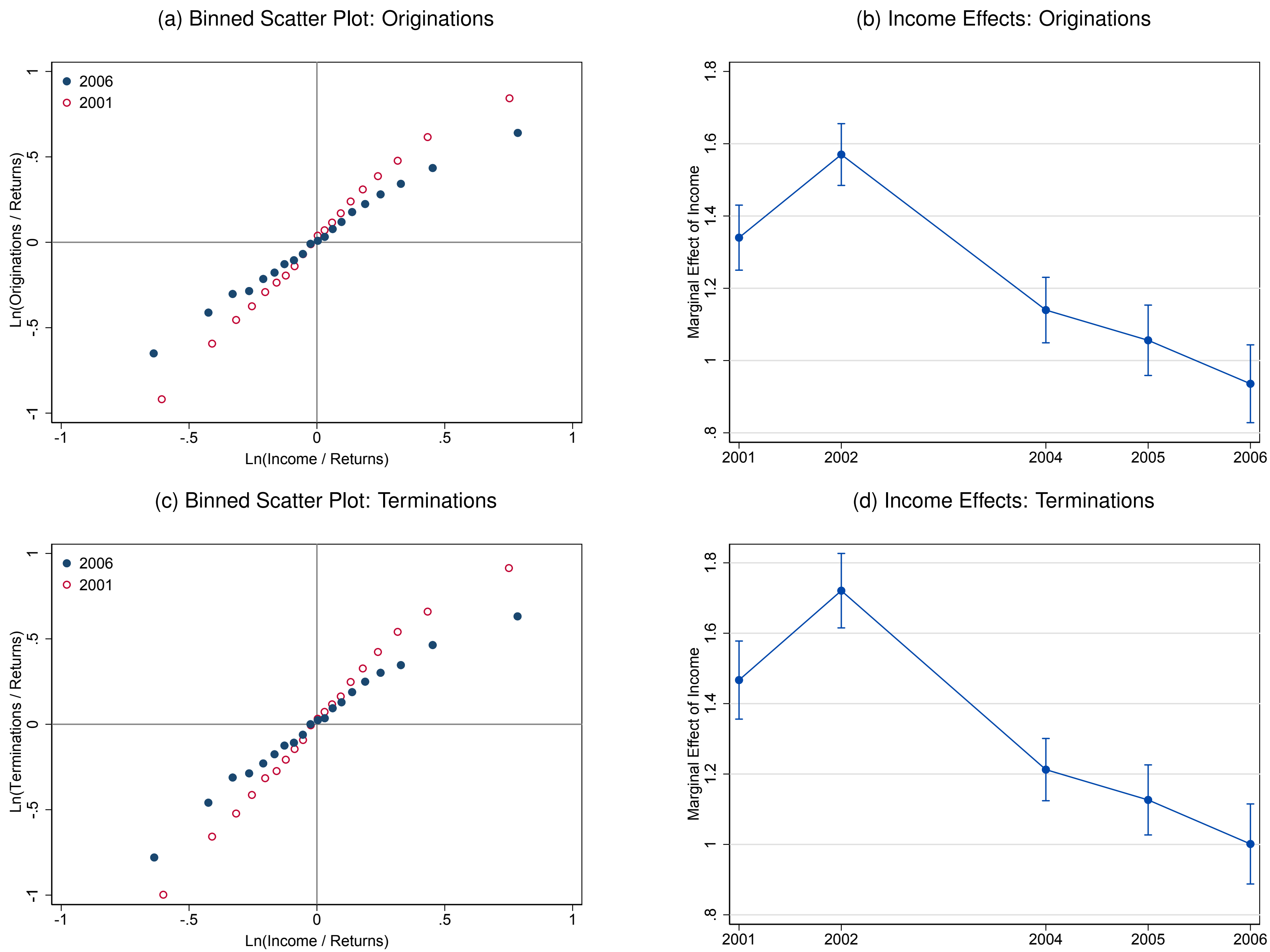


Figure 6. The Relationship Between Gross Mortgage Flows and Wage and Salary Income. *Note:* The binned scatter plots in the panels at left are generated from deviations of the log of the dollar value of originations or terminations per tax return and the log of wage income per tax return from CBSA $\times$ year means. The income coefficients in the panels at right are generated from returns-weighted regressions of either log originations or terminations per tax return on both income $\times$ year interactions and CBSA $\times$ year fixed effects. Standard errors are clustered by CBSA. *Sources:* NY Fed Consumer Credit Panel/Equifax and IRS Statistics of Income.

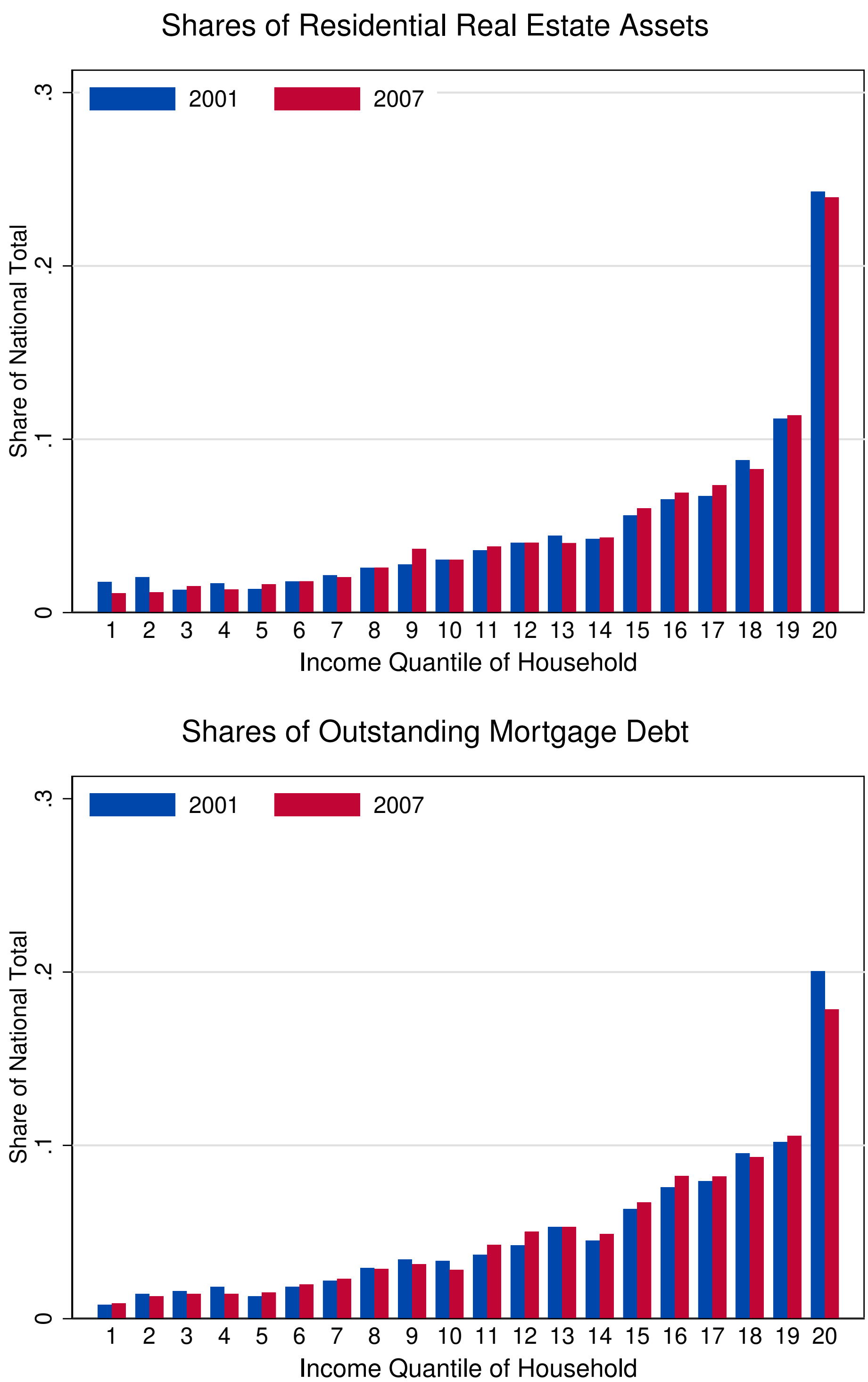
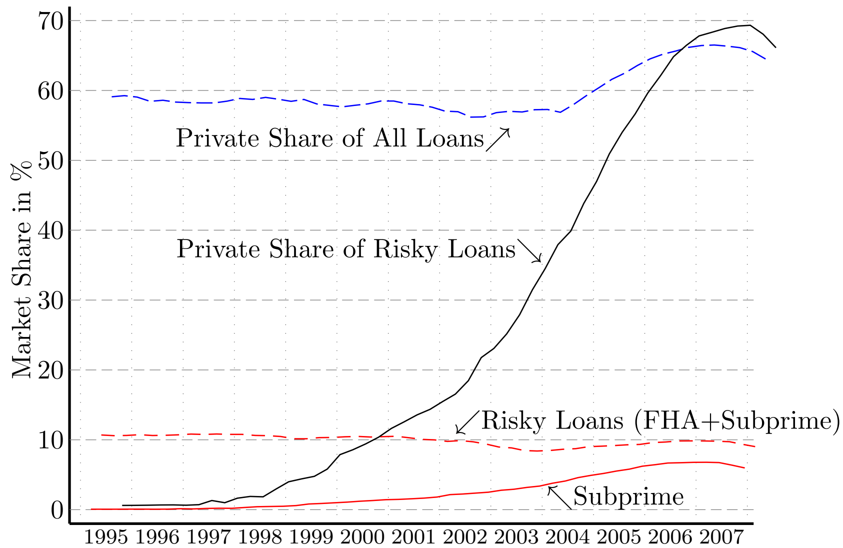


Figure 7. SCF Distributions of Mortgage Debt and Residential Real Estate Assets for 2001 and 2007 using 20 Income Quantiles. *Note:* The bins are based on wage and salary income. All households with zero wage and salary income are removed. Real estate refers solely to residential real estate. *Source:* Federal Reserve, Survey of Consumer Finances.



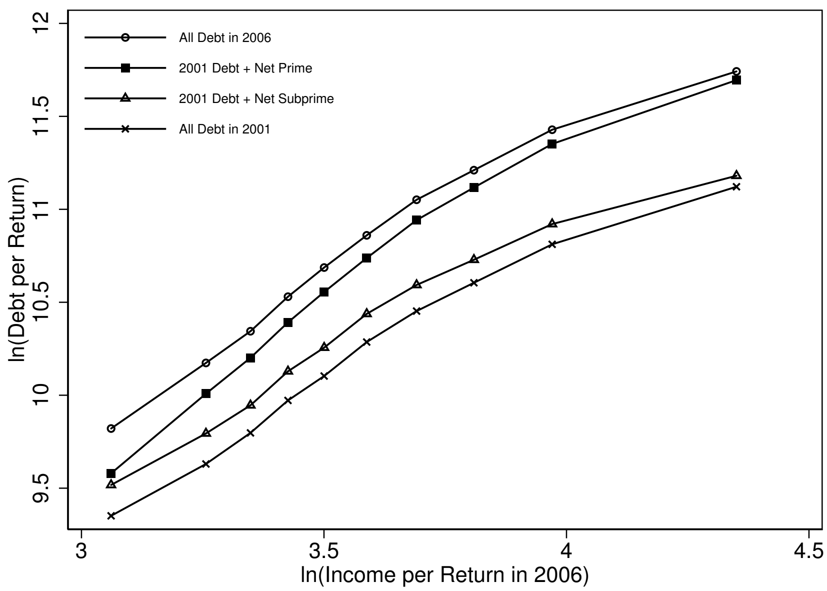


Figure 8. Subprime, FHA and the Growth of Lending to Marginal Borrowers *Note:* The top panel plots the share of the stock of mortgage debt not insured by government agencies (which we call the private share of mortgage debt). Risky loans are defined as the sum of FHA-insured loans and subprime. The stock of outstanding subprime debt comes from the CoreLogic ABS database. The remaining values are calculated from a table of historical mortgage debt outstanding that is produced by the Federal Reserve Board of Governors (https://www.federalreserve.gov/data/mortoutstand/current.htm). Outstanding FHA-insured loans are defined as the sum of loans on one- to four-family residences in Ginnie Mae pools, on Ginnie Mae's balance sheet, or otherwise insured by the FHA. The bottom panel shows how the stock of mortgage debt would have grown had there been only prime debt or only subprime debt. *Sources:* CoreLogic ABS database, Federal Reserve Board of Governors, and the NY Fed Consumer Credit Panel/Equifax.

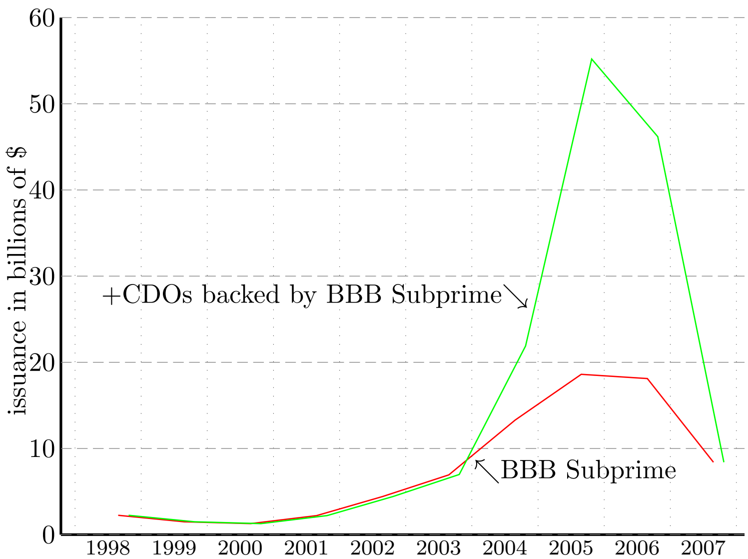


Figure 9. The Role of Synthetic CDOs. *Note:* This figure is based on Table 11 of Cordell, Huang, and Williams (2012). Cordell et al. do not break down CDO issuance into synthetic and cash CDOs, so we assume that issuers exhaust all BBB bonds in cash CDOs before they issue any synthetics. This assumption means we will always underestimate synthetic CDO issuance and therefore total issuance of debt tied to BBB-rated subprime securities. *Source:* Calculations in Cordell, Huang, and Williams (2012).

A. MODEL APPENDIX

This model builds on Hornstein (2009).

A.1. Household Problem

Infinitely lived representative households are composed of $N(t) = N(0)e^{nt}$ individuals. Households receive labor income, can borrow and save, and can allocate their expenditure across a consumption good and housing. Households maximize

$$\int_{t=0}^{\infty} e^{-\rho t} N(t) \log\left[\left(\frac{h(t)}{N(t)}\right)^{\theta} c(t)^{1-\theta}\right] dt$$

where ρ is the subjective discount rate; N is household size, which grows at rate $\dot{N}/N = n$; h is real units of housing; and c is consumption.

Household wealth a grows at:

$$\dot{a}(t) = N(t)y(t) + r(t)a(t) - N(t)c(t) - p(t)x_h(t). \tag{17}$$

The dynamics of the stock of housing follows:

$$\dot{h}(t) = x_h(t).$$

We assume that the aggregate stock of housing is fixed and does not depreciate (think of it as land).

We assume that all households share the same individual income growth rate $\dot{y}/y = g$, discount factor ρ, and household size N, and face a flow limit on how much they can spend on housing relative to income:

$$r(t)p(t)h(t) \leq \phi N(t)y(t). \tag{18}$$

Integrating equation (17) forward using integration-by-parts and the no-Ponzi-game condition ($\lim_{T\to\infty} e^{-R(t,T)}a(T) = 0$, where $R(t,T) = \int_{s=t}^{T} r(s)ds$) yields the lifetime budget constraint:

$$\int_{s=t}^{\infty} e^{-R(t,s)} \left(N(s)c(s) + p(s)\left(r(s) - \dot{p}(s)/p(s)\right)h(s)\right) ds = a(t) + p(t)h(t) + \int_{s=t}^{\infty} e^{-R(t,s)} N(s)y(s) ds. \tag{19}$$

The Hamiltonian is:

$$H = N\log((h/N)^{\theta}c^{1-\theta}) + \lambda\,(ra + Ny - Nc - px_h) + \mu(x_h) + \psi(rph - \phi Ny).$$

The first-order conditions (FOCs) are:

$$\begin{aligned}
\lambda &= (1-\theta)/c \\
p\lambda &= \mu \\
\dot{\lambda} &= \rho\lambda - \tfrac{\partial H}{\partial a} = \rho\lambda - r\lambda = (\rho - r)\lambda \\
\dot{\mu} &= \rho\mu - \tfrac{\partial H}{\partial h} = \rho\mu - \theta\frac{N}{h} - \psi rp.
\end{aligned}$$

Households can differ in θ, $y(0)$, and their endowments of housing. We assume that there exist lender and borrower households. At time 0, lender households own all the housing. Both lenders and borrowers start with zero assets ($a(0) = 0$ for all households). Borrowers have no endowment of h or a. Lenders have no labor income ($y_L = 0$), no endowment of ($a_L(0) = 0$), an endowment of $\overline{h}$ units of housing, and they derive no utility from consuming housing services ($\theta_L = 0$).

We assume that there are two types of borrowers. Type $b1$ and $b2$ borrowers differ in income $y_{b2} > y_{b1}$ and preference for housing $\theta_{b1} > \phi(\rho-n)/(\rho+g) > \theta_{b2}$, which, in equilibrium, implies that type $b1$ borrowers are constrained and type $b2$ borrowers are unconstrained. We justify the negative correlation between θ and y by pointing to a large literature on the link between budget shares on housing and income (see Federal Housing Administration 1947 and, more recently, Albouy, Ehrlich, and Liu 2016).

This implies that the FOCs for unconstrained households are:

$$\frac{\dot{c}}{c} = r - \rho.$$

$$\frac{\theta_{2b}c_{2b}}{(1-\theta_{2b})h_{2b}/N} = p(r - \frac{\dot{p}}{p}). \tag{20}$$

A.2. Equilibrium

In equilibrium, there is balanced growth with

$$r(t) = r = \rho + g \tag{21}$$

and

$$\frac{\dot{p}(t)}{p(t)} = g + n,$$

which implies that:

$$r(t) - \frac{\dot{p}(t)}{p(t)} = \rho - n.$$

Consumption for constrained households is:

$$c_{1b} = (\rho - n)(a + ph_{1b})/N + \left(1 - \frac{\phi(\rho - n)}{\rho + g}\right) y_{1b}, \tag{22}$$

and their real estate holdings are:

$$h_{1b} = \phi N y_{1b}/rp. \tag{23}$$

Individual consumption for unconstrained households is:

$$c_{2b} = (1 - \theta_{2b})\left(y_{2b} + (\rho - n)(a + ph_{2b})/N\right), \tag{24}$$

and their real estate holdings are:

$$h = \frac{\theta N y}{p \cdot (r - \dot{p}/p)}. \tag{25}$$

To derive equation (24), we use equations (19), (20) and (21). Equation (20) implies that:

$$Nc_{2b} + p(r - \frac{\dot{p}}{p})h_{2b} = (1/1 - \theta_{2b})Nc_{2b}.$$

Balanced growth implies that $y(t) = y(0)e^{gt}$ and $c(t) = c(0)e^{gt}$. Equation (21) implies that $R(t) = (\rho + g)t$. As a result, we can rewrite equation (19) as:

$$1/(1-\theta)\int_{s=t}^{\infty} e^{-(\rho+g)(s-t)} c_{2b}(t) e^{g(s-t)} N(t) e^{n(s-t)} ds = \\ a(t) + p(t)h_{2b}(t) + \int_{s=t}^{\infty} e^{-(\rho+g)(s-t)} y_{2b}(t) e^{g(s-t)} N(t) e^{n(s-t)} ds \tag{26}$$

or

$$\tfrac{1}{1-\theta}c_{2b}(t)N(t)/(\rho-n)=a(t)+p(t)h_{2b}(t)+N(t)y_{2b}(t)/(\rho-n),$$

which we re-arrange to get equation (24). The derivation of equation (22) is similar.

If α is the share of type $b1$ borrowers in the economy, and $\overline{h}$ is the aggregate stock of housing then:

$$p=\frac{N}{\overline{h}}\left((1-\alpha)\frac{\theta_{b2}y_{b2}}{r-\dot{p}/p}+\alpha\frac{\phi y_{b1}}{r}\right)=\frac{N}{\overline{h}}\left((1-\alpha)\frac{\theta_{b2}y_{b2}}{\rho-n}+\alpha\frac{\phi y_{b1}}{\rho+g}\right). \tag{27}$$

Implications for the cross-section of housing assets follow from the substitution of the equilibrium price (equation [27]) into the demand function for constrained households (equation [23]):

$$\frac{h_{b1}}{\overline{h}}=\frac{\alpha\frac{\phi y_{b1}}{\rho+g}}{(1-\alpha)\frac{\theta_{b2}y_{b2}}{\rho-n}+\alpha\frac{\phi y_{b1}}{\rho+g}}. \tag{28}$$

A.3. Endogenous Constraint

The endogenous constraint replaces equation (18) with a constraint that depends on the user cost of housing rather than just the interest cost:

$$p(r-\dot{p}/p)h\le\overline{\theta}Ny. \tag{29}$$

The equilibrium price with the endogenous constraint is

$$p=\frac{N}{\overline{h}}\frac{(1-\alpha)\theta_{b2}y_{b2}+\alpha\overline{\theta}y_{b1}}{r-\dot{p}/p}=\frac{N}{\overline{h}}\frac{(1-\alpha)\theta_{b2}y_{b2}+\alpha\overline{\theta}y_{b1}}{\rho-n}, \tag{30}$$

meaning that the equilibrium share of constrained households is:

$$\frac{h_{b1}}{\overline{h}}=\frac{\alpha\overline{\theta}y_{b1}}{(1-\alpha)\theta_{b2}y_{b2}+\alpha\overline{\theta}y_{b1}}. \tag{31}$$

Equation (15) shows that with the endogenous constraint, shocks to n or ρ have no effect on the allocation of housing across the population. In other words, an increase in n or ρ can generate an increase in house prices without any cross-sectional reallocation of house spending.

A.4. Different Assumption about Capital Gains

We compare equilibrium allocations pre- and post-shocks based on the assumption that lenders and borrowers start with the same initial allocations (essentially that lenders own all real estate). We now show that this assumption does not affect our findings.

Let p' and h' be prices and demand after the shock, which occurs at time t. In the text, we assume that $a(t) = 0$ and $h(t) = 0$ for all borrower households and $h(t) = \overline{h}$ for lender households. Suppose instead we assume that borrowers retain ownership of their homes at time t. This implies that assets for borrowers post-shock are $a(t) = -ph$, and the value of their real estate is $p'h$. Assets for lenders are $a(t) = ph$.

Assume there is a shock that raises ϕ. Using equations (24) and (20), equilibrium holdings of housing for unconstrained borrowers are now:

$$\begin{aligned} h'_{2b} &= \theta_{2b}\tfrac{Ny_{2b}+(\rho-n)(p'-p)\bar{h}}{p'(\rho-n)} \\ &= \theta_{2b}\tfrac{Ny_{2b}}{p'(\rho-n)} + \theta_{2b}\tfrac{p'-p}{p'}\bar{h}. \end{aligned}$$

If we divide through by $\bar{h}$, we get:

$$\frac{h'_{2b}}{\bar{h}} = \frac{p}{p'} + \theta\frac{p'-p}{p'}.$$

As long as $\theta < 1$, unconstrained households will consume less housing in response to the relaxation of the constraint.

A.5. Rental Market

We now add a rental market and show two key results. First, if borrowers do not face constraints on their spending in the rental market, then an exogenous relaxation in credit constraints has no effect on either prices or equilibrium allocations of housing. The only potential effect is to increase the homeownership rate. This result parallels that of Kaplan, Mitman, and Violante (2019), who draw similar conclusions in a much richer framework. Second, if borrowers face limits on spending in the rental market, then an exogenous relaxation of the constraint can lead to an increase in house prices, but it will have no effect on the price-rent ratio. In contrast, a shock to house price growth always leads to increases in prices and the price-rent ratio regardless of whether there are binding constraints.

Borrowers can choose either to rent or to own with different budget constraints:

$$\text{Owner:} \quad \begin{aligned} \dot{a}(t) &= N(t)y(t) + r(t)a(t) - N(t)c(t) - p(t)x_h(t) \\ \dot{h}(t) &= x_h(t) \end{aligned}$$

$$\text{Renter:} \quad \dot{a}(t) = N(t)y(t) + r(t)a(t) - N(t)c(t) - \text{rent}(t)h(t).$$

If a household chooses to rent, then the lifetime budget constraint is

$$\int_{s=t}^{\infty} e^{-R(t,s)} \left(N(s)c(s) + rent(s)h(s)\right) ds = a(t) + \int_{s=t}^{\infty} e^{-R(t,s)} N(s)y(s)ds.$$

For owners, equation (19) remains the same. The dynamic budget constraint for lenders is now:

$$\begin{aligned} \dot{a}(t) &= \text{rent}(t)h(t) + r(t)a(t) - N(t)c(t) + p(t)x_h(t) \\ \dot{h}(t) &= x_h(t). \end{aligned}$$

Lenders still derive no utility from housing, but they can now choose to either lend borrowers the money to buy a house or retain the properties and rent them. The intratemporal housing optimization condition for investors ensures that the rent equals the user cost:

$$\underbrace{(r - \frac{\dot{p}}{p})p}_{\text{user cost}} = \text{rent}. \tag{32}$$

The intratemporal housing optimization condition for households implies that:

$$\frac{c}{h}\left(\frac{\theta}{1-\theta}\right) = \underbrace{(r - \frac{\dot{p}}{p})p}_{\text{user cost}} = \text{rent}.$$

It is easy to see that unconstrained borrowers and lenders will be indifferent between owning and renting. If, as in Kaplan, Mitman, and Violante (2019), there are no constraints in the rental market, then borrowers facing binding constraints will always rent. Relaxing the borrowing constraint will have no effect on prices or rents. The only potential effect is that if the constraint is no longer binding, some households will switch from preferring renting over owning to indifference, which is why relaxing the constraint can increase the homeownership rate.

It is important to stress that equation (32) implies that the price-rent ratio equals $\rho - n$. It is therefore independent of any constraints on spending on housing. This holds *even* if we put binding constraints on the amount that households can spend on rent:

$$\text{rent} \cdot h \leq \phi_{rent} y.$$

In other words, only a shock to house price growth, which assumes an increase in the population growth rate n, would generate an increase in the price-rent ratio.

B. DATA AND REGRESSIONS APPENDIX

B.1. Reconciling Previous Results in the Literature

In this section we will reconcile our empirical results with those from Mian and Sufi (2009) and Adelino, Schoar, and Severino (2016). We also settle two remaining debates between those two papers. The first debate concerns the use of individual-level borrower income from HMDA versus zip-code-level income from the IRS. The second debate concerns the role of second liens in HMDA.

B.1.1. Mian and Sufi's Debt-Stock Regression

Although virtually all the regressions in Mian and Sufi (2009) involve the *flow* of debt, one regression has growth in the *stock* of debt on the left-hand side. This regression, reprinted as column 1 in Table B.1, shows a statistically significant and positive effect of a zip code's share of subprime borrowers on debt growth between 2002 and 2005. Yet this coefficient is economically small. Theoretically, the subprime fraction can range from zero to one, so a coefficient estimate of 0.050 implies that a zip code where *all* residents were subprime borrowers in 1996 would experience a 5 percentage point higher increase in annualized mortgage debt growth from 2002 to 2005 relative to a zip code with *no* subprime borrowers. Yet the true range of the subprime fraction is much smaller. As displayed in the lower panel of Table B.1, the standard deviation of the subprime fraction is only 0.113, so the implied two-standard-deviation effect of the subprime fraction is $2 \times\ 0.113 \times 0.050 = 0.011$, or 1.1 percentage points. This is a small effect relative to the average debt-growth rate of 0.145 (14.5 percent). Note also that the stock regression in Mian and Sufi's main text is run on their baseline sample of about 3,000 zip codes. These zip codes are those with Case-Shiller price data, but price data are not needed for this regression. Accordingly, in the online appendix the authors run the debt-stock regression on a larger sample of about 17,500 zip codes. The resulting subprime coefficient is even smaller (0.031 versus 0.050).[1]

[1] The two-standard-deviation effect is $2 \times 0.128 \times 0.031 = .008$. The mean of the dependent variable in the larger sample is 0.125.

Even this subprime effect is too large, because the regression in Mian and Sufi (2009) is misspecified. Once the regression is correctly specified, the coefficient on percent subprime is statistically insignificant. As pointed out by Adelino et al. (2016), the flow regressions in Mian and Sufi's paper regress *total originations* in a zip code on income *per return*. The same is true in their stock regression, where the dependent variable is the change in the total stock of debt in a zip code from 2002 to 2005. Consequently, changes in the number of households in a zip code distort their results.

We illustrate this point in Table B.1. Column 1 is the original regression from Table V of Mian and Sufi (2009). Columns 2 and 3 are our replications of their result. It is unclear whether the regression in Mian and Sufi (2009) is weighted, so column 2 is unweighted, whereas in column 3 we weight the zip-code-level observations by the number of tax returns in 2002. Column 3 comes closer to the Mian-Sufi results. Like Mian and Sufi, we find a small positive coefficient on the subprime fraction, although ours is smaller than theirs (0.0460 versus 0.050). There are a number of reasons why we cannot replicate their result exactly, which we detail below.

In column 4, we add growth in the number of tax returns (our proxy for household growth), which enters very significantly and dramatically improves the fit of the regression. The large coefficient on establishment growth declines, indicating that this variable had been proxying to some extent for changes in population in the earlier regressions. Most importantly, the subprime coefficient declines by about 45 percent, to 0.0269, and is no longer statistically significant. Because the returns-growth coefficient is estimated to be close to 1, the other coefficients are little changed when debt-per-return is used as the dependent variable, as in column 5.

We were not able to replicate Mian and Sufi's debt-stock regression exactly because we are missing a few pieces of information. First, we don't have access to their data on the fraction of subprime borrowers in each zip code as of 1996. The Equifax records in the New York Fed Consumer Credit Panel begin in 1999, so we can calculate subprime fractions for that year. Second, we don't have the zip-code-level crime data. It turns out that the crime data are not important for our results, although they could help generate the specific subprime coefficient that Mian and Sufi estimated. Lastly, we cannot replicate the sample of zip codes used by Mian and Sufi exactly, although we are confident that we come close. This sample is defined by the availability of Case-Shiller house price data. Our investigation of that data indicates that about 3,000 zip codes had house price data that were not imputed from some larger geographical area (such as county or metropolitan statistical area). We are confident that this small sample of zip codes approximates Mian and Sufi's baseline sample.

B.1.2. The Purported Negative Correlation between Income and Debt

The central finding in Mian and Sufi (2009) is that zip-code-level growth in income is *negatively correlated* with growth in HMDA purchase-mortgage originations between 2002 and 2005.[2] This result comes from a regression of the *change* in the *total* flow of purchase-mortgage originations (the aggregate dollar value) between the two years on the corresponding *change* in IRS income:

$$\Delta Purchase\ Originations_{i,2002-05} = \delta \Delta Income_{i,2002-05} + \phi_{county} + \epsilon_i, \tag{33}$$

where i indexes zip codes and ϕ_{county} are county-level fixed effects. The estimated negative coefficient for δ in this regression is the source of the claim for a negative correlation.[3] Looking across other subperiods of their data, the authors find no other negative correlations between income growth and growth of purchase-mortgage credit. Mian and Sufi (2009) therefore interpret the negative correlation for 2002–2005 as a fundamental change in lending patterns at the height of the boom.[4]

The regression in Mian and Sufi (2009) is misspecified. To see why, note that the regression is in growth rates, not levels. Using log differences as a growth rate, we can rewrite their regression as:

$$\Delta Purchase\ Originations_{i,2002-05} = \\ \delta \ln(Income_{i,2005}) - \delta \ln(Income_{i,2002}) + \phi_{county} + \epsilon_i.$$

This form of the regression illustrates that it is appropriate to project debt changes on income changes only when the lending-income relationship is stable across the two years, that is, if the levels relationship equals δ in both 2002 and 2005. This is an appropriate assumption in most panel-data studies, but the whole point of the lending-income regression in Mian and Sufi (2009) is to determine whether the relationship between lending and income changed between 2002 and 2005.

One can specify a regression in changes to test for an evolution in the lending-income relationship. The correct regression in changes can be built up from two levels regressions. Consider any left-hand-side variable y and independent variable x. We can write the levels

[2] The negative-correlation finding appears in both Figure III and Table IV of Mian and Sufi (2009), and involves income and credit growth relative to county means. The original paper uses zip-code-level data from one year (1991) that are no longer made publicly available by the IRS, due to concerns about data quality.

[3] Of course, a *regression* coefficient is not the same as a *correlation* coefficient, and a large absolute value for a regression coefficient is consistent with a small correlation if the R^2 from the regression is small. This case is relevant for debt and income at the zip-code level, as the low R^2 in the Mian-Sufi regressions mean that true correlations between income growth and credit growth are always very small.

[4] This finding has proven highly influential among economists studying the mortgage boom. By the fall of 2017, Mian and Sufi (2009) had accumulated more than 1,500 Google Scholar citations.

relationships between y and x in two potential periods as

$$y_1 = \beta_1 x_1 \quad \text{and} \quad y_2 = \beta_2 x_2,$$

where error terms are ignored for convenience. Some algebra shows that the change in y from period 1 to period 2 can be written in two ways:

$$\Delta y = \beta_2 \Delta x + (\beta_2 - \beta_1) x_1$$
$$\Delta y = \beta_1 \Delta x + (\beta_2 - \beta_1) x_2.$$

Both of these equations suggest a regression of Δy on the change in x and a level of x. If the first-period level x_1 is used, as in the first equation, then the coefficient on Δx will be the levels relationship in the second period, β_2. The opposite situation occurs in the second equation. Note that in both cases, however, the change in the relationship $\beta_2 - \beta_1$ is easily estimated as the coefficient on the included level term, either x_1 or x_2. The intuition behind this interpretation is straightforward. In our application, the level regressor will tell us whether (say) poorer zip codes experienced higher growth in new mortgage debt than richer ones, after conditioning on income growth within each zip code. If this higher growth occurred, then the levels relationship between new debt and income must have changed.

The two equations also illustrate that omitted-variables bias will result if the levels term is omitted from a lending-income regression that is specified in differences. Standard econometric theory implies that the direction of this bias will depend on two factors, the first being the sign of the coefficient on the omitted variable. The second factor involves the correlation between Δx and levels of x. In our application, this correlation relates the growth rate of income between 2002 and 2005 for high-income and low-income zip codes.

We can directly sign the first factor of the bias. The coefficient on the omitted variable is equal to $\beta_2 - \beta_1$. To illustrate the sign of the omitted-variables bias, we run a yearly level regression of the *total amount of newly originated purchase-mortgage debt* on average income at the zip-code level. The top panel of Figure B.1 contains the results. We can see β declines during the housing boom, making $\beta_2 - \beta_1$ negative.

We explore the omitted-variables bias empirically in Table B.2. The first two columns most closely approximate the specification in Mian and Sufi (2009). The first regression, denoted Model 1, follows Mian and Sufi (2009) by using growth in the total dollar value of purchase-mortgage originations from HMDA on the left-hand side. The income measure is the change in average IRS income in the zip code. The model replicates the negative coefficient on income growth that Mian and Sufi also found.[5] Model 2 in the next row adds

[5]We replicate the sign, but not the exact numerical estimate in Mian and Sufi (2009). This is for a few reasons. We do not use annualized growth rates, and we also use growth rates between 2002 and 2006,

the income level of each zip code as of 2006. This regression shows that what Mian and Sufi (2009) characterize as a *negative correlation* is in reality the *decline in a positive correlation*, equivalent to the pattern that was displayed in the top panel of Figure B.1.

B.1.3. The Debate between Mian and Sufi (2009) and Adelino, Schoar, and Severino (2016)

The innovation in Adelino, Schoar, and Severino (2016) is that they split the dependent variable from the regression in Mian and Sufi (2009) into the *number* of purchase mortgage originations and their *average values*. A replication of the Adelino et al. result appears as Model 3 in Table B.2. This model confirms the discussion in Adelino, Schoar, and Severino (2016): The most significant change in origination patterns relates to greater numbers of new mortgages in low-income areas, not to higher average mortgage amounts. In particular, about nine-tenths (= 0.34/0.38) of the decline in the estimated income effect in Model 2 occurs through a relative increase in the number of mortgages in low-income zip codes. The rest is due to larger mortgage sizes.

However, the critical distinction between levels and changes is unclear in Adelino, Schoar, and Severino (2016). For the most part, the authors emphasize results from growth-on-growth regressions that omit income-level terms.[6] In the bottom two panels of Figure B.1 we plot results from levels regressions using the average loan amount and number of loans originated on the left-hand side. This confirms and clarifies the result in Adelino, Schoar, and Severino (2016). The β_t for the average mortgage amount in the bottom left panel does not vary significantly over time. Mathematically, if the average size of new mortgages is rising proportionately during the boom, while the total amount of new mortgage debt is growing faster in the low-income areas, then it must be the case that the *number* of new mortgage originations is growing faster in the low-income zip codes. The bottom right panel of Figure B.1 verifies that this is true.

Adelino, Schoar, and Severino (2016) also include individual-level regressions of mortgage origination amounts on income using HMDA data. These show little change in the debt-income relationship over the course of the 2000s housing boom. Mian and Sufi (2017) counter the critique in Adelino, Schoar, and Severino (2016) in two ways. First, they claim that any regressions using individual income from HMDA are invalid because HMDA income suffers from borrowers misreporting their income on their loan applications. We consider this debate settled. In Foote, Loewenstein, and Willen (2018), we show that the results in

rather than 2002 and 2005. Our choice of years is motivated by the large change in the originations-income relationship between 2002 and 2006. Regressions using other years generate similar results and are available from the authors on request.

[6] One table (Table 10) of Adelino, Schoar, and Severino (2016) is estimated in levels. This table suggests a flattening out of the relationship between the number of purchase-mortgage originations and income, but no such flattening for average origination amounts.

Adelino, Schoar, and Severino (2016) are independent of the measure of income used. In that paper, we show that the results using HMDA income are identical to those using income from the American Housing Survey (AHS), which does not suffer from the same problems. We also instrument for HMDA income using census income to confirm that any overstatement of income in HMDA is not masking a declining relationship between mortgage debt originations and income during the 2000s. It is not: The relationship during the housing boom is flat.

The second rejoinder in Mian and Sufi (2017) is that they claim that after correcting for the presence of second liens in HMDA, there was a negative correlation between the *average* mortgage amount originated and income when running their *original misspecified regression* with HMDA data from 2004 and 2006.[7] Using an algorithm to identify second liens in HMDA (this algorithm is described in Foote, Loewenstein, and Willen 2018) and our correctly specified regression, we show that this is incorrect.

The two middle columns of Table B.2 replicate the previous regressions after correcting for the presence of second liens in HMDA. This adjustment makes effectively no difference to the original misspecified regression run in Mian and Sufi (2009), which had total mortgage debt originations on the left-hand side, nor the corrected regression that includes the 2006 level of income. However, it does make a difference to the regression with average mortgage origination amounts on the left-hand side. Now the change in the coefficient from 2002 to 2006 is significant and negative. The average mortgage amount did increase more in lower-income zip codes from 2002 to 2006. However, as we will discuss in the next section, the question is not whether mortgage flows increased more, but whether the outstanding stock of mortgage debt on balance sheets grew more in lower-income zip codes.

The contribution of this paper is to note that the question of whether mortgage debt was reallocated toward low-income borrowers requires studying the *stock* of debt, not just the inflows.[8] In Model 4a, we run the regression using the growth rate of a standard mortgage debt variable in our earlier paper, namely, the stock of household-level mortgage debt aggregated at the zip-code level and normalized by the zip code's number of tax returns.

Consistent with the debt-stock results in the earlier work, the small coefficient on the income-level term (–0.05) suggests no large changes in the stock of debt across the income distribution. Model 4b splits the debt-growth variable into two parts: the growth rate of mortgage debt per household (upper row) and the growth rate of the total number of mortgaged households (lower row).[9] Ignoring rounding, the two income-level coefficients

[7]See Table 1 in Mian and Sufi (2017). They use 2004 as the starting year because that is the first year second liens are identified in the public HMDA data.

[8]Higher originations may not send the stock of debt higher if the rate of mortgage terminations also increases. The labor markets analogy is that a higher job finding rate may not reduce the stock of unemployed workers if job separations rise as well.

[9]This decomposition interprets the number of tax returns as the number of households, as we did in the previous model and throughout FLW16.

in Model 4b must add up to the corresponding level coefficient of the aggregated model immediately above it, Model 4a. It is therefore not surprising that both of the income-level coefficients in Model 4b are small.

Up to now, for consistency with both Mian and Sufi (2009) and Adelino, Schoar, and Severino (2016), the models in this table have used AGI as the measure of zip-code-level income. The last two columns of Table B.2 use salary and wage income. There are two effects of doing so. First, the implied relationship in 2002 between the level of the stock of mortgage debt and the level of income strengthens—from 0.42 when using AGI to 0.74, an increase that is expected if AGI were a noise proxy for wages. A second and more important effect of using wage earnings is indicated by the very small coefficients on the levels terms in the new regressions. The very modest boom-era change in the debt-income relationship that are suggested by the levels terms in the AGI model falls to essentially zero when wage and salary income is used instead.[10]

B.2. Supplemental Figures

The following section includes supplemental figures either referenced in the main text or discussed below.

B.2.1. Unconditional Distributions of Mortgage Debt

The top panel of Figure B.5 depicts returns-weighted zip-code-level kernel distributions of log mortgage debt per return from the CCP/IRS. Over time, this distribution moves to the right and flattens out.[11] This would appear to be evidence against a credit expansion to previously underserved households, because such a shift would tighten the distribution of debt as low-debt households moved to the right more than high-debt households. The bottom panel of Figure B.5 shows that the introduction of CBSA fixed effects eliminates the widening of the distribution, but the resulting densities show no evidence that the debt of low-debt households went up relative to that of high-debt households. The two densities are, in fact, almost identical.

The CCP distributions indicate that some cities boomed and experienced high debt growth across all zip codes within the city, while other cities experienced less growth. But

[10]Two final differences between our regressions and those of both Mian and Sufi (2009) and Adelino, Schoar, and Severino (2016) are that we use all available zip codes and weight our regressions by the number of IRS tax returns. Both Mian and Sufi (2009) and Adelino, Schoar, and Severino (2016) limit their regressions to a subset of well-populated zip codes, which inadvertently leads to the same conclusions as weighting. Mian and Sufi (2009) and Adelino, Schoar, and Severino (2016) also do not drop nonoccupant owners from the HMDA data. We determined that this does not significantly affect the results, and have removed them from all the regressions reported thus far.

[11]The standard deviation rose from 0.41 in 2001 to 0.48 in 2006.

within each local market, debt grew at similar rates in high- and low-debt areas. The lack of any narrowing in the within-CBSA distributions is also inconsistent with the claim that the housing boom reallocated debt to areas within cities with previously low levels of debt.

	Mian-Sufi (2009)	Our Replication			
	(1)	(2)	(3)	(4)	(5)
Dependent Variable	ΔStock	ΔStock	ΔStock	ΔStock	Δ(Stock/Return)
Subprime Fraction	0.050**	0.0248	0.0460*	0.0269	0.0265
	(0.015)	(0.0198)	(0.0221)	(0.0147)	(0.0150)
Δ (Income/Return)	0.360**	0.178*	0.256**	0.188**	0.195**
	(0.044)	(0.0732)	(0.0942)	(0.0652)	(0.0684)
Δ Establishments	0.805**	0.775***	0.819***	0.227***	0.179***
	(0.058)	(0.151)	(0.109)	(0.0497)	(0.0478)
Δ Employment	–0.040	-0.00953	-0.0163	-0.0168	-0.0165
	(0.026)	(0.0193)	(0.0184)	(0.0121)	(0.0118)
Δ Crime	0.251*				
	(0.117)				
Δ Tax Returns				1.070***	
				(0.100)	
Weighted by Returns?	Not Mentioned	No	Yes	Yes	Yes
Standard Deviation of Subprime Fraction	0.113	0.139	0.135	0.135	0.135
2-SD Subprime Effect	0.011	0.007	0.012	0.007	0.007
Mean of Dep Var.	0.145	0.160	0.157	0.157	0.157
R-squared	0.33	0.44	0.48	0.63	0.49
N	2,946	3,092	3,092	3,092	3,092

Table B.1. Mian-Sufi Replications. *Note:* Parameter estimates and regression statistics in column 1 are reprinted from column 5, Table V, pp. 1472–1473 of Mian and Sufi (2009). The standard deviation of the subprime fraction in column 1 is taken from the summary-statistics table in Mian and Sufi (2009), as is the mean of the dependent variable. The subprime fraction in column 1 is the share of subprime borrowers in the zip code as of 1996. In columns 2–5, the subprime fraction is defined as of 1999, the first year for which Equifax debt data are available in the New York Fed Consumer Credit Panel. All growth rates are annualized percentage growth rates from 2002–2005. Income is defined as adjusted gross income (AGI). All regressions include county-year fixed effects. Standard errors in columns 2–5 are clustered by county. *Sources:* New York Fed Consumer Credit Panel/Equifax, IRS Statistics of Income, and Zip Code Business Patterns.

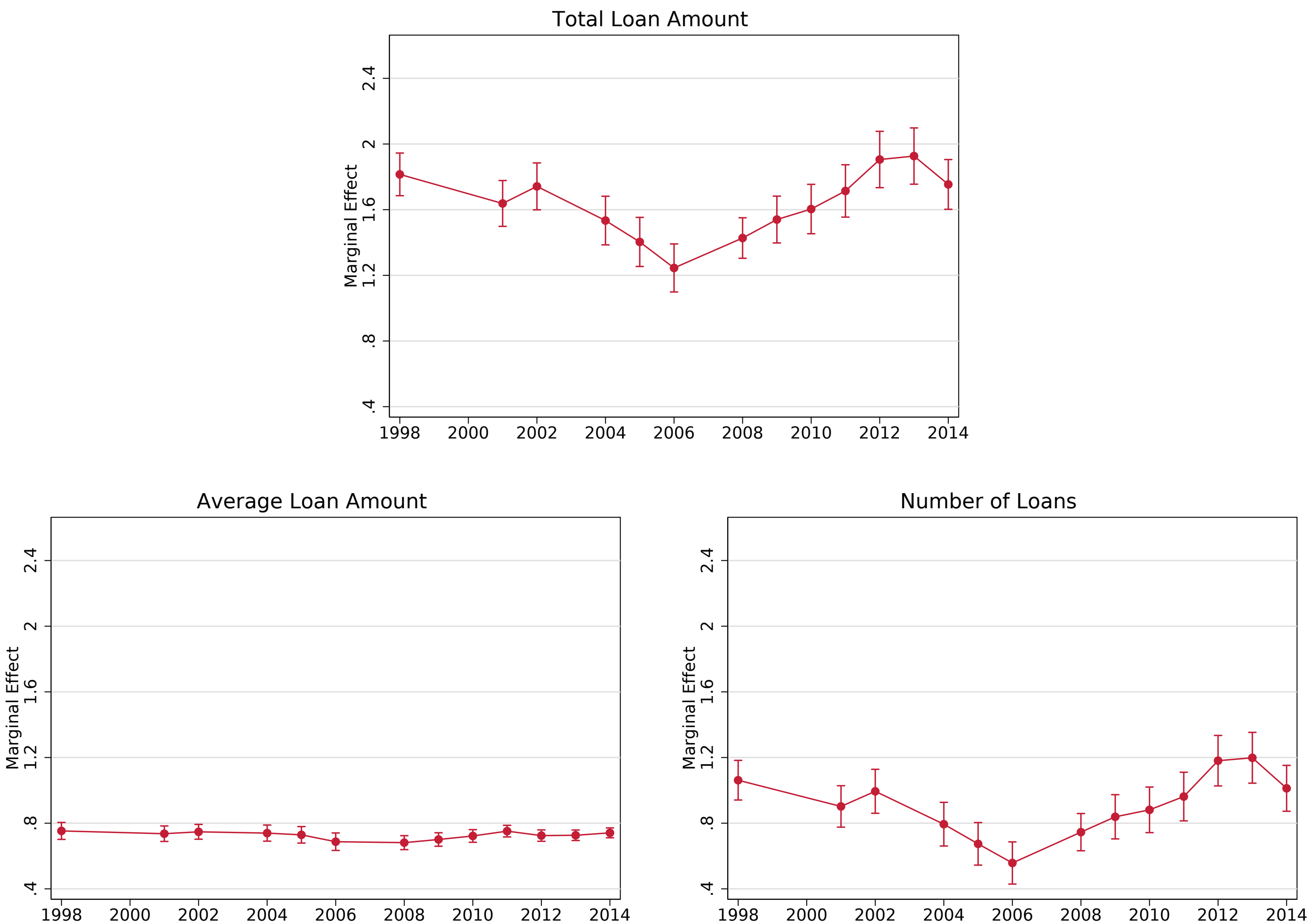


Figure B.1. Zip-Code-Level Mortgage Debt on Income. *Note:* These panels graph income coefficients (and 95 percent confidence intervals) from regressions of average purchase-mortgage origination amounts, total purchase-mortgage amounts, and the number of purchase-mortgage originations from HMDA on average salary and wage income from the IRS. All specifications include CBSA and year fixed effects and are weighted by the number of IRS tax returns in the zip code, which is our measure of the number of households. *Sources:* HMDA and IRS Statistics of Income.

			Accounting for 2nd Liens in HMDA			
	AGI Growth Rate	**2006 AGI Level**	**AGI Growth Rate**	**2006 AGI Level**	**Wage & Salary Growth Rate**	**2006 Wage & Salary Level**
Model 1						
HMDA Purchase Growth Rate	–0.20**		–0.20**			
	(0.09)		(0.09)			
Model 2						
HMDA Purchase Growth Rate	0.66***	–0.32***	0.66***	-0.32***		
	(0.11)	(0.03)	(0.09)	(0.02)		
Model 3						
HMDA Growth Rate: Avg. Purchase Mortgage Amount	0.23***	–0.001	0.20***	–0.07***		
	(0.03)	(0.01)	(0.03)	(0.01)		
HMDA Growth Rate: No. of Purchase Mortgages	0.43***	–0.31***	0.46***	–0.25***		
	(0.10)	(0.02)	(0.10)	(0.02)		
Model 4a:						
Equifax Debt Stock / Tax Returns Growth Rate			0.42***	–0.05***	0.74***	–0.02
			(0.05)	(0.01)	(0.05)	(0.01)
Model 4b:						
Equifax Growth Rate: Mortgage Debt per Mgted. Household			0.17***	–0.03***	0.23***	–0.01
			(0.02)	(0.01)	(0.04)	(0.01)
Equifax Growth Rate: Mortgaged Households / Tax Returns			.24***	–0.02***	0.51***	–0.002
			(0.00)	(0.01)	(0.06)	(0.01)

Table B.2. Decomposing the Negative Correlation Between Growth in Purchase Mortgages and Income Growth: 2002–2006. *Note:* Each row in this table is a separate regression. The first two columns contain results using AGI as the measure of income on the right-hand side and do not correct for the presence of second liens in HMDA. The remaining four columns correct for the presence of second liens. The last two columns use salary and wages as the measure of income. Model 1 replicates the negative sign of the correlation between purchase-mortgage growth and AGI growth reported in Mian and Sufi (2009). Model 2 adds the level term to the regression to show that the relationship between purchase-mortgage originations and AGI was never negative in levels. Model 3 follows Adelino, Schoar, and Severino (2016) by dividing purchase-mortgage originations into the average size of each purchase mortgage and the number of purchase mortgages. This regression shows a significant decline in the slope of the positive relationship between purchase-mortgage originations and income only when considering the number of purchase mortgages, not the average purchase amount. Model 4a considers the per-return stock of mortgage debt, while Model 4b divides this stock into debt per mortgaged household and the proportion of households that have a mortgage. *Sources:* NY Fed Consumer Credit Panel/Equifax and IRS Statistics of Income.

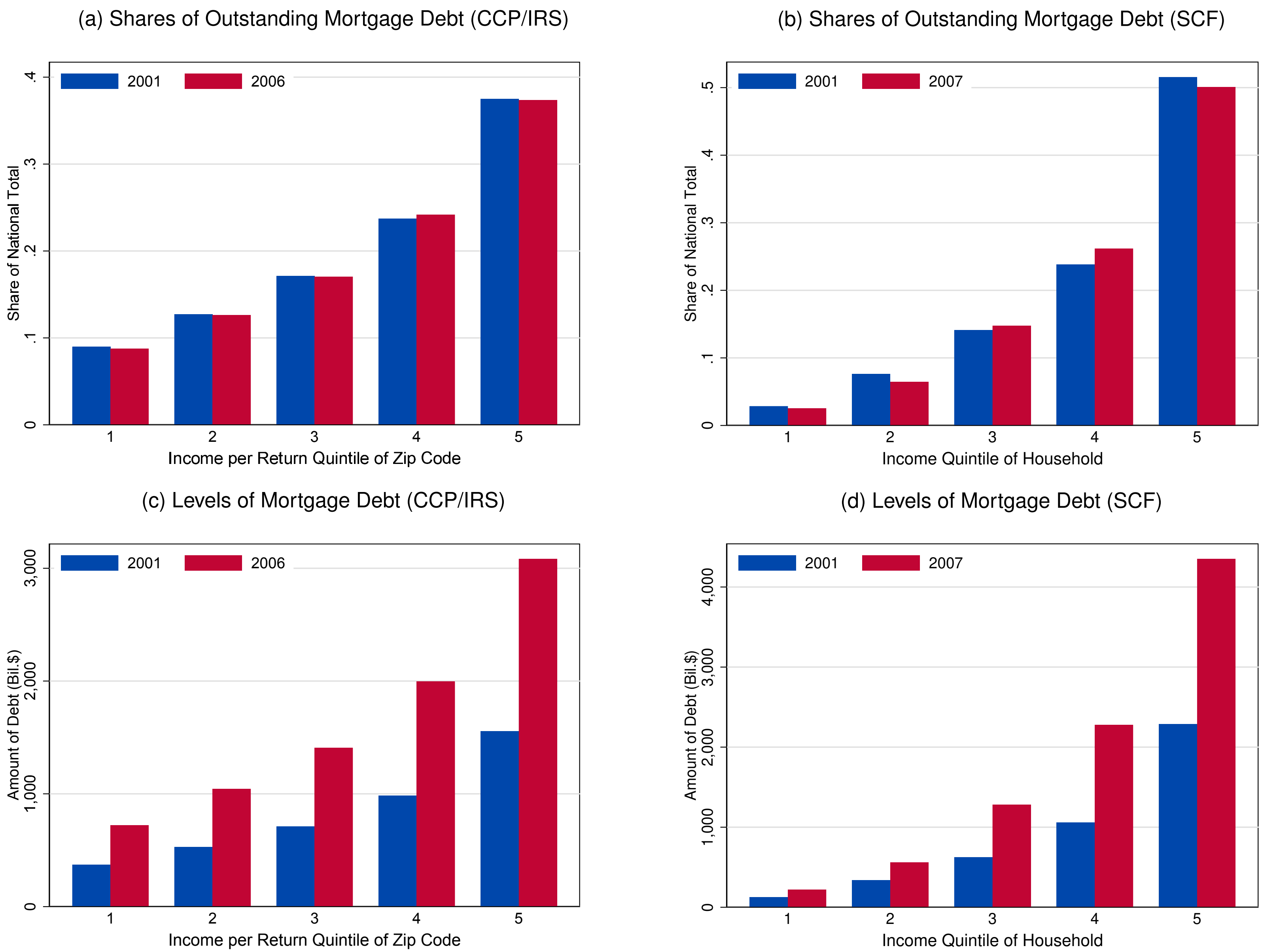


Figure B.2. Distributions of Mortgage Debt With Respect to Adjusted Gross Income (for Zip Codes) and Total Income (for Households). *Note:* The income measure used throughout the main text is salary and wage income. This figure uses AGI as the income measure for zip codes in the left panels, and total income from the SCF for households in the right panels. *Sources:* NY Fed Consumer Credit Panel/Equifax, IRS Statistics of Income, and Federal Reserve, Survey of Consumer Finances.

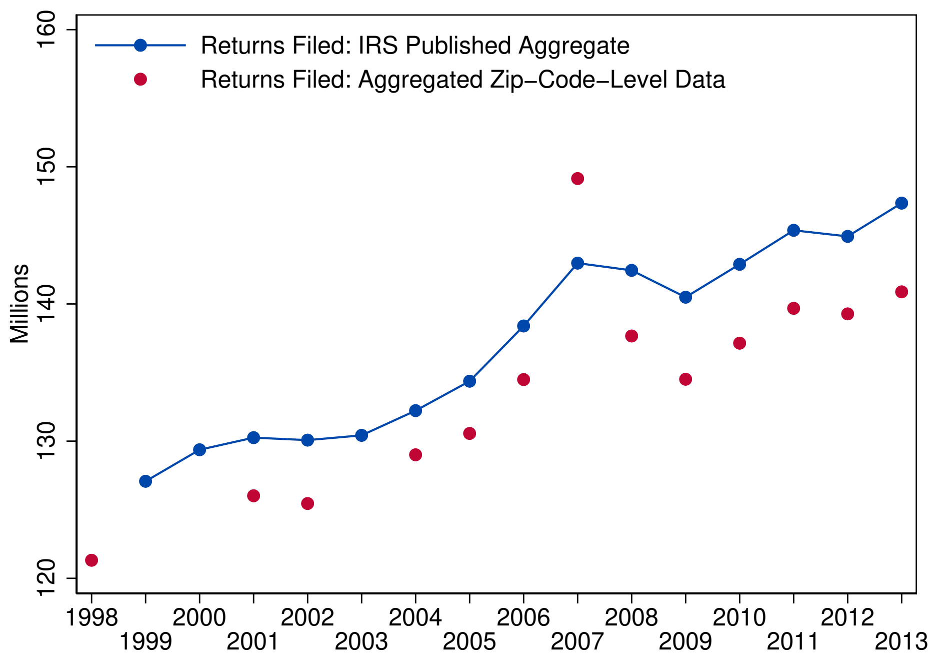


Figure B.3. Two Measures of Aggregate Individual Income Returns Filed. *Note:* The blue line depicts the total number of individual income returns filed for the given tax year as published by the IRS. The 2007 value for this series omits returns filed by individuals for the sole purpose of receiving the 2007 economic stimulus payment. The red dots depict annual aggregates implied by the zip-code-level IRS data; the 2007 value for this series includes all filers. *Sources:* Internal Revenue Service, Statistics of Income Historical Table 1 (available at https://www.irs.gov/uac/SOI-Tax-Stats-Historical-Table-1), and Internal Revenue Service (2007).

Figure B.4. Equifax/IRS Distributions of Debt for 2001 and 2007 using Alternative Income Definitions. *Note:* These graphs are analogous to the Equifax/IRS zip-code-level bar charts in Figure 2, which depict distributions for 2001 and 2006, rather than 2001 and 2007. The lower panels in this figure also use AGI rather than wage and salary income. *Sources:* NY Fed Consumer Credit Panel/Equifax and IRS Statistics of Income.

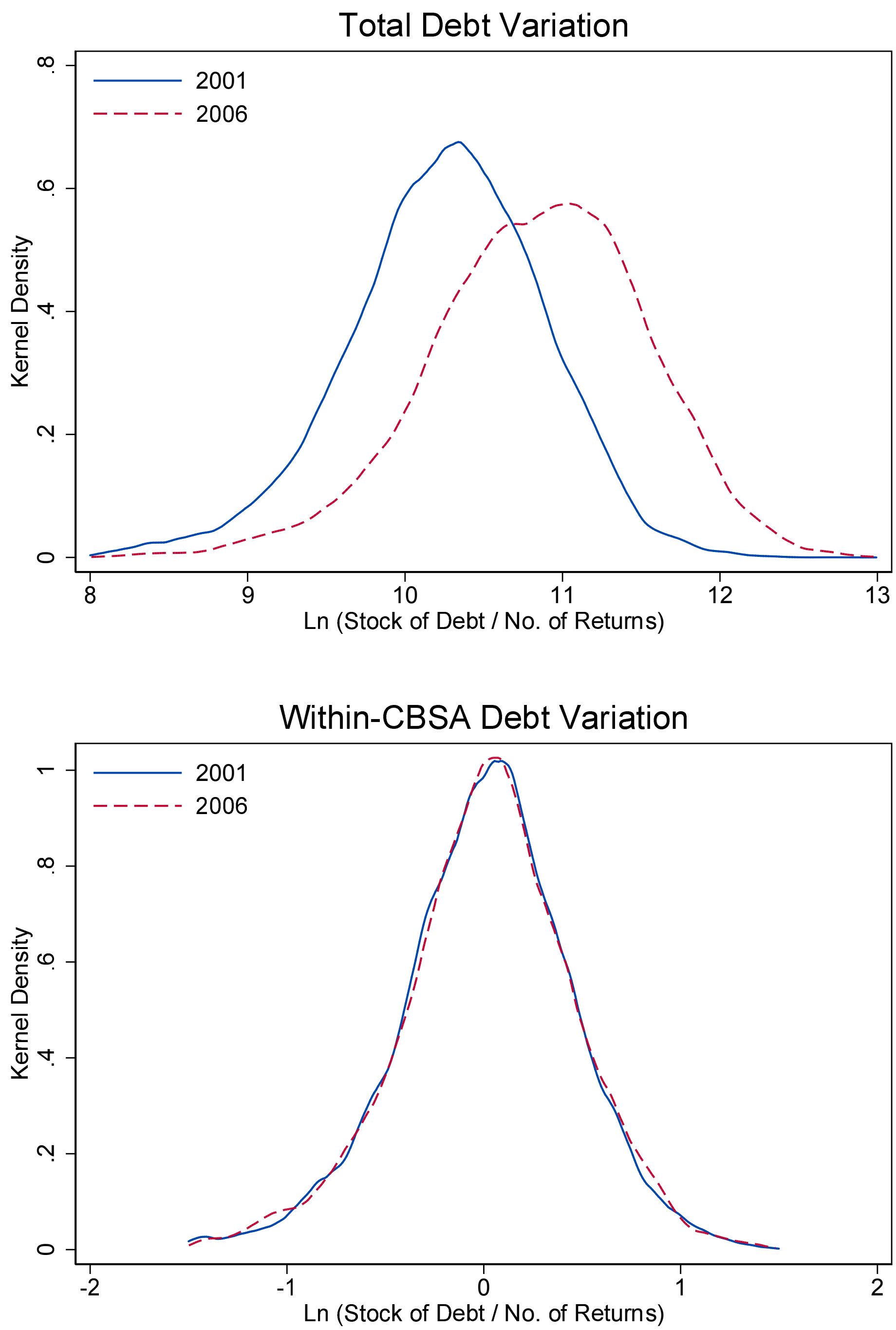


Figure B.5. Distributions of Mortgage Debt. *Note:* All densities are weighted kernel densities of average zip-code-level mortgage debt per tax return. The weight is the number of income tax returns in the zip code. The bottom panel depicts densities after the log of zip-code-level debt per return is deviated from means corresponding to CBSAs. Zip codes outside of CBSAs are excluded. *Sources:* NY Fed Consumer Credit Panel/Equifax and IRS Statistics of Income.

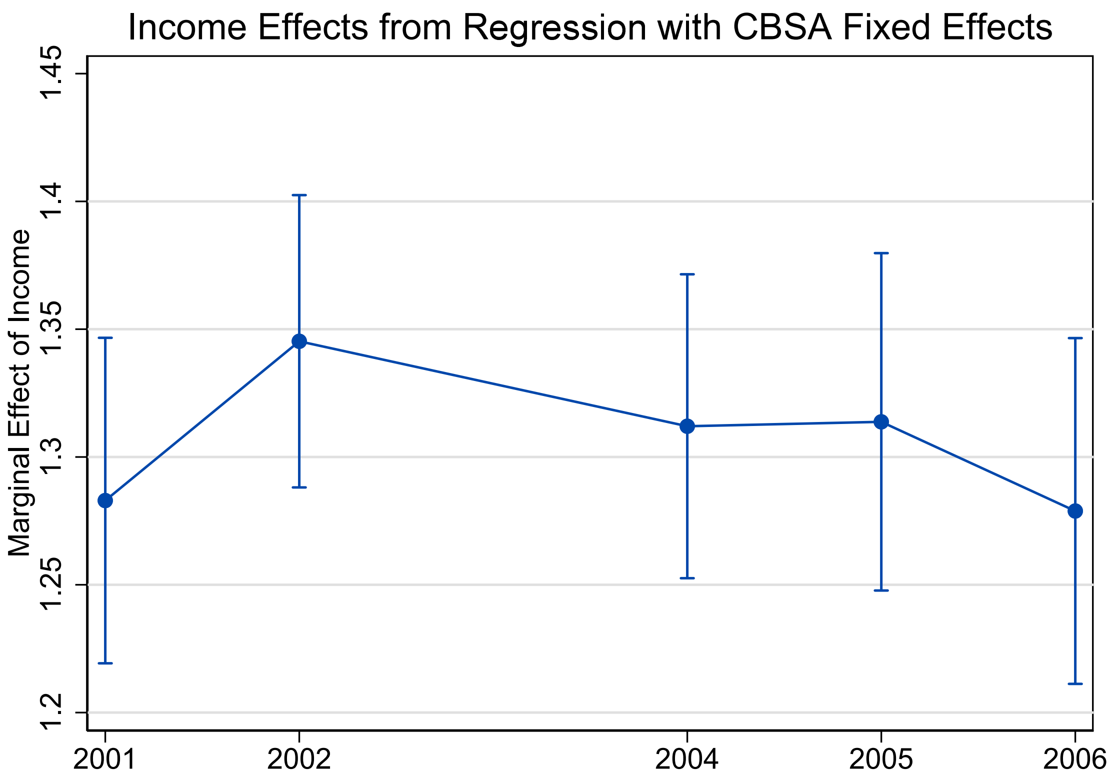


Figure B.6. Income Coefficients from Regression with CBSA Fixed Effects. *Note:* The estimated β_ts using CBSA fixed effects rise very slightly from 2001 to 2002 and fall gently thereafter, so that by 2006 the income coefficient has essentially returned to its 2001 value. The exact difference between the 2006 and 2001 coefficients is –0.01, a gap that is neither economically nor statistically significant. *Sources:* NY Fed Consumer Credit Panel/Equifax and IRS Statistics of Income.

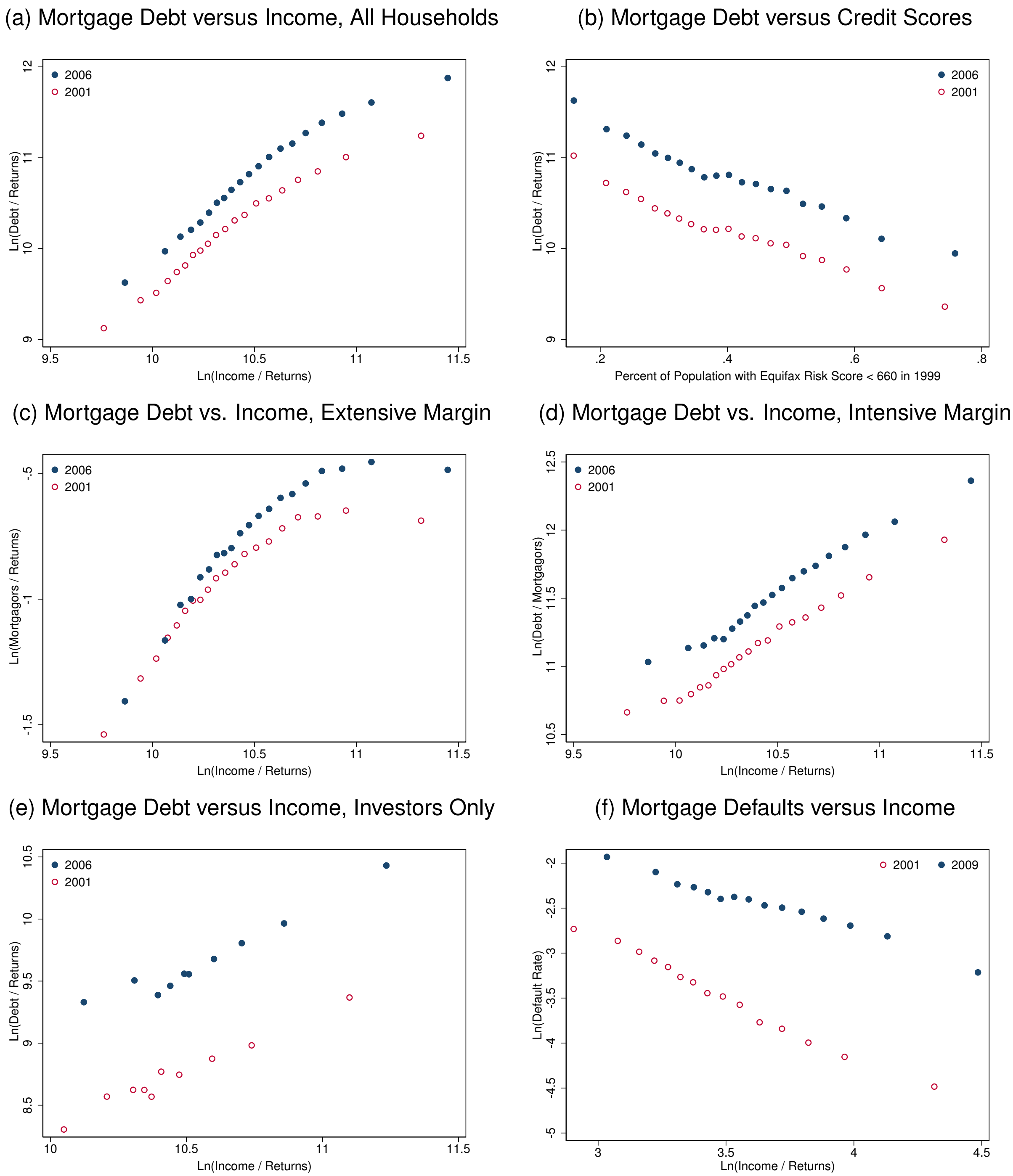


Figure B.7. Evolution of Various Indicators. *Note:* All show binned scatter plots of zip-code-level measures in the New York Fed Consumer Credit Panel. We compare 2001 and 2006 in all panels except panel F, where we compare 2001 and 2009. *Sources:* NY Fed Consumer Credit Panel/Equifax and IRS Statistics of Income.

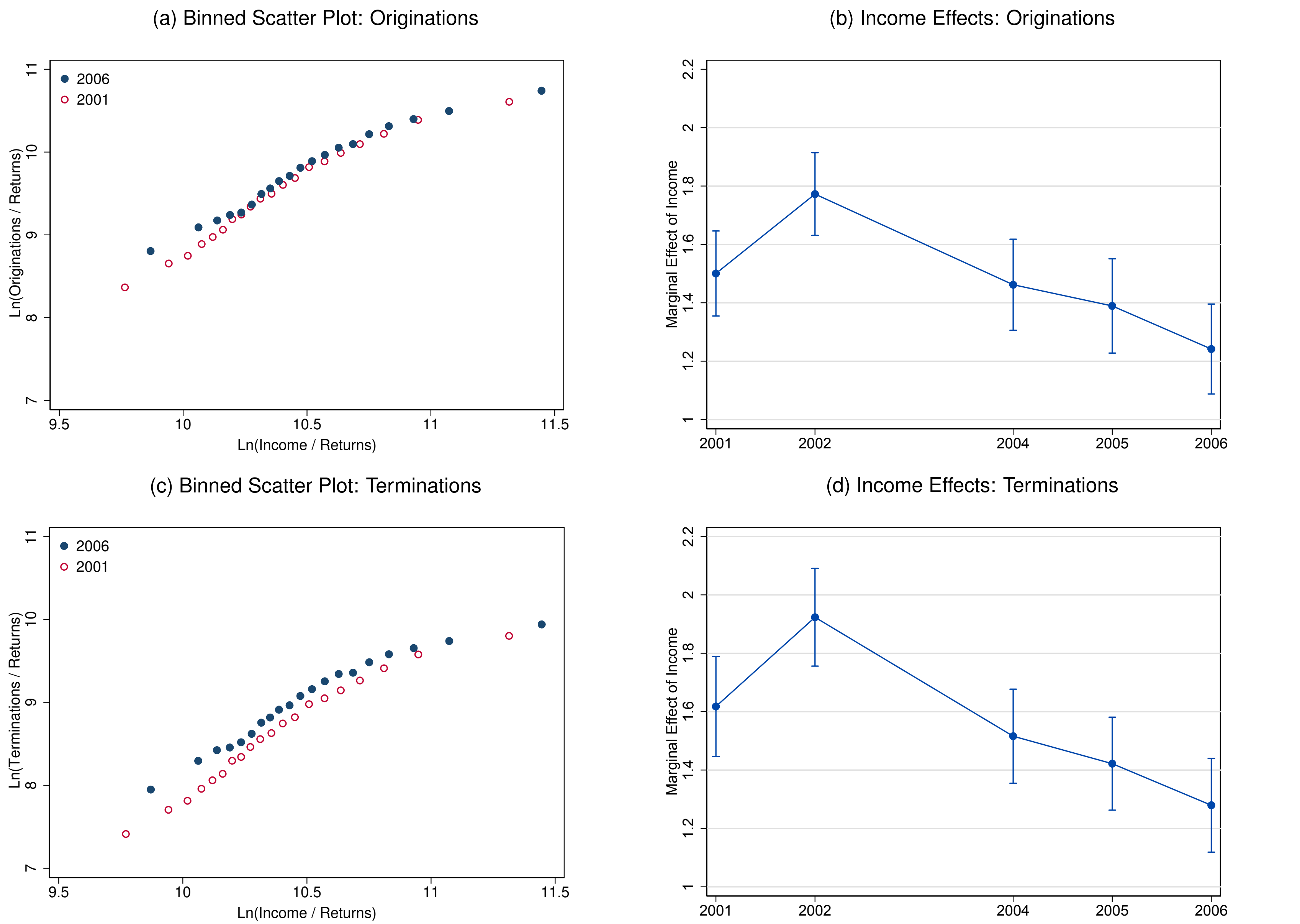


Figure B.8. The Relationship Between Gross Mortgage Flows and Wage and Salary Income Across Zip Codes. *Note:* Standard errors are clustered by CBSA. *Sources:* NY Fed Consumer Credit Panel/Equifax and IRS Statistics of Income.