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

Christopher L. Foote† Lara Loewenstein‡ Paul S. Willen§

July 6, 2016

Abstract

The reallocation of mortgage debt to low-income or marginally qualified borrowers plays a central role in many explanations of the early 2000s housing boom. We show that such a reallocation never occurred, as the distribution of mortgage debt with respect to income changed little during the boom. Additionally, although the homeownership rate began rising in the mid-1990s, it peaked before the mortgage boom ended, and there is no evidence that increases in homeownership during the boom were concentrated among low-income or marginal borrowers. Previous cross-sectional research stressing the importance of low-income borrowers and communities during the mortgage boom was based on the *inflow* of new mortgage originations alone. As a result, it could not detect offsetting *outflows* in mortgage terminations that left the allocation of debt with respect to income stable over time.

*The views in this paper are not necessarily those of the Federal Reserve Bank of Boston or the Federal Reserve System. We have received helpful comments from Manuel Adelino, Neil Bhutta, Jesse Bricker, Onesime Epouhe, Ben Friedman, Kris Gerardi, Alice Henriques, Kristoph Kleiner, Jonathan Parker, Antoinette Schoar, Rosen Valchev, and seminar participants at the Atlanta and Cleveland Feds, Brandeis, and the Homer Hoyt Institute. We also thank Brigitte Madrian and Stephen Zeldes, who invited one of us to discuss Adelino, Schoar, and Severino (2016) at the NBER's Summer Institute. Work on that discussion encouraged us to write this paper.

†Federal Reserve Bank of Boston. Email: Chris.Foote@bos.frb.org.
‡Federal Reserve Bank of Boston. Email: Lara.Loewenstein@bos.frb.org.
§Federal Reserve Bank of Boston. Email: Paul.Willen@bos.frb.org.

1 Introduction

The early 2000s saw a large expansion of mortgage debt in the United States. As measured in the Federal Reserve's Flow of Funds accounts, 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. During this period mortgage debt grew much faster than income did, so there was a marked increase in the mortgage debt-to-income ratio, as seen in the top panel of Figure 1. The bottom panel of the figure shows that growth in the debt-to-income ratio followed a significant increase in the homeownership rate, although by 2007 this rate had fallen back to near its 2001 level. In this paper, we analyze the cross-sectional allocation of debt during the mortgage boom with particular attention to how the debt was allocated with respect to income. Our findings contradict conventional theories that the mortgage boom was driven by disproportionate borrowing at the lower end of the income distribution.[1]

We characterize the cross-sectional allocation of debt during the mortgage boom with four main findings. First, there was no reallocation of mortgage debt towards low-income individuals. To be sure, low-income borrowing expanded during the boom, with much of this debt packaged into the subprime mortgage-backed securities that caused serious problems during the financial crisis. Yet borrowing by high-income individuals rose at similar rates, so that the distribution of debt with respect to income remained stable over time. This stability emerges clearly in a number of datasets, including the Federal Reserve's Survey of Consumer Finances (SCF), a comprehensive study of U.S. household balance sheets. The top left panel of Figure 2 depicts the shares of total outstanding mortgage debt held by households in various quantiles of wage income in the 2001 and 2007 waves of the SCF. No quantile significantly increases its share of debt in the early 2000s as aggregate debt levels rise. The top right panel of Figure 2 focuses on the debt-income relationship more closely by presenting a binned scatter plot of log mortgage debt against log wage income in 2001 and 2007. There is an approximately log-linear relationship between income and debt that shifts up nearly equally across the income distribution during the boon, indicating that debt rose by similar percentage amounts for low-income and high-income households alike. The lower two panels perform a similar analysis using a separate dataset that combines zip code-level mortgage debt data from the Equifax credit bureau with similarly aggregated income data from the Internal Revenue Service. The Equifax/IRS dataset is much larger than the SCF; there are around 40,000 zip codes in the country, while the SCF covers only about 3,000-

[1]A good summary of the conventional theory is found in Amromin and McGranahan (2015), who write that most research on pre-recession credit markets, including mortgage markets, suggest that this period "was characterized by the liberalization of credit access to households that had previously found it difficult to qualify because of poor credit records, insufficient income, or both. The liberalization of credit access has largely been ascribed to financial innovation through securitization markets that allowed loan originators to offload credit risk to a broad set of private investors" (p. 147).

6,000 households every three years. Despite these differences, the zip code-level dataset confirms the SCF's bottom line: the debt distribution changed little during the mortgage boom because the debt-income relationship shifted up nearly equally.[2] Mathematically, the combination of the stable debt distribution and the positive relationship between debt and income in the cross-section implies that in dollar terms, most of the new mortgage debt taken out during the boom went to the wealthy. For example, from 2001 to 2006, calculations based on the Equifax/IRS dataset show that the highest–income borrowers accounted for about \$1.5 trillion in new debt, while mortgage debt for the lowest-income quintile rose by only \$320 billion.

The second finding is that increased homeownership among low-income or marginal borrowers was not an important driving force in the mortgage boom. Many commentators have assumed that a credit expansion took place along this extensive margin, as marginal or low-income individuals—who would have been denied credit before the boom—began to get loans. A look back at Figure 1 shows that the extensive-margin hypothesis has problems explaining the behavior of debt in the early 2000s, as the homeownership rate ended the mortgage boom about where it began. To study the relationship between homeownership and income more closely, we draw on individual-level data from the Current Population Survey (CPS) and the SCF as well as zip code-level data from the Equifax/IRS dataset. We also exploit the individual-level credit records in the Equifax dataset, which do not have income information but do include a type of credit score. Overall, there is no evidence of a broad expansion of homeownership among low-income or marginal borrowers during the mortgage boom, particularly after conditioning on age. In fact, income becomes a more-important, not less-important, predictor for homeownership after the mortgage boom begins, especially for young households. And, consistent with Bhutta (2015) and Albanesi et al. (2016), the analysis of individual-level Equifax credit records indicates that transitions into mortgage borrowing became less frequent for persons with low credit scores during the mortgage boom, as part of a general decline in first-time home buying. It is of course well known that many lenders relaxed their credit standards during the boom. But the data suggest that the effect of this relaxation on the extensive margin of debt was offset by the rapid increase in house prices, which made first-time buying difficult. In any event, as a quantitative explanation for the massive increase in mortgage debt in the early 2000s, any theory that rests on a broad extensive-margin credit expansion for low-income individuals will fail to fit the facts.

Throughout this paper we draw a key distinction between the *stocks* of debt on house-

[2] In the main text, we explain how the zip code-level dataset is constructed and why a peculiarity of IRS income-data collection in 2007 causes us to date the mortgage boom as ending in 2006 rather than 2007 when using the Equifax/IRS dataset. As it turns out, all of the zip code-level results remain robust to using 2007 as the last year of the mortgage boom, as discussed in the internet appendix. We also show that the slight tilt of mortgage debt toward richer borrowers in the scatter plot using the Equifax/IRS data arises from shifts in debt between city-level housing markets, not within them.

hold balance sheets and the two gross *flows* of debt, which are originations and terminations. Confusion in the academic literature has resulted from the common practice of using incomplete data on gross mortgage flows to infer changes in stocks of debt. For example, Mian and Sufi (2009) use data from the Home Mortgage Disclosure Act (HMDA) to argue that the allocation of mortgage credit changed fundamentally during the housing boom, in ways that channelled more mortgage credit to marginal or low-income borrowers. HMDA data are a near-comprehensive data source for new mortgage applications and originations, and for many topics related to the allocation of credit, such as the possibility of racial discrimination, a sole focus on originations is appropriate.[3] But many times, the origination of a new mortgage (for example, from a home buyer) is offset by the termination of another mortgage (for example, from the seller). Yet HMDA does not cover terminations, and this lack of information has led to disputes over the lessons that HMDA origination patterns really hold for the boom. In a recent paper, Adelino, Schoar, and Severino (2016) have challenged Mian and Sufi's conclusions by showing their original findings were driven by shifts in the numbers of new mortgages originated, not by higher dollar values of mortgages. Yet Adelino, Schoar, and Severino (2016) still use HMDA data, so they cannot tell whether these newly originated mortgages reflect only higher transactional volumes in low-income areas—as they contend—or a true expansion of mortgage credit along the extensive margin—as Mian and Sufi (2015) have countered. Data on mortgage stocks are needed to accurately measure household balance sheets, and in what we view as the third contribution of the paper, we combine flow and stock data to completely characterize the mortgage markets studied by these authors and others. Our results show that it was higher transactional churn, not a reallocation of mortgage credit, that lay behind the original HMDA results.

The final finding of the paper is that rapid growth of subprime loans did not *cause* a reallocation of mortgage debt toward low-income borrowers, but rather *prevented* a reallocation of debt toward the wealthy. We use a separate source of comprehensive data on securitized subprime loans to confirm that these loans were more common among low-income borrowers. But in relation to the stock of all outstanding mortgage debt, growth in alternative mortgage products like subprime or Alt-A loans was dwarfed by growth in prime loans, which were favored by richer borrowers. Even among the alternative products, the aggregate value of Alt-A loans—which were generally low-documentation mortgages made to borrowers with high credit scores—grew at a somewhat faster rate than subprime loans did. Subprime debt also failed to result in a disproportionate increase in defaults in low-income areas. We use the comprehensive Equifax dataset to confirm that in *absolute* terms, increases in defaults were larger in poorer areas. But defaults were not concentrated in low-income areas, be-

[3]The Boston Fed's study of racial discrimination (Munnell et al. 1996) was based on HMDA data supplemented with additional information from lenders.

cause in *relative* terms increases in defaults in richer communities were just as high, if not higher. Thus there is an analogy between the growth of mortgage debt during the boom and the growth of defaults during the bust. High-income communities always account for a disproportionate share of mortgage debt, so the scaling-up of mortgage debt by equal rates generated larger dollar-value changes in debt for high-income individuals and communities. Similarly, low-income communities always account for an outsize share of foreclosures, so the scaling-up of defaults during the bust generates large absolute increases in low-income foreclosures.

Other cross-sectional facts can undoubtedly be generated from disaggregated data on mortgage debt stocks. Some of those facts may highlight unique experiences for specific groups of borrowers. But all of those facts must be consistent with the findings below, most importantly the near-equal percentage rates of growth in mortgage debt across the income distribution. It is hard to reconcile this balanced growth with the common claim that expanded low-income borrowing set off a housing bubble, because low-income debt remained such a small fraction of overall debt accumulation throughout the boom. Rather than a shock to one corner of the mortgage market, the data support an aggregate force as the true driver the housing cycle. We discuss some potential aggregate factors in the conclusion.

2 Cross-Sectional Data on Debt Stocks and Income

2.1 Debt and Income Data from Equifax and the IRS

Zip code-level measures of mortgage debt used in this paper come from the Federal Reserve Bank of New York's Consumer Credit Panel, a quarterly, longitudinal five percent sample of individual credit histories supplied by the Equifax credit bureau. The dataset 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 dataset can be updated to incorporate new entrants over time.[4] Among other debt variables, the Equifax data contain detailed information on mortgage debt, including the amounts and dates associated with the origination of new loans, as well as outstanding balances for first mortgages, subordinate mortgages, and home equity lines of credit (HELOCs). We can also measure the number and value of mortgage terminations. We specify a termination as occurring in the last quarter that a mortgage appears in the data, and the value of that termination is the remaining balance when it is removed.

[4]As discussed above, we aggregate the Equifax records by zip code in order to match them with available income data from the IRS. When we do so, we multiply the aggregated debt data by 20, because the data come from a five percent sample of individuals.

A unique characteristic of credit-bureau data is its ability 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 Debt =

$+$ Gross Inflows

- **Purchase mortgages and other originations,** where other originations include interest 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.

Other data sources are exclusively focused on inflows, and specifically on originations. The HMDA data used in previous research follow a law passed in 1975 that requires certain financial institutions to report individual-level data relating to mortgage applications and originations, including the dollar amount of each new mortgage and the census tract of the house backing the loan. As far as originations go, HMDA is an appropriate and nearly comprehensive data source, but as noted earlier, HMDA data cannot be used to measure mortgage terminations or debt stocks.[5] Data from public registries of deeds suffer from a similar limitation, in that they provide good coverage of originations but problematic coverage of terminations.[6]

In addition to information on mortgage debt, Equifax contains a small number of individual characteristics of borrowers, such as age and an end-of-quarter credit score. This credit score is created by Equifax, and it resembles a FICO score in that a higher value of either score indicates a lower probability of default over the near term. We have found the mode

[5]HMDA's coverage of originations is very good but still incomplete. Only mortgage companies and depository institutions with offices in metropolitan areas are required to report, and the reporting of home equity lines of credit (HELOCs) is optional. There is also limited information about the individuals applying for mortgages (only race, income, and gender), and some researchers have questioned the accuracy of the borrower-level income data reported on HMDA forms (Mian and Sufi 2015).

[6]The dataset in Ferreira and Gyourko (2015) is based on public-records data supplied by the DataQuick company. The lack of precise information on mortgage terminations in that dataset makes it hard for the authors to know whether a new, non-purchase mortgage represents the refinance of an existing loan or a new mortgage that adds to the homeowner's existing stock of debt. The authors assume that a new non-purchase mortgage is a refinance if its value is more than half of either the imputed current price of the home or of the total mortgage balance taken out when the home was purchased.

of the credit-score distribution moves to the right somewhat over time, but this movement is not too worrisome because it does not become severe until 2010, after the mortgage boom ends. We also use the Equifax score only to distinguish the creditworthiness of individuals within a given year, and not to measure changes in individual-level creditworthiness over time.

Loan-level datasets that are generated by mortgage securitizers or mortgage servicers also provide information on originations and terminations, but neither type of dataset is comprehensive. The CoreLogic Private Label Securities ABS Database provides loan-level data only for mortgages that have been packaged into non-agency securities (that is, securities not backed by the government-sponsored enterprises Fannie Mae, Freddie Mac, and Ginnie Mae). For this specific group of mortgages, which includes virtually all subprime loans, the coverage of the CoreLogic dataset is excellent, as it contains the loans in almost all non-agency securities issued since 1992. The CoreLogic dataset includes an expansive set of variables for each loan, but this dataset cannot measure the aggregate stock of debt, because (as discussed below) even at the peak of the boom, subprime and other types of non-agency loans made up a small share of the overall market.[7] Yet CoreLogic data can be used to measure cross-sectional patterns in the use of securitized subprime and Alt-A debt, and we do so below.[8] The loan-level dataset from McDash Analytics has broader coverage, because it is based on data supplied by mortgage servicers (typically banks) and therefore includes agency and portfolio loans as well as non-agency loans. Unfortunately, the collection of servicers in McDash is not generally considered representative of the entire mortgage market until at least 2005.

A disadvantage of the Equifax dataset is that it contains no information on income. As a result, we follow previous research and construct aggregates of debt at the zip-code level, to be merged with zip code-level income data published by the IRS. Zip code-level data is available from IRS on a host of income variables, including adjusted gross income (AGI) and salary and wage income, for the years 1998, 2001, 2002, and 2004–2012.[9] In addition to the income variables, we also use the number of returns and the number of exemptions in the IRS dataset to measure zip code-level households and population, respectively.

The IRS income data are based on the universe of tax returns filed in a given year, so

[7]The CoreLogic database was originally called the LoanPerformance database after the company that developed it. The CoreLogic data include the loan-to-value ratio, the debt-to-income ratio, the credit score at origination, and the level of documentation used to originate the loan. The CoreLogic company also supplies a separate dataset of repeat-sales house-price indexes, which is explained more fully below.

[8]Alt-A loans were loans to prime borrowers that did not qualify for standard prime pools, typically because of reduced documentation. The name is derived from the fact that lenders referred to prime borrowers as "A" borrowers, as opposed to the "B" and "C" borrowers who were considered subprime.

[9]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.

they are comprehensive, but still imperfect. For one thing, the IRS uses suppression rules to ensure that no individual information can be backed out of the published zip code-level data, and these suppression rules change from year to year. An additional source of potential measurement error arises from yearly changes in the share of earners who file tax returns. The number of filers rose sharply in 2007, as people were encouraged to file returns in order to receive economic-stimulus payments, as seen in Figure 3. In the internet appendix, we show that the additional filers have little effect on income aggregates, implying that these filers reported low (or zero) incomes. However, by distorting our measure of the number of households in each zip code, the 2007 spike in returns could also distort some results if we define the mortgage boom as ending in 2007. Consequently, when using the zip code-level data, we choose 2006 as the ending year of the boom instead. Fortunately, robustness checks presented in the internet appendix indicate that the distortion induced by the extra filers in 2007 is not severe, as our main zip code-level results hold even when we end the boom in 2007. Another measurement issue related to the IRS data is what type of income to use. In the empirical work below, income is defined as salary and wage income, which is likely to be the most important type of income considered by lenders when underwriting mortgage loans. A type of income that lenders are *not* likely to consider is capital gains, which is included in AGI. Here again, measurement issues are not too much of a concern. The internet appendix shows that our main results are robust to defining income either as salary and wages or as AGI.

Table 1 presents summary statistics for the zip code-level Equifax/IRS dataset. 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 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. As expected, median mortgage-debt levels and house values are positively correlated with income, as are credit scores. Because credit scores are well known to rise with age, one potential explanation for the latter correlation is that richer zip codes tend to include older residents. Yet the table also shows that median age varies little across income quintiles. Two other facts relate directly to changes in the cross-sectional distribution of debt. First, the amount of total mortgage debt grew significantly for all income groups; from $51,000 to $73,000 per return in the lowest-income quintile of zip codes, and from $130,000 to $215,000 in the richest quintile. Second, the proportion of mortgaged households grew only modestly across the income distribution; from 27 to 32 percent for the poorest zip codes and from 51 to 58 percent for the richest. Ideally, the Equifax data would tell us whether individuals owned homes, but we only know whether or not individuals hold mortgage debt. Homeownership information is available in the SCF, however, to which we turn next.

2.2 Household-Level Data from the Survey of Consumer Finances

The large size of the Equifax/IRS dataset will allow a detailed look at cross-sectional debt patterns both within and across housing markets, but its limited demographic and housing-tenure information as well as its zip code-level nature suggest the need for additional information.[10] We generate a number of results using individual-level data from the SCF, a triennial survey of households conducted by the Federal Reserve. Sample sizes in the SCF range from just over 3,000 households in 1989 to more than 6,000 by 2010, so the SCF is too small to use when examining mortgage debt within individual housing markets. Yet what the SCF lacks in size it makes up for in quality, as it provides a complete characterization of household-level balance sheets, including data on various types of mortgage debt.[11] Income data include information on both total income (comparable to AGI) and wage and salary income. The SCF also includes a host of demographic variables, including the age, marital status, and race of the household head. We use the summary datasets that pull together key SCF variables from 1989 through 2013, which are made publicly available by Federal Reserve's Board of Governors.[12] The internet appendix shows that both the SCF and Equifax measures of mortgage debt correlate well with the Flow of Funds measure of debt, and that our aggregates of SCF and Equifax debt match aggregates constructed from the same datasets by other researchers.

Summary statistics for SCF data in 2001 and 2007 appear in Table 2.[13] The table makes it clear that the mortgage debt variable in the SCF is a comprehensive measure, including debt on properties other than the primary residence as well as HELOCs. The top panel uses data from all households and defines income as total income. The lower panel of Table 2 defines income as salary and wages, excluding households with zero values of that variable. As noted in the introduction, similar growth rates of mortgage debt across the income distribution generate much larger dollar increases in debt for quintiles with the highest incomes. For example, Panel A, which uses total income, indicates that the average household in the lowest income quintile saw its mortgage debt increase from \$5,294 to \$10,795 from 2001 to

[10] Because the Equifax/IRS dataset is defined at the zip-code level, its results could be influenced by the migration of households across zip-code boundaries.

[11] The SCF includes separate information on debt secured by the household's primary residence as well as data on any other real estate debt. We always combine these two measures. Like the total debt measure in the Equifax data, the SCF debt measure encompasses first mortgages, subordinate mortgages, and HELOCs.

[12] Variables included in the summary datasets are those used in the regular analyses of SCF data published in the *Federal Reserve Bulletin*. See Bricker et al. (2014) for the most recent *Bulletin* article, and `http://www.federalreserve.gov/econresdata/scf/scfindex.htm` to download either the raw SCF data or the summary data files.

[13] The SCF contains five copies, or "implicates," of the data for each household, with missing or confidential data imputed differently across each implicate. Users of the SCF are instructed to perform statistical tests on each implicate separately, using sample weights, and then combine the resulting parameter estimates and variance-covariance matricies using the Repeated-Imputation Inference (RII) of Rubin (1987). The summary statistics Table 2 are simple averages of the five within-implicate weighted averages.

2007. The comparable increase a household in the highest income group was from \$122,314 to \$219,228. The table also includes information on both the share of mortgaged households in each quintile as well as homeownership rates. Both of these statistics are stable or rise only modestly across all income groups.[14] Finally, the last two columns of the table present information on the asset side of household balance sheets, specifically housing values. These columns illustrate the rapid rise in house prices during the mortgage boom.

3 Income and the Distribution of Mortgage Debt

3.1 Unconditional Distributions of Debt

This section explores the distribution of debt during mortgage boom, detailing the stable relationships between debt and income discussed in the introduction. To set the stage for this analysis, we first examine unconditional distributions of debt at both the household and zip-code levels. The top left panel of Figure 4 depicts household-level kernel distributions of the log of mortgage debt in 1995, 2001, and 2007 from the SCF. Over time, this distribution moves to the right as aggregate mortgage debt rises. The shape of the debt distribution also changes, narrowing from 1995 to 2001. A narrowing of the unconditional debt distribution indicates that low-debt households in the left-hand part of the 1995 distribution experienced relatively greater increases in debt through 2001. After that, however, the distribution appears to flatten out, indicating the opposite pattern; during the 2001–2007 mortgage boom households with high amounts of debt saw relatively greater debt growth. An analysis of distributional statistics such as standard deviation and interquartile range confirms that the SCF debt distribution narrowed throughout the 1990s. These statistics remain relatively constant in the 2000s, however, implying that the boom-era widening near the mode of the distribution was offset by movements in dispersion near the tails.[15]

The remaining panels of Figure 4 depict returns-weighted zip code-level kernel distributions of log mortgage debt per return from Equifax. These data are not available for 1995, so the panels include distributions only at the start and end of the mortgage boom (2001 and 2006). Interestingly, in the early 2000s the movement in the aggregate debt distribution is qualitatively similar to the movement in the SCF distribution over the corresponding period (note the difference in horizontal scales, however). The zip code-level distribution also

[14]The second column of figures in the table shows the number of unweighted SCF observations for each quintile. When these observations are weighted, they generate equal numbers of households in each quintile. The number of unweighted observations is largest for the richest quintile, to allow the SCF to accurately characterize the long right tail of the wealth distribution. The number of unweighted observations is not an integer because each SCF household is represented by five implicates, and the income fields often differ across implicates.

[15]See the internet appendix for details.

appears to widen, and here the behavior of the standard deviation confirms this formally, as it rises from 0.41 in 2001 to 0.48 in 2006. The bottom two panels exploit the rich geographic dimension of the Equifax/IRS dataset to ask whether this widening stemmed from between-city or within–city markets in debt. As pointed out in previous research, looking within individual housing markets holds constant any factors affecting the market as a whole. In this paper housing markets are defined as cities, more specifically as Core Based Statistical Areas (CBSAs).[16] By construction, the within-CBSA distributions depicted in the lower left panel are both centered at zero, because they are distributions of debt *relative* to CBSA means. The stable shape of the distributions indicates that increased dispersion in total debt from 2001 to 2006 arises from the increase in the dispersion between cities, as confirmed in the lower right panel.[17]

The Equifax distributions therefore indicate that during the housing boom, mortgage debt withing various housing markets moved together. Some cities boomed and experienced high debt growth, while other cities experienced less growth. But within each local market, debt grew at similar rates in high- and low-debt zip codes. These distributions therefore argue against the common claim that the housing boom reallocated debt to those areas that previously had low levels of debt, because this type of reallocation would have narrowed the within-CBSA debt distributions.

A related claim is that the boom reallocated debt toward low-*income* communities. Yet if these low-income communities were also low-debt communities, then the same critique applies: there should have been a narrowing of the debt distribution in the early 2000s. However, we must be careful about using the *unconditional* distributions in Figure 4 to make statements about the allocation of debt *conditional* on income. The unconditional distributions will obviously be affected by changes in the debt-income relationship, but these distributions are formally determined by the way that the debt-income relationship interacts with the distribution of income across communities.[18] The same point applies to the introductory bar charts in Figure 2. The stability of those debt distributions does not rule out a shift in the relationship between income and debt, because those distributions are also

[16]The government defines CBSAs as groups of counties or county equivalents that are integrated around an urban core with at least 10,000 residents. Those based on urban cores with between 10,000 and 50,000 people are called micropolitan statistical areas, and CBSAs based on larger urban cores are called metropolitan statistical areas. In 2003, the CBSA classification system replaced the government's previous urban classification system, which was based on metropolitan statistical areas alone.

[17]Formally, the between variation in the Equifax debt density rises from 0.18 in 2001 to 0.24 in 2006. The within-CBSA variation rises from 0.23 to 0.24. Note that the sum of within and between variation sum to total variation in the two years (0.41 and 0.48).

[18]To see this, note that $f_1(d) = \int_0^\infty f(d|y)g(y)dy$, where f_1 is the marginal (or unconditional) distribution of debt d, $f(d|y)$ is the distribution of debt conditional on income y, and $g(y)$ is the distribution of income. This equation makes it clear that changes in the distribution of income $g(y)$ also matter for the marginal distributions $f_1(d)$. The potential impact of $g(y)$ means that the effects of changes in the conditional debt-income relationship $f(d|y)$ may be not be directly evident in the unconditional distributions.

affected by shifts in the distribution of income. As a result, in order to learn about the debt-income relationship, we have to estimate this conditional relationship directly. We did so nonparametrically with the binned scatter plots that also appeared in Figure 2. We do so parametrically by regressing debt on income in the next subsection.

3.2 Debt and Income: Regression Estimates

We first specify a *conditional expectation function* for debt and income. A parametric form for this function is

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

which assigns debt d to unit i in housing market c in year t as a function of income y. Here, unit i could refer either to a zip code (in the Equifax/IRS data) or to a household (in the SCF). For households, the relationship between mortgage debt and income is also dependent on demographic factors including age, in part because older households have had time to amortize a larger fraction of their mortgages. Therefore, when we analyze debt at the household level we will always condition on age, as well as other demographic factors discussed below. The parameters of the function, α and β, have time subscripts to allow these parameters to change over time. Although simple, the conditional expectation function helps formalize a number of theories about the mortgage boom. One theory, noted above, is that credit flowed disproportionately to borrowers with low incomes. As suggested by Figure 2, the cross-sectional relationship between debt and income is strongly positive: richer people and communities tend to have higher debt levels. A reallocation of debt toward low-income borrowers would reduce this positive correlation over time, so that $\beta_{2006} < \beta_{2001}$. Alternatively, if debt and income are specified in natural logs, a uniform percentage increase in debt at each level of income would be expressed as rising values of the intercept α_t across time periods, with no changes in the relationship between debt and income summarized by β_t.

The estimated β_ts presented in Figure 5 confirm the broadly based nature of the debt expansion that was suggested by the introductory scatter plots. Consider first the Equifax estimates in the top panel.[19] These estimates, which can be interpreted as elasticities, lie in a fairly tight range between about 1.35 and 1.45, indicating that β_ts change little over time. If anything, the importance of income for debt grows slightly, as the effect for 2006 is about 0.07 higher than the effect in 2001, a difference that is statistically significant but economically small. Below, we will investigate whether this increase resulted from between-

[19] The estimates in top panel of Figure 5 are not generated from separate regressions, but rather from a pooled regression in which the constant and the income terms in equation 1 are interacted with yearly dummies. The two methods are equivalent statistically, although the pooled regression turns out to be easier to run. Like the scatter plots, the regressions are weighted by the number of returns in the zip code.

city or within-city movements in debt, but the important point here is that the regressions provide no evidence that income became a less-important determinant of debt.[20]

The bottom panel of Figure 5 presents household-level estimates using the SCF. Here, the income coefficients are estimated with a Poisson regression of mortgage debt on wage income and other demographic variables.[21] The SCF income effects are also stable over time, though 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, there is no evidence of a sustained decline in the importance of income on debt from 2001 to 2007.

3.3 Debt and Income: Within-City and Between-City Movements

The regression specification above is easily adapted to study debt patterns within and between housing markets, though as noted above only the Equifax/IRS dataset is large enough for this purpose. For the within–CBSA analysis we replace the intercept α_t in the parametric model with year-specific city fixed effects,

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

so that a finding of $\beta_{2006} < \beta_{2001}$ reflects a reallocation of debt toward areas with low incomes relative to other areas in the same city. Alternatively, the regression with city-level effects could support a story in which the relative debt-income relationship is unchanged, so that $\beta_{2006} = \beta_{2001}$. In this case, changes in the overall distribution of debt would owe more to between-city movements, that is, to changes in the distribution of the α_{ct}s.

The top two panels of Figure 6 investigate these alternatives with a look at debt and income relative to local means. The binned scatter plot in the top left panel is constructed by deviating both the debt and income variables from CBSA means, separately by year, and then averaging these deviations into 20 bins for each year. Because debt and income are

[20]The standard error on the difference between the 2001 and 2006 income coefficient 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 return. We found that even though the implied relationship between debt and income is not perfectly linear in logs, the relationship shifted upward uniformly across the income distribution, as the binned scatter plot suggests.

[21]A Poisson regression of y_i on x_i is specified as $y_i = exp(\alpha + \beta x_i + \epsilon_i)$. For the SCF regressions, the left-hand-side variable is the level (not log) of the household's total mortgage debt and the regressor of interest is the log of household wage income. 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. Like the Equifax/IRS regressions, the SCF regressions are run as a single pooled regression, in which the right-hand-side variables are all interacted with yearly dummies.

both measured as deviations, the upward movement apparent in the earlier scatter plot is absorbed by movements in the city averages, so both plots go through the origin. There is no significant shift in the slope of these plots, and the panel to the immediate right confirms the stability with regressions.[22] 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 $-.01$, a gap that is neither economically nor statistically significant.

The debt-income relationship across housing markets is analyzed in the lower two panels of Figure 6. There are 937 CBSAs in the dataset, as opposed to more than 40,000 zip codes, so we use 10 rather than 20 bins for the CBSA-level scatter plot in the lower left panel. Unfortunately, even with 10 rather than 20 bins the CBSA-level plot is fairly choppy. The panel does suggest a steepening in the between-city debt-income relationship, however, and this pattern is borne out by the CBSA-level regressions in the lower right panel.[23] Thus, between-city movements help explain the small but statistically significant increase of 0.07 that we found for the income effect β in the previous subsection, when zip code-level Equifax debt was regressed on IRS income without regard to CBSA location.

To be clear, these regression estimates should not be interpreted as structural parameters. Exogenous increases in either household or zip code-level incomes could bring about changes in debt that differ from the estimated income effects presented above. The estimates using city-level data are especially problematic, because the causality in that debt-income relationship could easily run from booming local housing markets to rising local incomes, not the other way around. However, as methods of estimating potential changes in the cross-sectional relationship between mortgage debt and income, both the scatter plots and the reduced-form regressions are quite informative. And in neither the SCF nor the Equifax/IRS datasets do these methods suggest a reallocation of mortgage debt toward low-income borrowers during the early 2000s.

4 Marginal Borrowers and the Extensive Margin of Mortgage Debt

4.1 Understanding Changes in Homeownership Rates

The lack of a reallocation of debt to the lower part of the income distribution contradicts many conventional stories about the mortgage boom, which are often based on expanded

[22]As noted in footnote 19 the regressions are run as a single pooled regression, so the introduction of CBSA fixed effects merely requires interacting CBSA dummies with the yearly dummies.

[23]Specifically, there is an increase of 0.35 in the value of the city-wide income coefficient from 2001 to 2006, which has a t-statistic of 2.3 and a p-value of 0.021.

borrowing opportunities for previously constrained borrowers. A specific investigation of the extensive margin of debt is therefore warranted.[24] To examine the extensive margin we first look at homeownership rates, which as seen in Figure 1 started rising several years before the mortgage boom began. Previous research has described the demographic, socioeconomic and financial factors that affect homeownership, and a full accounting of these factors is beyond the scope of this paper. Yet some basic facts about the U.S. homeownership rate over the last few decades put its recent movements into context.

As seen in Figure 1, the overall U.S. homeownership rate fell throughout the early 1980s and then moved sideways for about a decade thereafter. Because homeownership varies strongly with age, this type of aggregate movement could have resulted mechanically from population aging, but Garriga, Gavin, and Schlagenhauf (2006) show that by itself, aging does a poor job of explaining movements in the aggregate homeownership rate during this period. Moreover, Fisher and Gervais (2011) show that after 1980 homeownership rates declined within narrowly defined age groups, particularly among the young. Using data from the decennial censuses, the CPS, and the American Housing Survey, Fisher and Gervais (2011) show that homeownership among 25–29 year-olds declined by 7 to 9 percentage points in the two decades after 1980. For 40–44 year-olds, the decline was around 5 to 6 percentage points. The authors attribute the decline among younger cohorts to delays in the average age of first marriage and to increases in life-cycle earnings risk.

After 1995, the aggregate homeownership rate started rising, and here again movements among younger cohorts were more pronounced. Census data show that among households headed by someone under 35, the homeownership rate rose by about four percentage points from 1994 to 2001, while the corresponding increase for 45–54 year-olds was only about 1½ percentage points.[25] Yet most authors writing about the post-1995 increase in homeownership have focused not on age but on income and creditworthiness, linking the rise in homeownership to new loans made to low-income or marginally qualified borrowers. For example, Rajan (2010) is critical of Clinton administration policies designed to expand homeownership, quoting a 1995 White House document that encouraged the public and private sectors to be "creative" in reducing financial barriers to homeownership. "Simply put," Rajan writes,

> the Clinton administration was arguing that the financial sector should find creative ways of getting people who could not afford homes into them, and the

[24] As discussed in the introduction, the extensive margin of debt involves the expansion of borrowing to new individuals who were previously without debt, or the effect that individual income has on the probability of borrowing. The intensive margin involves the average amount of debt that each person takes out, or the conditional relationship between individual incomes and average debt balances.

[25] Because homeownership rises with age, the increase in the rate for young people came on top of a lower base in 1980 (37.4 percent for 25–29 year-olds vs. 75.2 percent for 45–54 year-olds).

> government would help or push whenever it could. Although there was some distance between this strategy and the NINJA and 'liar' loans (loans for which borrowers could come up with creative representations of their income because no documentation was required) that featured so prominently in the crisis, the course was set. (p. 36)

Other authors have written that the financial sector needed no encouragement from government to expand credit along the extensive margin, which Wall Street did by developing expensive and complicated mortgage products. Stiglitz (2010) writes that

> had the designers of these mortgages focused on the ends—what we actually wanted from our mortgage market—rather on how to maximize *their* revenues, then they might have devised products that would have *permanently* increased homeownership....Instead their efforts produced a whole range of complicated mortgages that led to a slight *temporary* increase in homeownership, but at great cost to society as a whole. (p. 5, emphasis in original)

These critiques differ in their emphasis, but both authors blame the financial system for originating loans to borrowers who were insufficiently willing or able to pay those loans back. But other research on the mortgage-finance industry suggests that from the mid-1980s through at least 2001, the housing-finance system was improving its ability to allocate credit to the "right" borrowers. Gerardi, Rosen, and Willen (2010) use 1970–2005 data from the Panel Survey of Income Dynamics (PSID) to estimate the relationship between current mortgage borrowing and future income growth. In a well-functioning financial market, these two variables should be strongly and positively correlated, but this correlation is muted by financial frictions and borrowing constraints. Indeed, as a general matter, the classic paper of Carroll and Summers (1991) noted that average consumption and income paths were tightly linked within educational categories, suggesting that (for example) borrowing constraints prevented young college graduates who anticipated high future income from smoothing their consumption paths over time. As a result, the consumption paths of these graduates closely tracked their current-income paths, as was the case for individuals in other educational categories as well. The finding of Gerardi, Rosen, and Willen (2010) that current housing expenditures became more tightly linked to future income after the mid-1980s suggests that the borrowing constraints were becoming less restrictive in the mortgage market, a pattern that those authors attribute to the additional depth to that market that was provided by securitization.

These analyses suggest that a good way to study the increase in homeownership after 1995 is to disaggregate the data by education and age. Figure 7 uses micro-level data from the CPS to plot homeownership rates disaggregated by age group and educational attainment from 1994 onward.[26] The large and well known increases in homeownership among younger age groups is clear in this figure—note the difference in vertical scales across panels—but the figure also suggests some interesting educational differences within age groups. Each panel compares homeownership rates for household heads with a high-school education or less (blue line) to rates for household heads with some college or a college degree (red line). For the youngest age groups, headed by persons under 25, both groups experience increases in homeownership from the mid-1990s through the mid-2000s. For 25–29 year-olds, however, the homeownership rate rises far more for the better-educated group; indeed, the rate for the high-school-or-below group is essentially stable until it declines in the wake of the housing bust. Similar though less-pronounced differences between educational groups are also apparent in other panels. For some age groups, the lesser-educated groups experience rising homeownership rates after 1995, but these increases are generally smaller, and end earlier, than the increases for better-educated groups.

To the extent that education is positively correlated with income—or expectations of income growth—the patterns in Figure 7 argue against the view that the early years of the post-1995 homeownership expansion was driven by marginal borrowers. Though the disaggregation is crude, the financial system appears to be allocating credit to the more-qualified borrowers within each age group. Most important for our purposes, there appears to be no qualitative reversal of the post-1995 educational patterns when the mortgage boom begins in earnest in 2001.

4.2 Income, Homeownership, and Mortgage Borrowing

We next present a regression analysis of current income and homeownership using SCF data. Figure 8 plots estimated income effects from logit regressions of homeownership on the household-specific variables that were also used in the total-debt regressions in the lower panel of Figure 5.[27] As was the case for the income effects in the total-debt regressions, these results are not structural estimates, but they do measure the partial correlation of income and homeownership holding a number of demographic effects constant. In particular, the regressions determine whether current-income differences between renters and owners are

[26]The CPS is used by the Census to calculate homeownership rates for its quarterly reports, and the internet appendix shows that aggregated CPS microdata matches the reported Census figures.

[27]These regressors are the age group of the household head (under 35, 35-44, 45-54, and 55-64), the log of nominal household wage income, the number of children in the household, and binary indicators for whether the household head is married with spouse present and for nonwhite status of the household head. Note that educational categories are not included. As with the total-debt regression, the estimates are generated by a single pooled regression in which all of the demographic factors are interacted with yearly dummies. The estimated income effects in the figure are marginal effects on probabilities (not raw logit coefficients), so (for example) the top panel shows that an increase in wage income of 100 log points raises the expected homeownership rate by around 15–20 percentage points, holding other demographic factors constant.

narrowing over time, as would be expected if mortgage credit were flowing along the extensive margin to low-income borrowers.

Consistent with the educational patterns above, the top panel of Figure 8 shows that the income effect on homeownership rises throughout the 1990s and early 2000s, until the peak of the mortgage boom in 2007. The lower, four-panel chart presents income effects that are specific to age groups, generated by interacting the age-group dummies with the wage-income regressor. The vertical scales in these panels are identical, so they make it clear that as a statistical matter, income matters most in distinguishing young homeowners from young renters. More important for our purposes are the changes in income effects over time. During the early 2000s, the importance of income rises most strongly for the youngest age group, a pattern that is consistent with the pronounced educational differences for young age groups noted in the CPS data. In no age group does the importance of income decline significantly over time.

The Equifax dataset can also be used to investigate the extensive margin of mortgage debt. As noted earlier, there is no indicator for homeownership in the Equifax data; we only know whether an individual currently owes money on a mortgage. But for our purposes, measuring the relationship between income on "mortgageship" is as good or better as doing so for homeownership.[28] Figure 9 presents binned scatter plots of zip code-level shares of mortgaged households at the beginning and end of the mortgage boom (2001 and 2006). The upper plot uses unadjusted income and mortgage-share data, while the bottom deviates those variables from CBSA means.[29] As we might expect, both panels indicate a positive relationship between a zip code's income and the share of its residents that have mortgage debt. A large part of this positive correlation undoubtedly flows from higher rates of homeownership in high-income communities, but a zip code's share of mortgaged households is determined in part by how many residents own their homes free and clear. Indeed, at very high income levels the plots flatten out, perhaps reflecting the larger propensity for high-income persons to own their homes outright.

Most important are the changes in the relationship between debt and income over time. The top plot shows that this relationship shifted over the course of the boom—but at the top end of the income distribution, not the bottom. That is, in high-income zip codes, residents become more likely to hold mortgage debt during the boom, even without a change in the zip code's income. No such shift is evident at the other end of the income distribution. For low-income communities, changes in the share of mortgaged households arise predominately

[28]Indeed, mortgageship regressions using the SCF generate similar patterns as those generated by the homeownership regressions in Figure 8. See the internet appendix for details.

[29]The share of households in a zip code that have a mortgage is calculated by taking the average of two estimates. The upper bound is the number of outstanding first liens divided by the number of IRS tax returns. This does not correct for joint mortgages. The lower bound is the number of "couples" in Equifax with a mortgage: the number of people with a mortgage, with any joint mortgage divided by two.

from movement along a stable debt-income relationship, not from a shift in the relationship itself. The lower panel of Figure 9 repeats the analysis on a within-CBSA basis. Here, the conditional relationships have virtually identical shapes, suggesting that the high-income shifts in the top panel arise primarily from between-CBSA shifts in mortgaged-household shares. This finding lines up well with the importance of between–CBSA shifts for total debt levels discussed earlier.

4.3 Credit Scores and Mortgage Borrowing

So far, the focus of this paper has been on mortgage debt and income, but a high-income person can also be a bad credit risk and thus a marginal borrower. We therefore examine the extensive margin using the individual-level Equifax credit scores.[30] Yet such an exercise must confront two important issues, the first being endogeneity. When a borrower purchases a home and then makes a series of on-time payments, her credit score typically rises. Reverse causation therefore influences the raw correlation between the probability of having mortgage debt and an individual's current credit score. A second problem confounding the study of credit scores and the extensive margin is that as a general matter, a great deal of new debt is taken out by individuals with relatively low scores. People typically borrow to buy homes early in their adult lives, but on average young people have low credit scores because they have yet to build up substantial savings and they have relatively short histories of paying bills on time. Consequently, the life-cycle borrowing pattern exerts a negative influence on the cross-sectional relationship between credit scores and debt, regardless of the current state of lending standards.

Fortunately, information in the Equifax data allows us to circumvent these issues. Although the New York Fed Consumer Credit Panel begins in 1999, it contains a variable indicating the age of the oldest mortgage on record that is not covered in the dataset but that is covered in Equifax's master files. So, even though someone taking out a mortgage in, say, 1985 may not have a so-called mortgage tradeline in the Consumer Credit Panel, a separate variable will indicate that this person does have a mortgage originated in that year. Unless the mortgage still has a positive balance during or after 1999, we will not know the size of the 1985 mortgage, only its existence. Yet this knowledge will identify individuals taking out first mortgages after 1999, and an exclusive focus on first mortgages solves the endogeneity problem that arises when existing borrowers make on-time payments. Of course, the focus on first-time borrowers means that we will pick up a large number of young people, who as a group have low credit scores. But this second issue can be addressed by conditioning on age.

[30]The relationship between credit scores and income is the key focus of Albanesi et al. (2016) and as noted below is also explored in Bhutta (2015).

Figure 10 plots a collection of hazard ratios for individuals obtaining a mortgage for the first-time. For each hazard, the denominator is the number of persons in a given credit-score group who had not taken out a mortgage by year t-1. The numerator is the flow of persons from this risk set who take out their first-ever mortgage in year t. This approach builds on work in Bhutta (2015), who also investigates first-time-mortgage borrowing using Equifax data. An important difference between Figure 10 and Bhutta (2015) is that the figure defines credit scores *relative* to CBSA means, in order to hold constant factors that affect the creditworthiness of individuals throughout a given housing market.[31] The top panel shows a near-monotonic relationship between the probability of obtaining a first mortgage and creditworthiness throughout the sample period. In all years, individuals in the two best credit-score categories are always most likely to obtain a mortgage for the first-time, and individuals in the bottom group are always the least likely.[32] Importantly, the probability of transition declines during the mortgage boom for all credit-score groups. In absolute terms, declines for the highest groups are more substantial because these groups start the housing boom with the highest transition rates.

The four panels in the bottom half of Figure 10 split the sample by age. Credit-score quintiles are calculated within age groups, so a person in, say, the top group of young people may have a lower credit score than someone in a middle group of older persons. Looking across panels, a hump-shaped hazard of first-time mortgageship can be inferred, as transition rates rise from age 18–24 to age 25–35, then fall thereafter. Also, transition rates are monotonic for the youngest two groups, as persons in the highest credit-score groups are always most likely to transition, those in the second group are the second-most likely, and so on. For the two older groups, however, individuals in the highest two groups have only moderate transition rates. These age-specific patterns most likely result from selection: young people with high credit scores are more likely to have high incomes than high wealth, so they still must take on mortgage debt to acquire homes. Older people with high credit scores either already own their homes or are wealthy enough to purchase them without debt. By and large, however, the patterns suggest no substantial extensive-margin shifts in favor of poor credit risks.

The analysis in Figure 10 compliments the earlier results on the extensive margin in two

[31]The CBSA-level means are generated from all residents of the CBSA appearing in the Equifax dataset, not just those residents who have yet to obtain their first mortgage and are therefore included in the risk set. Also, we analyze the hazard ratios using individual years rather than the two-year groupings in Bhutta (2015) and we use a more-granular classification of credit scores.

[32]From 2004–2007, the top credit-score group is marginally less likely to transition to mortgageship than the second-best group, This pattern could indicate that the top group already owns homes free and clear. As we will see, after subsetting on age the top group of young persons is substantially more likely to transition than the second-highest group in all years. This pattern indicates that a previous home purchase is less of confound for individuals near the start of the life-cycle.

ways. First, the earlier analysis revealed that the positive cross-sectional relationships between income and either homeownership or mortgageship did not weaken during the housing boom. Yet these correlations could be influenced by labor market developments that favored people who are likely to own homes over those likely to rent. For example, if technical change tilts the distribution of income toward highly skilled workers, and if these workers are more likely to own homes, then the partial correlation of income and homeownership may grow, even as loosened lending standards allow more low-income people to buy homes. Using the individual-level data in the Equifax dataset to study the flow into mortgage borrowing provides another look at potential changes in lending standards that is less susceptible to this potential confound.

A second reason that Figure 10 is particularly valuable is that it suggests that rising housing prices during the boom had strong negative effects on first-time buying throughout the credit-score distribution. Loosened lending standards make it more likely that previously constrained individuals will buy homes, holding other factors constant. But in the early 2000s, other factors were not held constant—house prices in particular were rising rapidly. On balance, the negative effect of higher prices appears to have outweighed any positive effects of relaxed credit standards, so that first-time buying among low-credit score groups declined during the mortgage boom, along with first-time buying for everyone else. Thus, in light of the sharp rise in house prices, the truly surprising feature about the mortgage boom is not that most of dollar-increase the mortgage debt went to the wealthy. The real surprise is that the low-income individuals, who were least likely to own homes at the start of the mortgage boom, were able to increase their debt levels at the same rates as everyone else.

Later in the paper, we will investigate the role of subprime lending in the credit boom by asking what would have happened had subprime loans had not been available. But before we do, we shift the focus from stocks of debt and homeowners to the two gross flows of debt: mortgage originations and terminations. The gross-flow analysis provides some useful context for the housing boom, just as the study of gross job and worker flows has generated valuable insights on labor markets (Davis, Haltiwanger, and Schuh 1996; Shimer 2005). The gross-flow analysis also shows how the results above resolve some ongoing debates in the academic literature.

5 Rising Mortgage Churn in Low-Income Areas

The same regression framework used to investigate debt stocks can be also be applied to flows. Using the notation from section 3.2, the conditional expectation function for a gross flow of debt f in zip code i is $E(f_{cit}|y_{cit}) = \alpha_t + \beta_t \cdot y_{cit}$, where y denotes income and t denotes the year. Figure 11 uses this framework to study gross flows on a within-CBSA basis.[33] Each of the two rows of Figure 11 contains a binned scatter plot and a plot of estimated income effects for either the flow of mortgage originations (top row) or of terminations (bottom row). Thus the panels are analogous to the panels in the top row of Figure 6 that analyzed debt stocks.

In contrast to the stable income effects for debt stocks, there is a significant decline in the positive relationships between income and both gross flows during the mortgage boom. In the binned scatter plots at left, these declines are indicated by shallower slopes for the 2006 data relative to those for the 2001 data. The panels at right show the declines as lower values for the estimated βs, which decline from around 1.6 to 1.7 in 2002 to less than one in 2006. The reduced importance of income for flows is consistent with the stable income effects for relative stocks seen earlier, however. That is, the top panels of Figure 11 indicate progressively higher levels of mortgage originations in low-income areas, but the same pattern is also seen for terminations. Thus the two patterns offset one another, so that relative "mortgage churn" rises in low-income areas over time even as relative stocks of debt do not.[34]

5.1 Refinances and Purchases

What accounts for rising churn in low-income areas? One factor is undoubtedly the disproportionate participation of high-income borrowers in the refinancing boom of 2001–2003.[35] The reasons behind this boom are well known.[36] Due in part to aggressive monetary easing during and after the 2001 recession, the 30-year mortgage rate fell from around 8½ percent in early 2000 to about 5½ percent in mid-2003.[37] Higher levels of refinancing generate higher amounts of mortgage churn, and Figure 11 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.[38] As this wave fell off, the *relative* amount of churn

[33]See the internet appendix for analogous results without area-level fixed effects.

[34]Mortgage churn is closely related to what Adelino, Schoar, and Severino (2016) call the "velocity" of mortgage origination, as explained below.

[35]Because we do not have IRS income data for 2003, we cannot investigate the flow-income relationships for that year. But it is likely that the 2003 income effects for both originations and terminations were even larger the 2002 values.

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

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

[38]In his presidential address to the American Finance Association, Campbell (2006) highlighted three major financial mistakes often made by U.S. 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 indicates "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" (p. 1581). For

in low-income communities increased.

How were changes in purchases as opposed to refinances related to rising churn in low-income areas? It is likely that low-income zip codes experienced higher sales turnover as the boom progressed, and this turnover increases churn when sellers discharge their existing mortgages as buyers originate new ones. We are not able to consistently distinguish purchases from refinances in the Equifax data, so we cannot measure sales turnover directly using that dataset.

We can construct a measure of "purchase-mortgage intensity" by dividing the number of purchase-mortgage originations in a zip code (as measured in HMDA) by the number of first liens there (as measured in Equifax). Figure 12 shows that purchase-mortgage intensity rose in low-income communities from 2001 to 2006. At first blush, higher levels of purchase-mortgage intensity in low-income areas would appear to contradict the results in Figure 9 that indicated no relative changes in the shares of mortgaged households across high- and low-income areas. Yet the purchase-mortgage patterns are quite consistent with stable mortgaged-household shares, for two reasons. First, as noted above, sales transactions typically involve the origination of one mortgage and the termination of another, in which case the number of mortgaged households in the zip code does not change.[39] A second reason that higher numbers of HMDA purchase mortgages may not raise shares of mortgaged households in Equifax is that the people taking out these mortgages may be investors. When an investor purchases a property to rent out or rehabilitate, HMDA links that mortgage to the zip code of the property, but Equifax—correctly—links the mortgage to the home zip code of the purchaser/investor. If this individual already had a mortgage on her primary residence, then the purchase has no effect the mortgaged-household shares of either zip code.[40]

Unfortunately, the presence of investors prevents us from using HMDA data to disentangle purchases from refinances in the Equifax data, because HMDA does not tell us whether the investor lives, only the zip code of the property being purchased. Thus we are unable to determine how much of the increase in Equifax-measured churn in low-income areas during the boom is due to higher purchases as opposed to the ebbing of the refinance wave. An additional point relevant for existing research (discussed below) is that investors distort HMDA purchase patterns as indicators of the gross flows of debt into specific zip codes, and

additional evidence on high-income refinancing, see Figure A.15 in the internet appendix.

[39]The impact of simultaneous originations and terminations on credit allocation plays an important role in Gerardi and Willen (2009), which links HMDA data to property-level deed records in order to 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.

[40]Of course, if the seller of the property lived in it and had a mortgage, then the termination of his mortgage would reduce the share of mortgaged households in that zip code.

this distortion is probably worse for low-income zip codes because investor purchases are more prevalent there. The bottom two panels of Figure 12 replicate the top two panels of the same figure after removing investors from the purchase-intensity measure. The bars now show a much smaller shift in purchase intensity towards low-income areas, indicating that investment purchases are more prevalent in zip codes with low incomes. Investor information in HMDA must be used with caution, because an investor might inaccurately report his status as an owner-occupier during the loan-application process if doing so improves his chance of approval. But this potential misreporting bias means that the number of investor purchases as measured in HMDA is best considered a lower bound. Because the actual importance of investors is probably greater than the measured importance, the implication of Figure 12 is that a nontrivial component of the increase in relative purchase activity in low-income areas is due to investors, who then rented out their properties or rehabbed them to be flipped to other buyers.

5.2 Relationship to Previous Research

These gross-flow results help clarify and resolve some debates in the existing literature. In an original and highly cited contribution, Mian and Sufi (2009) used HMDA purchase mortgages to argue that during the boom, the relative availability of mortgage credit rose in zip codes with low average incomes or large numbers of subprime borrowers. Their inference was that mortgage credit was becoming more plentiful for persons who would have been denied credit before. Using the terminology of this paper, the authors were interpreting the growth in relative purchase-mortgage intensity for low-income areas as a true expansion of credit at the low end of the income distribution. In a subsequent paper, Adelino, Schoar, and Severino (2016) exploited the individual-level nature of the HMDA data to separate the flow of new purchase mortgages into two components: the average number of new mortgages in a zip code and the average amount of each individual mortgage. The authors show that the higher amount of purchase-mortgage credit that Mian and Sufi found was driven by higher numbers of mortgages in low-income communities, not by higher average amounts. Adelino et al. inferred from this finding that the higher "velocity" of mortgage origination was responsible for Mian and Sufi's results, and thus that there was no relative expansion of mortgage credit to low-income areas. In turn, Mian and Sufi (2016) have countered that nothing in Adelino et al. disproves their 2009 claim that credit became relatively more plentiful to previously constrained individuals, as long as the new mortgages in low-income areas allowed more low-income people to obtain mortgage credit.

Rarely can an important economic debate can be settled by simply getting the right data, but this is one of those times. Both Mian and Sufi and Adelino et al. agree that progressively more purchase mortgages were originated in low-income areas as the boom progressed, as we have also shown above using the same HMDA data. The two sides disagree only on the consequences of this higher gross flow for stocks of mortgage borrowers and of mortgage debt. Yet these stocks can be measured directly with the Equifax/IRS and the SCF datasets, and neither dataset indicates a relative expansion of mortgage debt along the extensive margin. As we have seen, both the CPS and the SCF suggest that household-level income effects on homeownership strengthened, not weakened, during the boom, while the Equifax/IRS dataset displays a remarkable stability in the distributions of both debt levels and shares of mortgaged households across zip codes. A separate way to infer changes in the stock of individuals holding mortgage debt is to measure the relevant flow at the individual level, rather than at the zip-code level as in previous research. This type of individual-level flow analysis, performed using the credit scores in Equifax, implied that first-time home purchasing declined across the credit-score spectrum, even for low-score individuals.[41] Mathematically, all of these findings are consistent with the purchase-mortgage patterns in low-income zip codes, if the rising originations were offset by rising terminations, as this section showed was true for *total* originations and *total* terminations. Additionally, our analysis of HMDA data confirms that a substantial fraction of the higher purchase mortgages in low-income areas studied in the previous literature went to outside investors, further undermining the use of HMDA data as indicators of a relative credit expansion. All told, even though Adelino et al. could not measure the relative stocks with HMDA data, their claim that a higher flow of purchase-mortgage originations did not result in a disproportionate growth of marginal homeowners is confirmed in other data.[42]

6 The Role of Subprime in the Credit Expansion

In both popular and academic discussions the recent housing cycle has been closely linked to subprime borrowing. We have shown that whatever effects subprime lending had on the housing market, it did not generate disproportionately high debt growth among low-income individuals and communities during the early 2000s mortgage boom, nor did it significantly expand mortgage borrowing for these individuals along the extensive margin. In

[41]To be sure, the individual flow-hazard rates are not dispositive regarding the stock of individuals, because individual-level flows *out* of mortgage borrowing might have changed in offsetting ways. But the claims that the stock of marginal borrowers grew are based on the hypothesis of larger flows into mortgage borrowing, not from smaller flows out, so the hazard-rate results are directly relevant.

[42]Adelino, Schoar, and Severino (2016) also use individual-level income data from HMDA to support their claims about the lack of an extensive-margin expansion of credit, and Mian and Sufi (2015) have countered that the individual-level income data in HMDA is especially subject to fraudulent overstatement at the lower end of the income distribution. We are now investigating the HMDA income data in more detail in a companion paper, but the main critique of HMDA data as a measure of the debt-income relationship still holds. Without knowing anything about the incomes of sellers, it is hard to say much about household balance sheets with HMDA income data alone.

this section, we focus more closely on subprime borrowing by asking three partial-equilibrium counterfactuals: what would have happened to total mortgage borrowing, the distribution of debt, and the absolute number of foreclosures had the subprime market not grown?

6.1 Without Subprime, Debt Growth Still Would Have Been Large

Even at its height, subprime borrowing made up a modest fraction of mortgage-debt stocks. An upper bound on the size of subprime borrowing is provided by the amount of total privately securitized mortgage debt, which includes Alt-A and jumbo prime debt and is measured by the Flow of Funds.[43] The heavy black line in the top panel of Figure 13 is the total amount of home mortgage debt on the liability side of household balance sheets from the Flow of Funds. The lighter gray line is a counterfactual amount of mortgage debt that would have occurred if the only growth in mortgage-debt liabilities after 2001:Q1 had been privately securitized debt.[44] The chart shows that some time after 2003, growth in privately securitized debt accounted for a nontrivial fraction of the growth of overall mortgage debt. But the large majority of debt accumulated during the mortgage boom was allocated outside of the private-label securities channel, through avenues that included portfolio lending, agency MBS, state and local housing authorities, and other sources.

The Flow of Funds does not disaggregate privately securitized debt into its major components: subprime, Alt-A, and prime jumbo loans. However, we can calculate the size of these components by aggregating the loan-level data in the CoreLogic ABS Private Label Securities ABS Database that was discussed in the data section. The red dashed line in the bottom panel of Figure 13 shows how much total mortgage debt would have grown if the only debt growth after 2001:Q1 had been privately securitized subprime loans. According to the CoreLogic database, outstanding subprime debt grew from about \$100 billion in 2001:Q1 to about \$955 billion by the middle of 2007, for a total increase of about \$855 billion. The dashed blue line in the panel adds the even larger in Alt-A debt, which rose from about \$60 billion in 2001:Q1 to about \$1.04 trillion by mid-2007, a total increase of about \$980 billion. The last counterfactual, depicted by the gray line, adds the relatively small amount of growth in jumbo securities. The main message of Figure 13 is that even though subprime made up a nontrivial portion of total debt growth during the mortgage boom, the vast majority of new mortgage debt was generated though other channels.

[43]Prime jumbo loans are those that are too large to be securitized by the government-sponsored agencies. See footnote 8 for the definition of Alt-A.

[44]The privately securitized debt level is the total amount of debt issued by asset-backed securities (ABS) issuers on mortgages for 1-4 family structures. In mortgage data, privately securitized debt is labeled ABS debt to distinguish it from the MBS securities that are backed by the government-sponsored agencies.

6.2 Without Subprime, Debt Would Have Been Reallocated Toward the Wealthy

How were the different types of mortgage debt allocated with respect to income? For each zip code in the Equifax/IRS dataset, we figure the total amount of subprime and ABS debt using the CoreLogic database. We then subtract these totals from the total amount of mortgage debt from the Equifax data, which generates an estimate of the total amount of prime debt in each zip code as a reminder. Figure 14 shows the average contributions of subprime, Alt-A, and prime debt to total debt-growth rates across the income distribution of zip codes from 2001 to 2006. The top panel ranks zip codes based on wage and salary income without regard to their CBSA location. As we would expect, the panel shows that subprime debt was more prevalent in low-income areas, though some residents of wealthy zip codes also took out subprime loans. The bottom panel bins the zip codes based on their incomes relative to CBSA means. The story here is generally the same, though the negative relationship between the use of subprime debt and average zip code-level income appears somewhat greater. Combining these results with the lessons about the modest size of subprime lending indicates that subprime lending did help low-income borrowers keep up with the prime-driven growth of mortgage debt in richer areas. But in no sense did subprime did not cause a reallocation of mortgage debt toward the poor, as is often claimed. Rather, subprime lending prevented a reallocation of debt toward the wealthy.

6.3 Without Subprime, There Would Have Been Many Fewer Foreclosures

The modest role of subprime during the mortgage boom contrasts with subprime's critical role during the 2008 financial crisis. This crisis was sparked by significant losses on privately securitized securities, which in turn were caused by massive subprime defaults. How does the central importance of subprime during the crisis square with the absence of disproportionate debt growth among low-income borrowers, as well as the moderate dollar amounts of subprime lending during the boom? To answer these questions, we measure how foreclosure rates varied with income before and after the mortgage boom. As it turns out, the resulting foreclosure patterns are quite consistent with the patterns of mortgage-debt accumulation. Just as debt was scaled up equally during the boom, so too were foreclosures were similarly scaled up across the income distribution. The difference between debt and foreclosures is that debt is positively correlated with income in the cross–section while foreclosures are negatively correlated. Foreclosure patterns thus not only fail to contradict the earlier results of this paper–they actually help confirm them.[45]

To show this, we again turn to the Equifax data, which allow us to calculate default rates by zip code. Individual mortgages in Equifax are classified as either current or delinquent, with the latter group further delineated by length of delinquency: 30, 60, 90, or 120+ days. The Equifax dataset is quarterly, so we can define the default rate in quarter t as the share of all active first liens in quarter $t-1$ that transition to 90-day delinquency in quarter t.[46] The top two panels in Figure 15 present binned scatter plots of the log of this default rate against income per return categories in 2001:Q4 and 2009:Q4. We choose the last quarter 2009 as the end period of comparison because the foreclosure crisis did not peak until well after house prices started falling. Because we use natural logs when measuring defaults, a uniform percentage increase in defaults across the income distribution shows up in the figure as a uniform shift upward in the implied relationship, as was the case with total mortgage debt.

The upper left panel of Figure 15 shows the relationship across all zip codes without regard to CBSA location. The panel shows a strong negative relationship between default rates and income, as defaults are always higher in zip codes at the bottom of the income distribution. But this plot also shows that over the course of the housing bust, defaults rose nearly proportionately in both high- and low-income communities, just as debt did. In fact, the default rate grew somewhat more in percentage terms in high-income income zip codes, as the slope of the conditional expectation function flattens from 2001 to 2009. The upper right panel makes the within-CBSA comparison, with both defaults and income measured relative to CBSA means. A modest flattening in the relationship between defaults and income is evident in this plot as well. For the most part, however, foreclosure results are mirror images of those for mortgage debt. High-income borrowers account for the lion share of mortgage debt, so their debt rose the most in absolute terms as the distribution of debt was scaled up during the boom. By constrast, low-income borrowers account for a high share of defaults, so foreclosures among those borrowers rise most in absolute terms during the bust.[47] But in no sense did the distribution of foreclosures become *concentrated* in low-income communities, because *shares* of foreclosures across communities remained stable.

The lower left panel of Figure 15 groups zip codes using credit scores rather than wage

[45]Adelino, Schoar, and Severino (2016) also examine foreclosures across the income distribution, but their emphasis is on the dollar value of defaults for a specific vintage of mortgages. Additionally, that paper uses the McDash data generated by mortgage servicers, so the results may be less representative of the entire mortgage market than results based on Equifax data.

[46]The resulting ratio is of course similar to a sample hazard. We define the number of active first liens in the previous quarter as all liens that are less than 90 days delinquent. These liens therefore comprise the risk set for loans that can become 90 days delinquent in the current quarter.

[47]The high absolute number of foreclosures in low-income communities has a policy implication; because foreclosures are relatively plentiful there, anti-foreclosure efforts by policymakers might best be targeted to low-income areas.

and salary income to investigate these shares further. Specifically, following previous research we classify zip codes based on the share of residents with a credit score below 660 in 1999. The panel plots the share of total defaults accounted for by zip codes in various credit score categories. The graph shows that zip codes with the most subprime borrowers had the highest share of defaults in 2001, while the least subprime had the smallest share. But as we would expect given the proportional scaling-up of defaults using the income measure, defaults were scaled up using credit scores as well. Consequently, the shares of defaults accounted for by zip codes in the various quintiles did not change over time. Indeed, consistent with the second-order tilt of foreclosures in high-income zip codes, the share of foreclosures accounted for by high-credit-scores rises a bit over time.

The final panel of Figure 15 investigates defaults by mortgage type, using zip code-level aggregates of subprime and Alt-A defaults from the Corelogic ABS database. Early in the crisis, subprime defaults account for a significant share of total foreclosures as measured in Equifax—almost 40 percent—consistent with the conventional story that subprime foreclosures helped spark the financial crisis. By 2009, however, the subprime share of total defaults had fallen to about 10 percent, and it continued to decline thereafter. This pattern suggests that within individual zip codes, those borrowers using subprime loans were the most susceptible to the downturn in the housing market. But it also illustrates that the overall housing crisis was not a "subprime" crisis alone, a point emphasized in Ferreira and Gyourko (2015).

At a fundamental level, the real reason subprime mortgages caused so many problems in the financial crisis was not that the stock of subprime debt had become especially large. Rather, it was that subprime loans were not insured by the government, as were the prime loans securitized by the government-sponsored agencies. Another reason that subprime losses disproportionately affected the financial system stemmed from the creation of synthetic collateralized debt obligations (synthetic CDOs). These instruments were collections of credit default swaps that referenced underlying tranches of bonds backed by subprime mortgages. With synthetic CDOs, investors could place additional bets on the performance of subprime mortgages even if Wall Street did not create any new subprime securities.[48] The famous Abacus deal, which was arranged by Goldman Sachs and on which the investor John Paulson made billions of dollars, was a synthetic CDO that like others had both winners and losers. But the losers were investment banks and other firms inside the financial system,

[48] Cordell, Huang, and Williams (2012) estimate that about one-third of the $641 billion in structured-finance CDOs issued between 1999 and 2007 consisted of synthetic references to underlying bonds. In the movie *The Big Short*, synthetic CDOs are illustrated with a blackjack game played by the singing star Selena Gomez and the behavioral economist Richard Thaler. Observers to the game take side bets on how the wages placed by Gomez and Thaler will turn out. The actual mortgage-backed securities are analogous to the original bets played by Gomez and Thaler, while the synthetic CDOs are similar to the side bets made by the spectators.

while the winners were mortgage-market outsiders (Foote, Gerardi, and Willen 2012). By concentrating the additional losses on the financial system, synthetic CDOs like the Abacus deal amplified the negative effect of subprime defaults.

7 Conclusions

To conclude, we state the four main lessons regarding the mortgage boom: mortgage debt grew proportionately across the income distribution; there was no disproportionate expansion of debt along the extensive margin to low-income or marginal borrowers; the level of mortgage churn in low-income communities even as debt stocks grew proportionately; and subprime lending was only moderately important in the boom, even though subprime defaults were hugely important in the bust.

Ultimately, these cross-sectional facts are most interesting if they tell us something about why the housing cycle occurred. The findings are hard to square with any theory of the cycle that assumes a reallocation of credit toward low-income borrowers. In fact, there are theoretical as well as empirical reasons to discount low-income borrowing as a causal factor in the housing boom. As illustrated in the seminal paper of Krusell and Smith (1998), formal models of asset markets with heterogeneous agents can allow poorer agents to behave differently from richer ones, so that a complete characterization of asset markets requires a sophisticated model that tracks wealth distributions over time. However, because poor people do not have much wealth, their behavior does not strongly influence these distributions. As a result, a formal model would have problems explaining a $1.5-trillion increase in mortgage debt at the top end of the income distribution with a relaxation of borrowing constraints at the bottom. Perhaps it is fortunate that this theoretical hurdle does not need to be overcome, in light of the empirical fact that mortgage debt grew proportionately across the income distribution.

Rather than a shock specific to low-income borrowers, the results above suggest that the housing cycle was driven by some aggregate factor. Low interest rates are a natural candidate. Perhaps the most careful analysis of interest rates during the housing boom comes from Glaeser, Gottlieb, and Gyourko (2013), who model the effect of interest rates on housing prices from both a theoretical and empirical perspective. Unfortunately, both perspectives suggest that movements in interest rates were not large enough to drive the cycle. “Interest rates do influence house prices,” they write, “but they cannot provide anything close to a complete explanation of the great housing market gyrations between 1996 and 2010” (p. 350). In addition to interest rates, Glaeser, Gottlieb, and Gyourko (2013) also correlate house prices with loan-approval rates and average down payments. The empirical impact of these two factors on prices is limited as well.[49] "This leaves us in the uncomfortable position of claiming that one plausible explanation for the house price boom and bust, the rise and fall of easy credit, cannot account for the majority of the price changes, without being able to offer a compelling alternative hypothesis" (p. 350).

Glaeser, Gottlieb, and Gyourko (2013) conclude by noting that overly optimistic house-price expectations could have fueled the boom. Rosy views of house-price growth were widely shared by potential home buyers as well as mortgage lenders, and such views can easily rationalize the behavior of both parties. Borrowers would have wanted to buy houses that were rising in price, and lenders would have been eager to write mortgages against this rapidly appreciating collateral.[50]

Yet Glaeser, Gottlieb, and Gyourko (2013) also note that if optimistic expectations were critical in the boom,

> ...this merely pushes the puzzle back a step. Why were buyers so overly optimistic about prices? Why did that optimism show up during the early years of the past decade and why did it show up in some markets but not others? Irrational expectations are clearly not exogenous, so what explains them? This seems like a pressing topic for future research (p. 350).

Some of this research is now taking place in the so-called distorted beliefs literature, in which rational expectations are augmented or replaced by beliefs that are influenced by expressly psychological factors.[51] To the extent that beliefs were distorted across the income distribution, then the expansive nature of the mortgage boom we have explored in this paper will likely support the distorted-beliefs explanation.

[49]The approval rates are measured using HMDA data while the data on down payments come from public deeds records collected by the DataQuick company.

[50]For average borrower-level expectations, see Case and Shiller (2003) and Case, Shiller, and Thompson (2012). For the price expectations of Wall Street analysts, see Gerardi et al. (2008).

[51]Papers that explore the formation of beliefs include Gennaioli and Shleifer (2010), Gennaioli, Shleifer, and Vishny (2012), Barberis (2013), Brunnermeier, Simsek, and Xiong (2014), Simsek (2013), Fuster, Laibson, and Mendel (2010), Geanakoplos (2009), and Burnside, Eichenbaum, and Rebelo (2016). In addition to Adelino, Schoar, and Severino (2016), empirical papers supporting the price-expectations theory include Cheng, Raina, and Xiong (2014) and Bayer, Mangum, and Roberts (2016).

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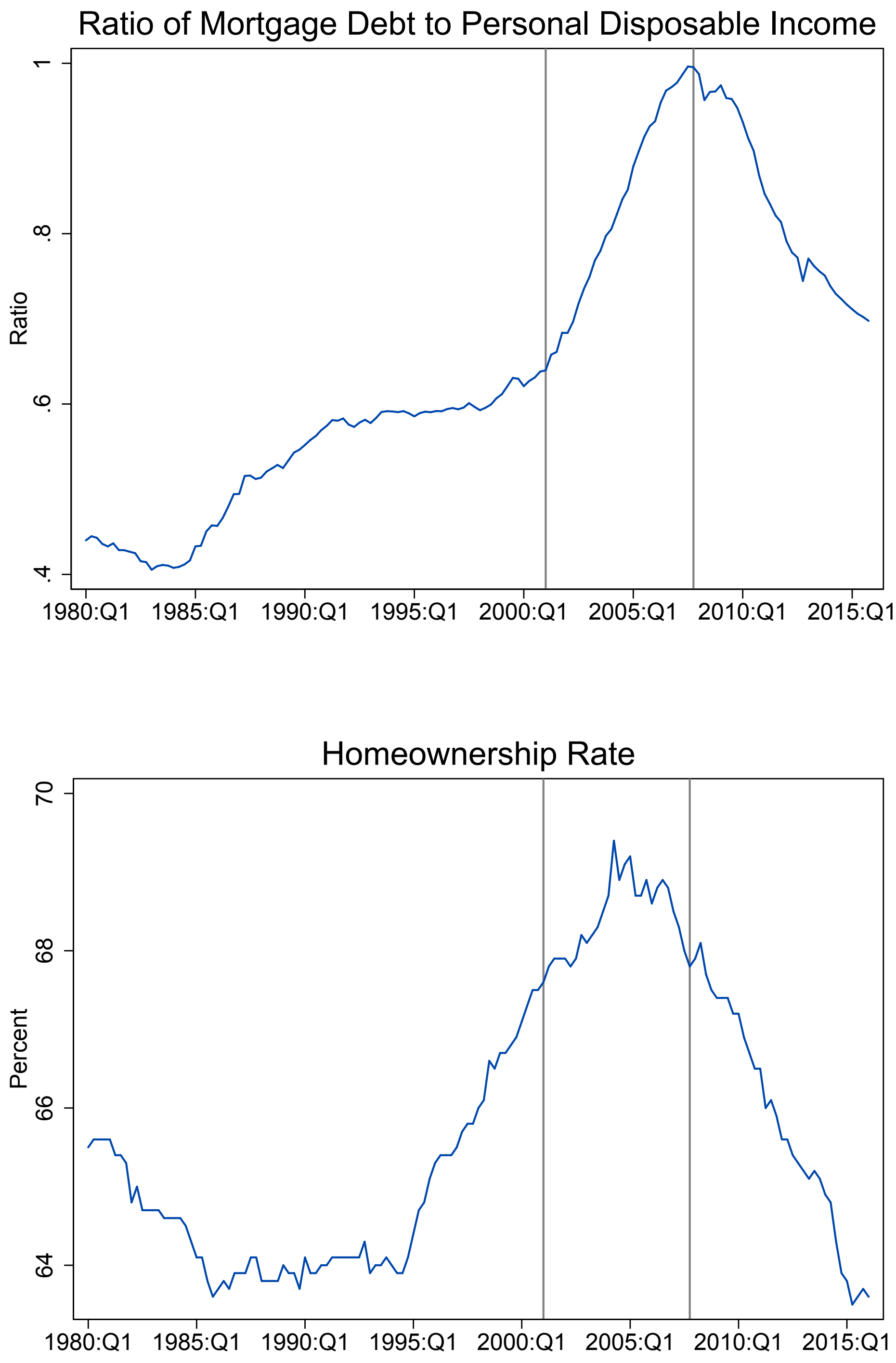


Figure 1. Mortgage Debt and Homeownership Rates in the United States: 1980:Q1 to 2015:Q4. *Note:* The mortgage debt ratio in the top panel is defined as total home mortgage liabilities in the household sector divided by total personal disposable income for the household and nonprofit sector. The income variable is seasonally adjusted at an annual rate. The homeownership rate in the lower panel is also seasonally adjusted. The gray vertical lines in each panel denote the quarters 2001:Q1 and 2007:Q4. *Source:* Board of Governors of the Federal Reserve System (Flow of Funds) for mortgage debt and income and Bureau of the Census for the homeownership rate.

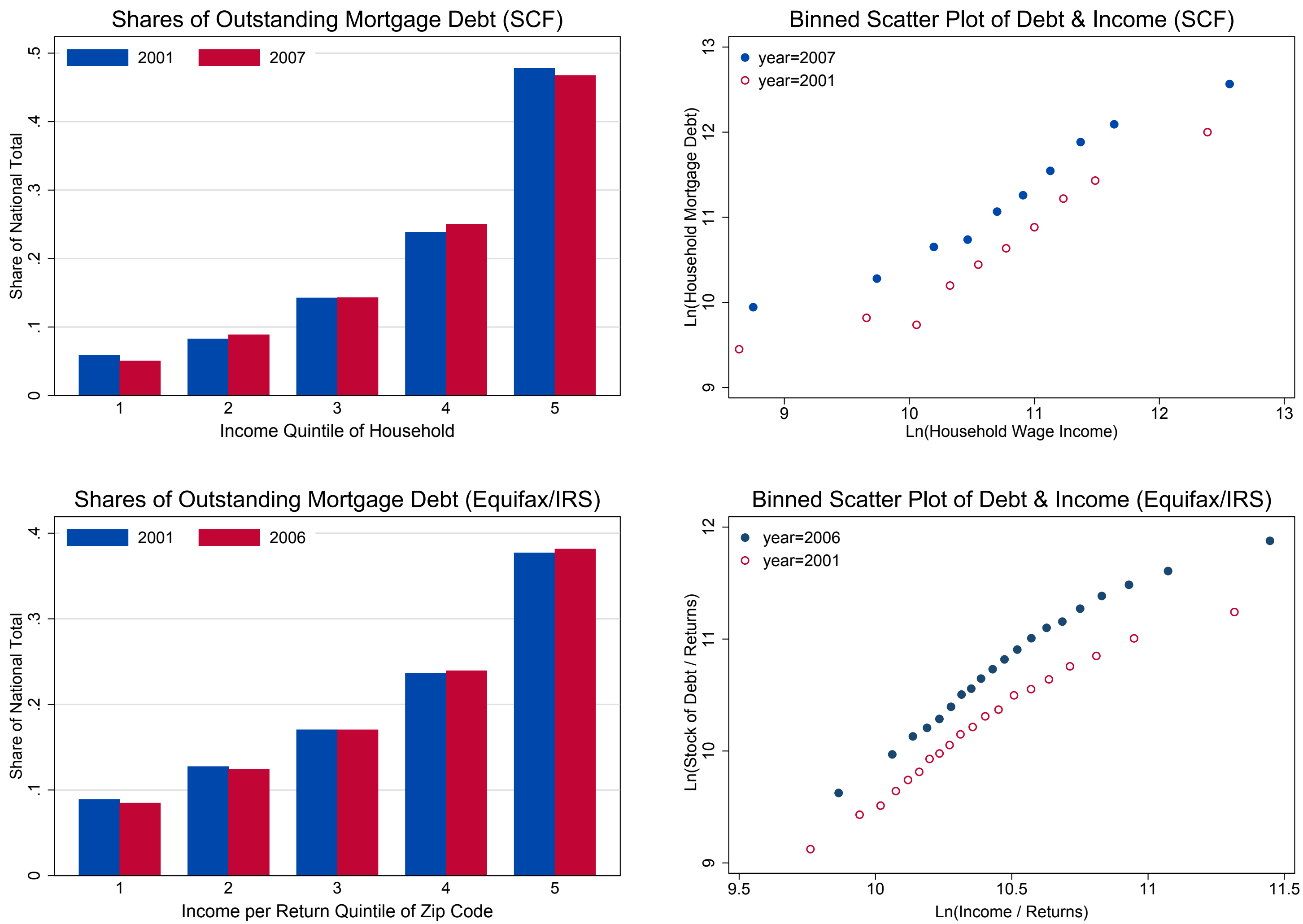


Figure 2. The Relationship between Mortgage Debt and Income among U.S. Households (top panels) and Zip Codes (bottom panels). *Note:* The top two panels use data from the Survey of Consumer Finances to depict the household-level relationship between wage income and mortgage debt in 2001 and 2007. The lower panels use debt data from the Equifax credit bureau 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. *Source:* NY Fed Consumer Credit Panel/Equifax, IRS Statistics of Income, and Survey of Consumer Finances.

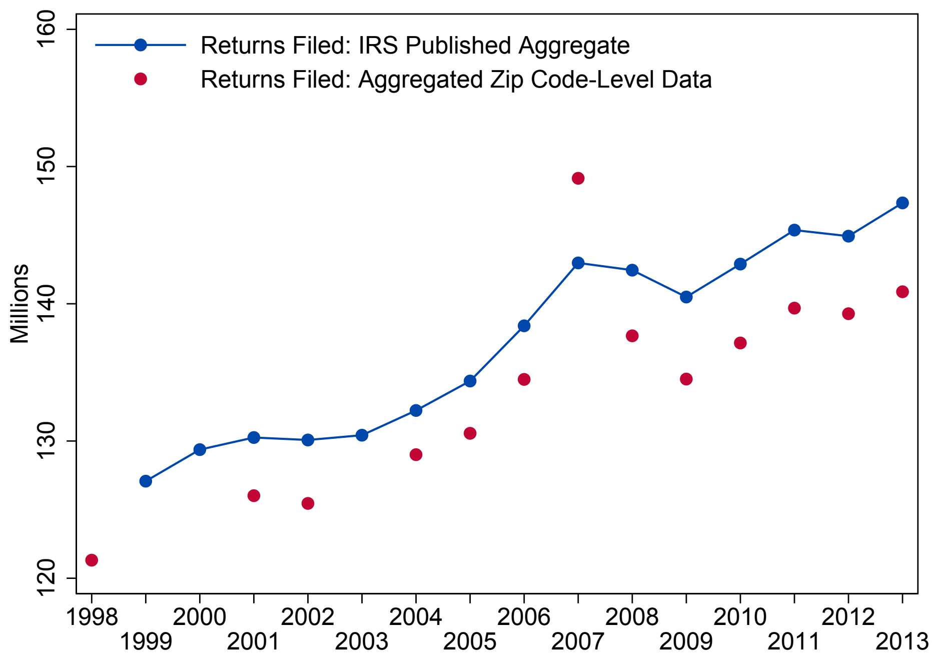


Figure 3. Two Measures of Aggregate Individual Income Returns Filed. *Note:* The blue line depicts the total number of individual income returns filed for the given tax year as published by the IRS. The 2007 value for this series omits returns filed by individuals for the sole purpose of receiving the 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. *Source:* 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).

	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 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 ($,000)	6	8	9	12	18
Mortgaged Households (%)	32	40	45	52	58
Median Age	47	47	47	46	47
Median Risk Score	656	689	707	729	754
Median House Price ($,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 Equifax/IRS Dataset. *Note:* Values at the zip code-level are summarized by return-weighted salary and wages per return quintiles from the IRS, so that 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. *Source:* NY Fed Consumer Credit Panel/Equifax, IRS Statistics of Income, CoreLogic, and Zillow.

					Debt on Primary Residence						Real Estate Assets	
Year	Income Quintile	No. of Unweighted Obs.	Mortgaged Households (% of Hholds)	Total Mortgage Debt	Total	Non-HELOC	HELOC	Other Mortgage Debt	Income	Home Ownership Rate (%)	Value of Primary Residence	Value of All Resid. Real Estate
Panel A: Income Defined as Total Income (Zero Incomes Included)												
2001	1	683.6	14	5,294	5,219	5,090	129	75	10,167	41	31,051	32,175
	2	659.4	28	13,044	12,510	12,166	344	535	24,453	58	63,403	69,047
	3	719.6	47	30,539	28,670	28,196	474	1,869	41,142	67	81,736	91,029
	4	705.2	64	55,464	52,439	51,451	988	3,025	66,705	82	136,648	153,193
	5	1,674.2	79	122,314	110,457	105,987	4,470	11,858	211,252	93	311,906	389,058
2007	1	664.2	15	10,795	9,661	9,321	340	1,134	12,690	41	56,960	64,258
	2	616.8	32	22,170	20,809	19,686	1,123	1,360	28,977	56	87,176	95,520
	3	648.8	52	56,299	54,035	52,965	1,070	2,264	47,872	70	137,874	152,275
	4	685.6	72	106,882	96,519	92,614	3,905	10,363	77,131	84	227,398	263,010
	5	1,801.6	81	219,228	184,652	174,227	10,425	34,576	257,914	94	537,018	714,545
Panel B: Income Defined as Wage Income (Zero Incomes Excluded)												
2001	1	590.8	26	15,581	14,953	14,451	502	628	10,713	44	52,955	66,497
	2	556.2	34	22,068	19,777	19,380	396	2,291	27,045	49	56,305	63,681
	3	563.2	55	38,015	35,834	35,159	676	2,180	43,065	69	85,389	94,221
	4	581.8	70	63,617	59,797	58,578	1,219	3,820	67,481	81	127,975	142,824
	5	1,091.8	84	127,374	117,407	112,853	4,553	9,968	168,217	92	292,371	349,305
2007	1	550.4	26	25,039	23,108	21,831	1,278	1,930	11,717	43	78,536	86,943
	2	522.8	39	43,960	39,013	37,286	1,727	4,948	30,618	52	93,208	106,750
	3	503.6	62	70,726	67,731	64,087	3,645	2,995	49,518	72	153,338	176,989
	4	560.0	77	123,914	110,677	106,423	4,255	13,237	77,340	83	234,546	271,525
	5	1,117.2	87	231,376	199,942	191,041	8,901	31,434	197,649	94	501,207	655,585

Table 2. Summary Statistics for Households in the Survey of Consumer Finances. *Note:* All variables are calculated as simple means of weighted averages from the five multiple implicates of the public-use summary data of the SCF. Figures are nominal dollar values unless otherwise noted. *Source:* Survey of Consumer Finances.

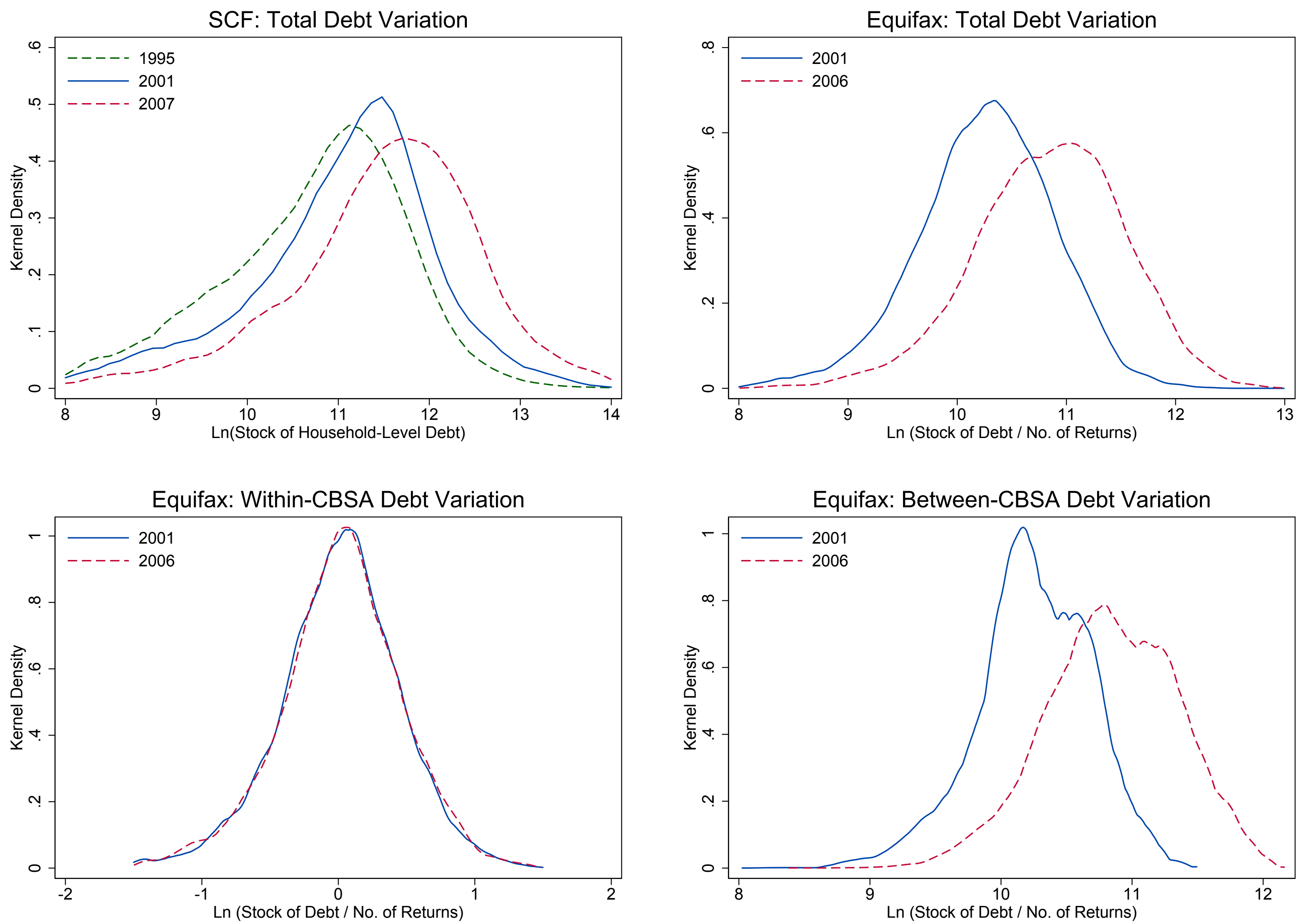


Figure 4. Distributions of Mortgage Debt. *Note:* All densities are weighted kernel densities of the log of household-level mortgage debt (SCF distribution in top left panel) or average zip code-level mortgage debt per tax return (Equifax distributions in remaining panels). Household-level weights are used for the SCF distribution and the number of income tax returns in the zip code is used to weight the Equifax distributions. The bottom left panel depicts Equifax densities after the log of zip code-level debt per return is deviated from means corresponding to Core Based Statistical Areas (CBSAs). The bottom right panel depicts the kernel densities of CBSA averages of debt. In all three distributions using the Equifax data, zip codes outside of CBSAs are excluded. *Source:* Survey of Consumer Finances, NY Fed Consumer Credit Panel/Equifax and IRS Statistics of Income.

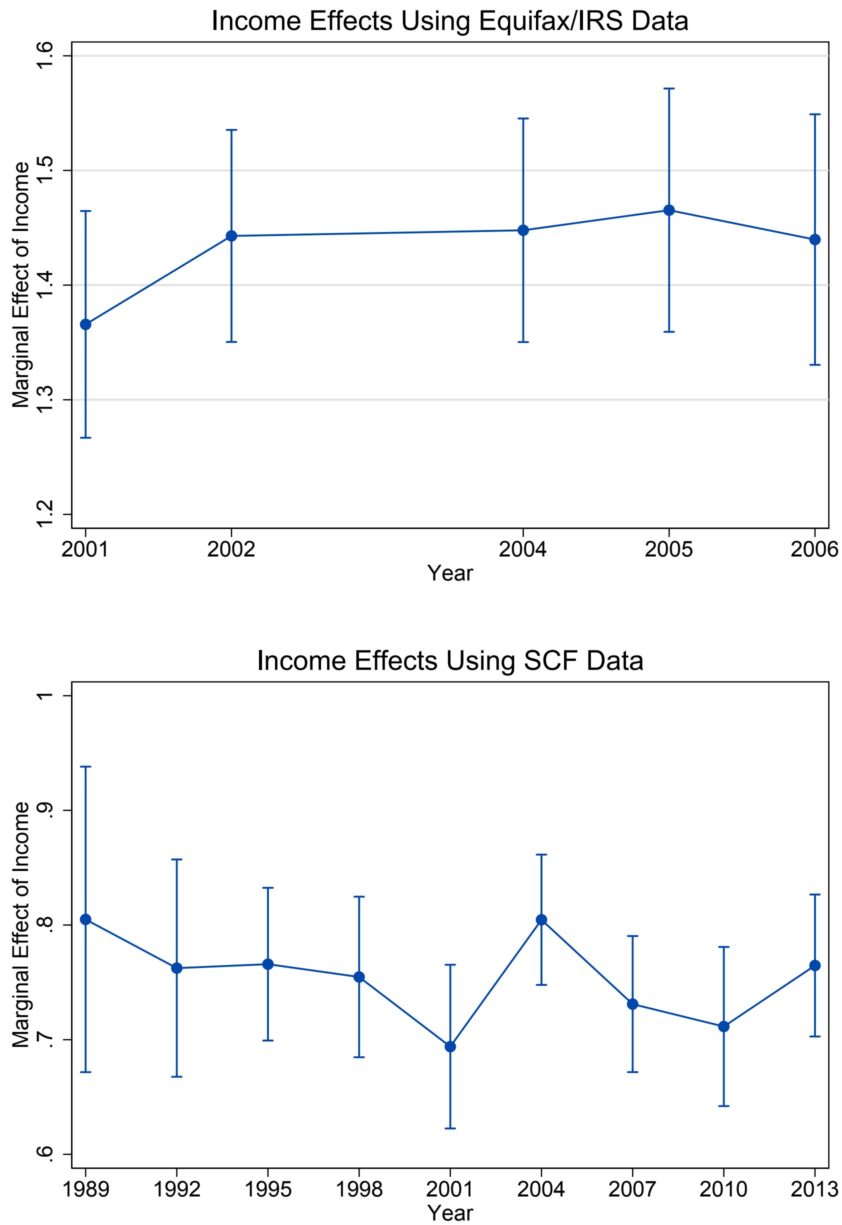


Figure 5. Regression Evidence on the Relationship between Mortgage Debt and Income among U.S. Zip Codes and Households. *Note:* The top panel graphs income coefficients (and 95-percent confidence intervals) from a returns-weighted regression of zip code-level mortgage debt on income for all years between 2001 and 2007, save for 2003 (when IRS income data are not available). Coefficients are generated from a single pooled regression that includes interactions of the income variable with yearly dummies, and 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. The reported coefficients are averages of estimates using the five implicates of the SCF. Standard errors are calculated as in Rubin (1987), but with no degrees-of-freedom adjustment. *Source:* NY Fed Consumer Credit Panel/Equifax and IRS Statistics of Income, and Survey of Consumer Finances.

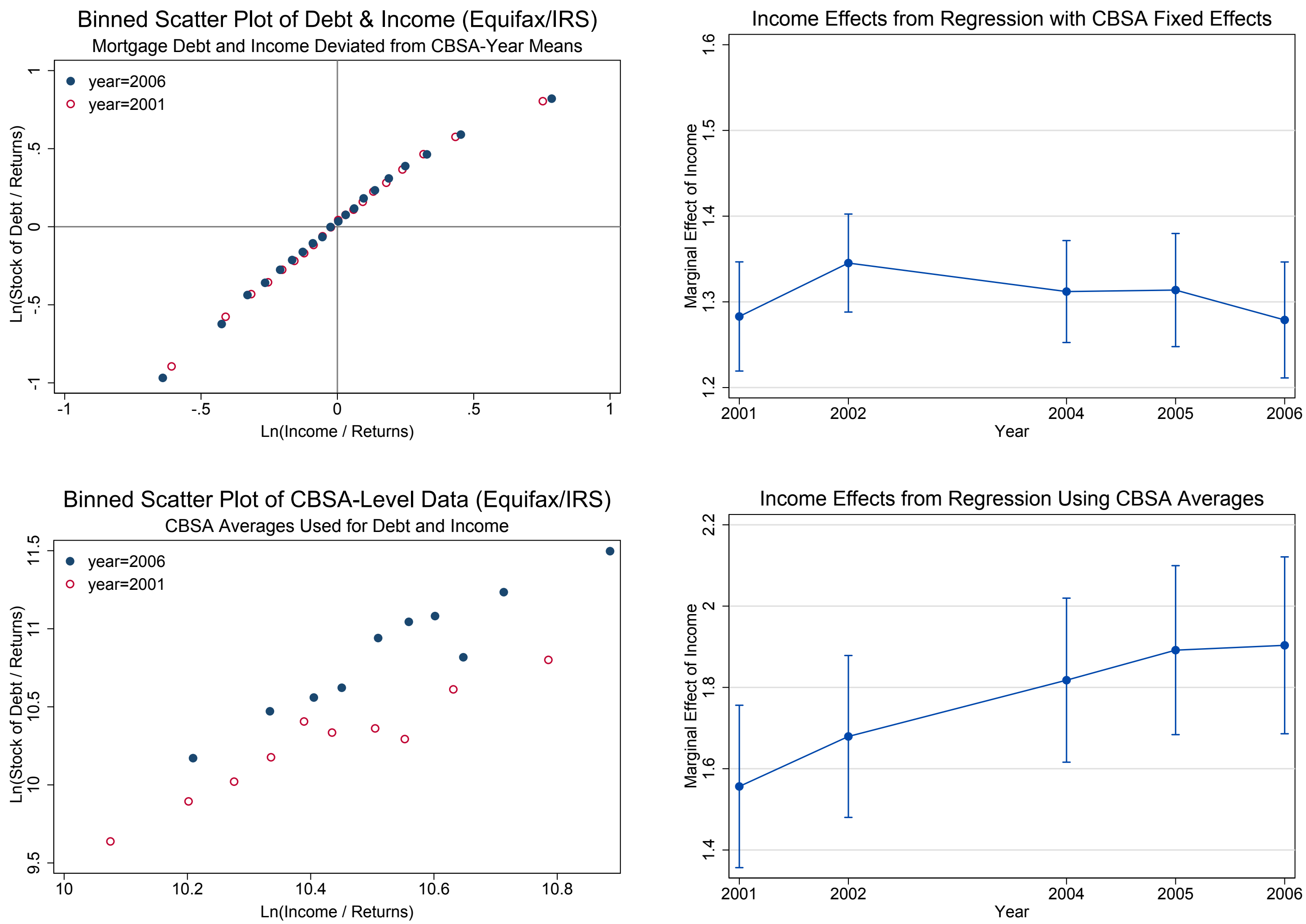


Figure 6. Within-CBSA and Between-CBSA Relationships between Mortgage Debt and Income among U.S. Zip Codes. The top left panel is a binned scatter plot of zip code-level debt and income after both variables have been deviated from returns-weighted CBSA-year means. The top right panel depicts the income coefficients from a returns-weighted debt regression that includes CBSA $\times$ year fixed effects as well as income $\times$ year interactions. Standard errors are clustered by CBSA. The lower two panels use data on CBSA-level averages of total mortgage debt and wage and salary income across the 937 CBSAs in the Equifax/IRS dataset. *Source:* NY Fed Consumer Credit Panel/Equifax and IRS Statistics of Income.

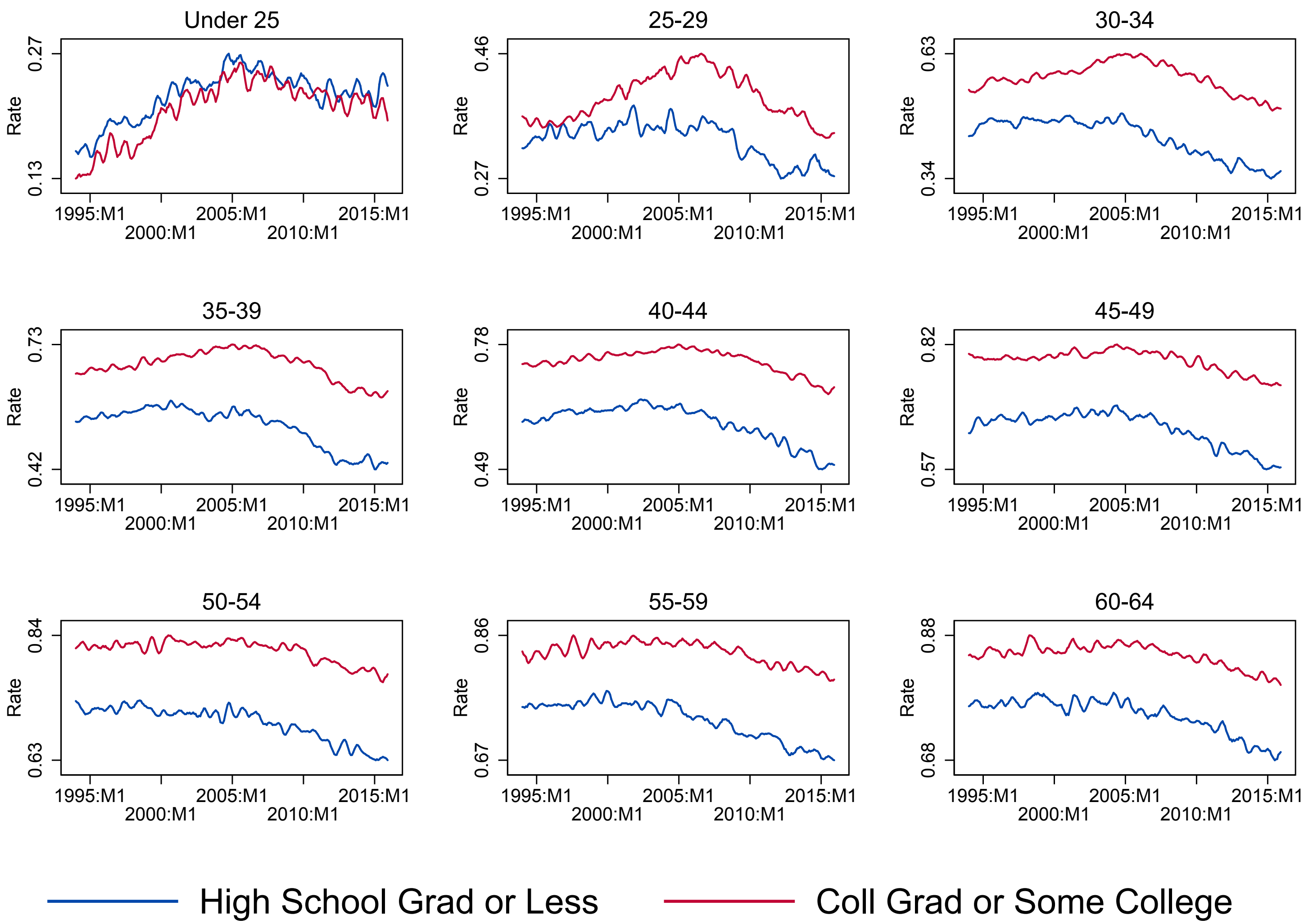
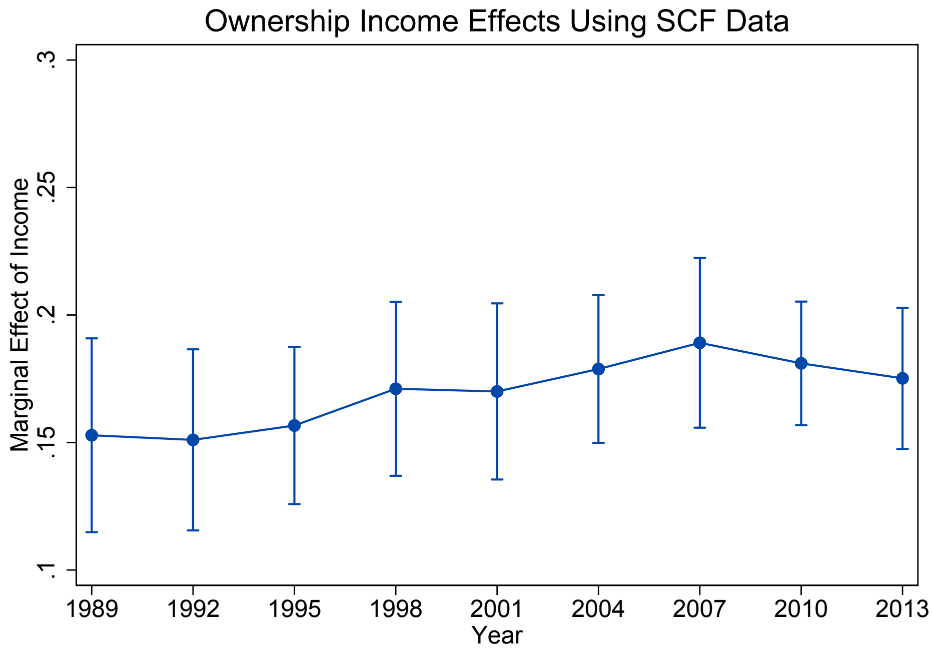


Figure 7. Homeownership Rates by Age and Educational Attainment of Household Head. *Note:* Rates are 6-month centered moving averages of monthly data. *Source:* Current Population Survey.



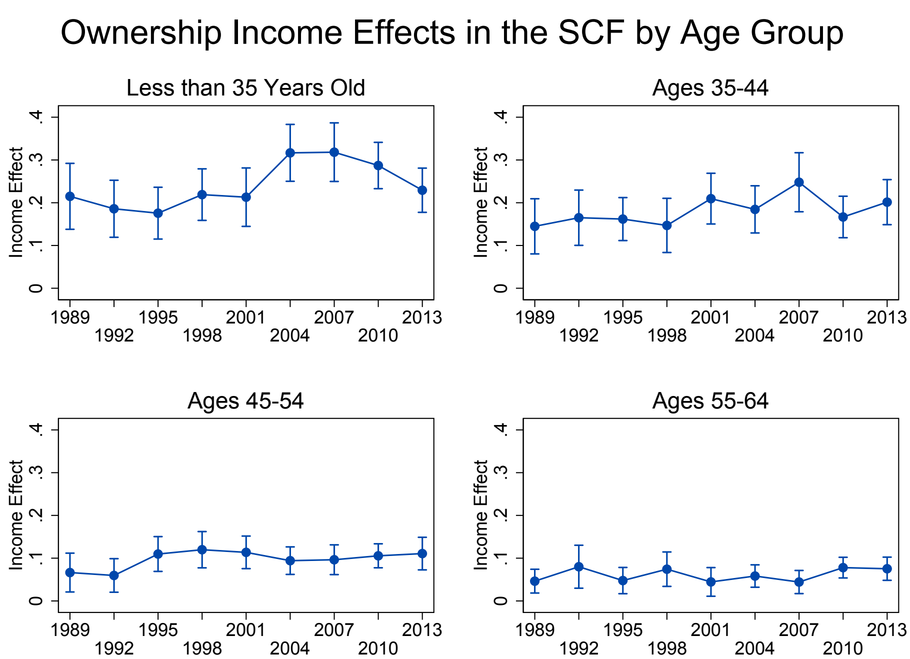


Figure 8. Regression Evidence on the Relationship between Homeownership and Income in the Survey of Consumer Finances. *Note:* These panels are derived from logit homeownership regressions with the same right-hand-side variables and sample restrictions as those used for the Poisson regressions for total debt depicted in the bottom panel of Figure 5. All panels plot marginal effect of log wage income on the probability of homeownership for all individuals (top panel) or for specific age groups (lower panels). The lower panels are generated from a regression in which the income regressor is interacted with dummy variables for the household head's age group. All income effects are marginal impacts on the probability of homeownership (not raw logit coefficients) and are calculated at the means of regressors from the first SCF implicate. *Source:* Survey of Consumer Finances.

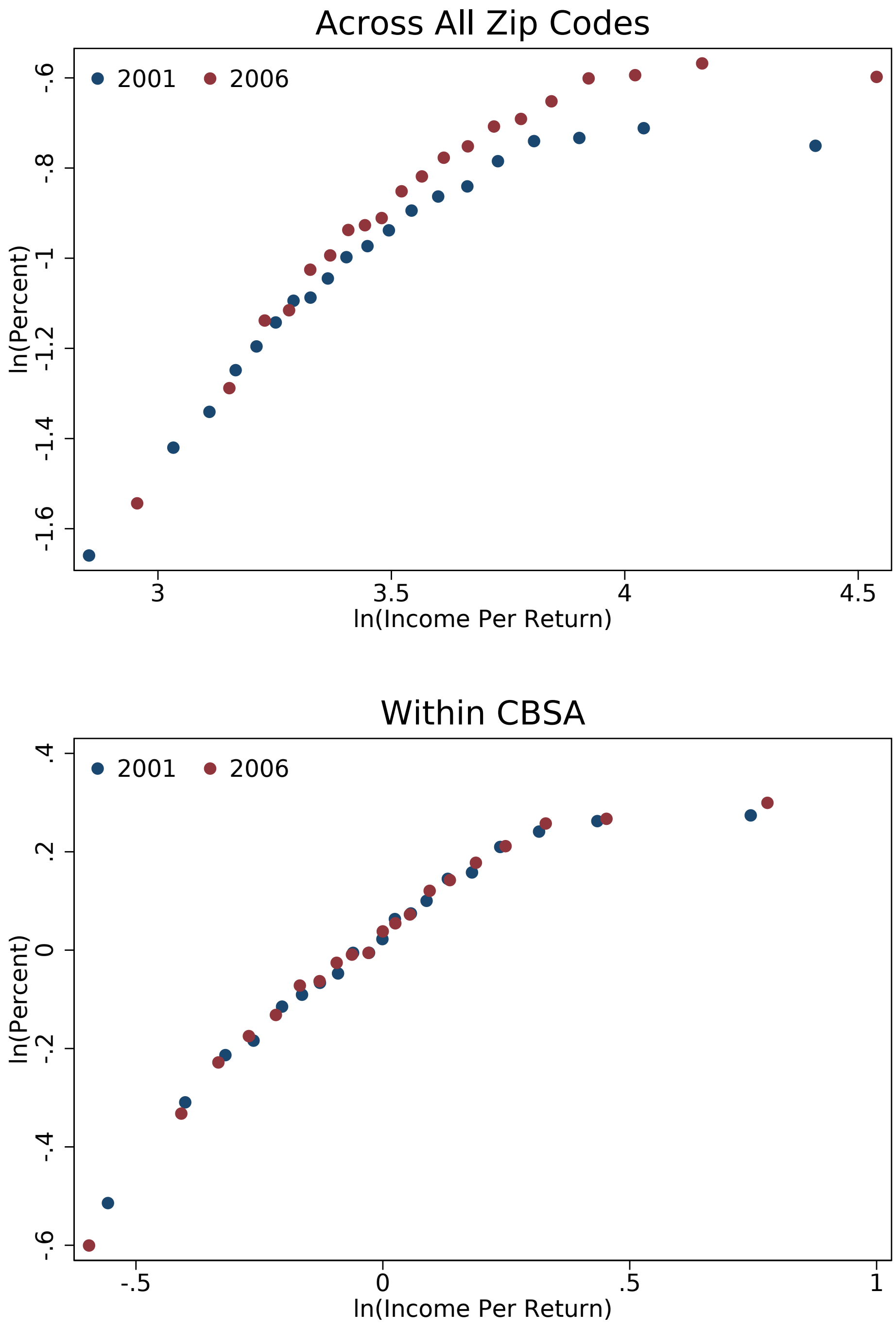


Figure 9. The Extensive Margin of Mortgage Debt Across Zip Codes: 2001 and 2006. *Note:* These panels plot the log of "mortgageship rates" across the wage-income distribution of zip codes, where mortgageship for a household is defined as the presence of any mortgage debt on a credit record. The debt and income data for the top panel is based on the distribution of income across all zip codes, while the bottom panel uses both log income and log mortgageship rates that have been deviated from CBSA means. *Source:* NY Fed Consumer Credit Panel and IRS Statistics of Income.

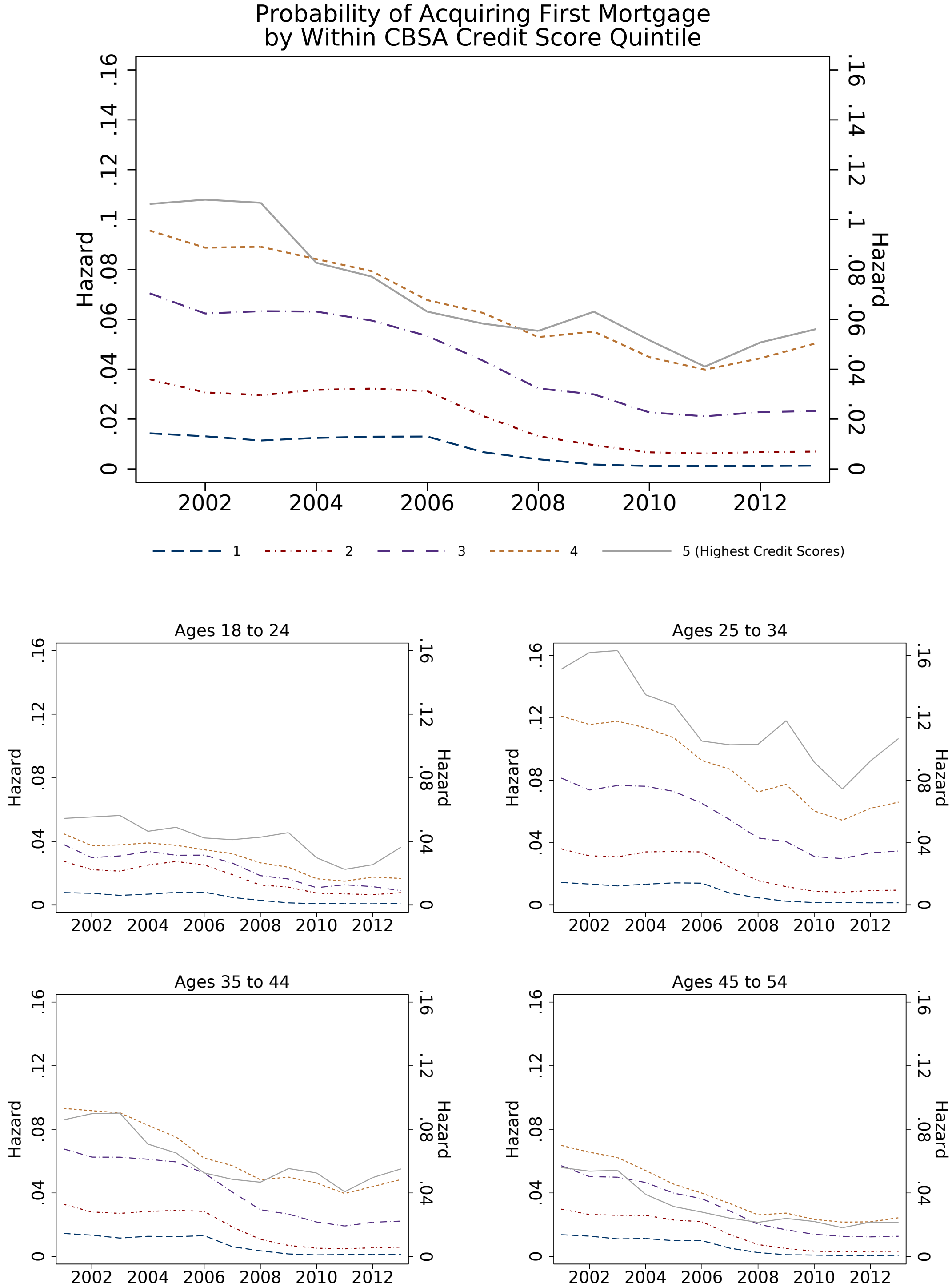


Figure 10. The Hazard Rate of First-Time Entry Into Mortgageship By Credit-Score Quintile: 2001-2013. *Note:* These graphs plot the probability of obtaining a mortgage for the first-time for individuals in specific credit-score quintiles over time. The probabilities are calculated by dividing the number of all individuals acquiring their first mortgages in a given year by the number of all people who had never taken out a mortgage by the previous year. The quintiles are based on credit scores relative to the average credit score for all residents of the CBSA; in the lower panels, the quintiles are calculated within age groups. The top panel displays rates for all individuals born in 1950 or later, while the bottom panels split this sample by age group. *Source:* NY Fed Consumer Credit Panel/Equifax.

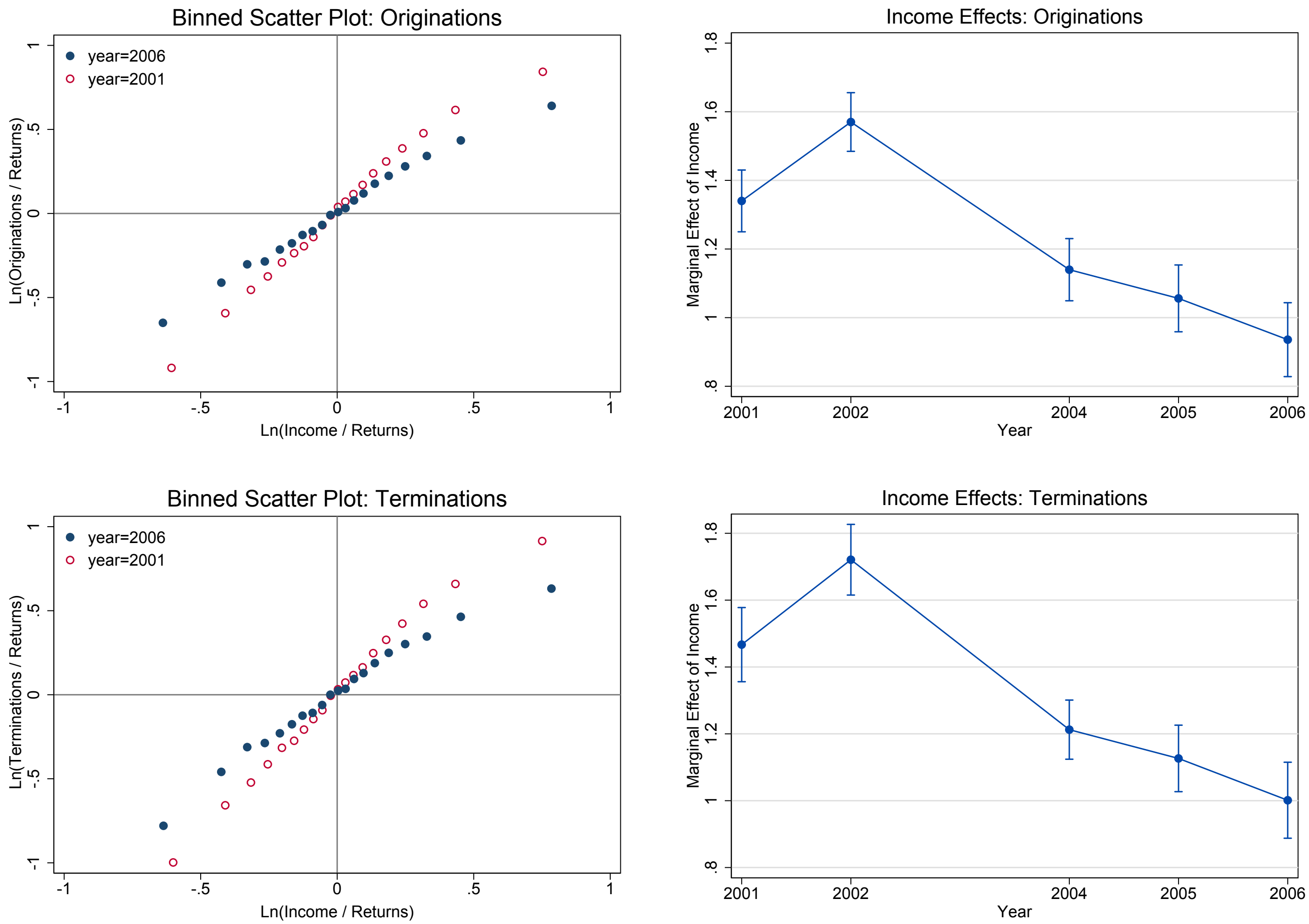


Figure 11. The Relationship Between Gross Mortgage Flows and Wage and Salary Income in CBSA-Deviated Data. *Note:* The binned scatter plots in the panels at left are generated from deviations of log originations or terminations per tax return and wage income per tax return from CBSA $\times$ year means. 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. *Source:* NY Fed Consumer Credit Panel/Equifax and IRS Statistics of Income.

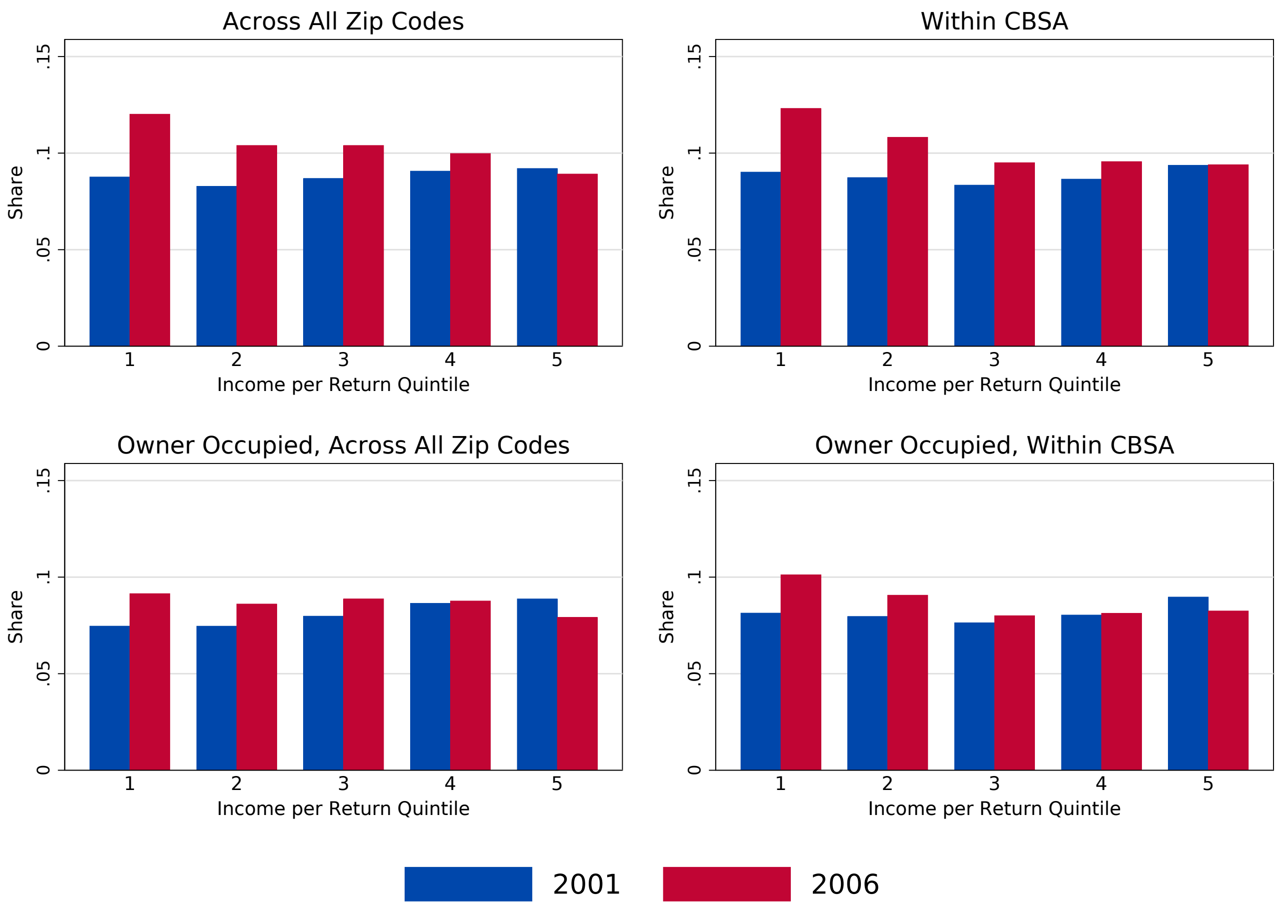


Figure 12. Purchase-Mortgage Intensity across Income Categories: 2001 and 2006. *Note:* Purchase-mortgage intensity is defined as the ratio of new purchase mortgages (as measured in HMDA) to outstanding first liens (as measured in Equifax). The top two panels show that over the course of the mortgage boom, this intensity increased relatively more in low-income zip codes. This pattern obtains both when looking across all zip codes (top left panel) and within CBSAs by using CBSA-deviated zip code-level data (top right panel). The bottom two panels measure purchase-mortgage intensity in the same way but use only self-reported owner-occupied purchases from HMDA. These panels indicate that much of the increase in purchase-mortgage intensity apparent in the top two panels was driven by investors rather than by owner-occupiers. *Source:* Home Mortgage Disclosure Act (for mortgage originations), NY Fed Consumer Credit Panel/Equifax (for outstanding first liens), and IRS Statistics of Income.

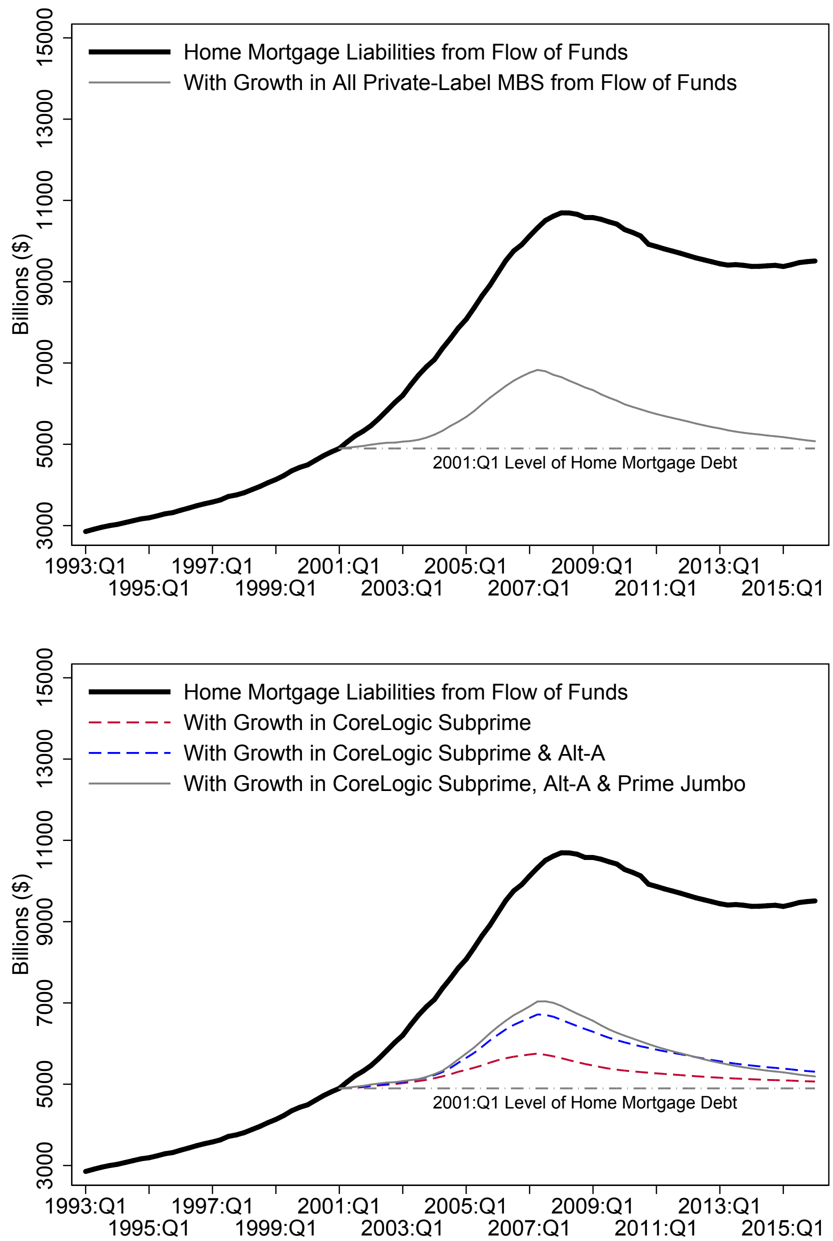
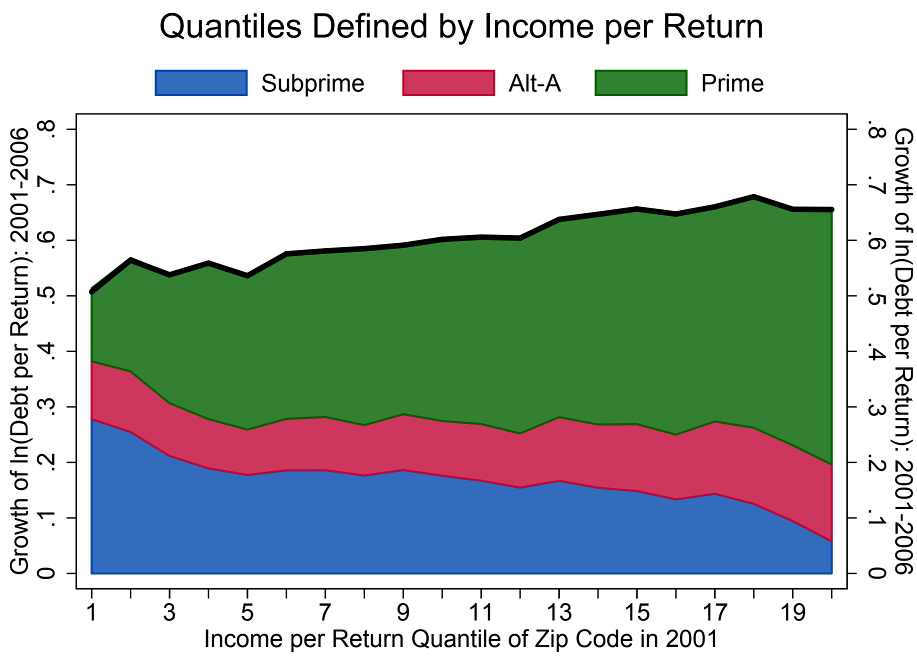


Figure 13. The Contribution of Private-Label Securitized Mortgage Debt to Total Mortgage Debt Growth. *Note:* In both panels, the heavy black line depicts U.S. aggregate mortgage liabilities for the household sector from the Federal Reserve's Flow of Funds. The top panel also depicts a counterfactual series for aggregate debt growth assuming post-2001:Q1 growth only in the Flow of Funds measure of privately securitized mortgage debt. The bottom panel presents counterfactuals assuming exclusive growth in selected components of privately securitized mortgage debt, as these components are measured in CoreLogic's Private Label Securities ABS Database. *Source:* Federal Reserve Board of Governors (Flow of Funds) and CoreLogic Private Label Securities ABS Database.



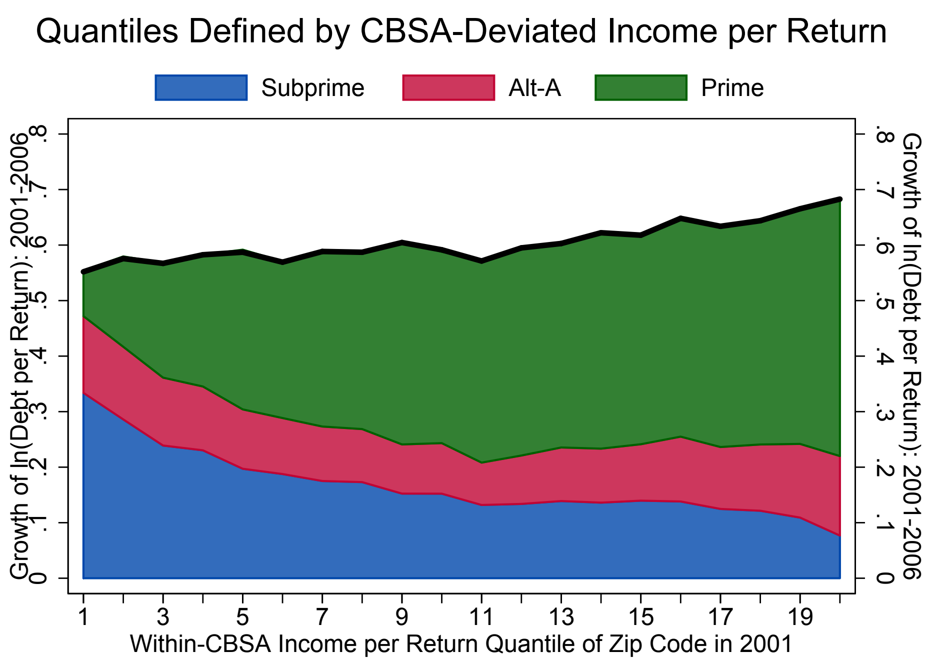


Figure 14. Mortgage Debt Growth by Debt Type Across the Income Distribution of Zip Codes: 2001-2006. *Note:* These graphs use data on subprime and Alt-A mortgage debt from the CoreLogic Private Label Securities ABS Database to show the 2001–2006 contributions of prime, subprime, and Alt-A debt for total debt growth among individual zip codes, sorted into 20 income-per-return categories. The top panel is based on the income distribution across all zip codes while the bottom panel uses income per return deviated from CBSA means. To be included in the sample for either panel, a zip code must be located within a CBSA and have at least 500 returns from 2001 through 2006. *Source:* NY Fed Consumer Credit Panel/Equifax, CoreLogic Private Label Securities ABS Database, and IRS Statistics of Income.

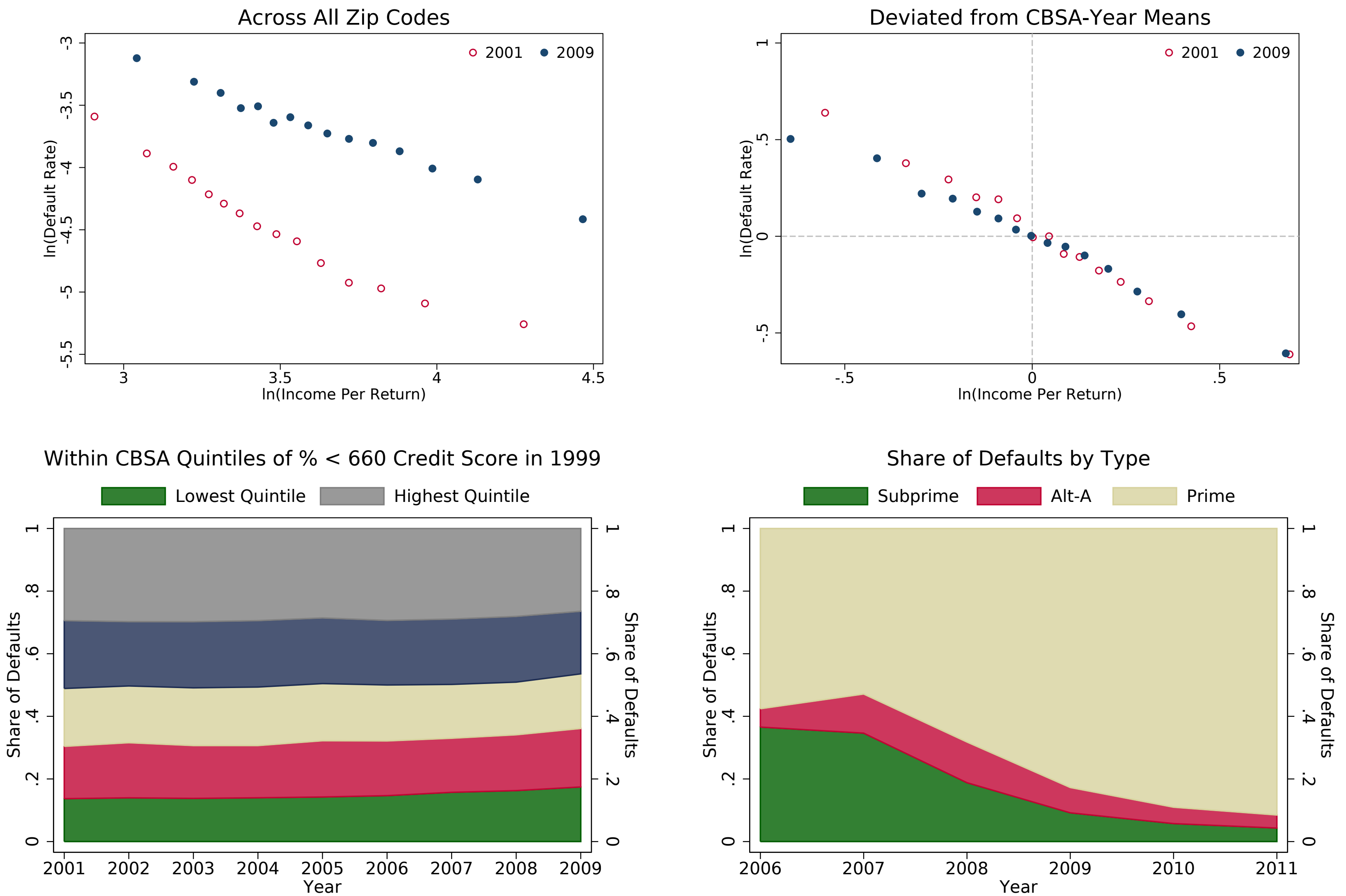


Figure 15. Relationships Between Income and Default Rates at the Zip Code-Level. *Note:* The two panels in the top row are binned scatter plots of default rates from Equifax and IRS salary and wage income for zip codes in 2001 and 2009. Income is expressed as the log of per-return values, while the default rate is the ratio of all transitions to 90-day delinquency divided by those at risk of transitioning. The default rate is a quarterly measure; for an estimate of the yearly default rate, take the anti-log and multiply by four. In the top left panel, the variables are not deviated from CBSA means, while in the top right panel they are. The bottom left panel shows that the share of defaults by return-weighted quintile of percent of borrowers with an Equifax credit score below 660 in 1999 was essentially constant from 2001 to 2009. The bottom right panel plots the share of all defaults by mortgage type from 2006 to 2011. *Source:* NY Fed Consumer Credit Panel/Equifax, CoreLogic Private Label Securities ABS Database, and IRS Statistics of Income.

A Internet Appendix

A.1 Comparisons of Mortgage Debt, Income and Debt Growth

Figure A.1 compares two aggregations of individual-level Equifax mortgage-debt balances from the New York Fed Consumer Credit Panel. The level of aggregation is either the state or the county. The horizontal axes of each panel measure our aggregations of debt for the given geographical unit, while the vertical axes measure aggregates calculated and published by the New York Fed itself. In all panels, the dots lie along 45-degree lines, giving us confidence that we are aggregating up to the zip-code level correctly when we construct our main cross-sectional dataset.

In the text, Figure 3 compared the aggregate number of returns from the zip code-level data with the aggregate number of returns published by IRS; the latter series omits any return filed for the sole purpose of receiving an economic-stimulus payment. In most years, the total number of returns in zip code-level data is smaller than the IRS's published total, in part because of the suppression rules. But as Figure 3 showed, in 2007 the zip code-level data imply many more returns, because these data include returns filed for the sole purpose of receiving stimulus checks. Figure A.2 compares aggregates of IRS income data rather than numbers of returns. The blue lines in this figure are national aggregates of either salary and wage income (top panel) or AGI (bottom panel) that are published by IRS. The red dots are aggregated data from the zip code-level IRS dataset that we use in the paper. In both panels, the published aggregate is larger than the zip code-level aggregate, probably because of the suppression rules that IRS applies to the zip code-level dataset before they release it. Even so, the two income aggregates follow similar time-series patterns—even in 2007, when the number of returns filed spikes up.

Figure A.3 compares estimates of the aggregate stock of mortgage debt from the Flow of Funds, the Equifax dataset, and the SCF in those years that the SCF is available. The Equifax totals are close to, but somewhat smaller than, the SCF and Flow-of-Funds totals. Yet our Equifax debt totals are essentially identical to some unreported Equifax totals calculated by Brown et al. (2015), who compare Equifax data with the SCF along a number of dimensions.[52] Two SCF aggregates are presented. The first comes from Henriques and Hsu (2014), who compare various SCF aggregates to their Flow of Funds counterparts. Even though Flow of Funds data are typically constructed from administrative records supplied by financial institutions and government agencies, rather than from surveys, Henriques and

[52]Specifically, in billions of 2010 dollars, Brown et al. (2015) estimate total mortgage debt in Equifax in 2004, 2007, and 2010 to be $7,631, $10,034, and $9,282, respectively. Our Equifax totals expressed in the same units and years are $7,741, $9,728, and $9,074. In addition, unreported work shows that our totals are close to those reported Bhutta (2015), which also analyzes mortgage debt in the New York Fed Consumer Credit Panel.

Hsu (2014) show that most balance-sheet measures in the SCF are close to the corresponding Flow of Funds estimates. This comparability is particularly true for mortgage debt, a pattern the authors attribute to the clarity of the mortgage debt concept and the stability of mortgage data collection procedures in both the SCF and the Flow of Funds over time. Figure A.3 replicates the close correspondence between mortgage debt in the Flow of Funds and Henriques and Hsu's SCF measure. Gratifyingly, the figure also shows that our SCF aggregates, based on the public-use summary SCF datasets, are essentially identical to Henriques and Hsu's, with the small differences between them probably resulting from the fact that we use the public-use version of the data. Note that comparability of the SCF data to the mortgage measure in the Flow of Funds requires the use of all mortgage data available, including HELOCs. This is why we include HELOCs and other types of secondary mortgages when using either the Equifax dataset or the SCF.[53]

A.2 AGI vs. Wages and Salaries and 2006 vs. 2007

Throughout the paper we use salary and wages to measure income, because this type of income is most likely to be the focus of lenders when they evaluate mortgage applications. An alternative choice would be to use AGI (for zip code-level analysis) and total income (for SCF analysis). Figure A.5 shows that our main results go through even when this alternative choice is made. The two left panels use zip code-level data from Equifax, with quintiles calculated using AGI per tax return. The two right panels use data from the SCF, with the quintiles calculated using the SCF's measure of total income. The top panels show the same similarity in debt evident in the introductory Figure 2 in both the zip code-level data and the SCF. The lower panels replicate the finding that, because mortgage debt rises with income in the cross section, equal debt-growth rates imply very large dollar amounts of new debt for the richest borrowers.

The main text also uses 2006 rather than 2007 as the last year of the mortgage boom when performing zip code-level analysis. (The ending-year issue is not relevant for the SCF.) This choice is necessitated by that spike in tax filing in 2007 illustrated in the text by Figure 3 and discussed earlier in this appendix. Recall that Figure A.2 implied that the additional filers had very low incomes, because their tax returns had little effect on 2007 levels of total AGI or of wages and salaries. Further evidence that the extra filers had low incomes appears in Figure A.6. This figure shows that zip code-level growth in the number of IRS returns filed in 2007 is not only much greater than in other years, but that 2007 growth covaries

[53] Recent work by Amromin and McGranahan (2015) and Amromin, McGranahan, and Schanzenbach (2015) also uses the Equifax dataset but splits mortgage debt into non–HELOC mortgage debt and HELOCs. Although these papers do not emphasize the point, they also find broadly similar growth rates of mortgage balances across the income distribution, even when HELOC balances are excluded.

negatively and monotonically with zip code-level income. As with the choice of income definition, however, the choice of ending year has little effect on the main results. Figure A.7 shows that using 2007 as the end of the boom for the zip code-level distributions generates the same patterns seen in earlier figures.

A.3 Debt Distributions Disaggregated by Lien Types

In the text, we investigate debt patterns using all types of mortgage debt: first mortgages, second mortgages, and HELOCs. Figure A.8 disaggregates the analysis by lien type. For reference, we include as the upper left panel of this figure the overall debt distribution with respect to income that appeared as part of the introductory Figure 2 in the text. The top right panel of Figure A.8 shows the distribution of first-mortgage debt. Because the large majority of outstanding debt consists of first liens, it is not surprising that the first-lien distribution remains stable over time. The lower left panel presents distributions of closed-end second mortgages. Here there is a pronounced change in the distribution, with high-income ZIP codes receiving much higher shares of second-mortgage debt in 2006 relative to 2001. The last panel shows distributions of HELOC debt. There is a slight tilt toward higher debt shares among richer quintiles, but this tilt is not as severe as in the previous panel. In any case, none of the panels in Figure A.8 indicate a significant increase in the share of debt held by low-income quintiles. Figure A.9 performs the same analysis using AGI rather than salaries and wages, with similar results.

A.4 Distributional Statistics for the SCF

The panels in Figure A.10 provides some formal statistics for the SCF distributions in top left panel of Figure 4. The top left panel graphs the mean and median debt levels for each year of the SCF, the top right panel depicts the standard deviation, and the two bottom panels plot the inter-quartile range and the 90th-10th percentile differences respectively.

A.5 Homeownership and Headship Rates in the CPS

Figure A.11 if a check of our homeownership rate calculations using the CPS microdata. We are able to exactly match the published Census data because the Census generates its homeownership statistics using the CPS. Figure A.12 plots headship rates, defined as the fraction of persons in the given age groups who are “reference persons” for their households in the CPS survey.

A.6 SCF Mortgageship Regressions by Age of Household Head

Figure A.13 depicts income coefficients from a regression of mortgageship on income. This analysis is structured analogously to the homeownership logits in Figure 8 in the text, and show essentially the same patterns.

A.7 Identifying First-Time Mortgageship in Equifax

As mentioned in the main text, Equifax includes a variable that gives the age of the oldest mortgage on record for each individual. Using this variable, we identify individuals taking out their first mortgage. However, the information in this variable needed to be cross-verified with other variables in Equifax before it became usable. We code someone as taking out their first mortgage if the individual is born in 1950 or later,[54] and the age of their oldest mortgage is zero within one quarter on either end of originating a first-lien mortgage. In other words, an individual could have a first-mortgage originated in the quarter just prior or just after Equifax indicates that the age of their first mortgage has gone from "no account on file" to zero. For the hazard ratios in the main text, we are interested in the probability of an individual taking out their first mortgage, so we do not correct for joint mortgages. However, in the data check described in the next paragraph we divide the number of joint mortgages by two.

Figure A.14 plots our estimate of the share of all purchase mortgages going to people taking out their first mortgage, along with the estimate of the share of all purchase mortgages going to first-time homeowners from the National Association of Realtors (NAR) Annual Survey. It should be noted that first-time mortgageship and first-time homeownership are not necessarily the same: it is feasible that someone inherited a home or bought a home with cash prior to taking out their first-ever mortgage. However, the two should be highly correlated. Our estimate is calculated using a 10 percent sample from Equifax and HMDA. The numerator is the number of first-time-ever mortgages originated in Equifax and the denominator is the number of owner-occupied purchase mortgages in HMDA. In comparison, NAR is a survey of over 100,000 homebuyers with a less than 10 percent response rate, so their final survey results have under 10,000 homebuyers and suffer from selection bias. Given that these two measures are each imperfect, their similarity is remarkable.

[54] We limit our analysis to borrowers born in 1950 or later because for borrowers born earlier, it is much more likely that the first mortgage recorded in Equifax is not actually their first mortgage. Namely, Equifax did not computerize its records until after 1970.

A.8 Gross Flows Analysis without Area-Level Fixed Effects

The two panels of Figure A.15 present the estimated income effects from regressions that have either total originations (top panel) or total terminations (bottom panel) on the left-hand side. They are analogous to the right-hand side panels of Figure 11, which are generated from regressions that also include CBSA $\times$ year fixed effects.

A.9 Effect of Subprime and Alt-A on Debt Growth: 2001-07

Figure A.16 replicates the main lessons of Figure 14 for debt growth, using 2007 as the ending year of the mortgage boom. Like Figure 13, which ends the boom in 2006, the appendix figure shows that the use of subprime mortgages grew more in low-income areas. Growth in Alt-A and prime mortgage debt tended to be higher in richer ZIP codes. The end result is that mortgage debt grew at broadly similar rates throughout the income distribution, both within and across CBSAs.

A.10 Yearly Foreclosure Regressions

Figure A.17 plots income coefficients from yearly regressions of foreclosure rates on the log of income, where both have been deviated from their CBSA-year means. The income coefficients trend up modestly, implying that foreclosures became relatively more prevalent in high-income ZIP codes within CBSAs during the housing bust. This figure complements the binned scatter plots in Figure 15, which also indicate somewhat higher growth in foreclosures in high-income ZIP codes relative to low-income ZIP codes. This relative pattern obtains even though absolute growth in foreclosures was lower in high-income areas.

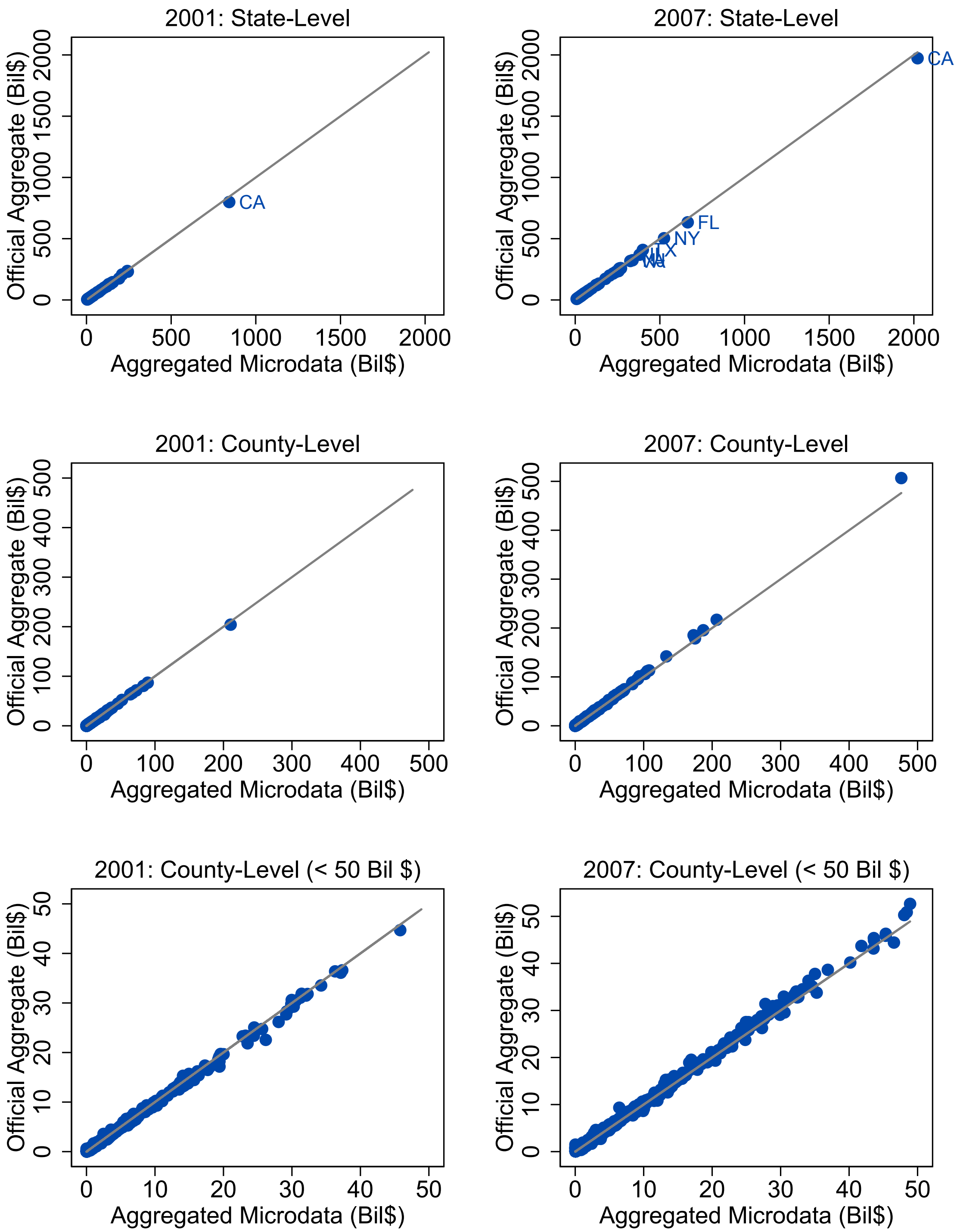


Figure A.1. Comparison of Aggregated Mortgage Debt Balances in the New York Fed Consumer Credit Panel. *Note:* Each of the panels above is a comparison of aggregated data from the microlevel records of the New York Fed Consumer Credit Panel. Aggregation along the horizontal axes was performed by the authors, while the vertical axes measure aggregates generated from the same dataset by the Federal Reserve Bank of New York. For the county-level data in the lower two rows, only counties with at least 10,000 consumers possessing credit records in 2010:Q4 are included. *Source:* New York Fed Consumer Credit Panel/Equifax.

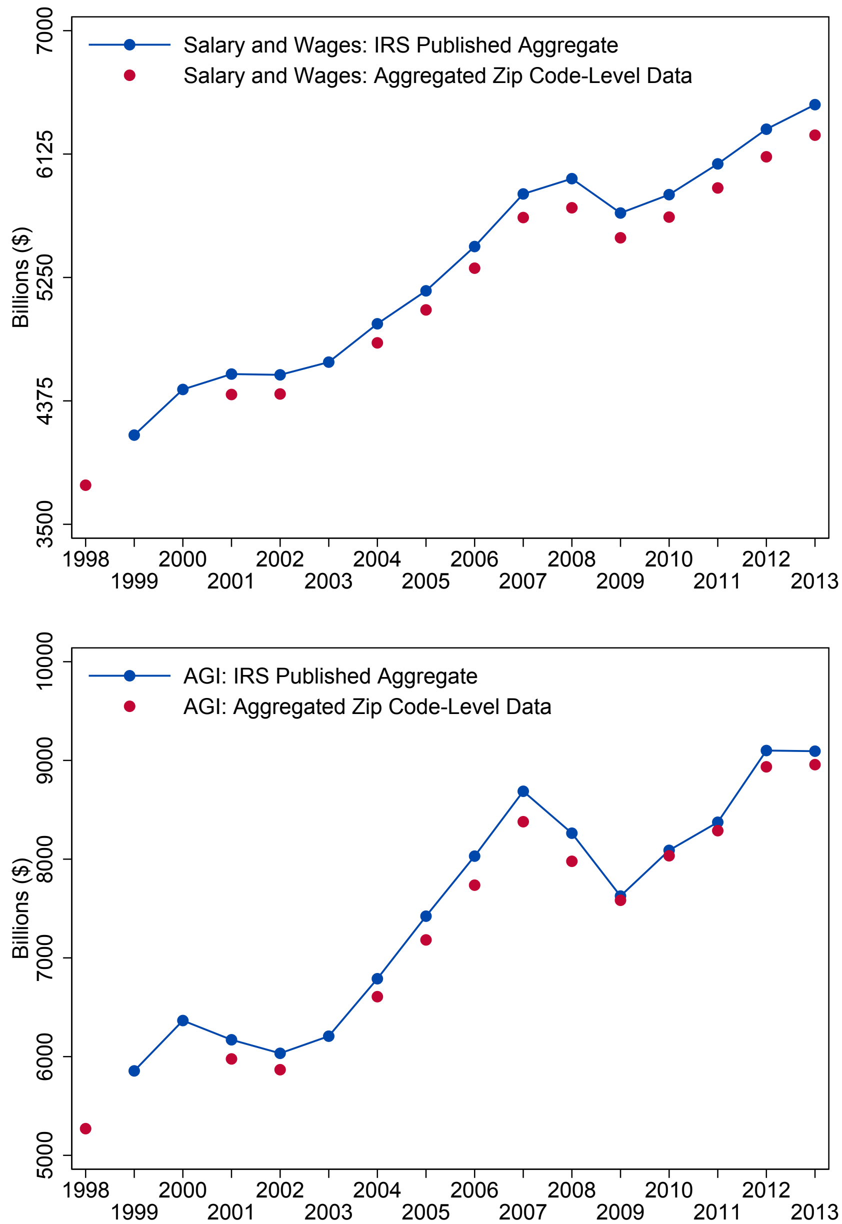


Figure A.2. Measures of Aggregate Salary and Wage Income and Adjusted Gross Income. *Note:* In each panel, the blue line depicts the given income aggregate as published by the IRS, and the red dots depict annual aggregates generated from the zip code-level IRS data. *Source:* Internal Revenue Service, Statistics of Income Historical Table 1 (available at `https://www.irs.gov/uac/SOI-Tax-Stats-Historical-Table-1`).

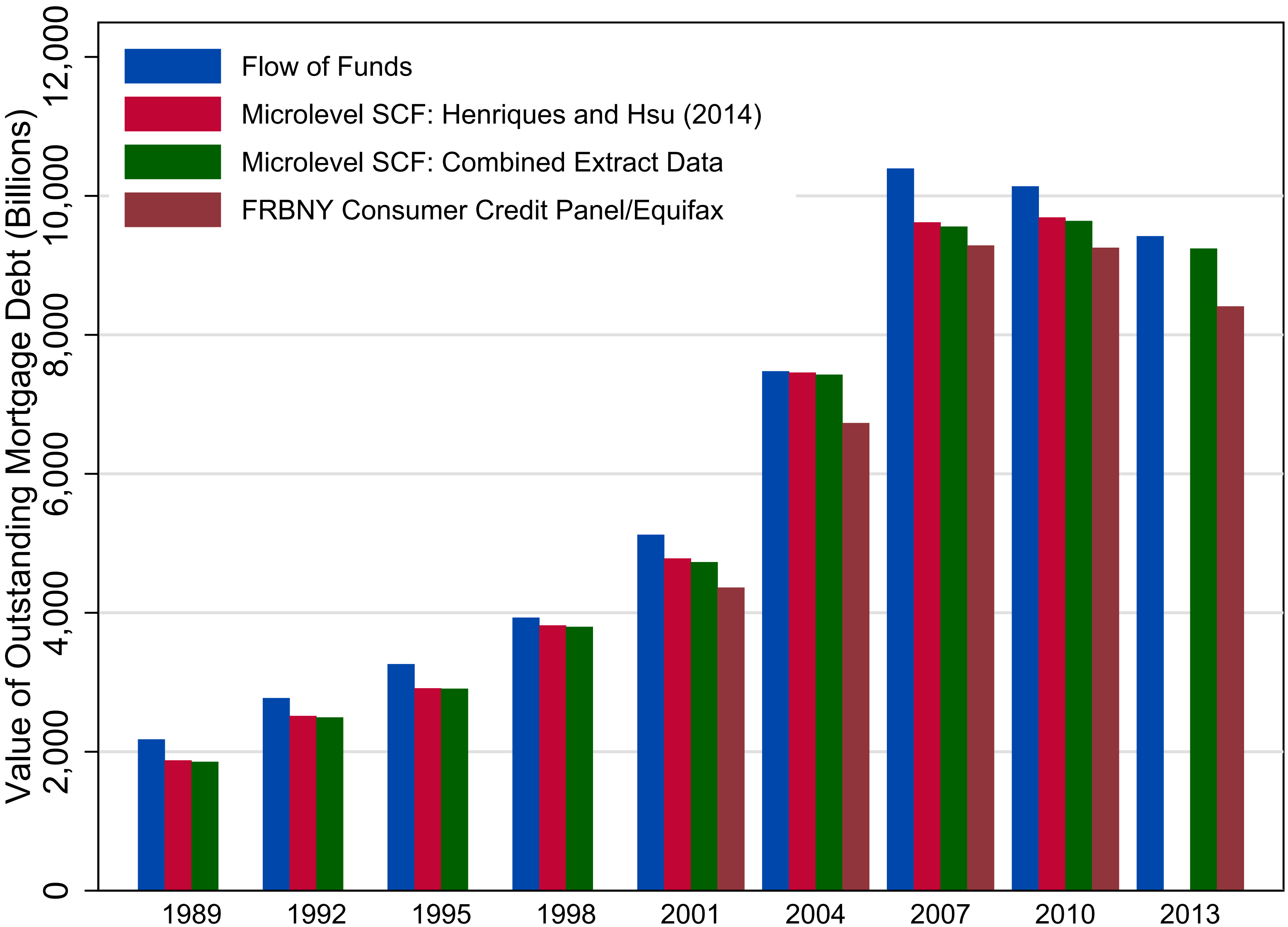


Figure A.3. Alternative Measures of Aggregate U.S. Mortgage Debt. *Source:* Board of Governors of the Federal Reserve System (for Flow of Funds); Table 9.1 (p. 250) of Henriques and Hsu (2014); authors' calculations using the Combined Extract Data of the Survey of Consumer Finances; and authors' calculations using the NY Fed Consumer Credit Panel/Equifax.

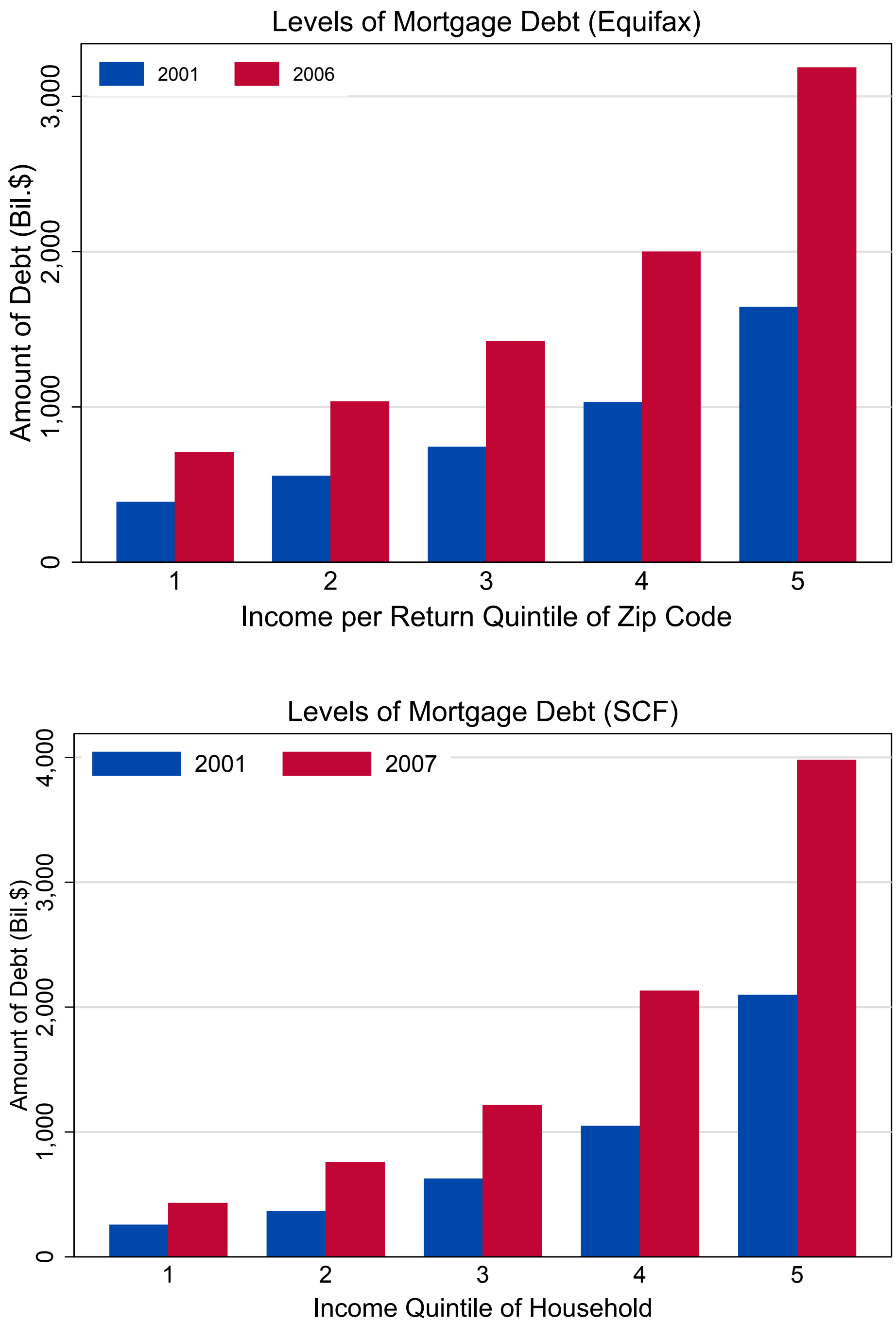


Figure A.4. Levels of Outstanding Debt in Equifax/IRS and SCF Datasets. *Note:* Income is measured as salary and wages in the Equifax/IRS dataset and as wage income in the SCF. *Source:* NY Fed Consumer Credit Panel/Equifax and Survey of Consumer Finances.

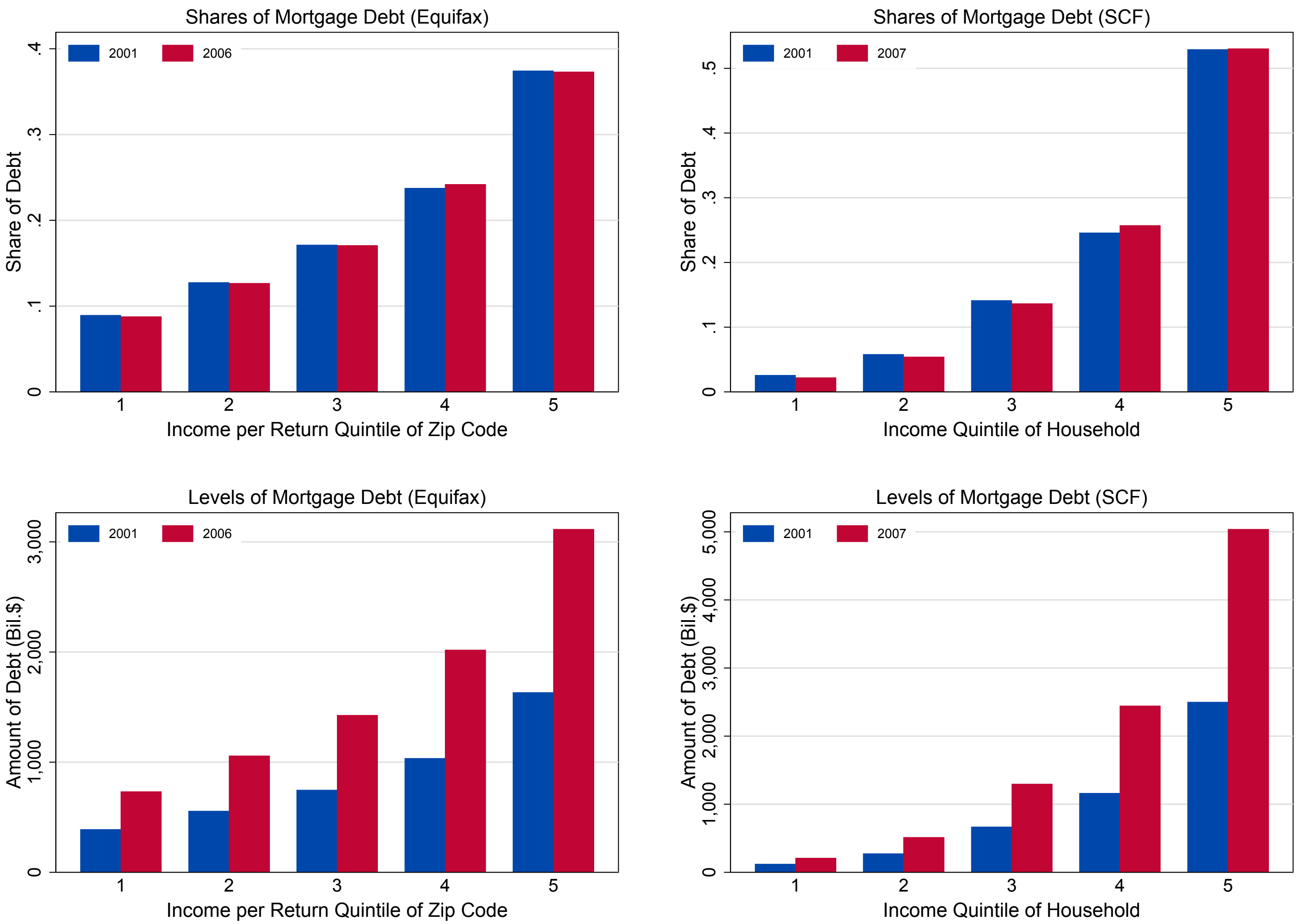


Figure A.5. Distributions of Mortgage Debt With Respect to Adjusted Gross Income (for Zip Codes) and Total Income (for Households). *Note:* The income measure used throughout the main text is salary and wage income. This figure uses AGI as the income measure for zip codes in the left panels, and total income from the SCF for households in the right panels. *Source:* NY Fed Consumer Credit Panel/Equifax, IRS Statistics of Income, and Survey of Consumer Finances.

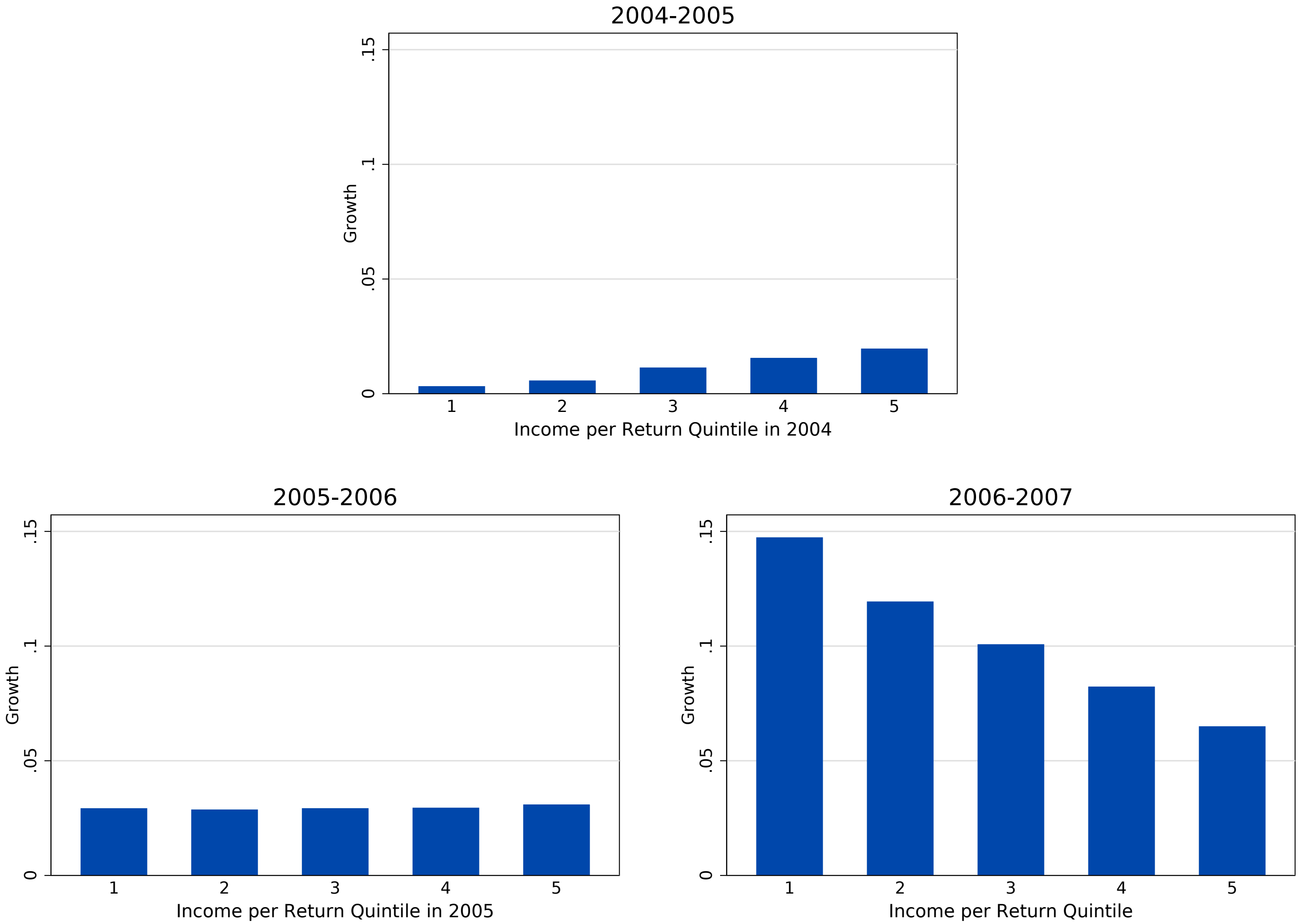


Figure A.6. Growth in IRS Returns by Income Quintile. *Note:* The top panel shows the growth in the total number of zip code-level tax returns between 2004 and 2005, grouped by zip code-level income in 2004. The bottom panels provide analogous information for returns growth in 2005-2006 and 2006-2007. The bottom right panel shows the strong inverse relationship between zip code-level returns growth and income between 2006 and 2007 that was generated by a surge of low-income persons who filed solely to take advantage of the 2007 tax stimulus. *Source:* IRS Statistics of Income.

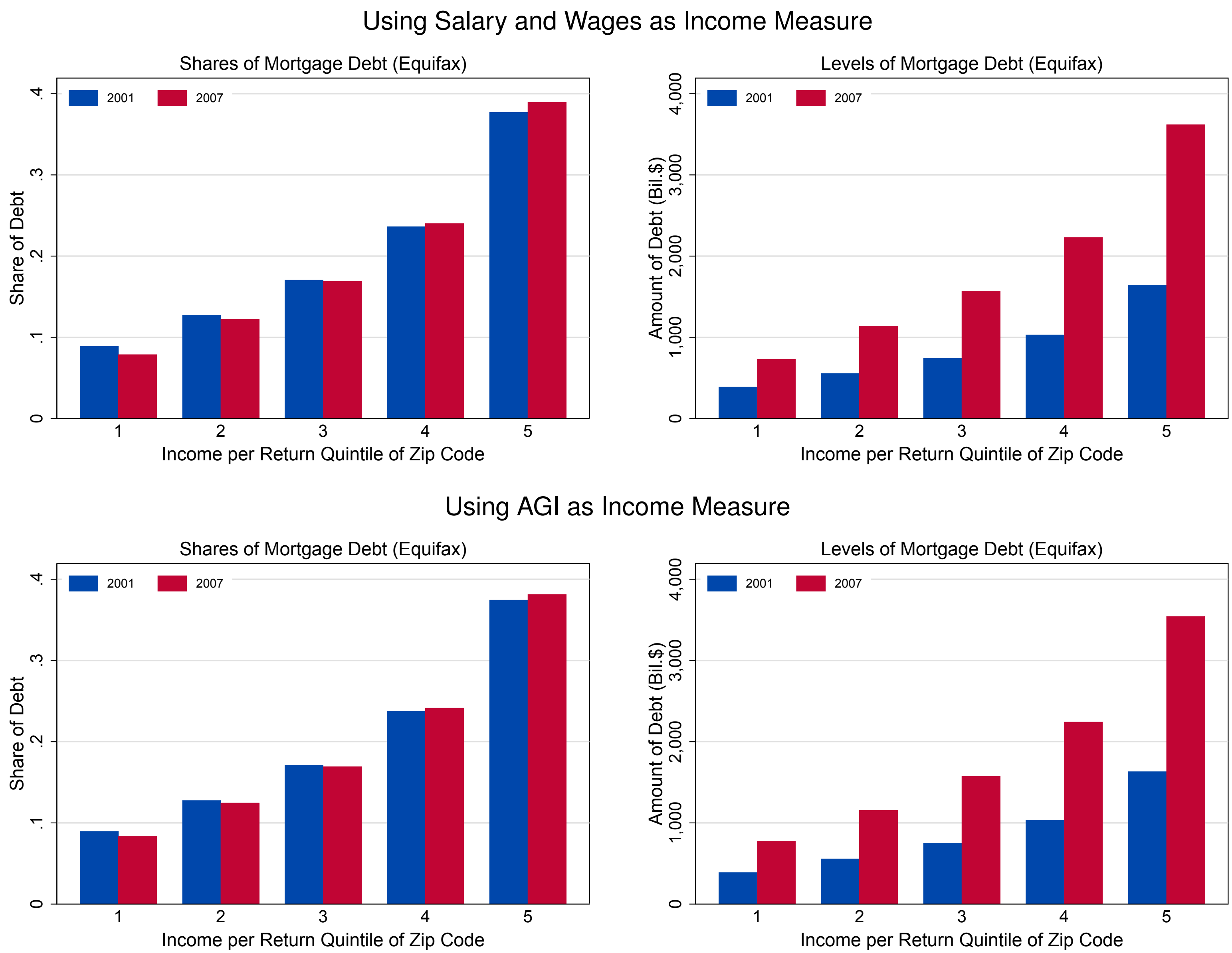


Figure A.7. Equifax/IRS Distributions of Debt for 2001 and 2007 using Alternative Income Definitions. *Note:* These graphs are analogous to the Equifax/IRS zip code-level bar chart in Figure 2 and to the levels charts depicted in Figure A.4, which depict distributions for 2001 and 2006, rather than 2001 and 2007. The lower panels in this figure also use AGI rather than wage and salary income. *Source:* NY Fed Consumer Credit Panel/Equifax, IRS Statistics of Income, and Survey of Consumer Finances.

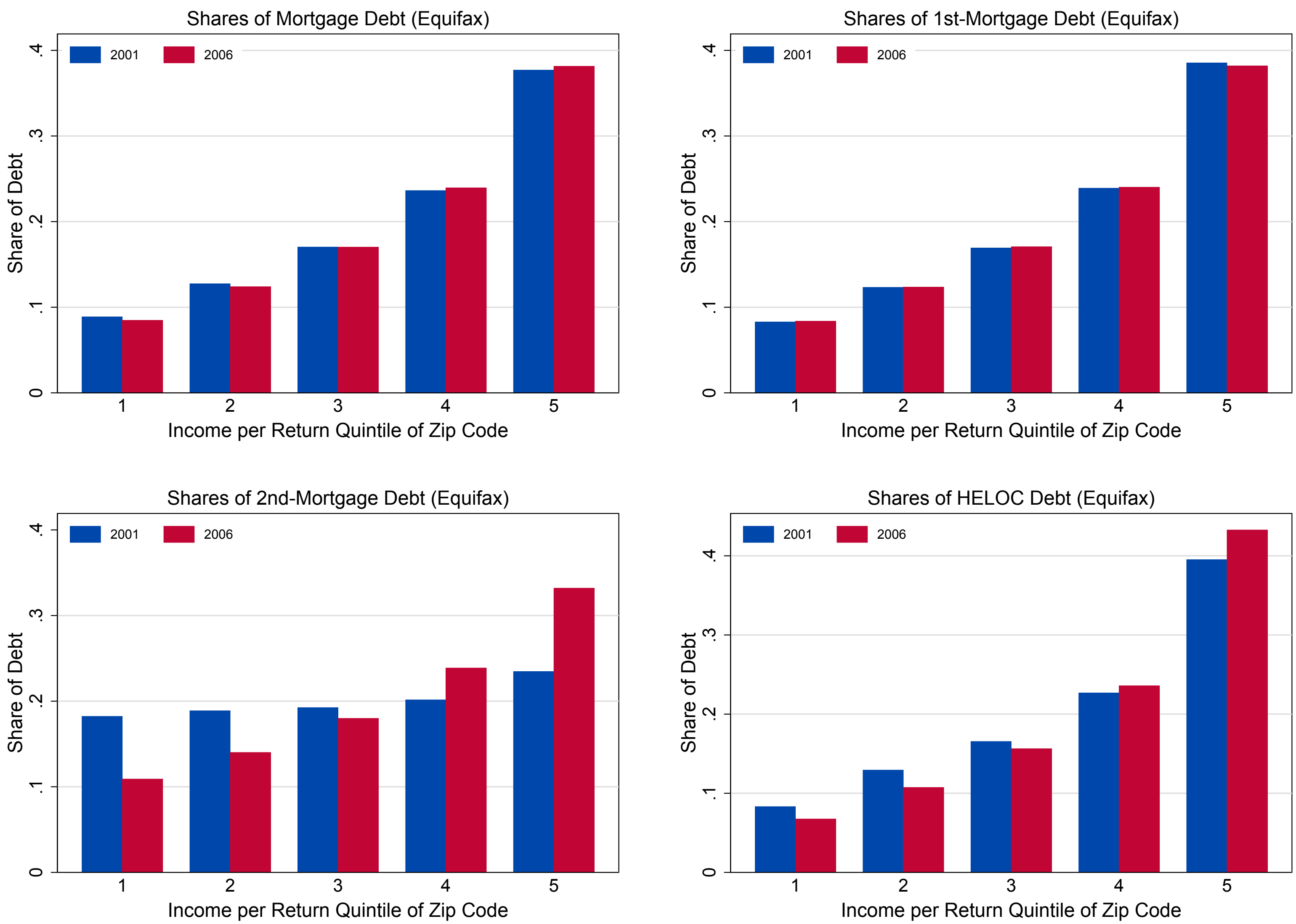


Figure A.8. Equifax/IRS Distributions of Debt by Mortgage Type, using Salary and Wages as Income Definition. *Note:* First mortgages include all purchase and refinance mortgages that are neither home equity loans nor home equity lines of credit (HELOCs). *Source:* NY Fed Consumer Credit Panel/Equifax and IRS Statistics of Income.

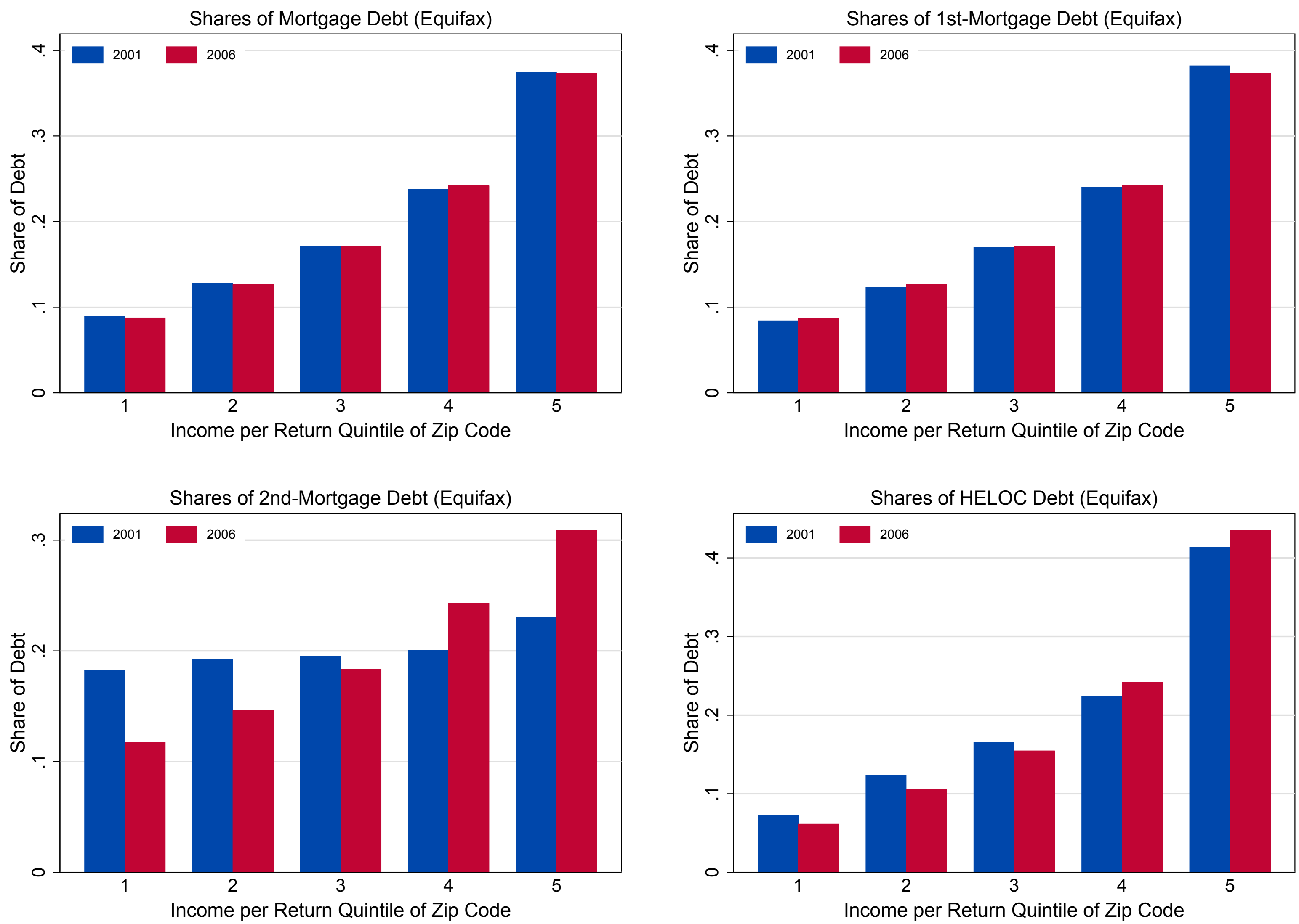


Figure A.9. Equifax/IRS Distributions of Debt by Mortgage Type, using AGI as Income Definition. *Note:* First mortgages include all purchase and refinance mortgages that are neither home equity loans nor home equity lines of credit (HELOCs). *Source:* NY Fed Consumer Credit Panel/Equifax and IRS Statistics of Income.

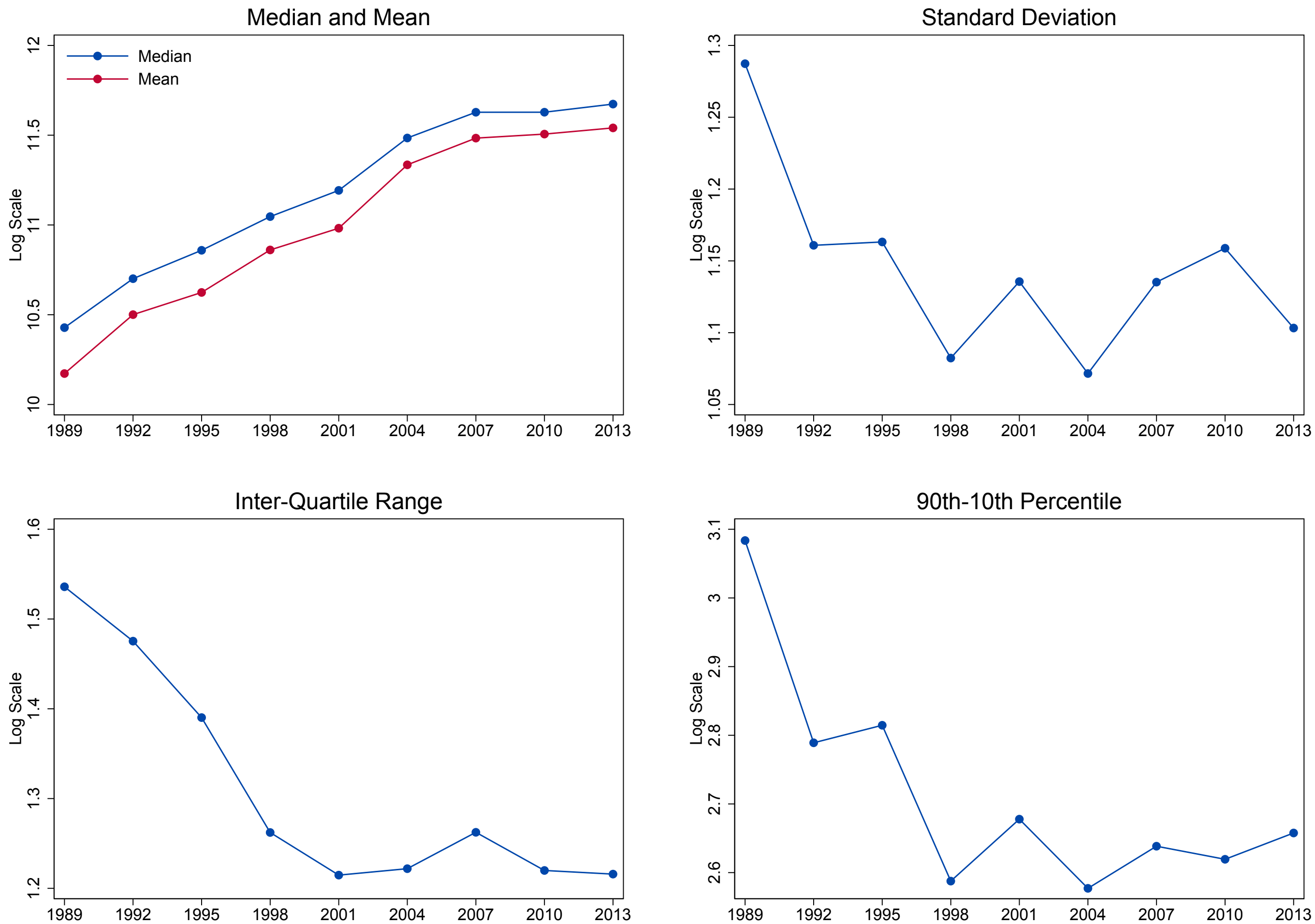


Figure A.10. Distributional Statistics for Household-Level Mortgage Debt in the Survey of Consumer Finances. *Note:* Statistics in these panels relate to the central tendency and dispersion in the distributions of household-level mortgage debt as measured in the Survey of Consumer Finances. Kernel estimates of these distributions for 1995, 2001, and 2007 appear in the top left panel of Figure 4. *Source:* Survey of Consumer Finances.

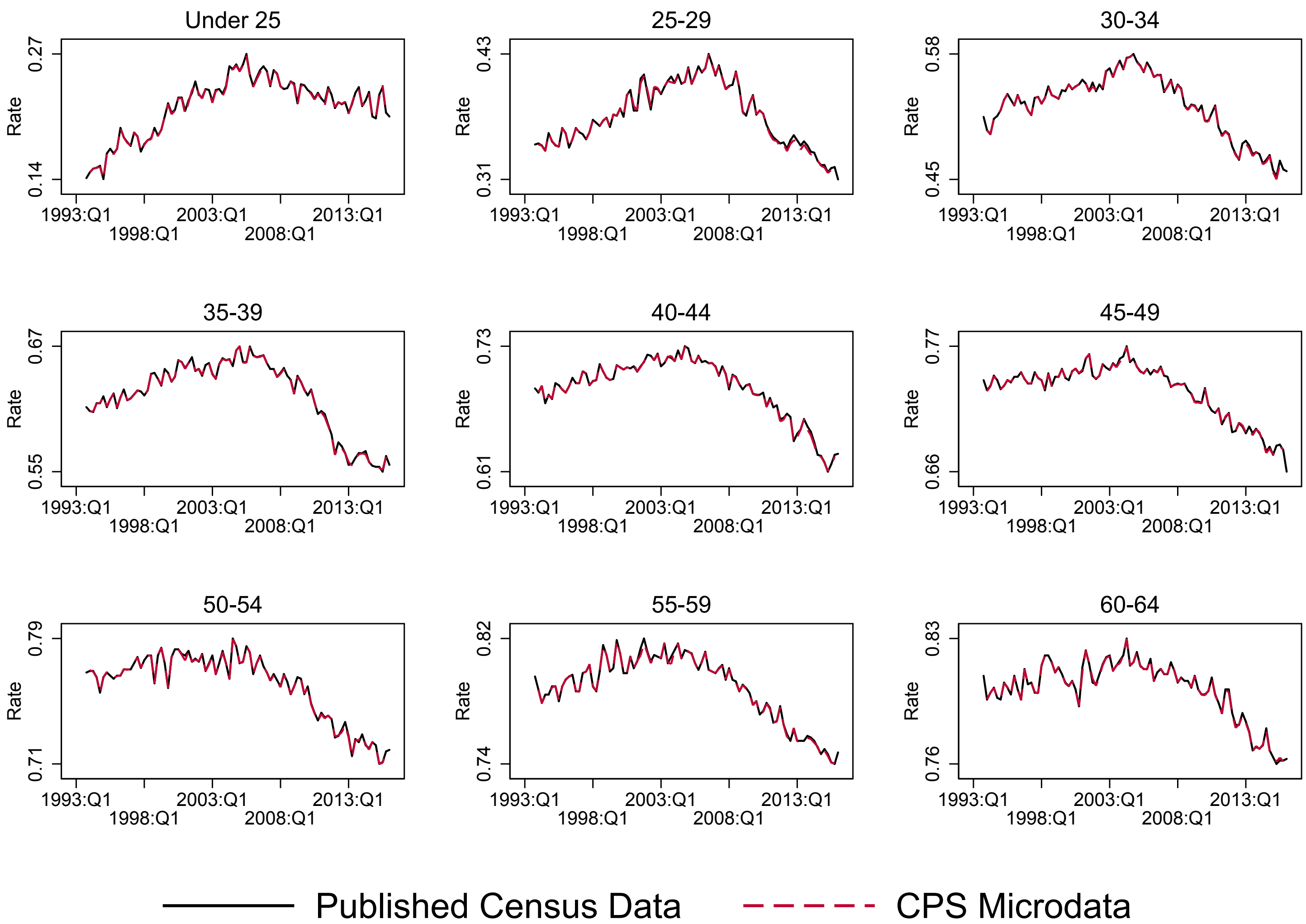


Figure A.11. Homeownership Rates by Age of Household Head. *Note:* Census rates are reported quarterly, and rates from CPS microdata are quarterly averages of monthly rates. *Source:* Census Bureau and Current Population Survey.

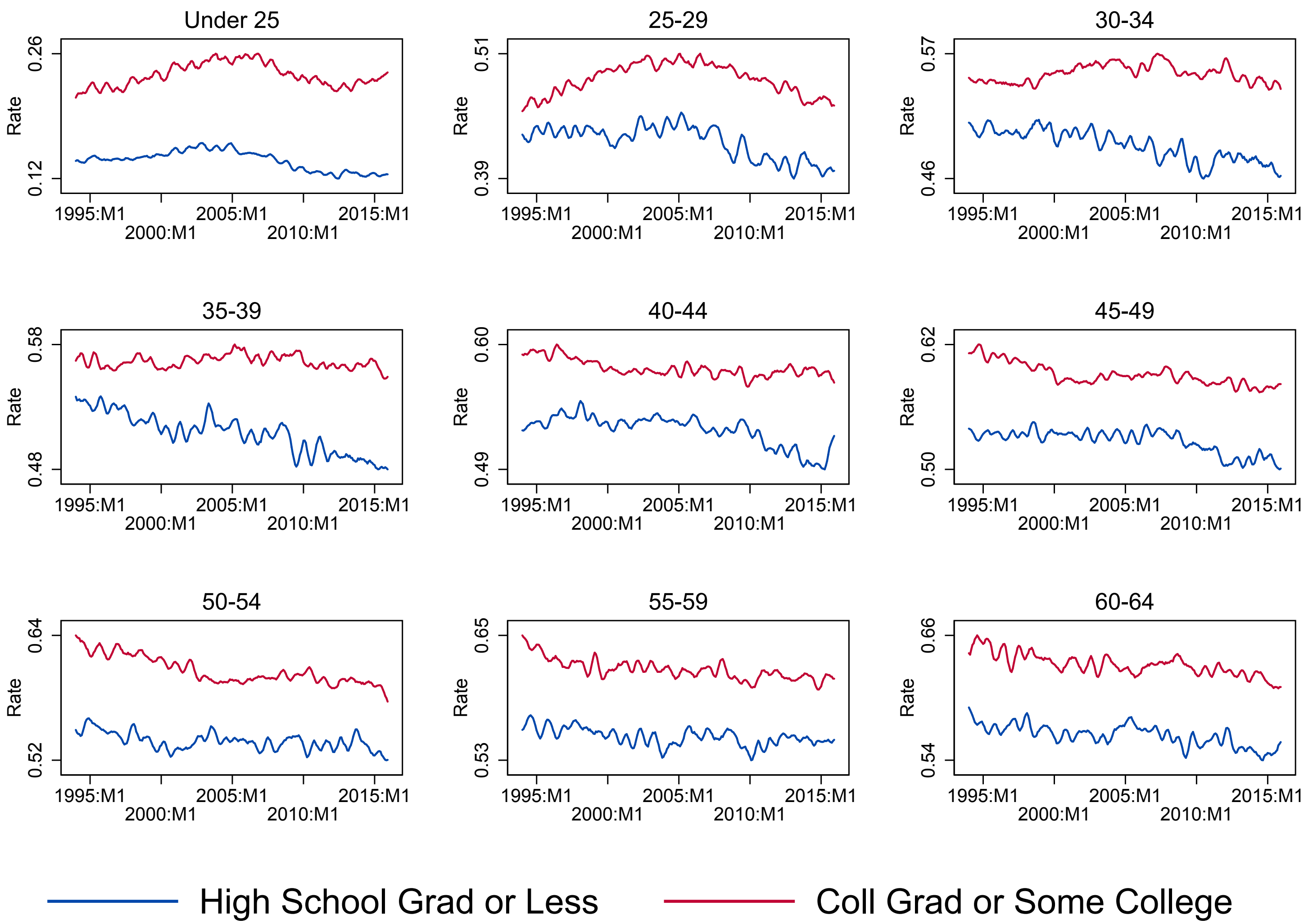
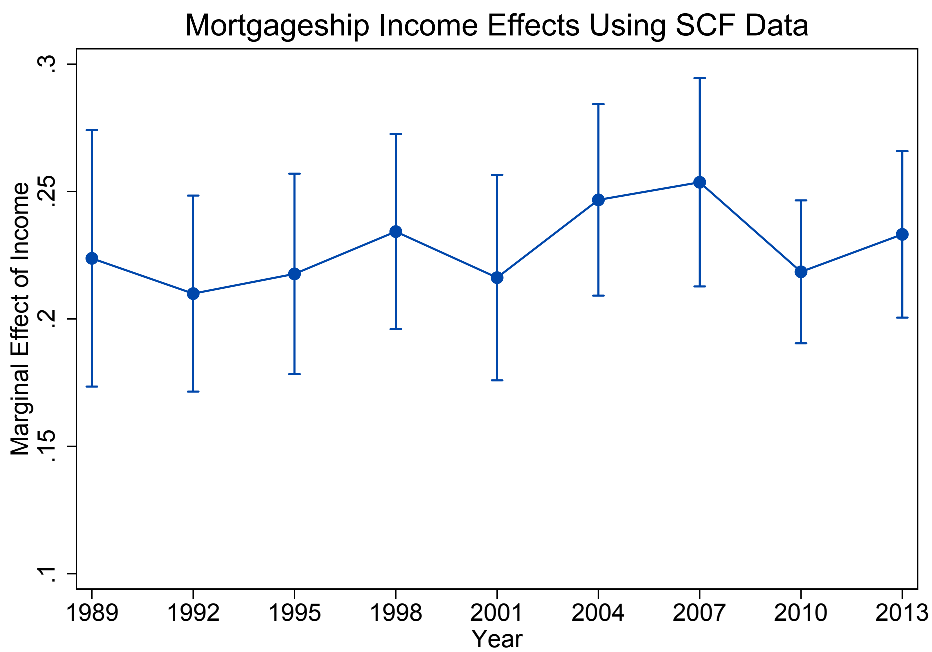


Figure A.12. Headship Rates by Age and Educational Attainment of Household Head. *Note:* Rates are 6-month centered moving averages of monthly data. *Source:* Current Population Survey.



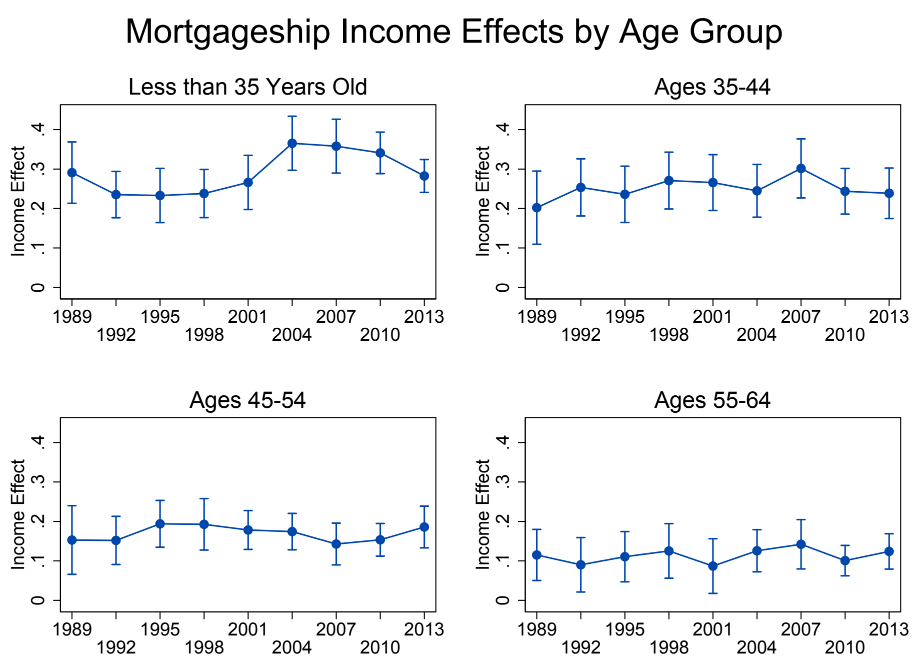


Figure A.13. Mortgageship and Income in the Survey of Consumer Finances. *Note:* Each panel depicts estimated effects of log income on binary indicators for "mortgageship," which is defined to be the presence of any mortgage debt for the household. All income effects are generated from logit regressions with the same right-hand-side variables and sample restrictions as the debt-value Poisson regressions depicted in the bottom panel of Figure 5 and the SCF homeownership regressions in Figure 8. The panels at bottom interacts the wage-income variable with indicators for the age group of the household head. All marginal income effects are calculated at the means of the regressors as measured by the first SCF implicate. *Source:* Survey of Consumer Finances.

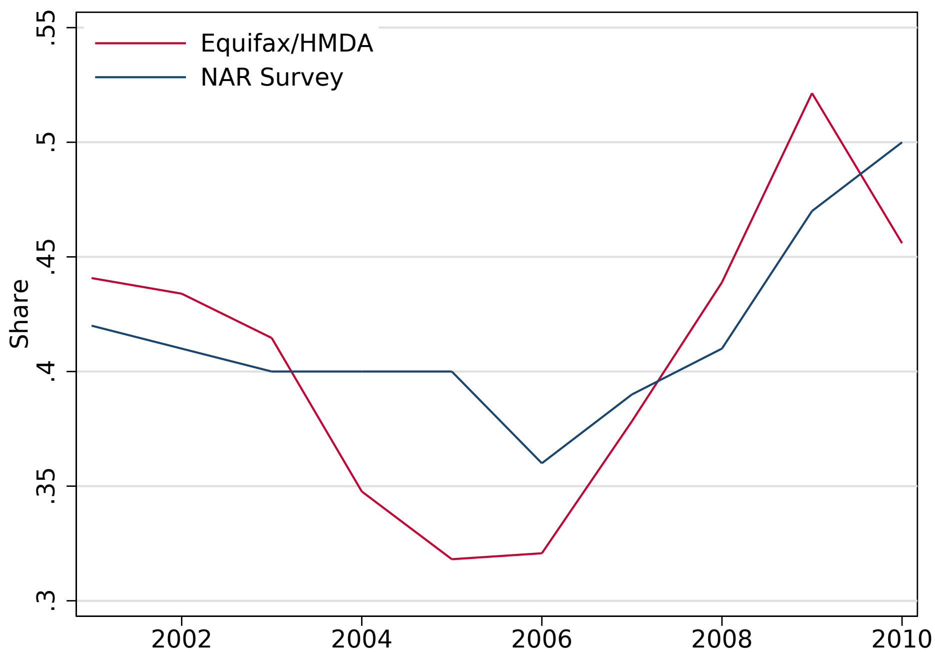
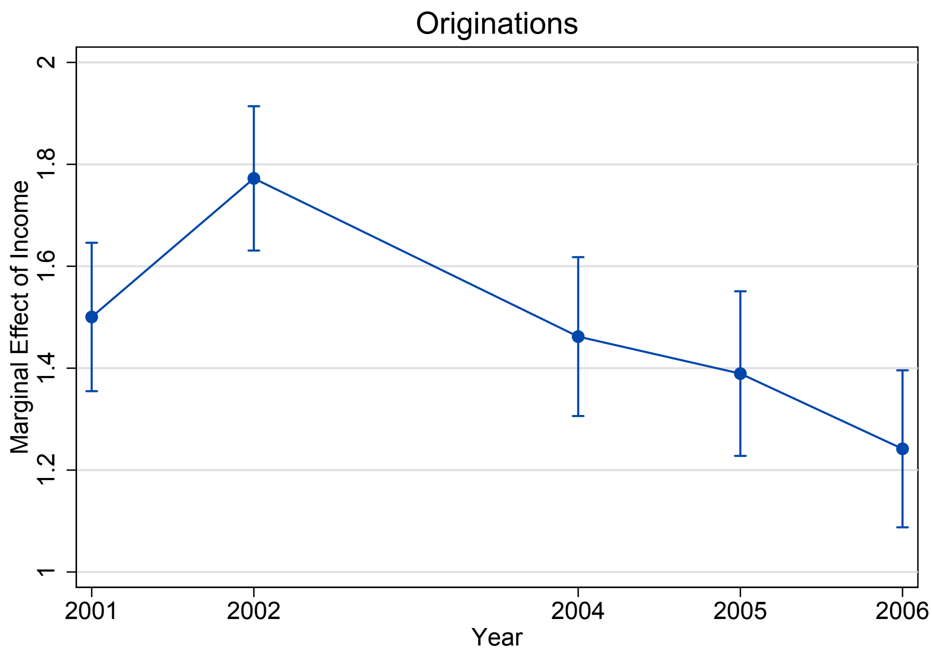


Figure A.14. Comparison of First-Time Borrower Share using Equifax and HMDA Data with First-Time Homebuyer Share Reported in the National Association of Realtors Survey. *Note:* The red line is the number of first-time mortgage borrowers in Equifax divided by the number of owner-occupied purchase mortgage originations from HMDA. The blue line is the share of homebuyers who are first-time homebuyers according to the National Association of Realtors Annual Survey. *Source:* NY Fed Consumer Credit Panel/Equifax and Internal, Home Mortgage Disclosure Act, and the National Association of Realtors.



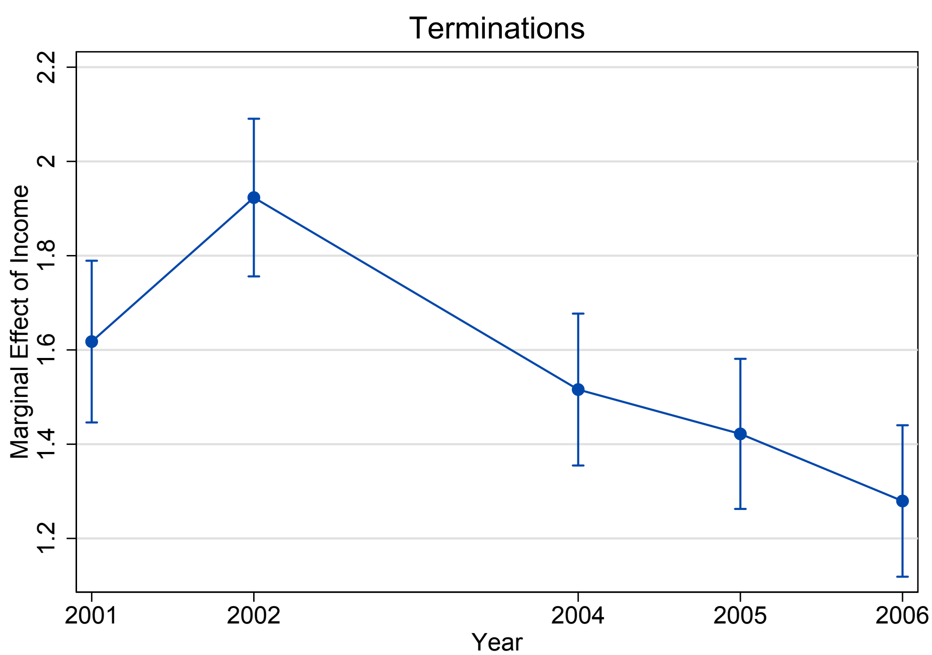
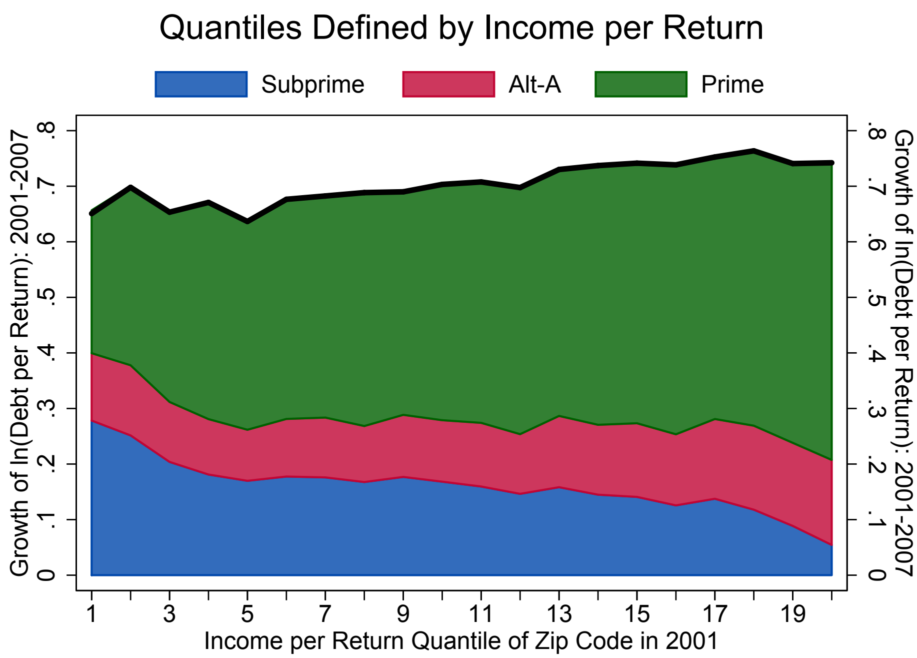


Figure A.15. Income Effects for Originations and Terminations without CBSA Fixed Effects. *Note:* Figure 11 in the main text displays income effects for originations and terminations when CBSA fixed effects are included. *Source:* NY Fed Consumer Credit Panel/Equifax and Internal Revenue Service Statistics of Income.



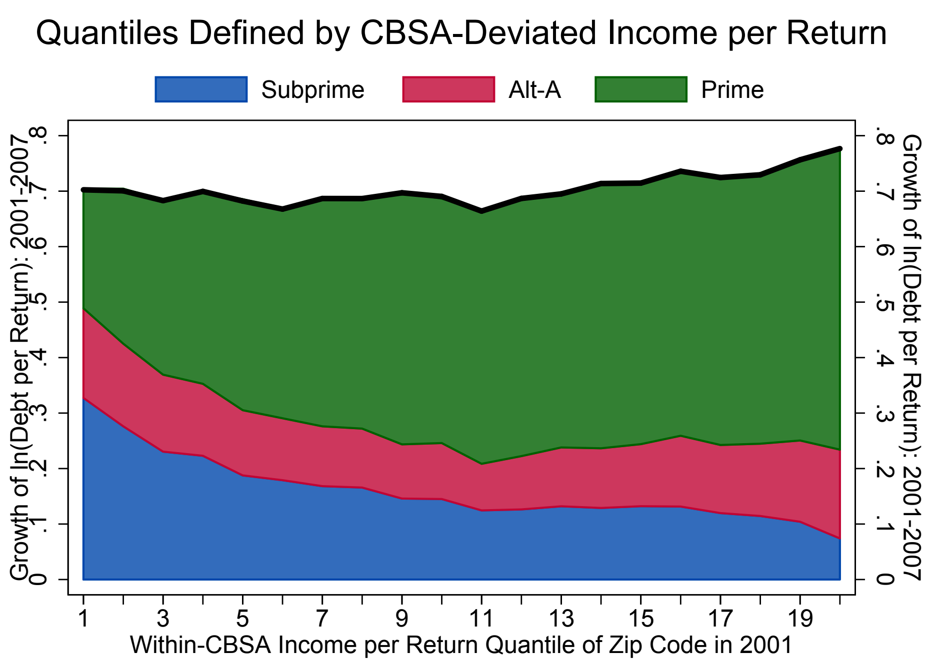


Figure A.16. Mortgage Debt Growth by Debt Type Across the Income Distribution of Zip Codes: 2001-2007. *Note:* These graphs are analogous to Figure 13, which is based on debt growth from 2001 to 2006 rather than growth from 2001 to 2007. *Source:* NY Fed Consumer Credit Panel/Equifax, CoreLogic Private Label Securities ABS Database, and IRS Statistics of Income.

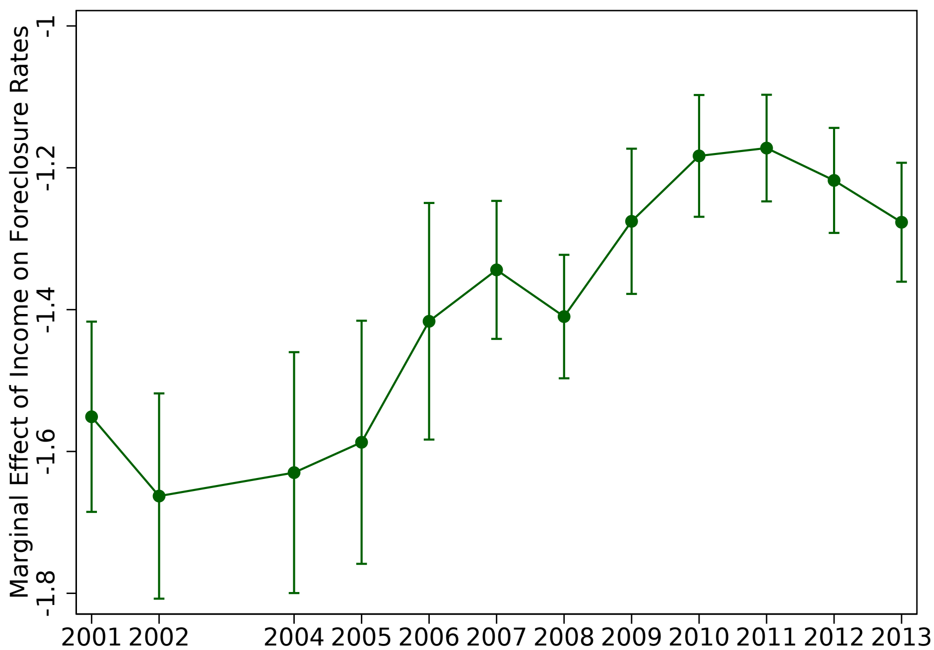


Figure A.17. Estimated Income Effects in Foreclosure Regressions. *Note:* This figure depicts yearly coefficients from a regression of zip code-level foreclosure propensities on income, where both have been deviated from CBSA-year means, from 2001 through 2012. These foreclosure-income regressions are structured similarly to the debt-income regression presented in the top right panel of Figure 6. *Source:* NY Fed Consumer Credit Panel/Equifax and IRS Statistics of Income.