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CROSS-SECTIONAL PATTERNS OF MORTGAGE DEBT DURING THE HOUSING BOOM: EVIDENCE AND IMPLICATIONS

Christopher L. Foote
Lara Loewenstein
Paul S. Willen

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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 even as the aggregate stock of debt grew rapidly. Moreover, because mortgage debt varies positively with income in the cross section, equal percentage increases in debt among high- and low-income borrowers meant that wealthy borrowers accounted for most new debt in dollar terms. Previous research stressing the importance of low-income borrowing was based on the inflow of new mortgage originations alone, so it could not detect offsetting outflows in mortgage terminations that left the allocation of debt stable over time. And while defaults on subprime mortgages played an important part in the financial crisis, the data show that subprime lending did not cause a reallocation of debt toward the poor. Rather, subprime lending prevented a reallocation of debt toward the wealthy.

Christopher L. Foote
Federal Reserve Bank of Boston
Research Department
600 Atlantic Avenue
Boston, MA 02210
chris.foote@bos.frb.org

Lara Loewenstein
Federal Reserve Bank of Boston
Research Department
600 Atlantic Avenue
Boston, MA 02210
Lara.Loewenstein@bos.frb.org

Paul S. Willen
Federal Reserve Bank of Boston
Research Department
600 Atlantic Avenue
Boston, MA 02210-2204
and NBER
paul.willen@bos.frb.org

1 Introduction

The early 2000s saw a large expansion of mortgage debt in the United States. The Federal Reserve's Flow of Funds accounts show that 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 substantial increase in the debt-to-income ratio, as seen in the top panel of Figure 1. In this paper, we study this mortgage boom with particular attention to how this 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]

The most important finding of the paper is that there was no reallocation of mortgage debt toward low-income individuals during the mortgage boom. To be sure, low-income borrowing grew rapidly, with much of this new debt packaged into the subprime mortgage-backed securities that caused so many problems during the 2008 financial crisis. Yet borrowing by high-income individuals rose at similar rates, so 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 periodic and 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 rises. The middle left 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 upward nearly equally across the income distribution, indicating that debt rose by similar percentages for low-income and high-income households alike. The top right and middle right panels in Figure 2 show similar results from 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 (IRS). 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 3,000–6,000 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

[1] Amromin and McGranahan (2015) write that a "voluminous" literature on early 2000s credit markets, including mortgage markets, has noted 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).

relationship shifted up nearly equally across the income distribution.[2] Mathematically, the combination of a stable debt distribution and a positive cross-sectional relationship between debt and income implies that, in dollar terms, most new mortgage debt went to the wealthy. This fact is illustrated in the bottom two panels of Figure 2. The Equifax/IRS panel at right shows that borrowers in the highest-income zip codes accounted for about $1.5 trillion in new debt from 2001 to 2006, while mortgage debt for the lowest-income quintile rose by only $320 billion.[3]

The stability of the debt distribution may seem surprising, because many commentators have assumed that the early 2000s featured a significant credit expansion along the *extensive margin*, with large numbers of marginal or low-income individuals able to qualify for mortgages and become homeowners for the first time. A look back at Figure 1, however, shows why the extensive-margin hypothesis has problems explaining the behavior of mortgage debt in the early 2000s. The lower panel of this figure depicts the U.S. homeownership rate, and a comparison of that panel with the debt-to-income ratio above it shows that the mortgage boom followed an increase in homeownership that originated in the mid-1990s.[4] But the lower panel also shows that the homeownership rate ended the 2001–2007 mortgage boom about where it began. To study the extensive margin of debt more closely, we use the SCF and Equifax/IRS datasets as well as individual-level credit records in the Equifax data, which lack income information but include a type of credit score. Overall, there is no evidence of a relative expansion of mortgage borrowing among low-income or marginal borrowers during the boom, particularly after conditioning on age. In fact, income becomes a more-important, not less-important, correlate of homeownership after the mortgage boom begins, especially for young households. And, consistent with Bhutta (2015), the individual-level Equifax credit records show that transitions into first-time 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. Of course, many lenders relaxed their credit standards during the boom. But the data suggest that the effect of this relaxation on the extensive margin of

[2]In the main text, we explain how the zip code-level dataset was 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 discussed in the internet appendix, all of the zip code-level results remain robust to using 2007 as the last year of the mortgage boom instead. We will also show that the slight tilt of mortgage debt toward richer borrowers in the scatter plot that uses the Equifax/IRS data arises from shifts in debt between city-level housing markets, not within these markets.

[3]In the internet appendix, we replicate the bar charts in Figure 2 that use SCF data with 20 rather than five income categories. The same lessons hold at the higher level of disaggregation, as debt shares are generally stable so that the rich take out the most debt in dollar terms. The appendix also relates our findings to those of Kumhof, Rancière, and Winant (2015), who study total debt (as opposed to mortgage debt) for the top 5 percent and bottom 95 percent of SCF households from 1983 onward.

[4]See the internet appendix for an alternative measure of homeownership: the total number of owner-occupied housing units divided by the total number of adults. Movements in this alternative measure are similar to movements in the standard homeownership measure.

debt was offset by the rapid increase in house prices, which made first-time buying difficult.

Throughout this paper we highlight the distinction between the stocks of debt on household balance sheets and the two gross flows of debt, originations and terminations. This distinction is sometimes unclear in existing research. For example, Mian and Sufi (2009) use data generated by the Home Mortgage Disclosure Act (HMDA) to argue that the allocation of mortgage credit changed fundamentally during the mortgage boom, in ways that channelled credit disproportionately to marginal or low-income borrowers. HMDA is a nearly comprehensive source of data on 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.[5] But many times, the origination of a new mortgage (for example, the mortgage of a home buyer) is offset by the termination of another mortgage (for example, the mortgage of a seller). Because HMDA does not cover terminations, HMDA data alone cannot be used to study the distribution of mortgage debt.

The stability of the cross-sectional distribution of debt supports an emerging "new narrative" on the housing cycle, which disputes the common claim that the cycle was driven primarily by an exogenous relaxation of credit constraints. In theory, relaxed constraints might raise effective demand and prices among low-priced homes, which could in turn spill over to higher-price segments of the market (Landvoigt, Piazzesi, and Schneider 2015). But it is hard to see how anything that raised mortgage debt among low-income borrowers by \$320 billion could have generated spillovers large enough to encourage \$1.5 trillion in new borrowing by the wealthy. By providing precise measures of debt stocks as well as flows, we build on Adelino, Schoar, and Severino (2016), the first paper to directly challenge the findings in Mian and Sufi (2009) regarding the allocation of debt. Adelino, Schoar, and Severino (2016) use HMDA data to show that the Mian-Sufi findings were driven by relatively high growth in the number of purchase mortgages originated in low-income zip codes, not by higher dollar values of mortgages. To the authors, this finding indicated that the original Mian-Sufi findings reflected only higher transaction volumes in low-income areas, not a reallocation of mortgage debt toward low-income borrowers. Yet without zip code-level data on mortgage terminations, stocks of mortgage debt, or numbers of mortgage borrowers, it is impossible to rule out the hypothesis that the higher transaction volumes in low-income zip codes resulted in more low-income homeowners—an extensive-margin expansion of credit that is consistent with the conventional theory. An analysis of both stocks and flows at different levels of geographic detail settles this question by ruling out an expansion of mortgage credit along the extensive margin. A disaggregated analysis of debt stocks also shows that even though subprime lending was disproportionately concentrated in low-income areas,

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

the overall amount of subprime debt remained relatively small, despite a rapid ramp-up of subprime originations during the last half of the boom.[6]

In the conclusion, we discuss how these empirical results might inform theoretical models. As pointed out by Foote, Gerardi, and Willen (2012), Glaeser, Gottlieb, and Gyourko (2013), and others, several empirical facts point to higher house-price expectations as a key driver of the housing cycle. The stability of cross-sectional distribution of mortgage debt with respect to income is consistent with the expectations theory as well. While capturing "bubble psychology" in a formal model is difficult, many models are now shedding light on the possible origins of such psychology, as well as the effect that bubbles could have on both the housing market and the wider economy.

2 Cross-Sectional Data on Debt Stocks and Income

2.1 Debt and Income Data from Equifax and the IRS

The 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 5 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.[7] Among other debt variables, the Equifax data contain detailed information on mortgage debt. Included are 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. A termination is defined as occurring in the last quarter that a mortgage appears in the data, and the value of that termination is defined as the remaining balance when the loan is removed.

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:

[6] In addition to Adelino, Schoar, and Severino (2016) and Bhutta (2015), other papers in the new-narrative literature include Albanesi, DeGiorgi, and Nosal (2016), which examines debt and credit scores, rather than debt and income, and Ferreira and Gyourko (2015). The latter paper shows that most foreclosures took place among prime borrowers, not subprime borrowers, with the implication that the foreclosure crisis "was largely one of sound borrowers falling into negative equity because of very large declines in house prices" (p. 21).

[7] 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 5 percent sample of individuals.

Net Change in Stock of Mortgage Debt =

+ Gross Inflows

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

− Gross Outflows

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

Other common 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 quite comprehensive, but, as noted earlier, HMDA data cannot be used to measure mortgage terminations or debt stocks.[8] Data from public registries of deeds suffer from a similar limitation, in that they provide good coverage of originations but problematic coverage of terminations.[9]

In addition to information on mortgage debt, the Equifax dataset contains a small number of borrower-level characteristics, such as age and an end-of-quarter credit score called the Equifax Risk Score. This score, created by Equifax, resembles a FICO score, in that a higher value indicates a lower probability of default over the near term. We have found the mode of the credit-score distribution moves to the right somewhat over time, but this movement is

[8]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, as we note below, some researchers have questioned the accuracy of the borrower-level income data reported on HMDA forms (Mian and Sufi 2016a).

[9]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.

not very worrisome because it does not become severe until 2010, after the mortgage boom ends. Also, we only use the Equifax score to distinguish the creditworthiness of individuals within a given year, not to measure changes in individual-level creditworthiness over time.

Loan-level datasets 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 that are not backed by any of the government-sponsored enterprises such as Fannie Mae, Freddie Mac, and Ginnie Mae). For this specific group of mortgages, which includes the large majority of subprime loans, the coverage of the CoreLogic dataset is excellent, as it contains an expansive set of variables for loans in almost all non-agency securities issued since 1992. Yet the CoreLogic dataset cannot measure aggregate debt stocks, because (as discussed below) subprime and other types of non-agency loans made up a small share of the mortgage market throughout the early 2000s.[10] CoreLogic data can be used to measure cross-sectional patterns in the use of securitized subprime and Alt-A debt, however, and we do so below.[11] 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 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. We therefore follow previous research and construct aggregates of debt at the zip-code level, and then merge the debt aggregates with zip code-level data on income from the IRS. Zip code-level information is available 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.[12] 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 comprehensive, because they are based on the universe of tax returns, but they are 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.

[10] The CoreLogic database was originally called the LoanPerformance database after the company that developed it.

[11] 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.

[12] 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.

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 potentially distort some results if the mortgage boom is defined 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 zip code-level results hold even with 2007 chosen as the boom's last year. 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 a great 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 highest-income 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 individuals hold mortgage debt. Homeownership information is available in the SCF, to which we turn next.

2.2 Household-Level Data from the Survey of Consumer Finances

The large Equifax/IRS dataset allows 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, suggests the need for additional data.[13] 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 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. As a result, the SCF is considered to be the best source of individual-level data on housing-related debt and wealth in the United States.[14] 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. As for income, information is available 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 available to the public by the Federal Reserve's Board of Governors.[15] 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.[16] The table

[13]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.

[14]In their study of wealth concentration, Saez and Zucman (2016) use a sample of anonymized individual-level tax returns, the Tax Model Files, to back out wealth estimates based on income flows and itemized deductions. Individual-level housing assets are inferred by capitalizing property tax payments in a way that is consistent with national aggregates. Mortgage debt is netted out of housing wealth by capitalizing mortgage-interest deductions in a similar way. While the Tax Model Files are a good source of housing wealth and debt for tax filers at the top of the income distribution—the focus of the Saez-Zucman study—the authors note that the tax-capitalization method is probably less accurate for less-wealthy filers, in part because these filers itemize their deductions less often. "The SCF is essential for accurately measuring housing and pension wealth, the main forms of wealth for the bottom 90 percent, and indeed our own estimates for housing and pension wealth rely on it," the authors write. "The value added of our estimates [based on the Tax Model Files] relative to the SCF is that they cover a longer period, are annual, and are more suited to capture the very top, if only because they include the 400 richest Americans" (p. 569, insertion added). See the internet appendix for more discussion of the Tax Model Files as a potential data source.

[15]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.

[16]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

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 defines income as salary and wages and excludes 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 high-income quintiles. For example, Panel A indicates that the average household in the lowest-income quintile of total income saw its mortgage debt increase from \$5,294 in 2001 to \$10,795 in 2007. The comparable increase for 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 and homeownership rates. Both of these statistics are stable or rise only modestly across all income groups.[17] Finally, the last two columns present information on the asset side of household balance sheets, specifically (self-reported) housing values, which rose rapidly during the boom.

3 Income and the Distribution of Mortgage Debt

3.1 Unconditional Distributions of Debt

Before we study the conditional relationship between mortgage debt and income, 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 on the left side of the 1995 distribution experienced relatively greater increases in debt through 2001. After that, however, the distribution appears to flatten out, suggesting that from 2001 to 2007, households with high amounts of debt saw 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

statistics in Table 2 are simple averages of the five within-implicate weighted averages.

[17] 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 (Kennickell 2007). The number of unweighted observations is not an integer because each SCF household is represented by five implicates, and the income fields often differ slightly across implicates for a given household.

near the tails.[18]

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 was qualitatively similar to the movement in the SCF distribution over the corresponding period (note the difference in horizontal scales, however). More importantly, the zip code-level distribution also appears to have widened, 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 movements in debt. As noted in previous research, looking within individual housing markets holds constant any factors that affect the market as a whole. In this paper, housing markets are defined as cities, more specifically as Core Based Statistical Areas (CBSAs).[19] By construction, both of the within-CBSA distributions depicted in the lower left panel are 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 arose from the increase in the dispersion between cities, as confirmed in the lower right panel.[20]

Taken together, the Equifax distributions indicate that mortgage debt levels for zip codes in the same city 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 areas. This finding is inconsistent with the claim that the housing boom reallocated debt to areas with previously low levels of debt, as this type of reallocation would have narrowed the within-CBSA debt distributions over time.

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 for statements about the allocation of debt *conditional* on income. The unconditional distri-

[18]See the internet appendix for details. Note that households with zero levels of mortgage debt are not included in the SCF distribution of Figure 4, but these households are included in both the bar charts and binned scatter plots of Figure 2 and the debt-income analysis in the next section.

[19]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.

[20]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 within and between variation sum to total variation in the two years (0.41 and 0.48).

butions will 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.[21] 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 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 potential parametric form for this function is

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

which assigns a debt stock d to unit i in housing market c in year t as a function of income y. 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 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 them to change over time.

Although it is simple, the conditional expectation function easily formalizes various theories about the mortgage boom. The standard view is that credit flowed disproportionately to borrowers with low incomes. As seen in Figure 2, the cross-sectional relationship between debt and income is positive (that is, richer borrowers have more debt), so a reallocation of debt toward low-income borrowers would reduce this correlation over time ($0 < \beta_{2006} < \beta_{2001}$). An alternative theory suggested by the changes in debt across years in Figure 2 is that debt rose by equal percentage amounts across the income distribution. If income were specified in natural logs, then we would expect the intercept α_t to rise over time, with no change in the cross-sectional relationship between debt and income ($\beta_{2006} = \beta_{2001}$).

[21] 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.

Estimated β_ts are presented in Figure 5 and confirm the alternative theory. Consider first the Equifax estimates in the top panel.[22] These estimates, which can be interpreted as elasticities, lie in a fairly tight range between about 1.35 and 1.45, indicating that the β_ts change little over time. If anything, the income effect grows slightly, with the 2006 coefficient about 0.07 higher than the 2001 coefficient, a difference that is statistically significant but economically small. Below, we investigate whether this increase resulted from between-city or within-city movements in debt, but the important point here is that the regressions provide no evidence that the conditional relationship between debt and income was reduced over time.[23]

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.[24] The SCF income coefficients fluctuate modestly over time, as they are somewhat elevated in 1989 and 2004 and lower than average in 2001 and 2010. As was the case with the zip code-level results, however, there is no evidence of a sustained decline in the importance of income to 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, although 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,

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

[22]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.

[23]The standard error on the difference between the 2001 and 2006 income coefficients is 0.02, and the t-statistic on the difference is 3.8. Because the binned scatter plot of Equifax data in Figure 2 suggests that the debt-income relation is not exactly log-linear (specifically, that the slope of the scatter plot is steeper at low incomes), we ran some unreported regressions that also include the square of income-per-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.

[24]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.

so that a finding of $\beta_{2006} < \beta_{2001}$ reflects a reallocation of debt toward zip codes with low incomes relative to other areas in the same cities. The alternative story is that the within-city relationship between income and debt is stable ($\beta_{2006} = \beta_{2001}$), so that changes in debt among zip codes are driven by changes in the distribution of city-level effects, α_{ct}.

The top two panels of Figure 6 investigate these alternatives. The binned scatter plot in the top left panel is constructed by deviating both the debt and income variables from CBSA means, separately in 2001 and 2006, and then averaging these deviations into 20 bins for each year. Because debt and income are both measured as deviations, the overall increase in debt during the boom is absorbed by the city averages, so both lines of points go through the origin. There is no significant shift in the slope of these lines, and the top right panel confirms the stability of the debt-income relationship with regressions.[25] The estimated β_ts using CBSA fixed effects rise very slightly from 2001 to 2002 and fall gently thereafter, so that by 2006 the income coefficient has essentially returned to its 2001 value. The exact difference between the 2006 and 2001 coefficients is –0.01, a gap that is neither economically nor statistically significant.

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 a smaller number of bins, the CBSA-level plot is fairly choppy. The panel does suggest a mild 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.[26] Thus, between-city movements help explain the small but statistically significant increase of 0.07 that we found for the overall income effect in the previous subsection, when Equifax debt was regressed on IRS income without regard to the CBSA location of the zip code.

To be clear, the regression estimates should not be interpreted as structural predictions of how exogenous increases in income should affect mortgage debt. For example, the across-CBSA results could reflect causality that runs from booming local housing markets to rising local incomes, not a causal relationship between city-wide income and city-wide debt. Indeed, the possibility of reverse causality at the CBSA level is one reason why the within-CBSA results are particularly useful. However, both the scatter plots and the reduced-form regressions are good ways to get a sense of how the cross-sectional relationship between debt and income might have changed over time. And in neither the SCF nor the Equifax/IRS datasets do these methods suggest a reallocation of mortgage debt toward low-income bor-

[25] As noted in footnote 22, 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.

[26] 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.

rowers during the early 2000s.

4 The Extensive Margin of Mortgage Debt

4.1 Income and the Extensive Margin

The movements in total debt analyzed in the previous section take place along two potential margins—the intensive margin (that is, the average amount of debt per borrower) and the extensive margin (the total number of borrowers). In this section, we focus on the extensive margin of debt in light of frequent claims regarding an expansion of credit to marginal borrowers. The first step in this analysis is to use SCF data to relate income to the presence of any mortgage debt on a household's balance sheet—what we call "mortgageship." This concept is related to homeownership, but mortgageship and homeownership are not equivalent because some people own their homes without any debt.[27] To do this, we run logit regressions of mortgageship on the household-specific variables that were also used in the total-debt regressions in the lower panel of Figure 5.[28] While they do not generate structural estimates, the regressions determine whether current-income differences between people with and without mortgages narrowed over time, as would be expected if growing numbers of low-income individuals were able to take out mortgages.

The top panel of Figure 7 shows that the income coefficients in the mortgageship regression trend higher from 2001 to 2007, suggesting that the current-income differences between borrowers and non-borrowers grew modestly during the mortgage boom. The lower, four-panel chart presents income coefficients that are specific to age groups, which are generated by interacting the age-group dummies with the income regressor. Because the vertical scales in these panels are identical, they make it clear that income gaps between borrowers and non-borrowers are widest among the youngest households. More important for our purposes are the changes in income effects over time. During the early 2000s, the income differences distinguishing borrowers from non-borrowers rose the most among the youngest households, but in no age group does the income difference decline significantly over time.

The Equifax dataset can be used to investigate the extensive margin of mortgage debt at the zip-code level, by relating a zip code's income to the share of its households that have a mortgage. Figure 8 presents binned scatter plots of mortgaged-household shares against

[27]The internet appendix shows that the income patterns we find for mortgageship are quite similar to the mortgageship results presented in this section.

[28]See footnote 24 for the list of regressors. 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 the top panel shows that an increase in wage income of 100 log points raises the expected homeownership rate by around 20–25 percentage points, holding other demographic factors constant.

income in 2001 and 2006. The upper plot uses unadjusted income and mortgage share data, while the bottom panel 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 the positive correlation undoubtedly flows from higher rates of homeownership in high-income communities, but a zip code's share of mortgaged households is also determined 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 of high-income persons to own their homes without any debt.

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 became more likely to hold mortgage debt during the boom, conditional on income. No such shift occurs at the other end of the income distribution. The lower panel of Figure 8 repeats the analysis on a within-CBSA basis. Here, the conditional relationships have virtually identical shapes, suggesting that the high-income shift in the top panel arises primarily from between-CBSA shifts in mortgaged-household shares. This finding lines up well with the importance of between–CBSA shifts for total debt illustrated by the regressions in section 3.

4.2 Credit Scores and the Extensive Margin

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 Risk Scores.[30] Any study of credit scores and debt must confront two potential problems, 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 correlation between the presence of mortgage debt and an individual's current credit score. A second problem confounding the study of credit scores and debt is that people typically borrow to buy homes early in their adult lives. On average, young people have low credit scores, because they have yet to build up substantial savings and have only managed debt for a short 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.

[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 the Equifax dataset with a mortgage: the number of people with a mortgage, with any joint mortgage divided by two.

[30]As noted below, the relationship between credit scores and mortgage debt is the key focus of Albanesi, DeGiorgi, and Nosal (2016) and is also explored in Bhutta (2015).

Fortunately, information in the Equifax data allows us to circumvent both problems. 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 "mortgage tradeline" for that loan in the Consumer Credit Panel, a separate variable indicates that this person does have a mortgage originated in 1985. 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 is sufficient to identify individuals taking out first mortgages after 1999, and focusing on the flow of those persons into first-time borrowing solves the endogeneity problem that arises when borrowers make on-time payments on existing stocks of debt. Of course, the flow of first-time borrowers will include many young people, who tend to have low credit scores. But the potential bias arising from the life-cycle borrowing pattern can be addressed by conditioning on age.

Figure 9 plots a collection of hazard ratios for individuals obtaining a mortgage for the first time.[31] For each year t, the denominator of the hazard ratio 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 9 and Bhutta (2015) is that the figure defines Equifax Risk Scores *relative* to CBSA means, in order to hold constant factors that affect the creditworthiness of individuals throughout a given housing market.[32] 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.[33] Importantly, the probability of transitioning into mortgageship 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.

[31]See the internet appendix for details regarding sample construction and a check of implied first-time mortgageship rates against other data.

[32]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.

[33]From 2004 to 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 by 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 much less likely to be a confounding factor for individuals near the start of the life cycle.

The four panels in the bottom half of Figure 9 split the sample by age. Credit-score quintiles are calculated within age groups, so the credit score of a young person in the top quintile for her age group may be lower than that of an older person in a lower quintile. Looking across panels, a hump-shaped hazard of first-time mortgageship can be inferred, as transition rates are highest for 25–34 year-olds. Transition rates are monotonic for the youngest two groups, as persons in the highest credit-score groups are always most likely to flow into first-time mortgageship, those in the second group are 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, no panel suggests a substantial extensive-margin shift in favor of poor credit risks.

Results on the flow of persons into first-time borrowing complement the earlier extensive-margin analysis in two ways. First, the SCF regressions showed that current-income differences between borrowers and non-borrowers did not decline during the housing boom. Yet these differences are influenced by labor market developments, which may have favored people 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 income differences between mortgage borrowers and non-borrowers in the SCF may grow, even if loosened lending standards allow more low-income people to buy homes. Using the individual-level data in the Equifax data to study the flow into mortgage borrowing is less susceptible to this potential confounding issue.

A second reason that Figure 9 is valuable is that it suggests that rising housing prices during the boom had strong negative effects on first-time buying across 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, as house prices rose rapidly. The negative effect of higher prices appears to have offset or outweighed the positive effect of relaxed credit standards, so that first-time buying among low-credit score groups declined during the mortgage boom, along with first-time buying by everyone else. Given the sharp rise in house prices, perhaps the truly surprising feature of the mortgage boom is not that most of the dollar increase in mortgage debt went to the wealthy. The real surprise is that the low-income individuals, who were the least likely to own homes at the start of the mortgage boom, were able to increase their mortgage debt levels at the same rates as everyone else.

Later in the paper, we investigate how the growth of subprime lending helped low-income individuals raise their debt levels at the same rates as high-income individuals did. Before we do, we shift the focus from debt stocks and the flows into mortgageship to the two gross flows of debt, mortgage originations and terminations. A gross-flow analysis provides some helpful 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). Gross-flow analysis is also useful for showing how the results above relate to previous studies of the mortgage boom.

5 Rising Mortgage Churn in Low-Income Areas

Figure 10 examines the zip code-level relationship between gross debt flows and income on a within-CBSA basis.[34] Each of the two rows of Figure 10 contains a binned scatter plot of income and either originations (top row) or terminations (bottom row), along with the plot of corresponding income coefficients. The panels are therefore analogous to the panels in the top row of Figure 6, which analyzed total debt stocks on a within-CBSA basis. In contrast to the results for debt stocks, the relationships between income and the two gross debt flows change over time. The binned scatter plots at left show a significant decline in the positive relationship between the two flows and income; in each plot, the slopes for the 2006 points are shallower than the slopes for the 2001 points. The two panels at right express these changes as falling estimates of income coefficients, which are generated from regressions analogous to the earlier debt-stock regressions. Yet the shifts in originations and terminations are the same. As a result of the offsetting nature of these shifts, the gross flow data imply that relative "mortgage churn" rose in low-income areas, even as relative debt stocks remained stable.

What accounts for the 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 by the Federal Reserve 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 10 suggests that high-income borrowers were more likely to participate in the 2001–2003 refinancing boom,

[34] See the internet appendix for analogous results without zip code-level fixed effects.

[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 than 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.

consistent with previous research on the propensity to refinance.[38] As this wave fell off after 2003, the *relative* amount of churn in low-income communities increased.

Another reason that relative mortgage churn increased in low-income communities is that sales volumes rose. In theory, the Equifax data could be used to measure the number of purchase-and-sale transactions that involved debt, but unfortunately we cannot consistently distinguish purchases from refinances in that dataset. We can, however, construct a measure of "purchase-mortgage intensity" by dividing a zip code's number of purchase-mortgage originations (as measured by HMDA) by its number of first liens (as measured by Equifax). The top panels of Figure 11 show that purchase-mortgage intensity rose in low-income communities from 2001 to 2006, looking across all zip codes (top left panel) or within CBSAs (top right panel). The lower two panels correct the measure of purchase-mortgage intensity for the presence of investors. In HMDA, each purchase mortgage is attached to the location of the house being purchased, not the zip code of the purchaser, and these locations differ in the case of non-owner-occupiers. The lower panels of Figure 11 depict a purchase-mortgage intensity measure that excludes investor purchases, and this correction substantially reduces the relative increases in purchase-mortgage intensity in low-income areas over time.[39] Although the corrected increases in low-income purchases are not particularly large, they do contribute to rising relative rates of mortgage churn in low-income areas that are apparent in Figure 10.

It is critical to understand, however, that higher purchase-mortgage intensity in low-income areas does *not* indicate that mortgage debt was shifting down the income distribution, because these purchase mortgages typically replaced the sellers' mortgages on the homes being transacted.[40] As a result of this offset, higher purchase-and-sale volumes have only indirect impacts on overall mortgage debt and cannot be used to infer cross-sectional changes in household balance sheets. Fortunately, the Equifax data allow us to correctly attach

[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 "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).

[39] Investor information in the HMDA data 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 the HMDA data is best considered a lower bound.

[40] 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.

mortgages to borrower locations and then keep track of mortgage debt stocks as well as flows. Although we cannot separate total gross flows in Equifax into purchases, refinances, and sales, we can measure both total stocks of debt and total gross flows. And as this section has illustrated, we can tie stocks and flows together by showing how changes in the patterns of the total gross flows offset each another, leaving the distribution of mortgage debt stocks stable over time.

6 Relationship to Other Research

6.1 Research on Debt and Income

Understanding that rising purchase-mortgage intensity does not necessarily signal a reallocation of debt is important for evaluating existing work on the housing boom. In an early contribution, Mian and Sufi (2009) used HMDA data to argue that the boom had reallocated debt toward low-income borrowers, a development they linked to incentive problems in the origination and securitization of subprime loans. The key piece of evidence that led the authors to make this claim was that at the zip-code level, changes in HMDA purchase-mortgage originations became *negatively correlated* with changes in incomes during the boom. One can show that, using Mian and Sufi's specific regression framework, the decline in the positive *levels* relationship between originations and income that we outlined in the previous section would generate a negative correlation between debt and income *changes*, like the one that Mian and Sufi found. Because Mian and Sufi looked primarily at purchase-mortgage originations and did not ask whether these originations were offset by terminations, they misinterpreted the increase in mortgage churn in low-income areas as a credit expansion to low-income borrowers.

In a recent paper, Adelino, Schoar, and Severino (2016) also argue that Mian and Sufi misinterpreted an increase in mortgage churn in low-income areas, but data issues prevented them from fully examining the empirical consequences of that result. Much of the analysis in Adelino, Schoar, and Severino (2016) uses HMDA data on purchase-mortgage flows, but the paper exploits the borrower-level nature of HMDA data to separate that gross flow into two components: the *number* of new purchase mortgages in a zip code and the *average amount* of each individual mortgage. Adelino, Schoar, and Severino (2016) shows that the key results in Mian and Sufi (2009) result from higher mortgage churn—what they call the "velocity" of mortgage origination—not from residents of low-income zip codes getting larger mortgages. In fact, the authors found that in relative terms, average mortgage size rose more in high-income zip codes than in low-income zip codes. The implication of this positive correlation between changes in average mortgage size and income was that "[t]he apparent decoupling of zip code-level credit growth and per capita income growth [implied by Mian and Sufi's negative correlation] is due solely to the negative relation between the number of new originations and per capita income growth" (p. 1637, insertion added). While Adelino, Schoar, and Severino (2016) recognized that higher mortgage churn is critical to Mian and Sufi's original finding, they were unable to explore the implication of that result because they lacked data on debt stocks and mortgaged-household shares at the zip-code level. They were therefore unable to determine whether the rising numbers of originations they found in low-income areas simply reflected higher transaction volumes or instead signaled that larger numbers of low-income borrowers were buying homes, which is the definition of an extensive-margin expansion of credit. The inability of HMDA data to rule out the extensive-margin possibility highlights the need for data on debt stocks and shares of mortgaged households, which can rule out that possibility.[41]

The debate about gross-flow patterns continues in Mian and Sufi (2016a), which argues that average mortgage size displays a small negative correlation with zip code-level income after accounting properly for second liens.[42] Mian and Sufi therefore claim that it is incorrect to state, as Adelino and coauthors did, that the negative correlation in their original 2009 paper resulted *completely* from higher churn in low-income areas, with no contribution from average mortgage size. While potentially interesting, this new finding has no bearing on our results. First, whether average mortgage size in low-income zip codes rose or fell slightly does not invalidate the finding that mortgage churn rose in low-income areas, and that this increase was originally confused in the literature with a significant credit expansion to low-income borrowers. Second, the apportionment of purchase-mortgage flows into average mortgage size and transaction volumes is a second-order issue. As we have illustrated, data on mortgage stocks can be used to directly measure the distribution of mortgage debt as well as any shifts in shares of mortgaged households over time, which are the ultimate objects of interest when calculating household debt burdens.[43]

[41] Adelino, Schoar, and Severino (2016) includes one figure that uses SCF data to measure stocks of debt, but that figure does not include data from people with zero debt, so it does not address the potential for a credit expansion along the extensive margin. Also, as noted above, the relatively small size of the SCF means that the Equifax data are needed to measure debt shifts across and between housing markets—a crucial distinction in Mian and Sufi (2009).

[42] The presence of second liens means that the number of total mortgage applications is larger than the number of purchase-and-sale transactions. Using the latter concept as the denominator when calculating average mortgage size generates a modest negative correlation of average size with income growth.

[43] Mian and Sufi (2016a) is also critical of the use of borrower-level income data in HMDA by Adelino, Schoar, and Severino (2016), because, Mian and Sufi claim, these data are more likely to be fraudulent in low-income zip codes. That critique is not relevant to this paper, because we never use HMDA data to measure income.

6.2 Research on Credit Scores and Income

Another research project related to ours is Albanesi, DeGiorgi, and Nosal (2016), which focuses on the relationship between debt and credit scores, not debt and income. As noted above, the endogenous feedback between debt and credit scores is likely to be larger than that between debt and income. Although taking out a mortgage to buy a home might raise one's income, doing so will almost certainly raise one's credit score if the subsequent mortgage payments are made on time.[44] Figure 12 illustrates the endogenous relationship between credit scores and debt in a way that clarifies both the contribution of Albanesi, DeGiorgi, and Nosal (2016) and some responses to their work. The figure presents a series of debt statistics for a random sample of individuals in the Equifax sample as of 1999, the dataset's initial year. The individuals are divided into separate groups corresponding to age in 1999 and Equifax Risk Scores in 1999. The top panel shows, first, that individuals in middle age had higher average levels of mortgage debt in 1999, and second, that within each age group, debt was positively related to credit score.[45] Both findings are intuitive. Middle-aged persons, who have recently entered their prime home-buying years, tend to have significant mortgage balances that are paid off as they grow older. And the positive relationship between debt and income within age groups reflects the two-way street of causality between debt and credit scores: persons with high scores can amass more debt, and having debt tends to raise one's score if payments are made on time.

Now consider a basic question about the mortgage boom: who took out the most debt, individuals with high credit scores in 1999 or low ones? It would be unsurprising to find that persons with low scores in 1999 took on the most debt in the mortgage boom, because young people, who tend to have low credit scores, take on mortgage debt to become homeowners in the normal state of affairs. We might therefore investigate debt growth within age groups. The middle panel of Figure 12 graphs the average dollar-value increases in debt for persons in the various demographic bins. The general within-age pattern of debt growth is positive, as individuals with high credit scores in 1999 subsequently added more dollars to their debt balances than similarly aged persons with lower scores.[46] The bottom panel of Figure 12 measures debt increases *relative* to each group's initial debt level. Now the within age-group relationship between debt growth and 1999 credit score is negative. That is, abstracting from individuals with the lowest credit scores (300-499), the bars in the bottom panel of Figure 12 get smaller within each age group as 1999 credit scores rise.

[44]As noted, our analysis of the flow of persons into first-time mortgageship status is not affected by this problem, as it abstracts from the effect of current debt on credit scores: no one in the risk set for transition into mortgage borrowing has any debt to begin with.

[45]The positive relation between debt and credit score is monotonic for all but the oldest age group.

[46]The positive relation is monotonic for the youngest age group and for the lower three credit-score groups among older age groups.

Because the relative changes in the bottom row are defined as the absolute changes in the middle row divided by the initial levels in the top row, it is easy to see why measuring debt growth in relative or absolute terms gives different answers about the boom. The middle panel shows that the better credit risks within each age group added more dollars to their debt levels between 1999 and 2007, but they started in 1999 with relatively more debt, too. The extra dollars they added were not enough to outweigh the effect of their high initial debt levels, so relative to their initial debt levels, their debt increases were lower than the increases for lower-score groups. The key factor driving these results is the endogeneity of the credit score in 1999, which reflects the ability of good credit risks to borrow more early on as well as the positive impact that their 1999 debt levels had on their 1999 credit scores.

Albanesi, DeGiorgi, and Nosal (2016) address the endogeneity concerns by essentially running the following regression:

$$\frac{\Delta D_{it}}{D_{i0}} = \alpha + \beta Score_{i,t-2} + \varepsilon, \tag{3}$$

where the left-hand side variable is the relative growth in mortgage debt D for individual i from an initial year zero to year t, and the regressor is the individual's credit score lagged by two years.[47] This specification can be thought of as intermediate choice between two polar cases. One polar case would regress relative debt growth on the individual's year-0 credit score: $Score_{i,0}$. As we have seen, life-cycle effects would bias downward this within-age-group estimate of β, because first-time home buyers are often young, and young people tend to have low credit scores. Even if age terms were added to the regression, causing β to be identified solely from within age-group comparisons, the mean reversion illustrated by the bottom panel of Figure 12 would continue to bias downward the coefficient. Additionally, using 1999 credit scores gives an increasingly out-of-date estimate of creditworthiness as time passes, and at the same time it prevents anyone entering the dataset after 1999 from contributing to the analysis. At the other polar extreme, we could regress debt growth on the time-t credit score: $Score_{i,t}$. In this case β would be biased upward if poor credit risks were exogenously extended credit during the boom and the mere extension of this credit raised their credit scores. By choosing a specification that lies between these two extremes, Albanesi, DeGiorgi, and Nosal (2016) hope to arrive at a specification that is as close as possible to the truth.

Clearly, sorting out the endogenity issues related to credit scores is an important topic for future work. But so far, no substantial evidence has emerged that debt was reallocated

[47] In practice, regressions of this type are not run on individual data, but rather on data that has been grouped along demographic characteristics, as in Figure 12. The main advantage of using grouped data is that doing so obviates the need to figure out what to do with individuals who have zero debt in the initial year.

toward bad credit risks during the boom.[48] The specification of Albanesi, DeGiorgi, and Nosal (2016) indicates that debt rose by at least 50 percent for all credit-score quartiles during the boom, and that the largest growth rates were in the center of the credit-score distribution. These findings are consistent with our results on the expansive nature of the mortgage boom across the income distribution. And our own credit-score analysis—which is based on the flow of persons into first-time borrowing and is thus less affected by reverse causation than the analysis of debt stocks—provides no evidence that persons with poor credit risks found it easier to enter mortgageship as the mortgage boom progressed.

7 What About Subprime?

The emerging research on the broadly based nature of the mortgage boom contradicts the common characterization of the mortgage boom as a subprime event, driven primarily by the disproportionate use of a complex mortgage instrument that turned toxic during the bust. Subprime mortgages and other forms of privately securitized debt did play a critical role in the 2008 financial crisis, because losses on those mortgages were not insured by the government, as were the prime loans packaged into agency securities by Fannie Mae, Freddie Mac, and other government-sponsored enterprises. But a close look at both outstanding stocks of debt and foreclosures confirms that the housing cycle was just that—a housing cycle—and not a subprime cycle alone.

7.1 Subprime Debt and Income

The first step in this analysis is simply to measure the amount of subprime debt, and in Figure 13 we focus on the subprime loans that were subsequently packaged into private-label mortgage backed securities. During the mortgage boom these securities included most subprime and Alt-A mortgages and some jumbo prime loans as well.[49] The heavy black line in the top panel of Figure 13 depicts the total amount of home mortgage debt on the liability side of household balance sheets as measured by the Federal Reserve's 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

[48] Mian and Sufi (2016b) also investigate individual-level growth in debt using the Equifax records, with a specification that is essentially equation 3 augmented with age effects. As Figure 12 illustrates, however, mean reversion is likely to bias the resulting estimate of β downward, and thereby overstate the relative debt growth enjoyed by poor credit risks.

[49] According to the Mortgage Market Statistical Annual, securitization rates for subprime and Alt-A loans as a class ranged from around two-thirds in 2002 to around 80 percent in 2005 and 2006. Securitization rates for prime jumbo loans ranged from about one-third to one-half over the same period.

securitized debt, which is also available in the Flow of Funds.[50] The chart shows that some time after 2003, growth in privately securitized debt accounted for a nontrivial fraction of the growth in 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 mortgage-backed securities (MBS), state and local housing authorities, and other sources.

The Flow of Funds does not disaggregate privately securitized debt into subprime, Alt-A, and prime jumbo loans. However, we can calculate the size of these components by aggregating the loan-level records in the CoreLogic ABS Private Label Securities ABS Database 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 aggregated CoreLogic data, outstanding subprime debt grew from about \$100 billion in 2001:Q1 to about \$955 billion by the middle of 2007, for an increase of about \$855 billion. The dashed blue line in the panel adds the even larger increase in Alt-A debt, which rose from about \$60 billion in 2001:Q1 to about \$1.04 trillion by mid-2007, an increase of about \$980 billion. The last counterfactual, depicted by the dashed gray line, adds the relatively small amount of growth in prime jumbo securities. The main message is that even though subprime debt grew nontrivially during the mortgage boom, the vast majority of new mortgage debt was generated though other channels.

The relative unimportance of subprime debt may seem odd to those who remember the wide attention that subprime originations received during the mortgage boom. But the stock-flow distinction we note many times above is especially important when studying subprime mortgages. For the most part, these mortgages were designed to be refinanced quickly, so the higher originations would have coincided with higher terminations.[51] The quantitative relationship between originations and stocks of subprime debt is illustrated by Figure 14, where the top panel depicts the share of subprime and Alt-A origination values as shares of all new originations during the 2000s. The red line shows that subprime accounted for about 20 percent of new origination values from 2004 to 2006. The bottom panel provides data on outstanding stocks of subprime and Alt-A loans that were privately securitized as a share of all mortgage debt. The subprime share hits a point of inflection in 2004, when subprime originations take off. But because any rapid increase in a flow generates a less-

[50]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 that are backed by the government-sponsored agencies.

[51]One of the most common types of subprime mortgages had a so-called hybrid structure, in which the interest rate would be fixed for the first two or three years of the loan, and then reset to float at a rate that was several percentage points above a benchmark short-term rate. The thinking was that the borrower would refinance at or shortly before the reset.

rapid increase in the corresponding stock, and because large amounts of subprime debt were being terminated as the new subprime mortgages were being originated, the corresponding increase in the subprime stock of debt was modest. Privately securitized subprime debt peaked at just over 9 percent of total outstanding mortgage debt in 2006. This share was comparable to the share of privately securitized Alt-A debt, which generally consisted of reduced-documentation loans to borrowers with prime credit scores.

To study the cross-sectional allocation of private-label debt with respect to income, we combine loan-level CoreLogic data with the zip code-level Equifax/IRS dataset. Specifically, for each zip code in the Equifax/IRS data, we figure the total amount of subprime and ABS debt in CoreLogic. Then, for each zip code, we subtract these totals from the total amount of Equifax mortgage debt, which generates the amount of prime debt as a remainder. Figure 15 shows the average contributions of subprime, Alt-A, and prime debt to growth rates of total debt 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 growth grew at faster rates in low-income areas, although 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, although the negative relationship between the importance of subprime debt and average zip code-level income appears somewhat greater. Combined with the earlier results on the overall stability of the debt distribution, the relatively small amount of subprime debt and its disproportionate allocation to low-income communities indicates that subprime did not cause a reallocation of debt toward low-income borrowers and communities. But by allowing these communities to keep up with aggregate housing demand, subprime lending helped prevent a reallocation of mortgage debt toward the wealthy.

7.2 Foreclosures and Income

Of course, the attention paid to the increase in subprime during the boom paled in comparison to the headlines that subprime received during the bust. As noted by Ferreira and Gyourko (2015), most economics papers written early in the crisis focused on the large number of subprime foreclosures, and thereby encouraged focusing on potential incentive problems in the subprime origination and securitization models. This focus undoubtedly received additional encouragement from the importance of subprime losses to the financial crisis. But using a large sample of public deeds records data that cover 96 metropolitan areas, Ferreira and Gyourko (2015) also show that defaults during the course of the housing bust occurred on prime mortgages. To be sure, subprime mortgages had higher default rates. But because they made up a relatively small share of mortgages, Ferreira and Gyourko (2015) estimate more than twice as many prime as subprime borrowers lost their homes over their full sample period (2009:Q1–2012:Q3).

The high proportion of subprime lending in low-income communities leads naturally to the question of how mortgage defaults were distributed across the income distribution. The cross-sectional relationship between foreclosures and either income or credit scores has received much recent attention. For example, Adelino, Schoar, and Severino (2016) use data from HMDA and the McDash mortgage-servicer dataset to infer that foreclosure rates are typically higher in low-income communities, as we would expect. However, the paper also shows that during the housing bust, the share of total McDash delinquency value accounted for by low-income zip codes went *down*. This movement occurred because the percentage increases in the (generally high) delinquency rates of low-income zip codes were smaller than the percentage increases in the (generally low) rates of high-income areas.

We can replicate and extend these results using the Equifax data.[52] 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.[53] The two panels in Figure 16 present binned scatter plots of the log of this default rate against log of income per return in 2001:Q4 and 2009:Q4. As was the case with debt, the use of natural logs means that a uniform percentage increase in defaults shows up as a uniform shift upward across the income distribution. The upper panel of Figure 16 shows the default-income relationship across all zip codes without regard to CBSA location. The lower panel deviates both variables from CBSA means. Both panels show a strong negative relationship between default rates and income, as defaults are always higher in low-income zip codes. But the plots also confirm that the default rate grew somewhat more in percentage terms in high-income zip codes, as the slopes of the conditional expectation functions flatten from 2001 to 2009.[54]

For our purposes, what is most striking about these plots is how they mirror the earlier results on mortgage debt, and thus support the idea that the housing cycle was an aggregate event. High-income borrowers tend to have a lot of mortgage debt, so an aggregate increase

[52]An extension is useful because, as noted in the data section, the McDash dataset does not become fully representative of the mortgage market until 2005. We also focus on foreclosure rates, rather than shares of total delinquency value, because the latter measure is influenced by differences in the average size of mortgages across zip codes, as well as differences in homeownership rates.

[53]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 fewer than 90 days delinquent. These liens, therefore, comprise the risk set for loans that can become 90 days delinquent in the current quarter.

[54]In a paper that uses individual-level credit scores rather than zip code-level income, Mian and Sufi (2016b) also find that the share of housing distress accounted for by the relatively creditworthy borrowers rose during the bust. But that paper's use of 1996 credit scores understates the total share of defaults during the housing bust that was generated by high-score borrowers, because borrower scores tend to rise with age (and thus with time).

in debt across all borrowers leads to large dollar-value increases in debt among the rich. Conversely, low-income borrowers have relatively high foreclosure rates, so the same percentage increase in defaults among all borrowers generates large absolute numbers of low-income foreclosures. While many of these low-income foreclosures were on subprime mortgages, the relatively small share of subprime on the overall market meant that, as Ferreira and Gyourko (2015) found, most defaults would come on prime mortgages. And the slightly larger percentage increases in foreclosures among richer communities—who were underrepresented in subprime—provides a further indication that the housing bust was not limited to the subprime market alone. All told, cross-sectional analysis of both debt accumulation and foreclosures indicates that research should focus on the aggregate factors behind the housing cycle, not on potential problems that are specific to any particular corner of the market.

8 Implications for Theory and Policy

If the bottom line of this paper is that aggregate factors drove the housing cycle, then the obvious follow-up question is what those factors were. One candidate is an exogenous expansion in the supply of loanable funds that reduced mortgage rates in the U.S. housing market. The interest-rate hypothesis is examined in detail by Glaeser, Gottlieb, and Gyourko (2013), as part of a broader examination of whether "cheap credit" can explain the boom.[55] The authors find that neither theory nor data support the interest-rate hypothesis. "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). The authors conclude by noting that overly optimistic house-price expectations could have fueled the boom, as 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. Shifting beliefs can also explain widespread foreclosures during the bust. When beliefs became less optimistic and housing prices fell, homeowners across the income distribution found themselves with negative equity, a necessary condition of default (Kau, Keenan, and Kim 1994).

The expectations theory of the housing cycle is supported by a number of facts about mortgage finance during the past several decades (Foote, Gerardi, and Willen 2012), and it is easy to find evidence that both borrowers and lenders were optimistic about house-price appreciation during the mortgage boom (Case and Shiller 2003; Case, Shiller, and Thompson 2012; Gerardi et al. 2008). But constructing a rational model of shifting beliefs

[55] This investigation into cheap credit as a potential driver of the cycle involved the availability of credit as well as its price. Glaeser, Gottlieb, and Gyourko (2013) correlated house prices with both loan-approval rates and average down payments, but found that the empirical impact of these two factors on prices was limited as well.

about future house prices is a theoretical challenge. A recent paper by Kaplan, Mitman, and Violante (2016) captures "bubble psychology" in a rational-expectations framework by assuming that agents move exogenously between two regimes regarding future housing preferences. In one regime, the agents believe that preferences for housing will be much higher in the future, while the other regime is less optimistic. Survey data on house-price expectations are used to calibrate this shock. Two other shocks occur to regulation in the mortgage market (summarized by household borrowing limits and borrowing costs) and to labor income. The recent U.S. housing cycle is then characterized as a particular set of shocks to beliefs, regulation, and income.

The belief shock emerges as by far the most important driver of housing prices in the Kaplan, Mitman, and Violante (2016) model. The importance of regulation shocks, by contrast, is tempered by the presence of an elastic rental market. The authors explain that in general, changes in borrowing constraints will matter to the aggregate housing market only if a substantial number of agents are constrained beforehand. In their model, the housing choices of households are not constrained very much, because households without the requisite down payment can simply rent. Moreover, whenever down payment restrictions are relaxed, these households wind up buying houses that are comparable to the ones they would have been renting, with minimal effects on aggregate housing demand or house prices.[56] More to the point of this paper, the model predicts that household debt levels rise proportionately across the income distribution, as long as optimistic beliefs about the housing market are widely shared.

Other theoretical questions follow naturally from the importance of beliefs to the housing cycle. Kaplan, Mitman, and Violante (2016) takes the shift in beliefs as exogenous, but papers in the so-called distorted beliefs literature go beyond the standard rational-expectations framework to ask how beliefs can be affected by psychological factors, social interactions, or both.[57]

[56]Expanded credit availability also has a small effect on housing prices in the model of Kiyotaki, Michaelides, and Nikolov (2011): "In our economy, tenants or credit-constrained homeowners are relatively poor and own a small share of aggregate wealth as a group. As a result, the effect of relaxing the collateral constraint on housing prices is largely absorbed by a modest conversion from rented to owned units" (p. 257). Interestingly, the authors model can match the empirical skews in the earnings and wealth distributions, but a general implication of Krusell and Smith (1998) still holds: In heterogeneous-agent economies, the behaviour of the poorest agents has a limited effect on wealth aggregates, because the share of total wealth held by these agents is small.

[57]Papers that explore the formation of beliefs and the financial consequences of distorting them 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). In the internet appendix, we discuss a contrasting theory of the debt boom proposed by Kumhof, Rancière, and Winant (2015), who link increases in overall debt to consumption rather than investment motives.

The aggregate nature of the housing cycle also raises important questions for policy. If a surge in unaffordable mortgages targeted at low-income borrowers had in fact caused a destabilizing housing cycle, then restricting non-traditional mortgages would have been good for both the macroeconomy and the borrowers themselves. But trade-offs emerge if subprime instead helped low-income borrowers keep up with everyone else. Restricting subprime lending would have reduced low-income borrowing and thus reduced the number of ensuing foreclosures. Yet the small amount of debt at the bottom of the income distribution suggests that this policy would not have derailed the boom itself, and most defaults turned out to be on prime mortgages anyway. More importantly, the relationship between foreclosures and income implies that restricting low-income lending will *always* reduce the foreclosure rate, because foreclosure is more common in low-income areas than high-income areas. Indeed, authors such as Goodman (2016) believe that after the housing crisis, the "credit box" shrank too much from a social point of view, causing too many people to be shut off from the benefits of homeownership.[58] If society believes that homeownership has positive externalities and should thus be widely shared, then regulators should be willing to tolerate a higher number of average foreclosures as credit flows down the income distribution. On the other hand, the case for low-income lending is weakened if foreclosure externalities are large, or if we believe that large declines in nationwide housing prices can no longer be ruled out. This paper has outlined how the distribution of mortgage debt *did* evolve during the mortgage boom. Its findings imply that the policy question of how this distribution *should* evolve in the future is more complicated than conventional explanations of the mortgage boom would suggest.

[58]The title of Goodman (2016) states that "squeaky-clean loans [have led] to near-zero borrower defaults—and that is not a good thing."

References

Adelino, Manuel, Antoinette Schoar, and Felipe Severino. 2016. "Loan Originations and Defaults in the Mortgage Crisis: The Role of the Middle Class." *Review of Financial Studies* 29(7): 1635–1670.

Albanesi, Stefania, Giacomo DeGiorgi, and Jaromir Nosal. 2016. "Credit Growth and the Financial Crisis: A New Narrative." *In process*.

Amromin, Gene, and Leslie McGranahan. 2015. "The Great Recession and Credit Trends across Income Groups." *American Economic Review* 105(5): 147–153.

Amromin, Gene, Leslie McGranahan, and Diane Whitmore Schanzenbach. 2015. "Consumer Credit Trends by Income and Geography in 2001-12." Federal Reserve Bank of Chicago. Available at `https://www.chicagofed.org/publications/chicago-fed-letter/2015/342`.

Barberis, Nicholas. 2013. "Psychology and the Financial Crisis of 2007–2008." In *Financial Innovation: Too Much or Too Little?*, Michael Haliassos, ed. Cambridge, MA: MIT Press.

Bayer, Patrick, Kyle Mangum, and James W. Roberts. 2016. "Speculative Fever: Investor Contagion in the Housing Bubble." National Bureau of Economic Research Working Paper No. 22065.

Bhutta, Neil. 2015. "The Ins and Outs of Mortgage Debt During the Housing Boom and Bust." *Journal of Monetary Economics* 76(1): 284–298.

Bhutta, Neil, and Benjamin J. Keys. 2016. "Interest Rates and Equity Extraction during the Housing Boom." *American Economic Review* 106(7): 1742–1774.

Bricker, Jesse, Lisa J. Dettling, Alice Henriques, Joanne W. Hsu, Kevin B. Moore, John Sabelhaus, Jeffrey Thompson, and Richard A. Windle. 2014. "Changes in U.S. Family Finances from 2010 to 2013: Evidence from the Survey of Consumer Finances." *Federal Reserve Bulletin* 100(4). Available at `http://www.federalreserve.gov/pubs/bulletin/2014/pdf/scf14.pdf`.

Brown, Meta, Andrew Haughwout, Donghoon Lee, and Wilbert van der Klaauw. 2015. "Do We Know What We Owe? Consumer Debt as Reported by Borrowers and Lenders." *FRBNY Economic Policy Review* 21(1): 19–44. Available at `http://www.newyorkfed.org/research/epr/2015/EPR_2015_comparisons_brown.pdf`.

Brunnermeier, Markus K., Alp Simsek, and Wei Xiong. 2014. "A Welfare Criterion For Models With Distorted Beliefs." *Quarterly Journal of Economics* 129(4): 1753–1797.

Burnside, Craig, Martin Eichenbaum, and Sergio Rebelo. 2016. "Understanding Booms and Busts in Housing Markets." *Journal of Political Economy* 124(4): 1088–1147.

Campbell, John Y. 2006. "Household Finance (Presidential Address to the American Finance Association)." *Journal of Finance* 61(4): 1553–1604.

Case, Karl E., and Robert J. Shiller. 2003. "Is There a Bubble in the Housing Market?" *Brookings Papers on Economic Activity* 2003(2): 299–342.

Case, Karl E., Robert J. Shiller, and Anne K. Thompson. 2012. "What Have They Been Thinking? Homebuyer Behavior in Hot and Cold Markets." *Brookings Papers on Economic Activity* 45(2): 265–298.

Cheng, Ing-Haw, Sahil Raina, and Wei Xiong. 2014. "Wall Street and the Housing Bubble." *American Economic Review* 104(9): 2797–2829.

Davis, Steven J., John C. Haltiwanger, and Scott Schuh. 1996. *Job Creation and Destruction*. Cambridge, MA: MIT Press.

Ferreira, Fernando, and Joseph Gyourko. 2015. "A New Look at the U.S. Foreclosure Crisis: Panel Data Evidence of Prime and Subprime Borrowers from 1997 to 2012." National Bureau of Economic Research Working Paper No. 21261.

Foote, Christopher L., Kristopher S. Gerardi, and Paul S. Willen. 2012. "Why Did So Many People Make So Many *Ex Post* Bad Decisions: The Causes of the Foreclosure Crisis." In *Rethinking the Financial Crisis*, Alan S. Blinder, Andrew W. Lo, and Robert M. Solow, eds., 136–186. The Russell Sage Foundation and the Century Foundation: New York, N.Y. and Washington, D.C.

Fuster, Andreas, David Laibson, and Brock Mendel. 2010. "Natural Expectations and Macroeconomic Fluctuations." *Journal of Economic Perspectives* 24(4): 67–84.

Geanakoplos, John. 2009. "The Leverage Cycle." In *NBER Macroeconomics Annual 2009*, Daron Acemoglu, Kenneth Rogoff, and Michael Woodford, eds., 1–65. Chicago, IL: University of Chicago Press.

Gennaioli, Nicola, and Andrei Shleifer. 2010. "What Comes to Mind." *Quarterly Journal of Economics* 125(4): 1399–1433.

Gennaioli, Nicola, Andrei Shleifer, and Robert Vishny. 2012. "Neglected Risks, Financial Innovation, and Financial Fragility." *Journal of Financial Economics* 104(3): 452–468.

Gerardi, Kristopher, Andreas Lehnert, Shane Sherlund, and Paul S. Willen. 2008. "Making Sense of the Subprime Crisis." *Brookings Papers on Economic Activity* 39(2): 69–159.

Gerardi, Kristopher, and Paul S. Willen. 2009. "Subprime Mortgages, Foreclosures, and Urban Neighborhoods." *B.E. Journal of Economic Analysis & Policy* 9.

Glaeser, Edward L., Joshua D. Gottlieb, and Joseph Gyourko. 2013. "Can Cheap Credit Explain the Housing Boom?" In *Housing and the Financial Crisis*, Edward L. Glaeser and Todd Sinai, eds., chap. 7, 301–359. Chicago: University of Chicago Press.

Goodman, Laurie. 2016. "Squeaky-Clean Loans Lead to Near-Zero Borrower Defaults–and That is Not a Good Thing." Urban Institute *Urban Wire* blog post, August 31. Avaialble at `http://www.urban.org/urban-wire/squeaky-clean-loans-lead-near-zero-borrower-defaults-and-not-good-thing`.

Henriques, Alice M., and Joanne W. Hsu. 2014. "Analysis of Wealth Using Micro- and Macrodata: A Comparison of the Survey of Consumer Finances and Flow of Funds Accounts." In *Measuring Economic Sustainability and Progress*, Dale W. Jorgenson, J. Steven Landefeld, and Paul Schreyer, eds., vol. 72 of *National Bureau of Economic Research Studies in Income and Wealth*, chap. 9, 245–274. Chicago: University of Chicago Press.

Internal Revenue Service. 2007. *Statistics of Income 2007: Individual Income Tax Returns (Publication 1304, Revised 07-2009).* Washington, DC. Available at `https://www.irs.gov/pub/irs-soi/07inalcr.pdf`.

Kaplan, Greg, Kurt Mitman, and Giovanni L. Violante. 2016. "Consumption and House Prices in the Great Recession." Working Paper.

Kau, James B., Donald C. Keenan, and Taewon Kim. 1994. "Default Probabilities for Mortgages." *Journal of Urban Economics* 35(3): 278–296.

Kennickell, Arthur B. 2007. "The Role of Over-Sampling of the Wealthy in the Survey of Consumer Finances." Survey of Consumer Finance Working Paper, Federal Reserve Board of Governors. Available at `http://www.federalreserve.gov/econresdata/scf/files/index_kennickell.html`.

Kiyotaki, Nobuhiro, Alexander Michaelides, and Kalin Nikolov. 2011. "Winners and Losers in Housing Markets." *Journal of Money, Credit and Banking* 43(2-3): 255–296.

Krusell, Per, and Anthony A. Smith, Jr. 1998. "Income and Wealth Heterogeneity in the Macroeconomy." *Journal of Political Economy* 106(5): 867–896.

Kumhof, Michael, Romain Rancière, and Pablo Winant. 2015. "Inequality, Leverage, and Crises." *American Economic Review* 105(3): 1217–1245.

Landvoigt, Tim, Monika Piazzesi, and Martin Schneider. 2015. "The Housing Market(s) of San Diego." *American Economic Review* 105(4): 1371–1407.

Mian, Atif, and Amir Sufi. 2009. "The Consequences of Mortgage Credit Expansion: Evidence from the U.S. Mortgage Default Crisis." *Quarterly Journal of Economics* 124(4): 1449–1496.

Mian, Atif R., and Amir Sufi. 2016a. "Fraudulent Income Overstatement on Mortgage Applications During the Credit Expansion of 2002 to 2005." Kreisman Working Papers Series in Housing Law and Policy No. 21. Available at `http://ssrn.com/abstract=2561366`.

Mian, Atif R., and Amir Sufi. 2016b. "Household Debt and Defaults from 2000 to 2010: The Credit Supply View." Kreisman Working Papers Series in Housing Law and Policy No. 28. Available at http://ssrn.com/abstract=2606683.

Munnell, Alicia H., Geoffrey M. B. Tootell, Lynne E. Browne, and James McEneaney. 1996. "Mortgage Lending in Boston: Interpreting HMDA Data." *American Economic Review* 86(1): 25–53.

Poterba, James, and Todd Sinai. 2008. "Tax Expenditures for Owner-Occupied Housing: Deductions for Property Taxes and Mortgage Interest and the Exclusion of Imputed Rental Income." *American Economic Review* 98(2): 84–89.

Rubin, Donald B. 1987. *Multiple Imputation for Nonresponse in Surveys.* Wiley Series in Probability and Mathematical Statistics. New York: John Wiley & Sons.

Saez, Emmanuel, and Gabriel Zucman. 2016. "Wealth Inequality in the United States since 1913: Evidence from Capitalized Income Tax Data." *Quarterly Journal of Economics* 131(2): 519–578.

Shimer, Robert. 2005. "The Cyclical Behavior of Equilibrium Unemployment and Vacancies." *American Economic Review* 95(1): 25–49.

Simsek, Alp. 2013. "Belief Disagreements and Collateral Constraints." *Econometrica* 81(1): 1–53.

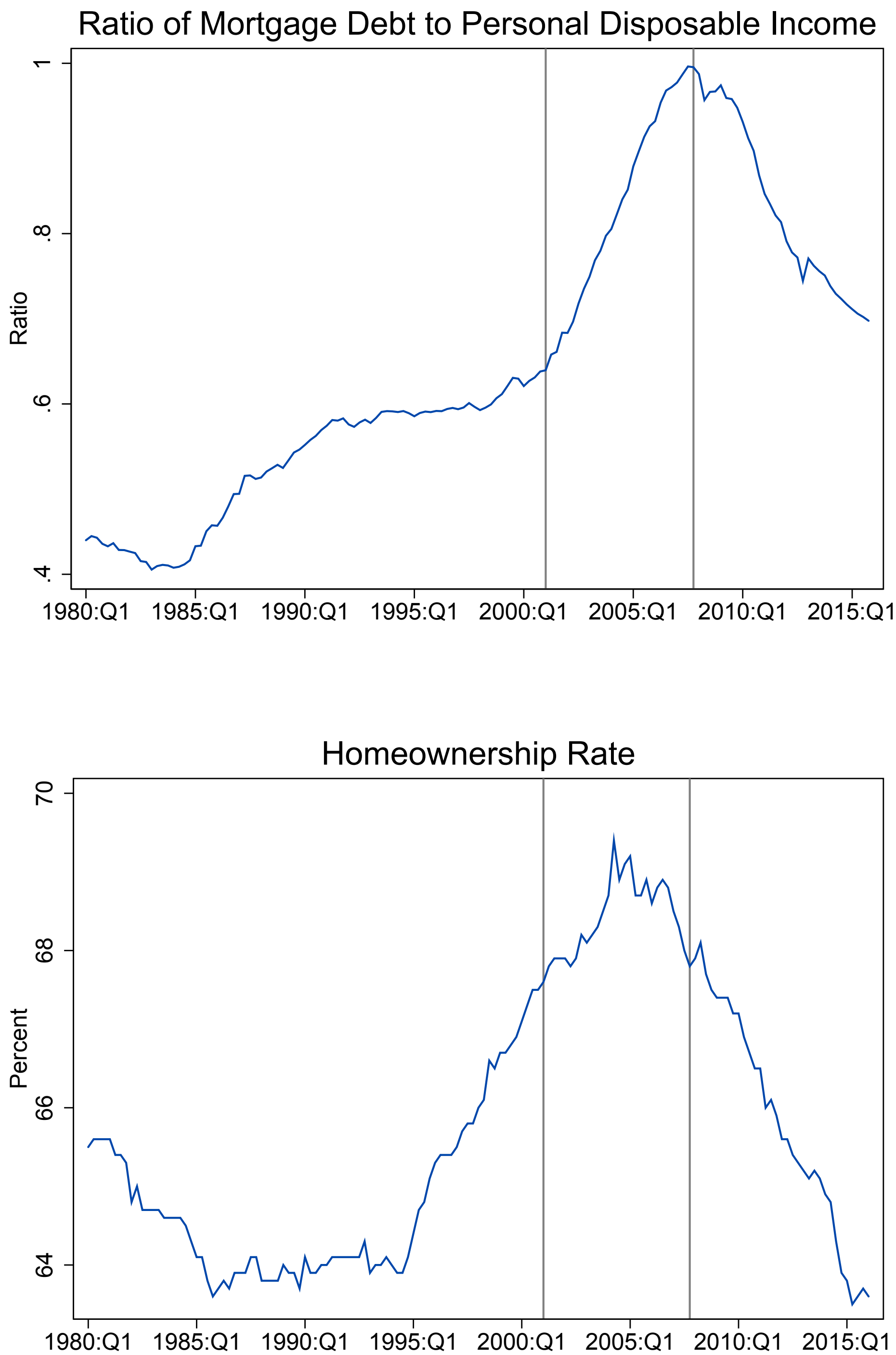


Figure 1. MORTGAGE DEBT AND HOMEOWNERSHIP RATES IN THE UNITED STATES: 1980:Q1 TO 2015:Q4. *Note:* The mortgage debt ratio in the top panel is defined as total home mortgage liabilities in the household sector divided by total personal disposable income for the household and nonprofit sector. The income 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.

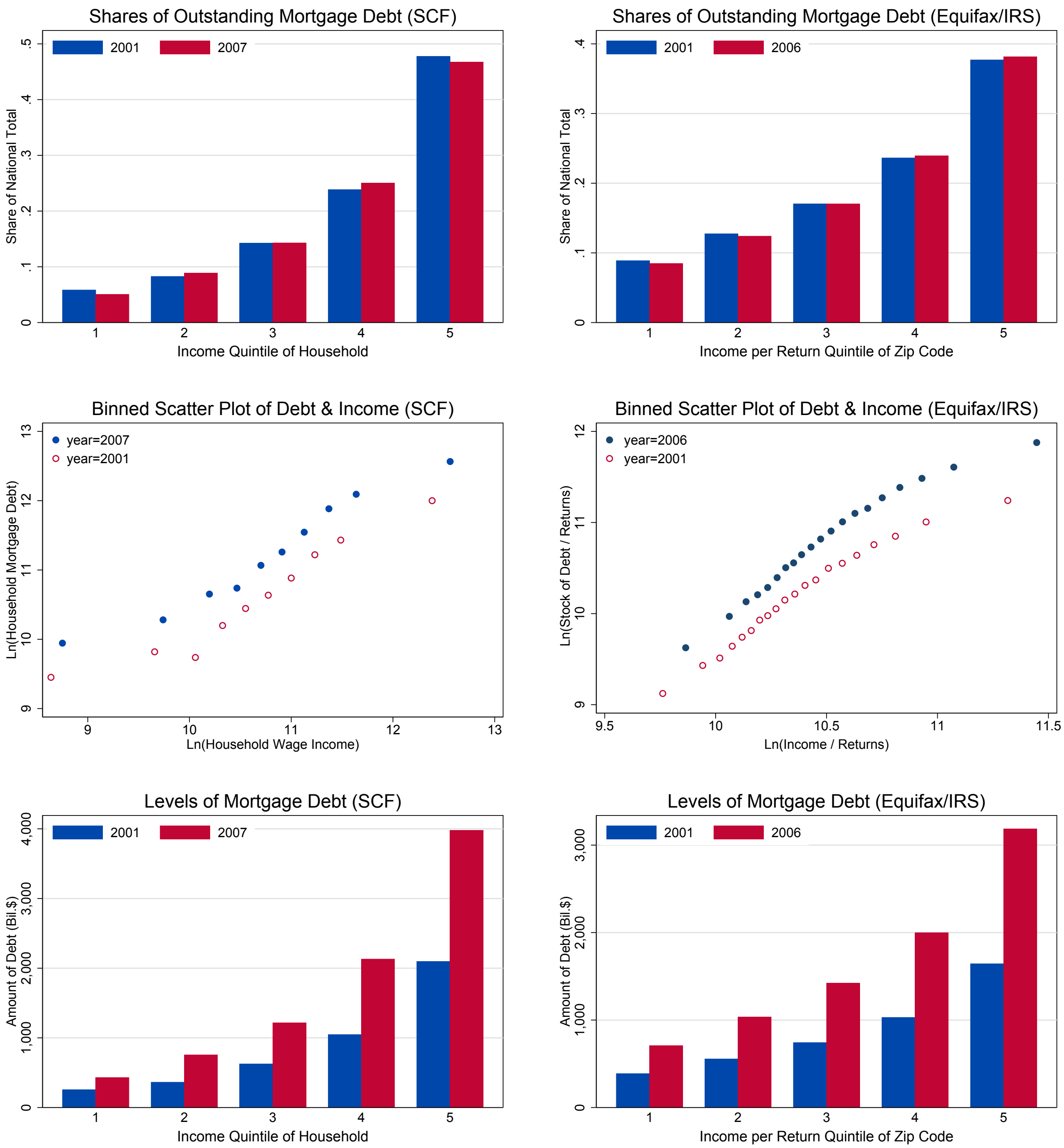


Figure 2. The Relationship between Mortgage Debt and Income among U.S. Households (Left Panels) and Zip Codes (Right Panels). *Note:* The panels at left use data from the Survey of Consumer Finances to depict the household-level relationship between wage income and mortgage debt in 2001 and 2007. The panels at right use debt data from the 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.

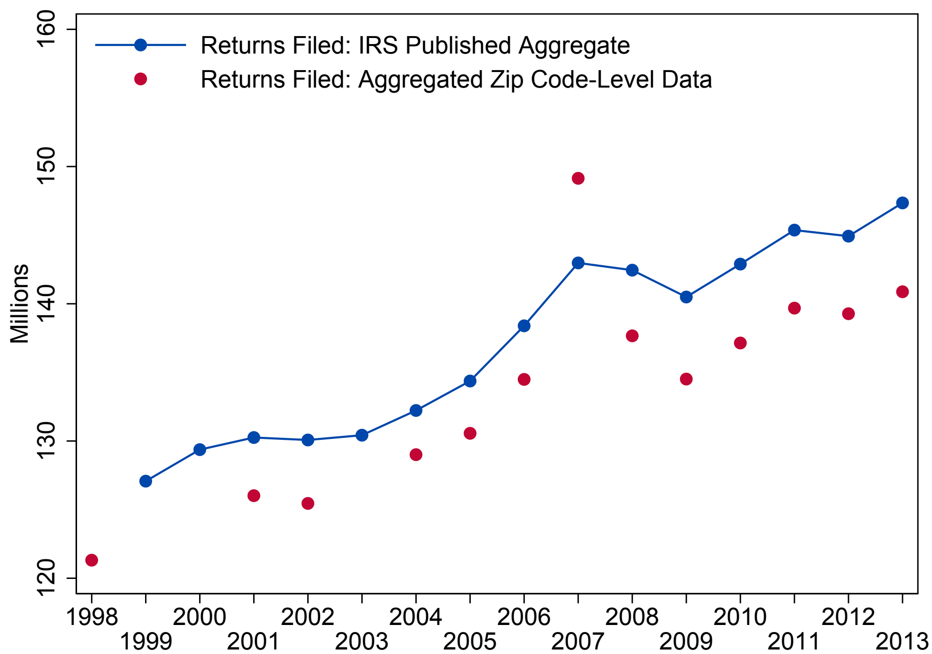


Figure 3. Two Measures of Aggregate Individual Income Returns Filed. *Note:* The blue line depicts the total number of individual income returns filed for the given tax year as published by the IRS. The 2007 value for this series omits returns filed by individuals for the sole purpose of receiving the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

Year	Income Quintile	No. of Unweighted Obs.	Mortgaged Households (% of Hholds)	Total Mortgage Debt	Debt on Primary Residence: Total	Debt on Primary Residence: Non-HELOC	Debt on Primary Residence: HELOC	Other Mortgage Debt	Income	Home Ownership Rate (%)	Real Estate Assets: Value of Primary Residence	Real Estate Assets: 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.

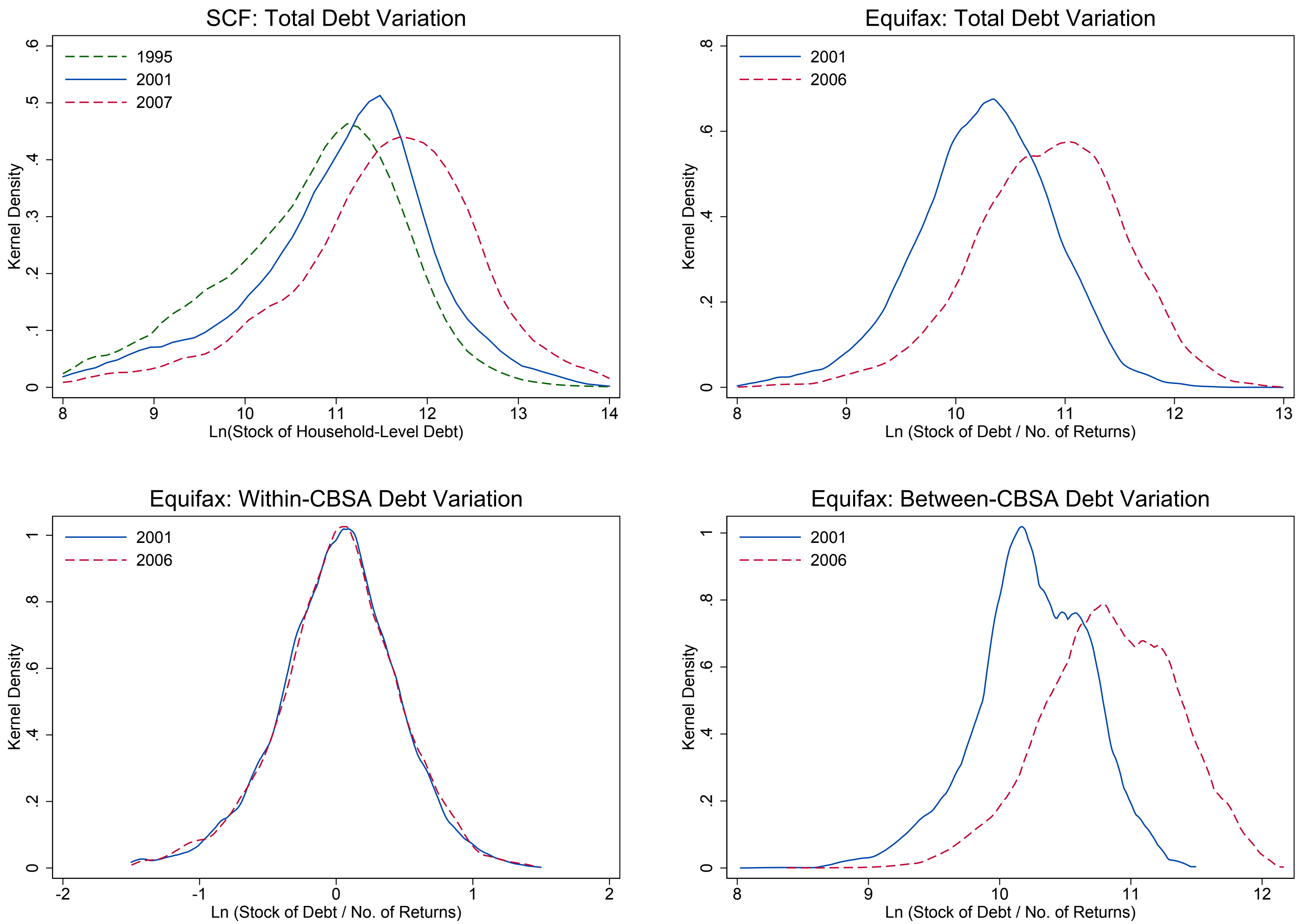
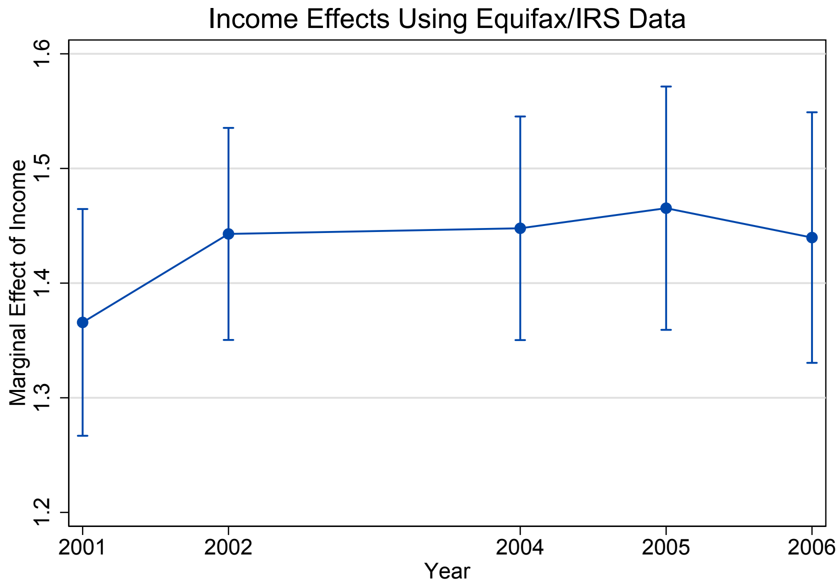


Figure 4. Distributions of Mortgage Debt. *Note:* All densities are weighted kernel densities of the log of household-level mortgage debt (SCF distribution in top left panel) or average zip code-level mortgage debt per tax return (Equifax distributions in remaining panels). Household-level weights are 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.



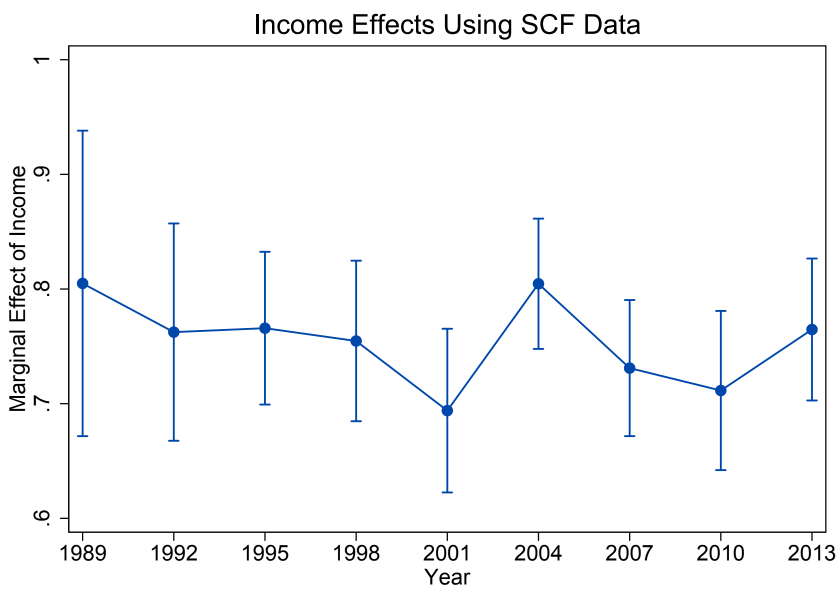


Figure 5. Regression Evidence on the Relationship between Mortgage Debt and Income among U.S. Zip Codes and Households. *Note:* The top panel graphs income coefficients (and 95 percent confidence intervals) from a returns-weighted regression of zip code-level mortgage debt on income for all years between 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.

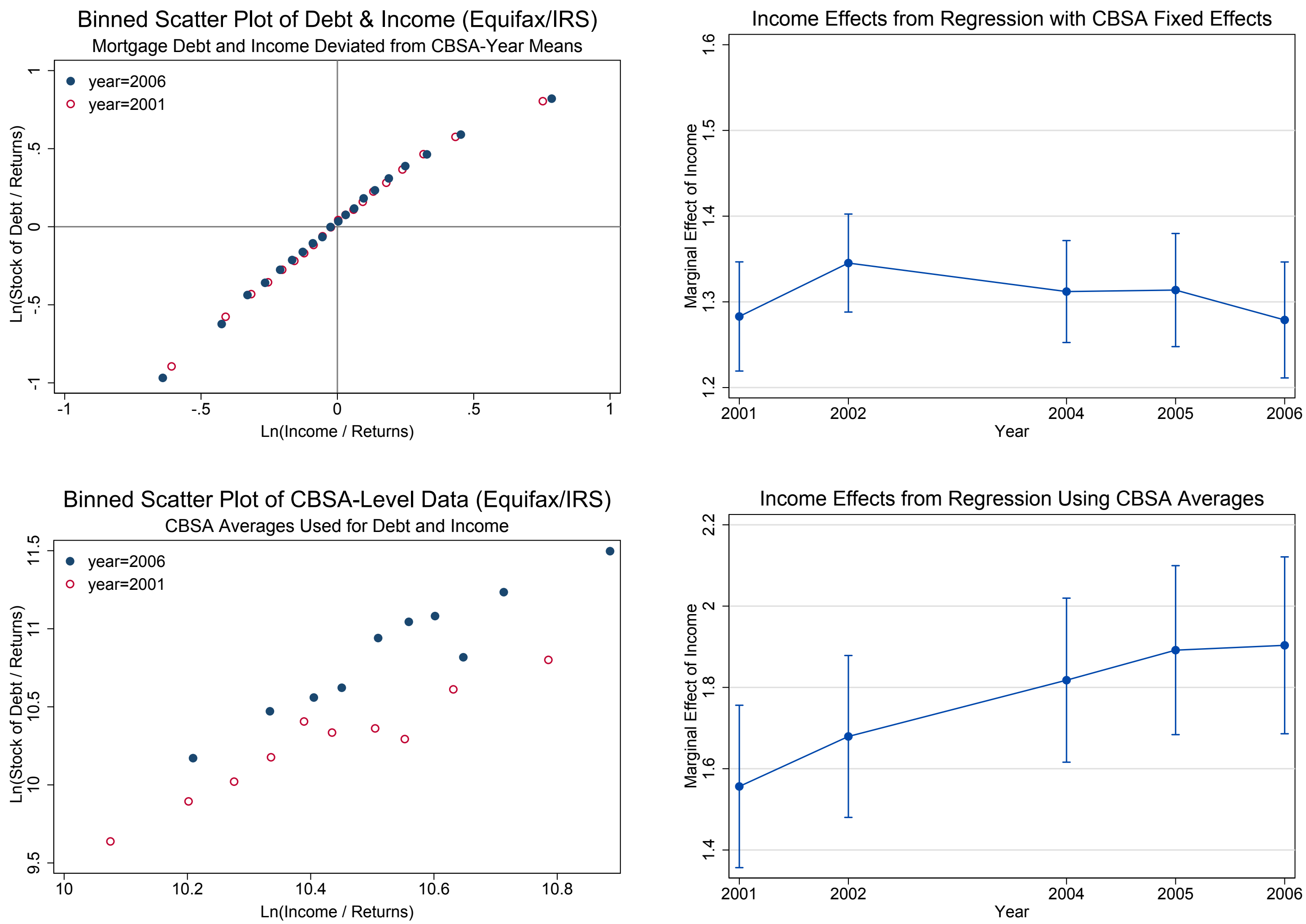
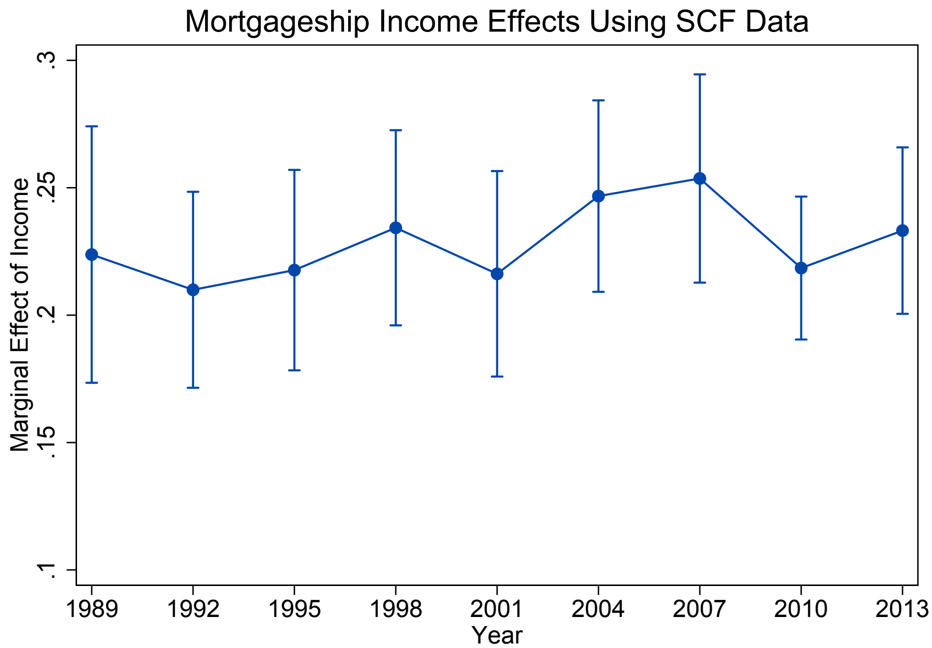


Figure 6. Within-CBSA and Between-CBSA Relationships between Mortgage Debt and Income among U.S. Zip Codes. The top left panel is a binned scatter plot of zip code-level debt and income after both variables have been deviated from returns-weighted CBSA-year means. The top right panel depicts the income 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.



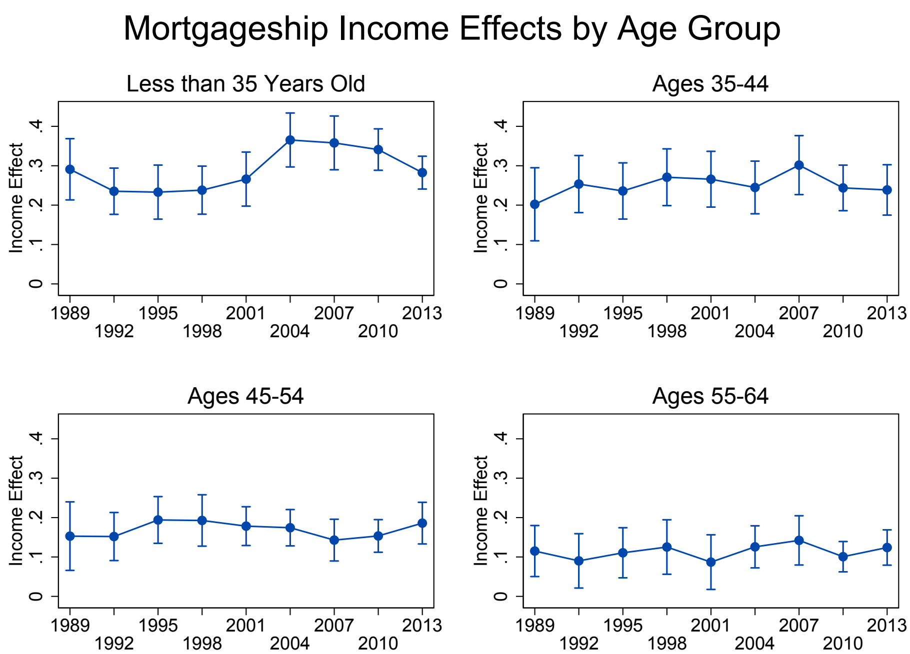


Figure 7. Mortgageship and Income in the Survey of Consumer Finances. *Note:* Each panel depicts estimated effects of log income on binary indicators for "mortgageship," which is defined to be the presence of any mortgage debt for the household. All income effects are generated from logit regressions with the same right-hand-side variables and sample restrictions as the debt-value Poisson regressions depicted in the bottom panel of Figure 5. The panels at bottom interact 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.

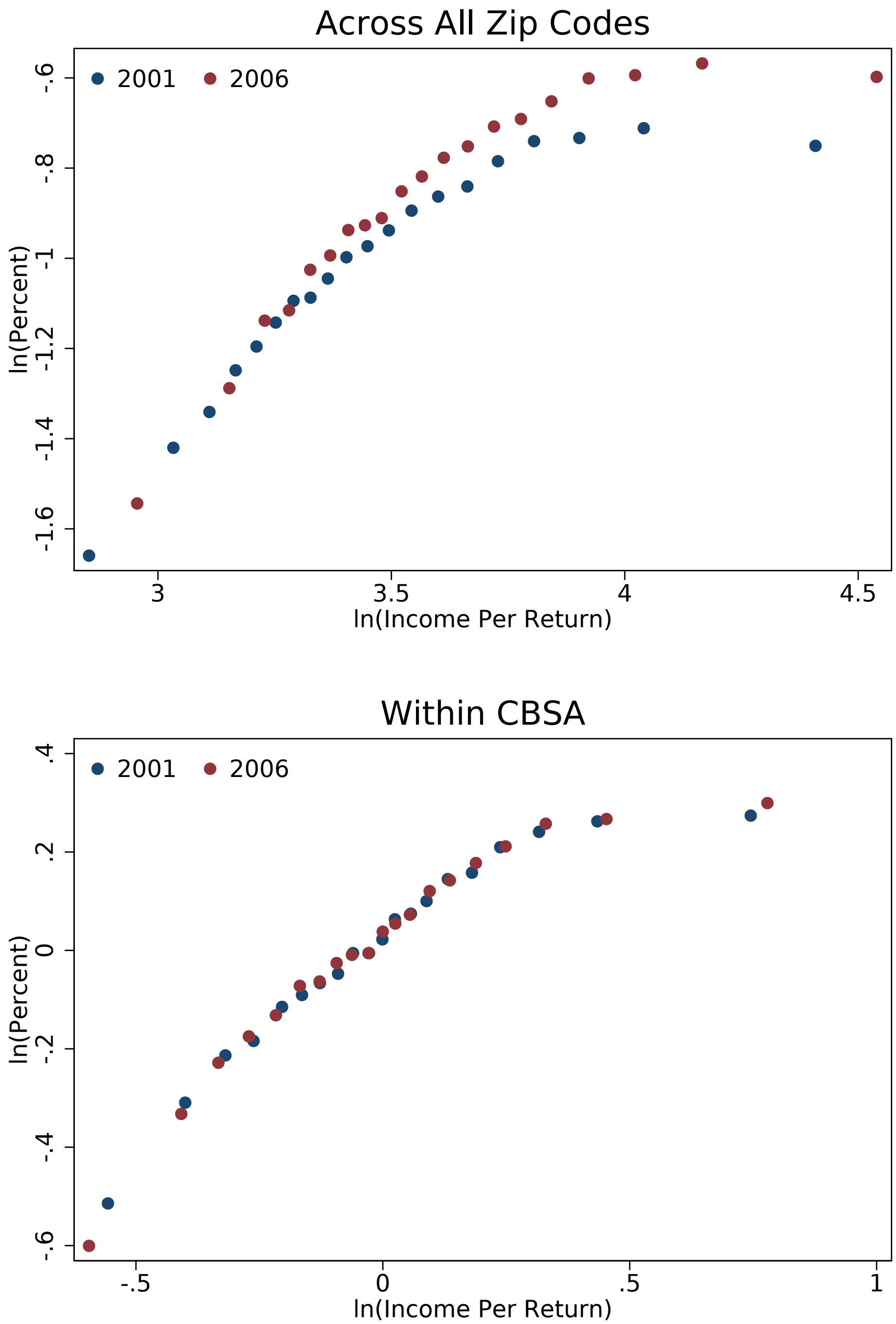


Figure 8. The Extensive Margin of Mortgage Debt Across Zip Codes: 2001 and 2006. *Note:* These panels plot the log of "mortgageship rates" across the wage-income distribution of zip codes, where mortgageship for a household is defined as the presence of any mortgage debt on a credit record. The debt and income data for the top panel are 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.

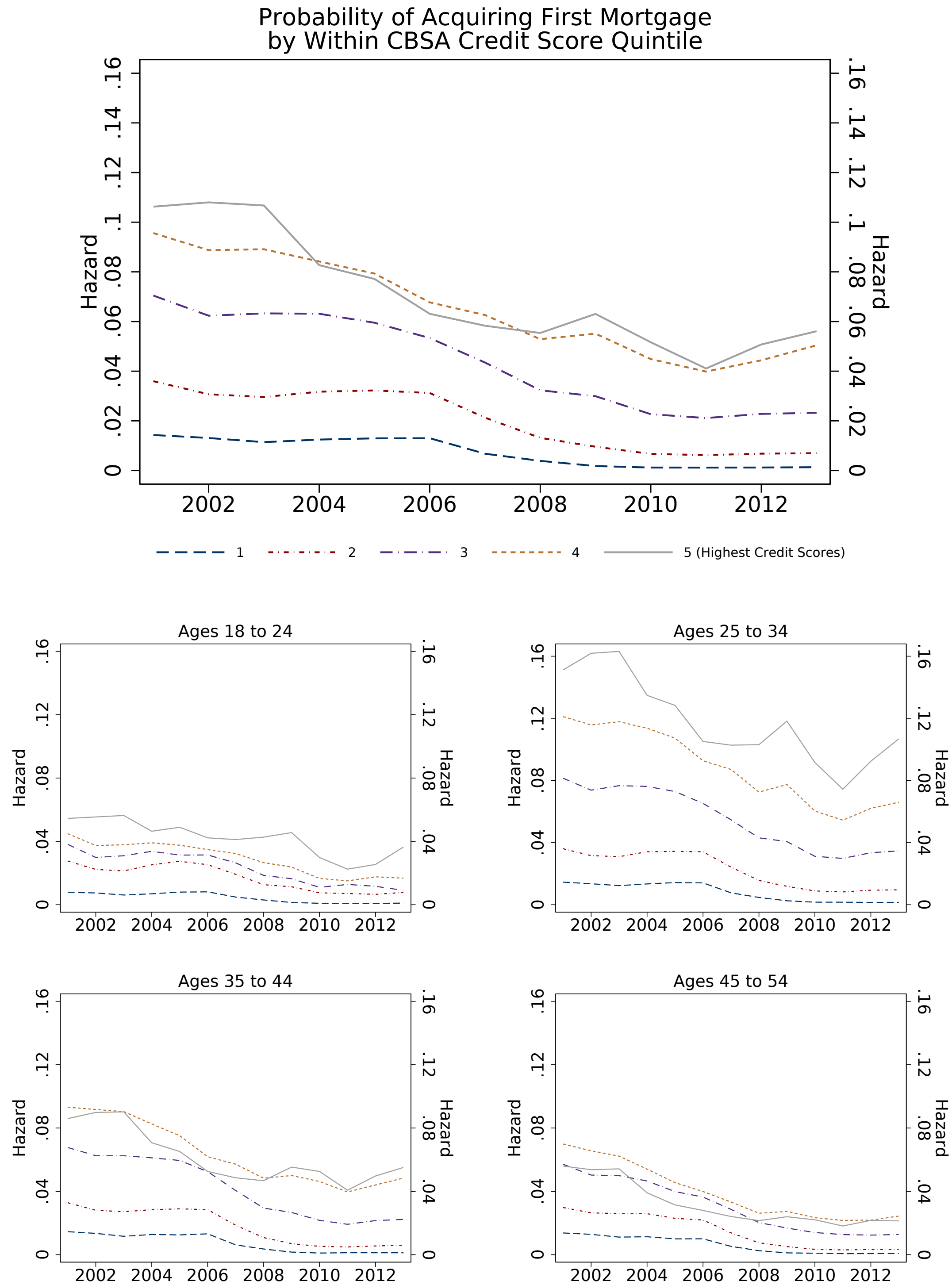


Figure 9. The Hazard Rate of First-Time Entry Into Mortgageship By Credit-Score Quintile: 2001-2013. *Note:* These graphs plot the probability of obtaining a mortgage for the first time for individuals in specific credit-score quintiles over time. The probabilities are calculated by dividing the number 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 of 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.

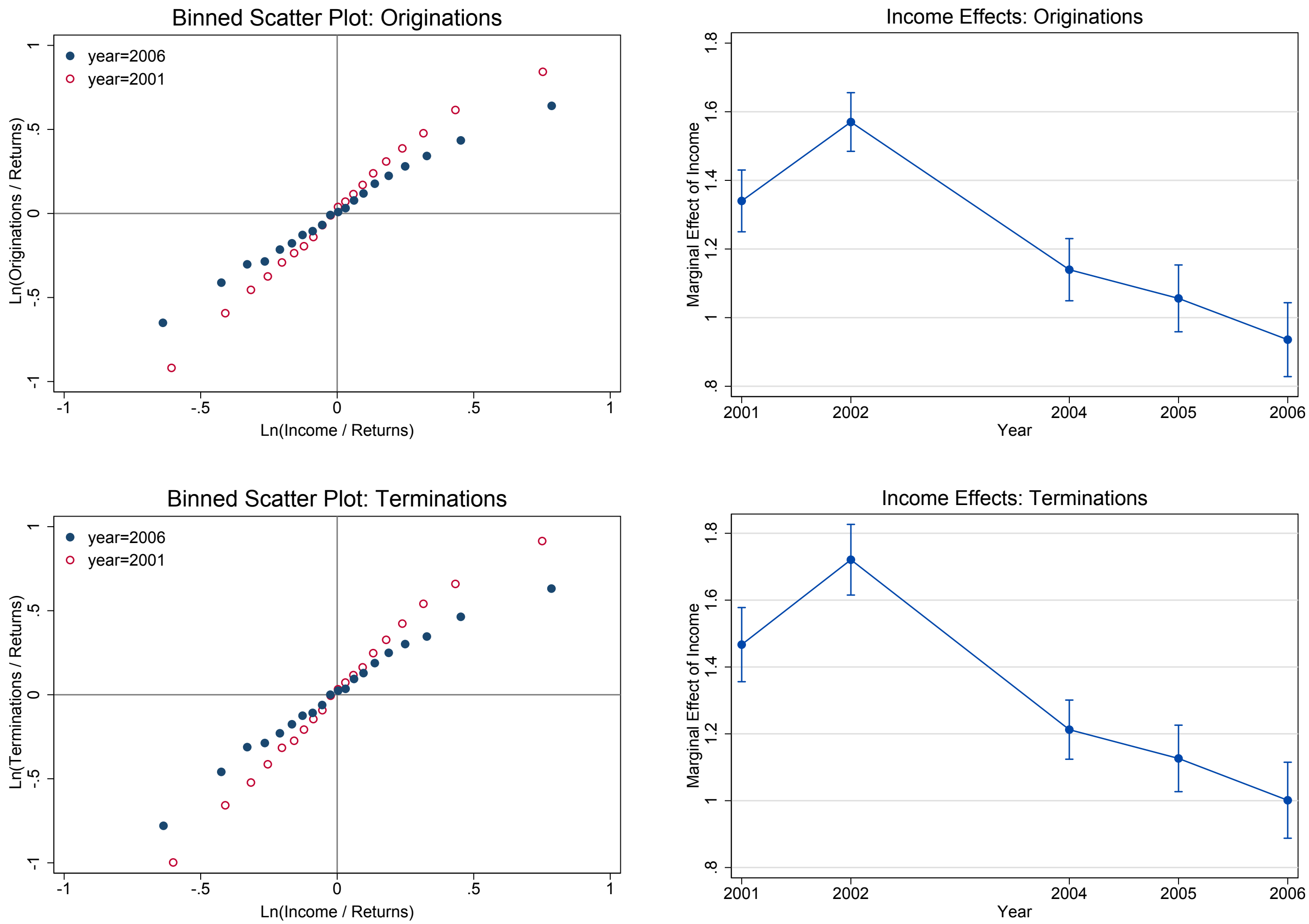


Figure 10. The Relationship Between Gross Mortgage Flows and Wage and Salary Income in CBSA-Deviated Data. *Note:* The binned scatter plots in the panels at left are generated from deviations of log originations or terminations per tax return and wage income per tax return from CBSA × year means. The 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 × year interactions and CBSA × year fixed effects. Standard errors are clustered by CBSA. *Source:* NY Fed Consumer Credit Panel/Equifax and IRS Statistics of Income.

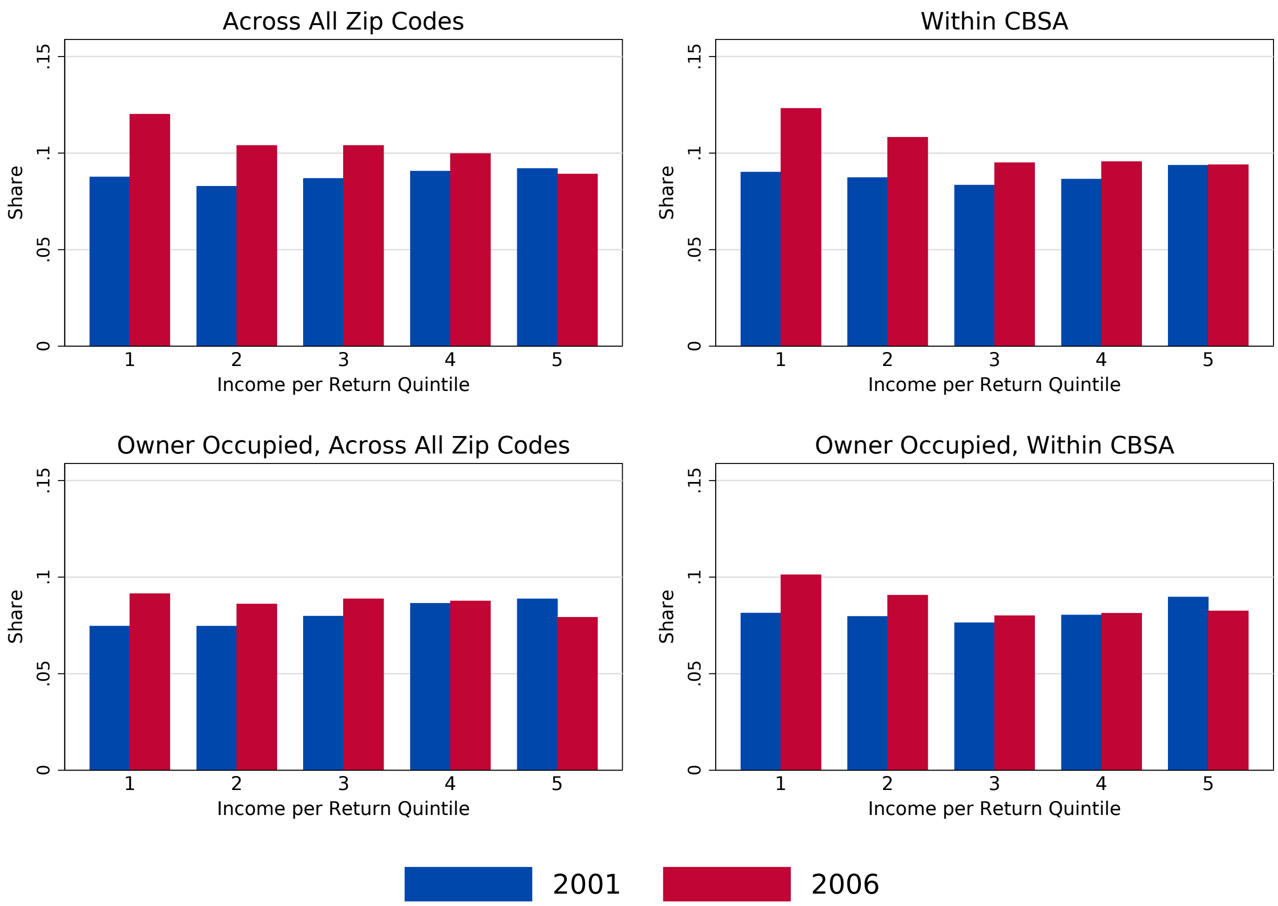


Figure 11. Purchase-Mortgage Intensity across Income Categories: 2001 and 2006. *Note:* Purchase-mortgage intensity is defined as the ratio of new purchase mortgages (as measured in HMDA) to outstanding first liens (as measured in Equifax). The top two panels show that over the course of the mortgage 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.

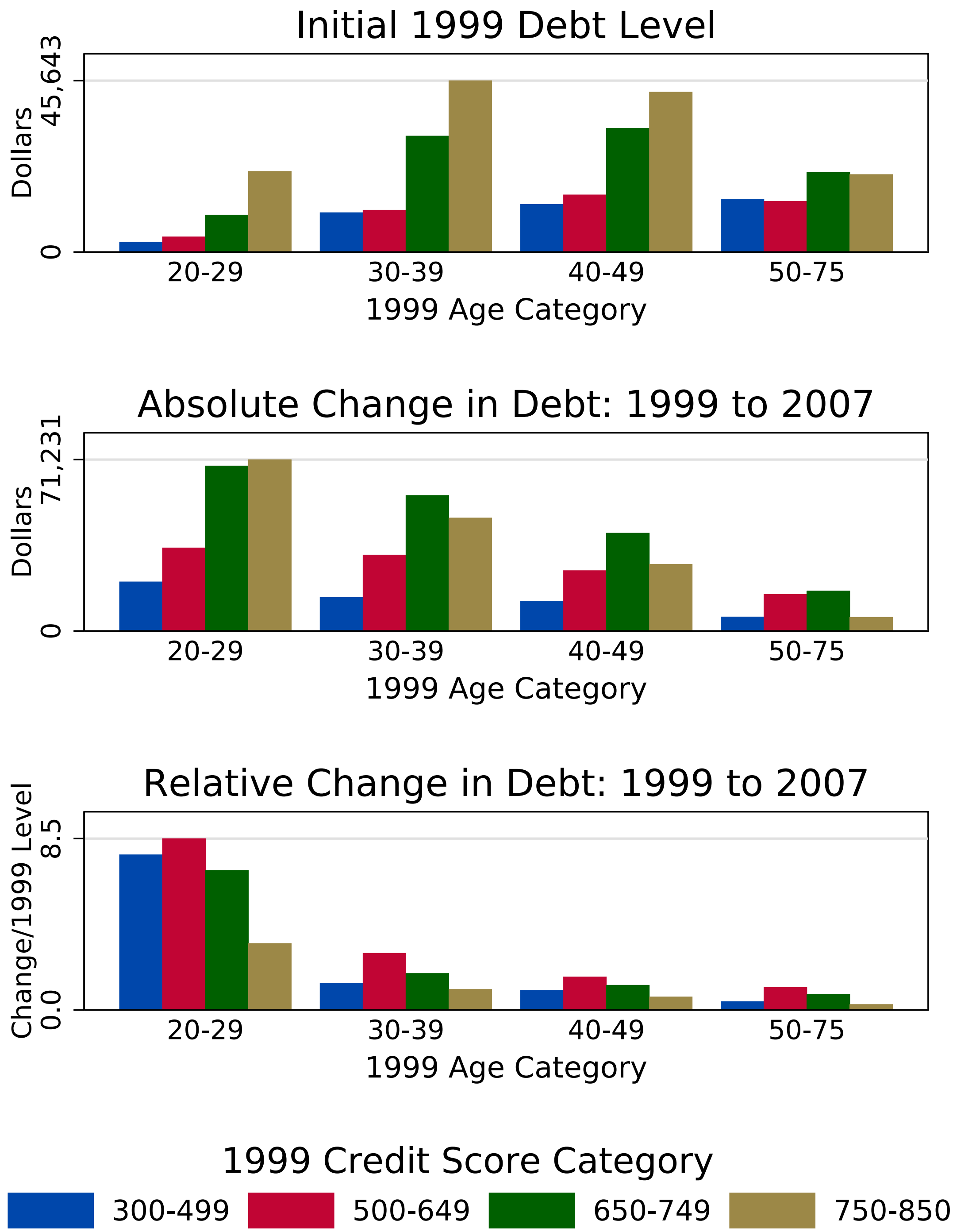


Figure 12. The Relationship Between 1999 Debt Levels and 1999-2007 Debt Growth by Credit Scores and Age in 1999. *Note:* The top panel depicts average dollar values of mortgage debt for demographic groups based on 1999 age and 1999 Equifax Risk Score, a type of credit score. The middle panel shows average absolute dollar-value changes in debt between 1999 and 2007 based on 1999 age and 1999 credit score. The bottom panel depicts average relative changes in debt, constructed by dividing the absolute changes in the middle panel by the initial levels in the top panel. *Source:* NY Fed Consumer Credit Panel/Equifax.

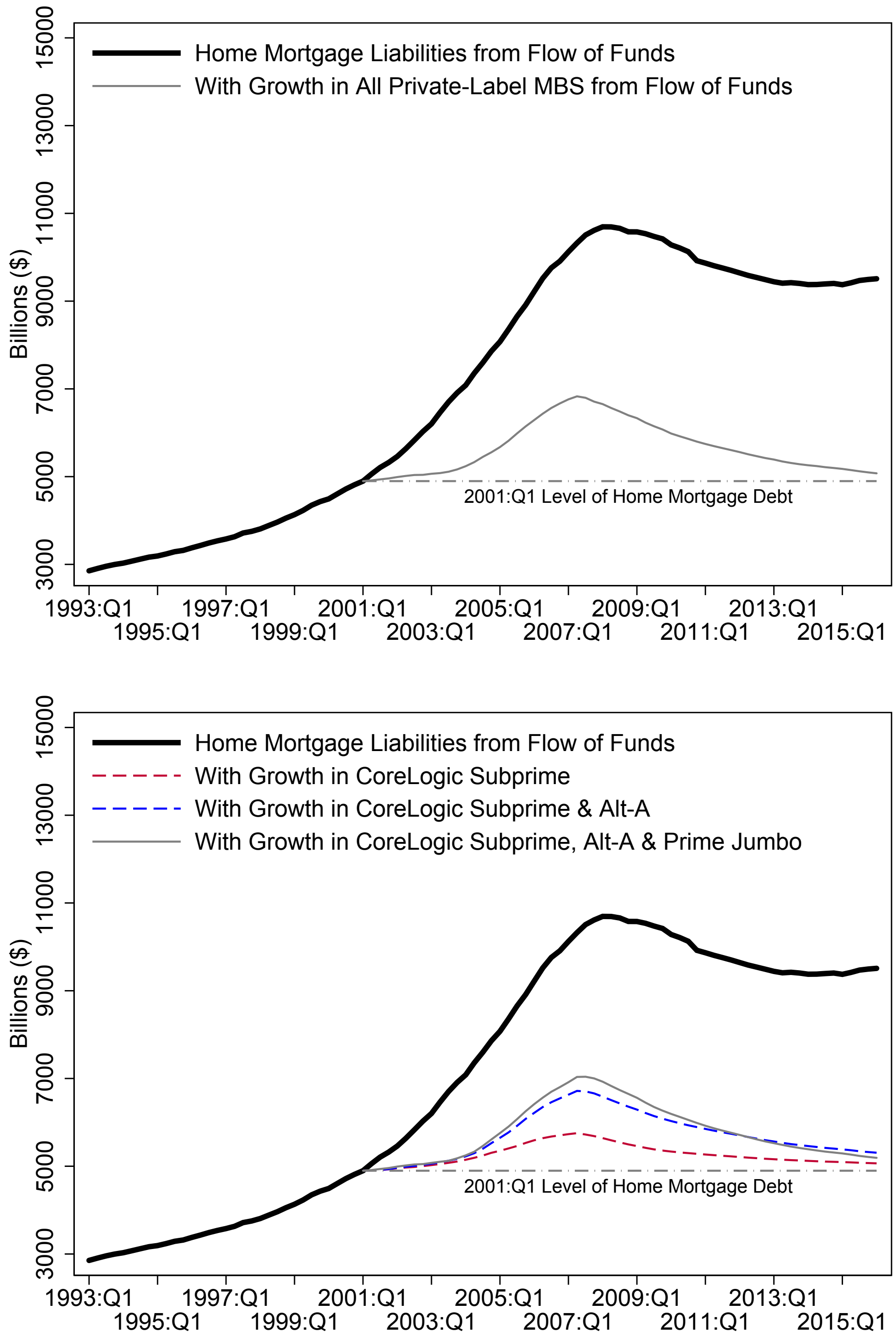


Figure 13. The Contribution of Privately Securitized Mortgage Debt to Total Mortgage Debt Growth. *Note:* In both panels, the heavy black line depicts U.S. aggregate mortgage liabilities for the household sector from the Federal Reserve's Flow of Funds. The top panel also depicts a counterfactual series 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 from the CoreLogic Private Label Securities ABS Database. *Source:* Federal Reserve Board of Governors (Flow of Funds) and CoreLogic Private Label Securities ABS Database.

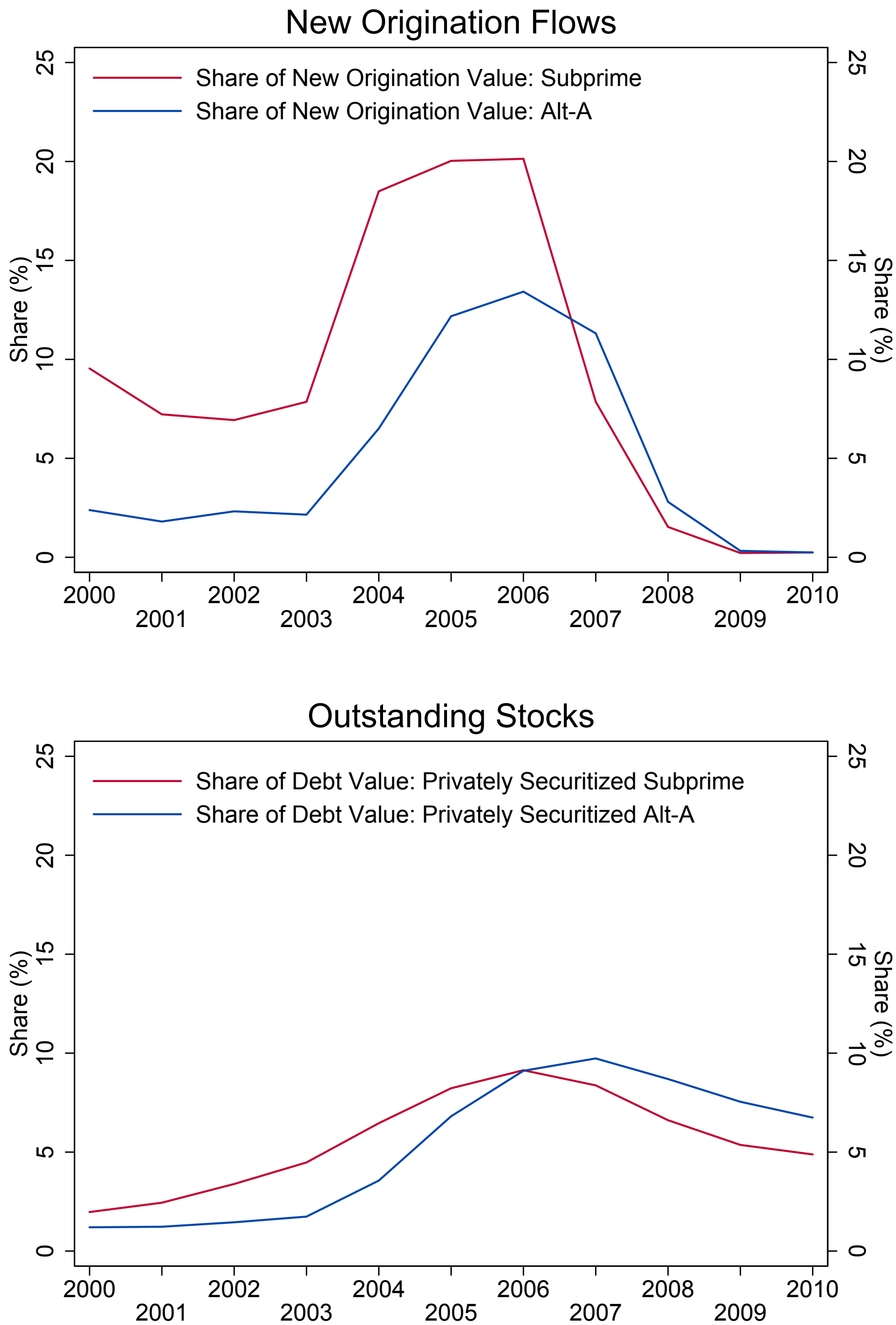
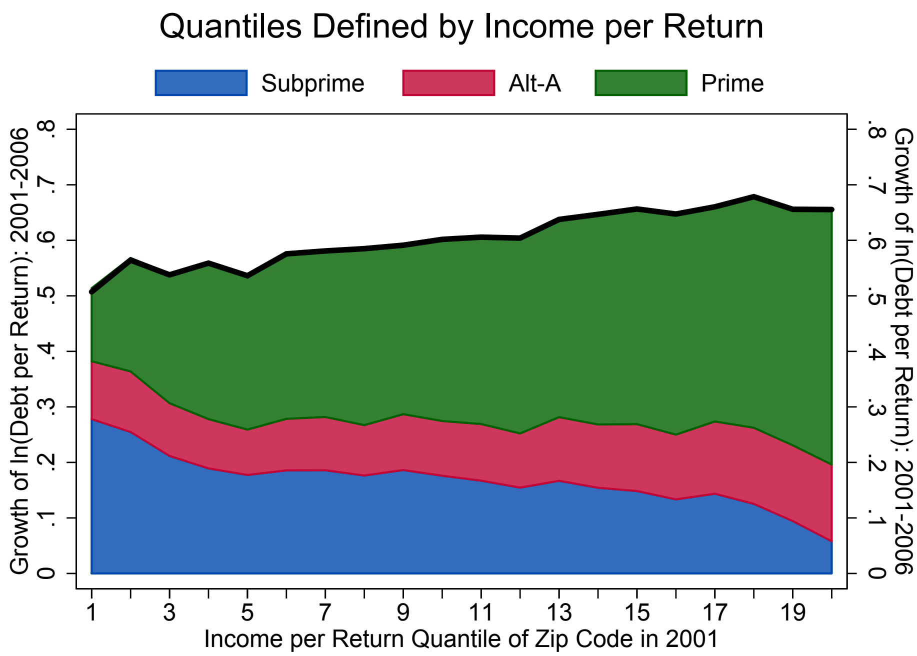


Figure 14. Shares of Subprime and Alt-A Debt among New Originations and Outstanding Stocks of Debt. Note: The top panel graphs the dollar value of new originations for all subprime and Alt-A loans as a share of the dollar value of total originations, according to the Mortgage Market Statistical Annual. The bottom panel depicts the dollar value of outstanding stocks of privately securitized subprime and Alt-A loans from the CoreLogic ABS database as a share of the total outstanding mortgage liabilities of households from the Flow of Funds. *Source:* Mortgage Market Statistical Annual, CoreLogic Private Label Securities ABS Database, Federal Reserve Flow of Funds, and Mortgage Bankers Association.



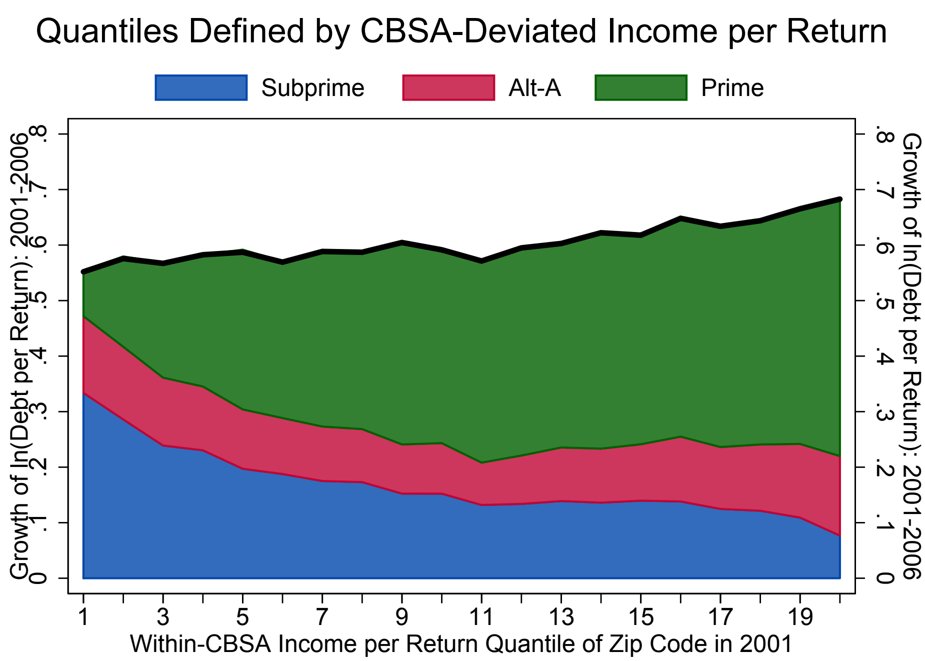
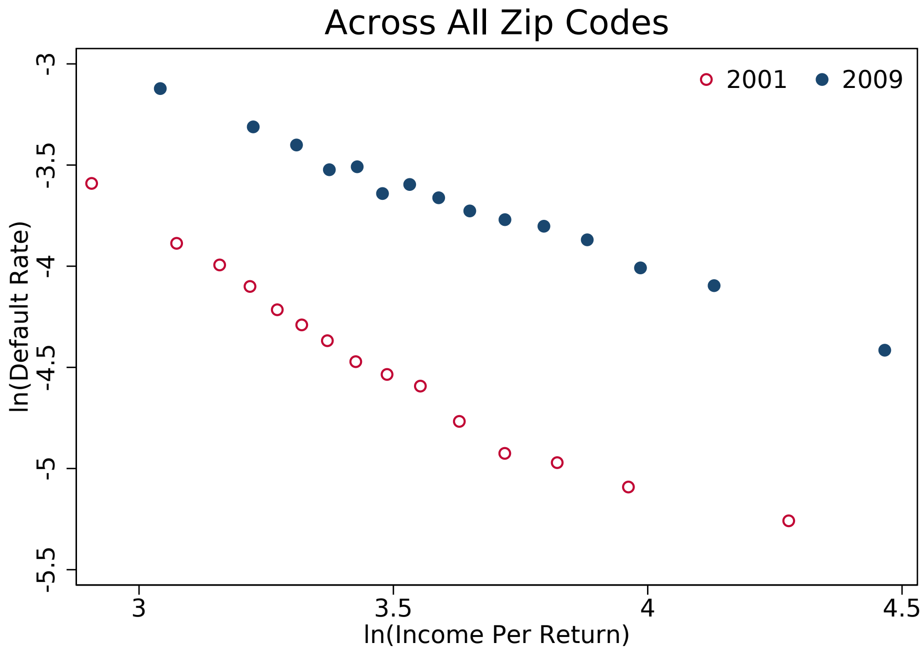


Figure 15. Mortgage Debt Growth by Debt Type Across the Income Distribution of Zip Codes: 2001–2006. *Note:* These graphs use data on subprime and Alt-A mortgage debt from the CoreLogic Private Label Securities ABS Database to show the 2001–2006 contributions of prime, subprime, and Alt-A debt for total 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.



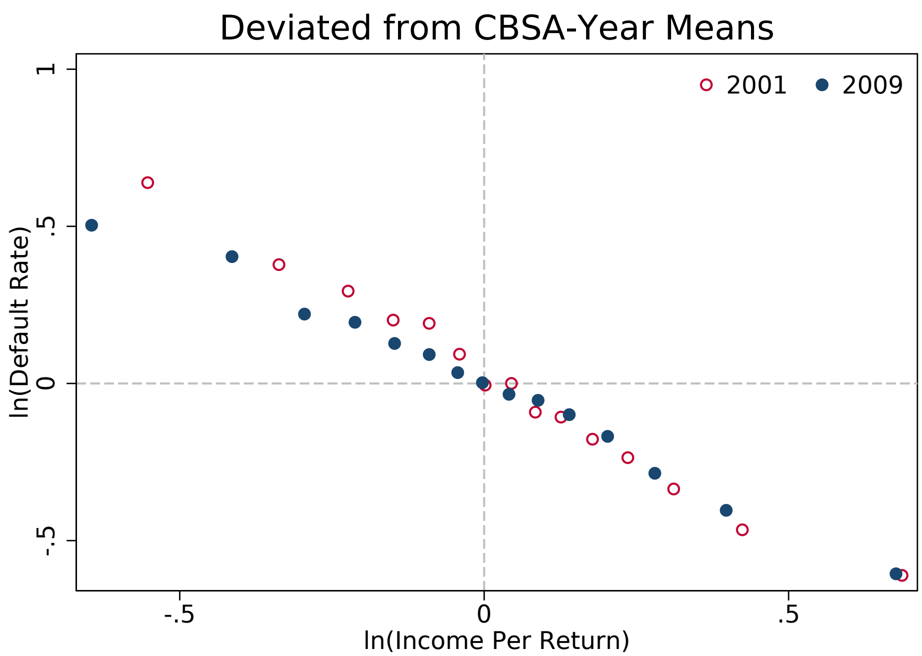


Figure 16. Income and Mortgage Default Rates at the Zip-Code Level. *Note:* These two panels are binned scatter plots of default rates from Equifax and IRS salary and wage income for zip codes in 2001 and 2009. Income is expressed as the log of per-return values, while the default rate is the ratio of 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 panel, the variables are not deviated from CBSA means, while in the bottom panel they are. *Source:* NY Fed Consumer Credit Panel/Equifax 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 axis of each panel measures our aggregation of debt for the given geographical unit, while the vertical axis measure aggregates that are 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 the zip code-level data is smaller than the IRS's published total, in part because of the suppression rules. But as Figure 3 shows, 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) 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 for which the SCF data are 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.[59] 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,

[59] 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.

Henriques and 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.[60]

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.4 shows that our main results hold 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 Figure 2 in the main text 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 the 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.5. 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

[60]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.6 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 Individual-Level IRS Data from the Tax Model Files

The analysis in the main text uses publicly available income data from the IRS that has been aggregated to the zip-code level. However, as noted in the text, the IRS also produces a public-use sample of anonymized individual-level tax returns, often referred to as the Tax Model Files. These files are well suited for studying the U.S. income distribution due to their large sample sizes (samples for recent years include around 150,000 individual tax records) as well as their excellent coverage of the highest-income tax filers. Recently, Saez and Zucman (2016) used the Tax Model Files to study changes in the U.S. wealth distribution over time, by capitalizing flows of reported income and deductions into stocks of wealth and debt. As part of that study, the authors constructed individual-level estimates of housing assets by capitalizing property tax payments in a way that forced implied totals to be consistent with national aggregates. Similarly, mortgage debt was netted out of housing wealth by capitalizing mortgage-interest deductions.

The Tax Model Files are much larger than the SCF and are available annually rather than every three years. Even so, the SCF provides better coverage of housing wealth and debt throughout the whole of the income distribution, in large part because lower-income filers are less likely to itemize their property-tax and mortgage-interest deductions. For homeowners who take the standard deduction rather than itemize, there is no way to capitalize their property-tax and mortgage-interest payments into stocks of housing wealth or mortgage debt. When the focus is on the stock of wealth at the top of the income distribution, as in Saez and Zucman (2016), low itemization rates in the middle and bottom of the income distribution are not a significant concern. But when the focus is on mortgage debt throughout the income distribution, as in this paper, the lack of housing-related information for the mass of tax filers is a serious drawback.

For an estimate of how serious this drawback is likely to be, we turn first to Poterba and Sinai (2008), a paper that assessed the likely incidence of various housing-related tax provisions for homeowners of varying ages and incomes. As part of that study, the authors used the NBER TAXSIM federal and state income-tax calculators to estimate how many homeowners in the 2004 SCF would be better off taking the standard deduction as opposed to itemizing their deductions, and thus becoming eligible for tax benefits such as the mortgage-interest deduction. The Poterba-Sinai results are displayed in the first two columns of Table A.1. The authors found that only 23.4 percent of homeowners with under $40,000 in annual income should itemize their deductions. The predicted itemization rate for homeowners with \$125,000–\$250,000 of income was 98.4 percent, while the comparable figure for homeowners with incomes above \$250,000 was 99.9 percent.[61] These results imply that Saez and Zucman (2016) have a near-complete sample of property-tax and mortgage-interest payments at the top of the income distribution. But applying the capitalization method to the lower parts of the income distribution would miss many homeowners.

To further illustrate the inverse relationship between income and itemization rates among homeowners, we make a similar calculation using the IRS zip-code level data. The 2007 data include information on the number of tax returns in each zip code that reported mortgage interest payments. Using the Equifax data to estimate the number of households with a mortgage in each zip code, we can then calculate the fraction of households with a mortgage who deducted their mortgage interest paid. We do this for five income quintiles of zip codes, using either average AGI or average salary and wages to construct quintiles. The results are reported in the remaining columns of Table A.1. Consistent with the predictions of Poterba and Sinai (2008), we find that a higher fraction of mortgaged households in high-income zip codes deduct mortgage interest payments. Because our calculation is done at the zip-code and not the household level, our results are not as extreme as those of Poterba and Sinai (2008). We find that around 45 percent of mortgaged households in the lowest-income quintile itemize their mortgages, compared to nearly 75 percent in the highest-income quintile.

The Poterba-Sinai calculation implies that 63.1 percent of all homeowners in the 2004 SCF should have itemized their deductions. That figure is quite close to the overall itemization rate of 63.8 percent that we find using the 2007 zip-code level data. Interestingly, Poterba and Sinai also report that their prediction is close to the fraction of 2004 SCF homeowners who reported they did in fact itemize on their most-recent return (63.3 percent). However, at a more disaggregated level, Poterba and Sinai find large differences in predicted vs. self-reported itemization rates among low- and middle-income homeowners. Among homeowners making less than \$125,000 per year, the self-reported itemization rate for those headed by individuals younger than 35 was 20 percentage points lower than predicted. For homeowners over 65, the self-reported itemization rate was about 20 percentage points higher than predicted. For our purposes, the implication of this finding is that it would be difficult to impute itemization rates among low- and middle-income filers based on income levels.

Finally, we note that an additional problem with using the capitalization method to

[61] The authors define household income as "adjusted gross income plus the following items: income from nontaxable investments, an estimate of employer contributions for FICA, payments from unemployment insurance and workers compensation, gross social security income, and any alternative minimum tax (AMT) preference items that can be estimated from the SCF" (p. 84).

estimate individual-level debt levels for low- and middle-income taxpayers is that this method assumes identical capitalization factors across income groups. When measuring stocks of wealth, as in Saez and Zucman (2016), the assumption of equal capitalization factors makes sense. Two individuals holding an identical bond will receive identical interest payments, even though one individual may be richer than the other. Because the interest rate on the bond is essentially the inverse of the capitalization factor, the capitalization factor used to infer stocks of bond holdings from flows of bond interest should therefore be identical across income groups. However, mortgage interest rates *paid* by two individuals are likely to differ with income.[62] As a result, assuming an identical capitalization factor to back out stocks of mortgage debt from flows of mortgage interest is less tenable when households have very different incomes.

A.4 Relationship to Kumhof, Rancière, and Winant (2015)

In a stimulating paper on the potential relationship between income inequality and financial crises, Kumhof, Rancière, and Winant (2015, henceforth KRW) use the SCF to motivate a general equilibrium model of lending across income groups. The model is designed to show how rising income inequality in the 1920s and the latter part of the 20th century could have contributed to the Great Depression and the Great Recession, respectively. In the model, households at the top of the income distribution lend to the rest of the population, so that these borrowers can maintain their consumption levels amid declining relative incomes. At some point, the lower-income households make a rational decision to default on their consumption loans, a choice that gives them financial relief but that also triggers a financial crisis. To motivate the model, the first part of the paper uses SCF data to plot the total debt-to-income ratio (DTI) of the top 5 percent of households along with that of the bottom 95 percent.[63] The DTI of the bottom 95 percent trends up from 1983 through 2007. The DTI of the richest 5 percent has no discernible trend from 1983 onward, although it does increase somewhat from 2001 to 2007. The data are thus consistent with a broad prediction of the KRW model: before the Great Recession, the debt burden of the bottom 95 percent of households grew relative to the debt burden of the households at the top.

The DTI plot motivates a model of *total* debt, not *mortgage* debt, but KRW's analysis of debt for different income categories has some similarities to ours, so comparison of the two approaches is informative. As a first step in this comparison, the two left-hand panels of Figure A.7 plot mortgage debt levels and shares across 20 bins of the income distribution, rather than the five bins used in Figure 2. The use of 20 rather than five categories allows an examination of mortgage debt of the richest 5 percent of households, one of the two income

[62] Mortgage interest rates are also likely to differ with the age of mortgages and other factors.

[63] See Panel A of Figure 2, p. 1222.

groups in the KRW graph. The additional bins do not change the main message of Figure 2, as debt shares remain relatively stable and the richest categories take out the most debt in dollar terms. The share of mortgage debt of the very top bin drops somewhat, but the top 5 percent of households takes out \$618 billion in new mortgage debt during the boom, more than the \$554 billion of the bottom 40 percent combined.

Like the income measure featured in the main results of this paper, income in Figure A.7 is defined as salary and wage income, whereas KRW use total income. Table A.2 therefore presents a series of mortgage-debt and income statistics for the bottom 95 percent and top 5 percent of the total-income distribution. The first two rows of the table emphasize the disproportionate representation of high-income households in outstanding mortgage debt. By definition, the top 5 percent of households always account for one-twentieth of all households, but their share of aggregate mortgage debt was slightly higher than one-fifth when the mortgage boom began in 2001. The next row shows that in dollar terms, the average household in the top 5 percent started the boom with an outstanding mortgage-debt balance of just over \$200,000, which rose to just under \$350,000 by 2007. In dollar terms, the richest group accounts for 20 percent of the aggregate dollar-value increase of additional mortgage debt from 2001 to 2007 (row 4). Because this percentage is slightly below the top group's 23 percent share of mortgage debt at the start of the boom (row 2), the top group's share of aggregate mortgage debt falls—to 21 percent—in 2007. The use of total income rather than salary and wage income therefore results in a small drop in the share of mortgage debt held by the top 5 percent, similar to the decline seen using salary and wage income in Figure A.7.

The KRW model studies how the debt burden of the bottom 95 percent affects its incentives to default and thus the health of the financial system, and it measures leverage using debt-to-income ratios (DTIs). Rows 5 through 8 of Table A.2 characterize the evolution of total household income for the two income categories. The first of these rows shows that average income of the high-income group is close to \$500,000 in 2001, rising to around \$630,000 six years later. The implied rate of income growth is larger than that experienced by the lower-income group, so the share of income earned by the top 5 percent rises, from 35 percent in 2001 to 37 percent in 2007. Row 7 shows that the mortgage DTI of the bottom 95 percent rises from 0.77 to 1.22, while that of the higher-income group increases from 0.41 to 0.55. Thus, the mortgage data are consistent with a visual implication of KRW's graph, as the absolute change in the DTI of the bottom 95 percent is larger than the absolute change of the top 5 percent from 2001 to 2007. When debt is defined as mortgage debt alone, as in Table A.2, the absolute increases in DTIs are 0.45 and 0.14, respectively (row 8). Differences in absolute DTI in the KRW figure appear even larger than this. This is almost certainly because the KRW paper plots total DTIs rather than mortgage DTIs, and KRW find that non-mortgage debt rises more quickly for the lower-income group.[64]

Absolute differences in DTIs could well be useful for motivating a general equilibrium model of indebtedness, but they are less informative about changes in the distribution of mortgage debt with respect to income.[65] If income levels of the two groups had not changed from 2001 to 2007, equal percentage increases in mortgage debt for the two groups would have generated equal percentage changes in DTIs. However, because the bottom 95 percent began the boom with a higher DTI than the top 5 percent (0.77 vs. 0.41), equal percentage changes in debt would have generated a larger absolute change in the DTI of the lower-income group. Additionally, the faster income growth experienced by the richest group from 2001 to 2007 would have reduced its relative DTI growth in both absolute and relative terms. When we consider *log changes* rather than *percentage changes*, the effects of changes in either debt or income on DTIs are exact (notwithstanding rounding). Row 9 of Table A.2 shows that the log changes in the two DTIs are 0.46 and 0.30, which are more similar than the absolute changes in the previous row. The difference of 0.16 in the log change is accounted for nearly equally by somewhat faster debt growth among the lower-income group (row 10) combined with somewhat slower income growth (row 11).

While our data are consistent with KRW's plot, we interpret the main reason behind the overall increase in debt differently than they do. Flow of Funds data indicate that mortgage debt grew much more quickly than non-mortgage debt during the early 2000s, so that the explanation of the overall debt boom during this period must involve mortgages.[66] Some mortgage debt undoubtedly supported consumption, in the spirit of KRW's model. But one-fifth of the aggregate mortgage-debt increase was accounted for by the richest 5 percent of households, a group that averaged nearly a half-million dollars in annual income at the start of the boom. This fact suggests that borrowing for investment, not consumption, was the true driver of debt accumulation. Along these lines, the right-most panels of Figure A.7 show that the disproportionate share of real estate *assets* held by the top 5 percent became even larger during the boom. Although these cross-sectional patterns suggest that investment motives were paramount during the boom, we recognize that a comprehensive comparison of consumption and investment motives must await future research.

[64] See Panel B of KRW's Figure 3 (p. 1222).

[65] While indebtedness is often measured with DTIs, using DTIs to study the evolution of debt in the cross-section is similar to using a less-flexible version of the benchmark log-log regression employed in the main text. The benchmark model regresses the natural log of mortgage debt for a cross-sectional unit on the log of its income and either a constant or city fixed effects. Working with DTIs constrains the coefficient that multiplies log income in this regression to equal one.

[66] Figure 1 shows that mortgage debt grew much faster than personal disposable income during the early 2000s, but we found in unreported work that non-mortgage debt grew about as fast as income during the boom.

A.5 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 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 indicates 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.6 Distributional Statistics for the SCF

The panels in Figure A.10 provide some formal statistics for the SCF distributions in the 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.7 Homeownership in the SCF

Figure A.11 depicts income coefficients from a regression of homeownership on income. This analysis is structured analogously to the mortgageship logits in Figure 7 in the text, and shows essentially the same patterns.

A.8 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 needs to be cross-verified with other variables in Equifax before it is usable. We code someone as taking out their first mortgage if the individual is born in 1950 or later,[67] and if the age of her oldest mortgage

[67] 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, because Equifax

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 a 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.12 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 possible that someone inherited a home or bought a home with cash prior to taking out a 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 home buyers with a less than 10 percent response rate, so their final survey results have under 10,000 home buyers and suffer from selection bias. Given that each of these two measures is imperfect, their similarity is remarkable.

A.9 Gross Flows Analysis without Area-Level Fixed Effects

The two panels of Figure A.13 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 10, which are generated from regressions that also include CBSA $\times$ year fixed effects.

A.10 Effect of Subprime and Alt-A on Debt Growth: 2001–2007

Figure A.14 replicates the main lessons of Figure 15 for debt growth, using 2007 as the ending year of the mortgage boom. Like Figure 15, 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.

did not computerize its records until after 1970.

A.11 Alternative Measures of Homeownership

Figure A.15 provides two estimates of the homeownership rate. The red line shows the standard homeownership rate, which is calculated by the Census Bureau as the share of occupied housing units that are occupied by owners. This rate is calculated using owner-occupied rates in the Current Population Survey/Housing Vacancy Survey. The blue line shows an alternative measure of homeownership suggested by Mian and Sufi (2016b), which is the total number of owner-occupied units divided by the population of adults aged 15 or older. The latter measure requires an estimate of the total number of owner-occupied units, which is periodically updated by Census based on changes in methodology or sample frames. Our estimate adjusts for the break in the estimate of owner-occupied units that occurs in 2000. This adjustment uses information on the total housing inventory in Table 953 of the 2004 Statistical Abstract of the United States.

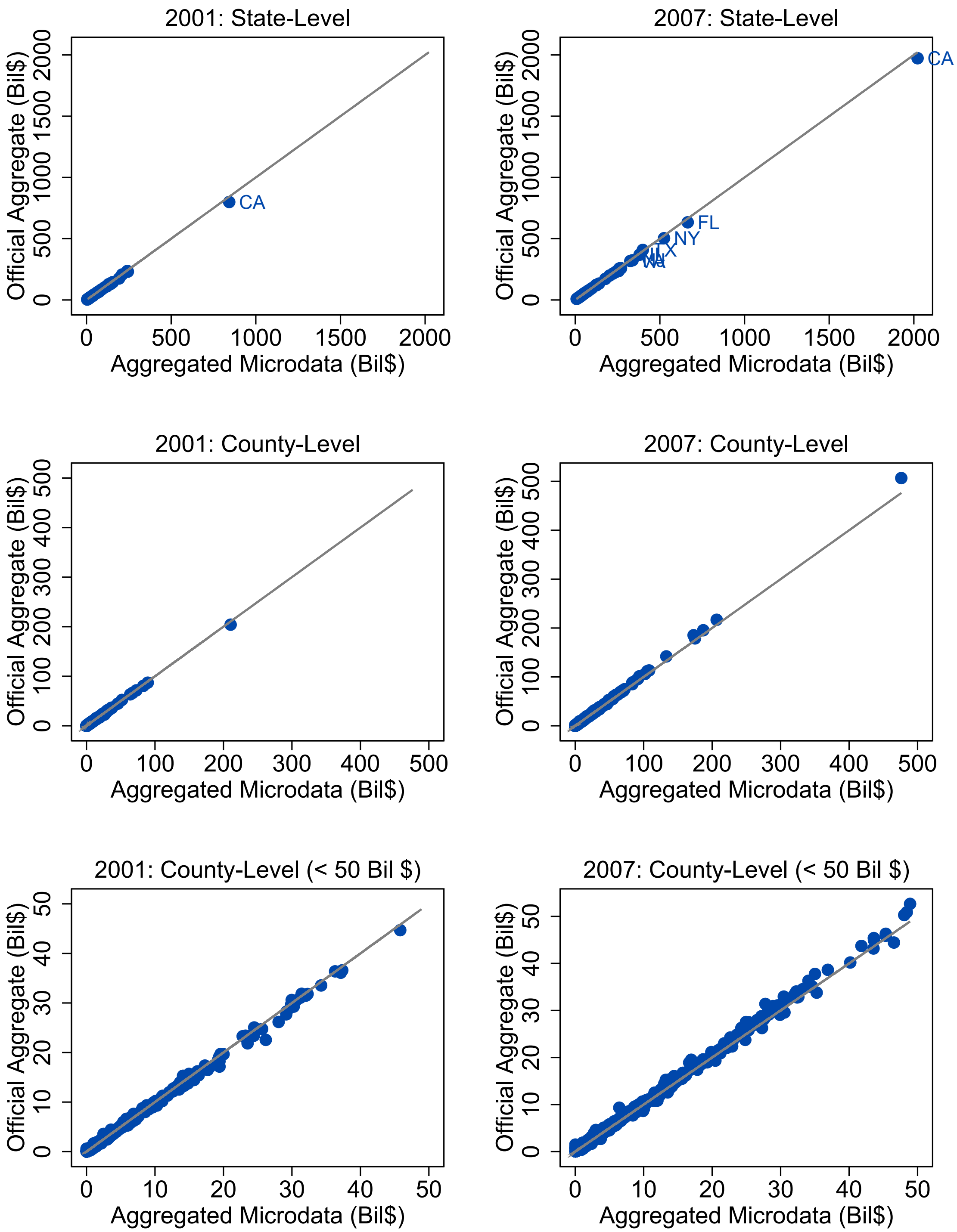


Figure A.1. Comparison of Aggregated Mortgage Debt Balances in the New York Fed Consumer Credit Panel. *Note:* Each of the panels above is a comparison of aggregated data from the microlevel records of the New York Fed Consumer Credit Panel. Aggregation along the horizontal axes was performed by the 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.

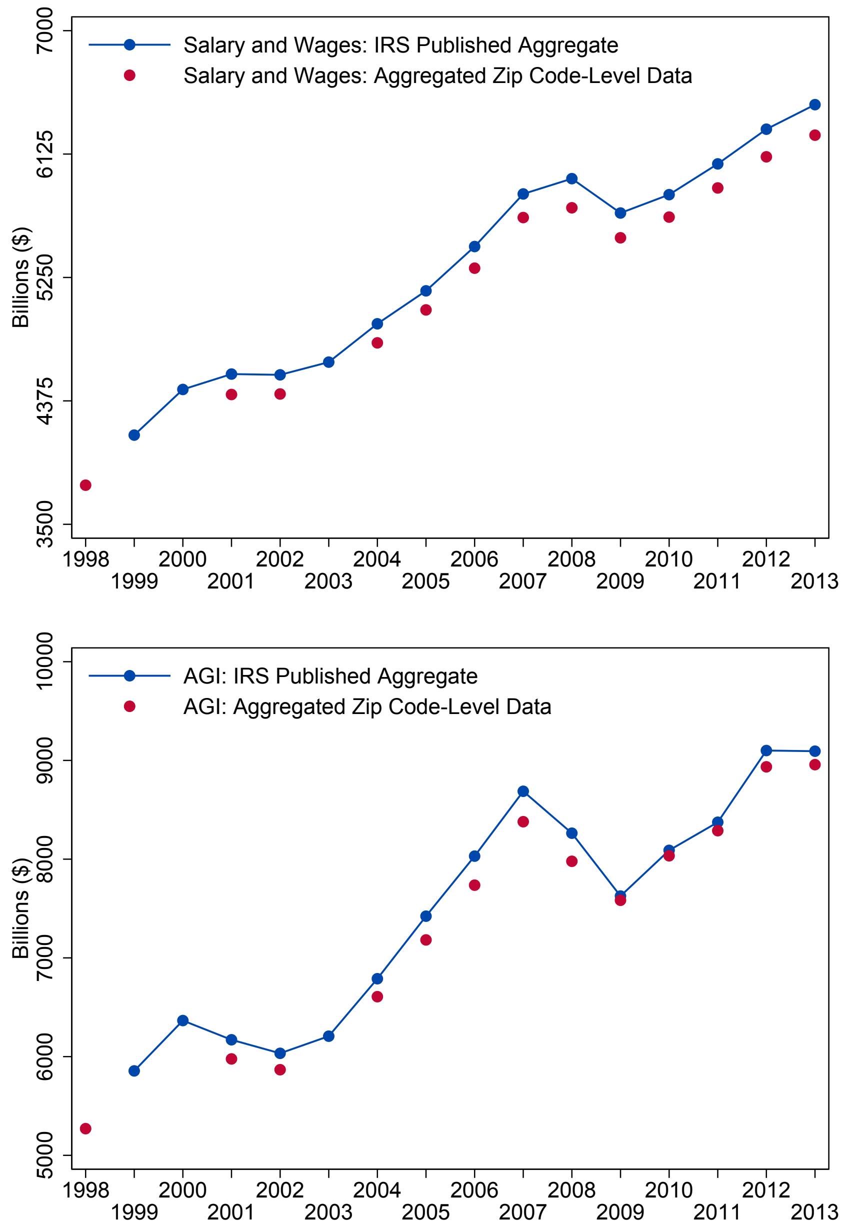


Figure A.2. Measures of Aggregate Salary and Wage Income and Adjusted Gross Income. *Note:* In each panel, the blue line depicts the given income aggregate as published by the IRS, and the red dots depict annual aggregates generated from the zip code-level IRS data. *Source:* Internal Revenue Service,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

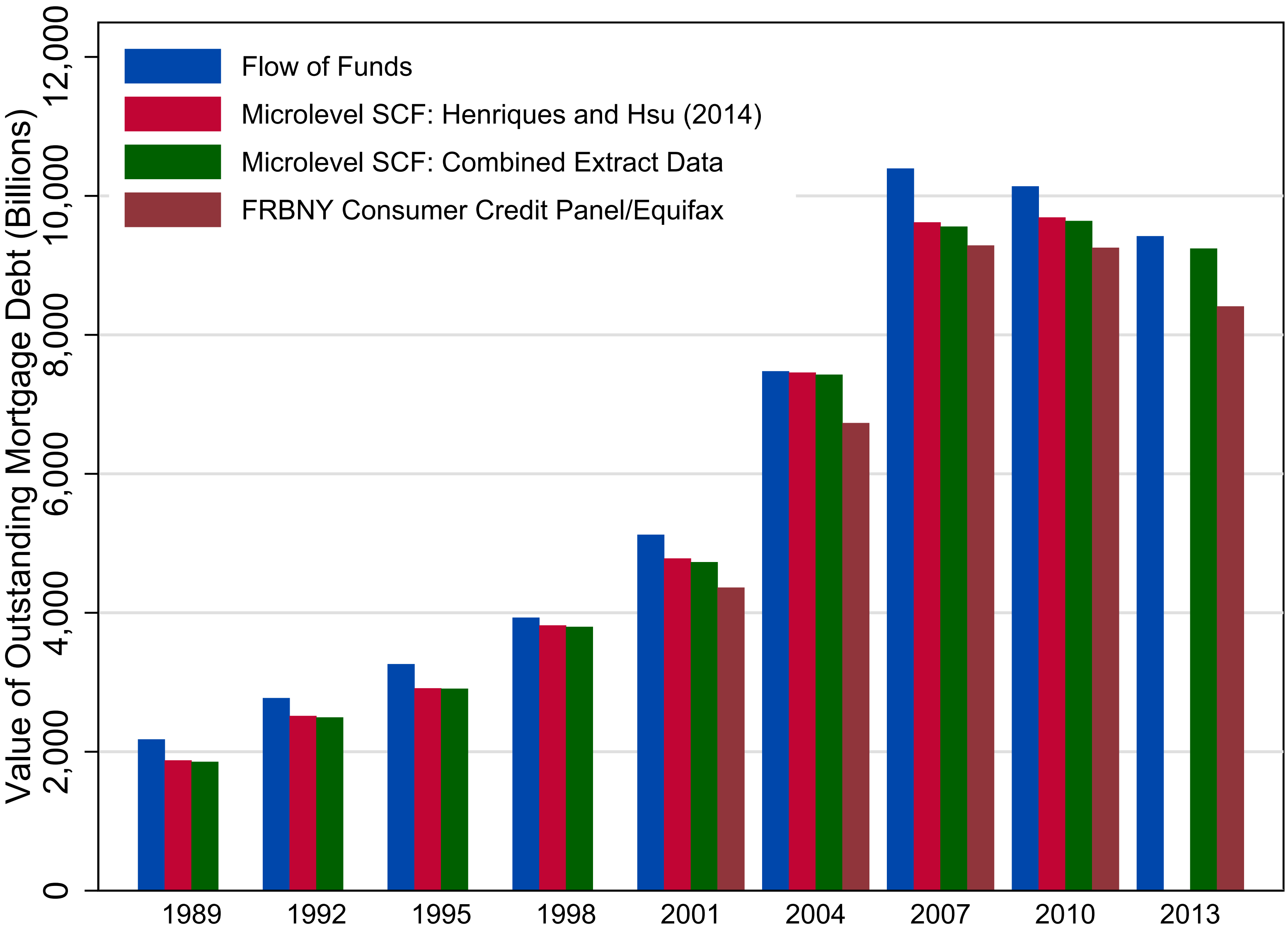


Figure A.3. Alternative Measures of Aggregate U.S. Mortgage Debt. *Source:* Board of Governors of the Federal Reserve System (for Flow of Funds); Table 9.1 (p. 250) of Henriques and Hsu (2014); authors' calculations using the Combined Extract Data of the Survey of Consumer Finances; and authors' calculations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

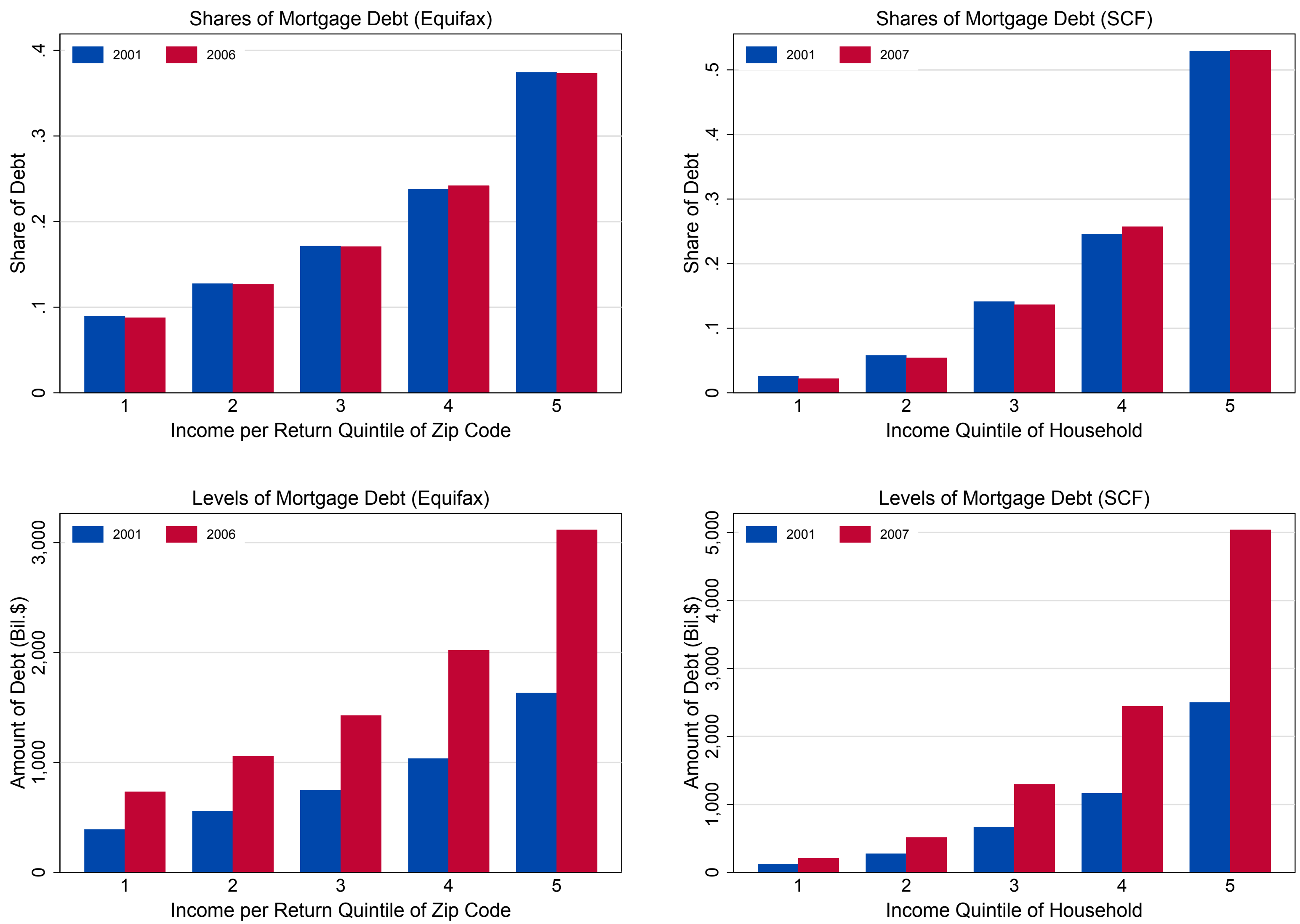


Figure A.4. Distributions of Mortgage Debt With Respect to Adjusted Gross Income (for Zip Codes) and Total Income (for Households). *Note:* The income measure used throughout the main text is salary and wage income. This figure uses AGI as the income measure for zip codes in the left panels, and total 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.

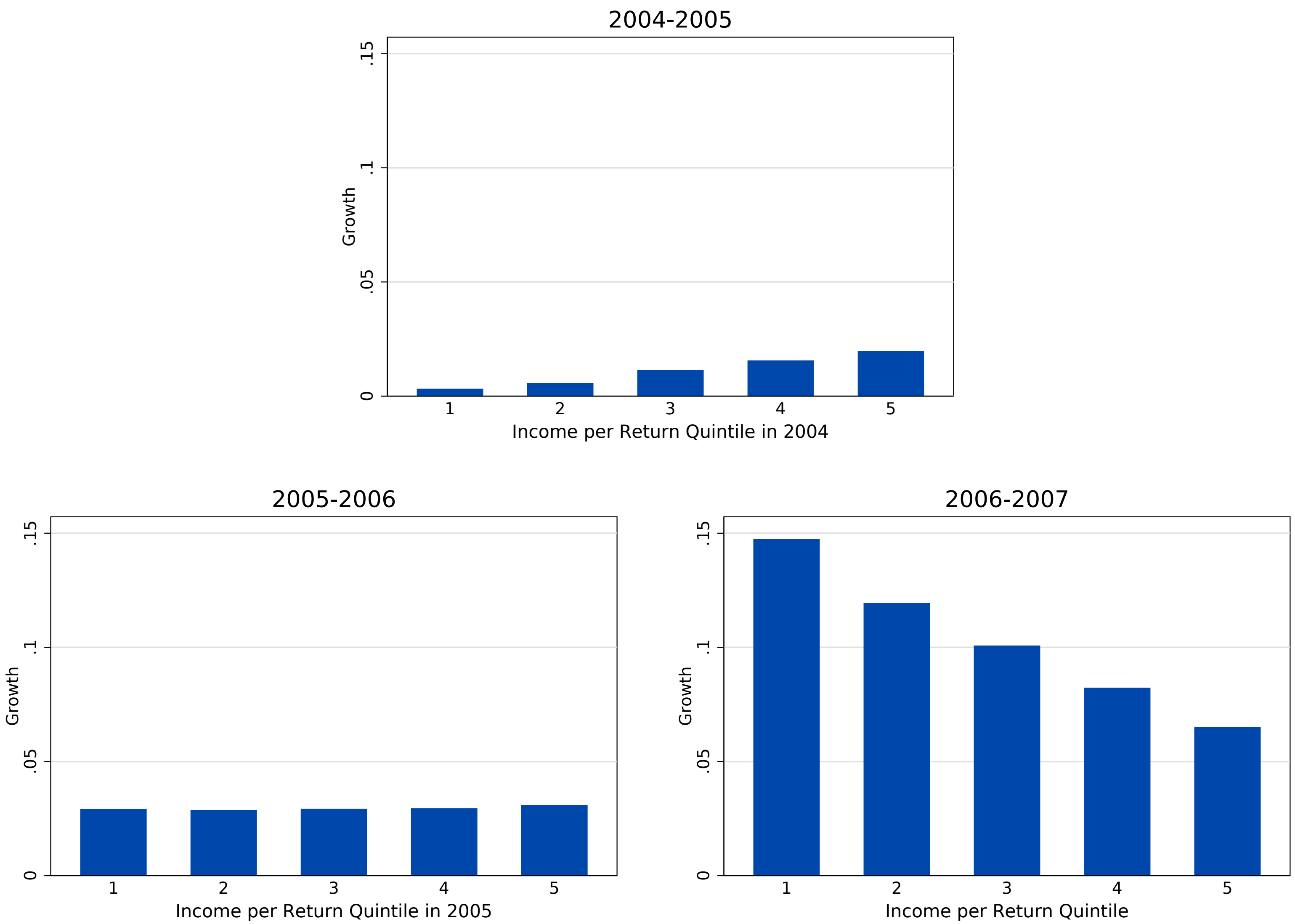


Figure A.5. Growth in IRS Returns by Income Quintile. *Note:* The top panel shows the growth in the total number of zip code-level tax returns between 2004 and 2005, grouped by zip code-level income in 2004. The bottom panels provide analogous information for returns growth in 2005–2006 and 2006–2007. 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.

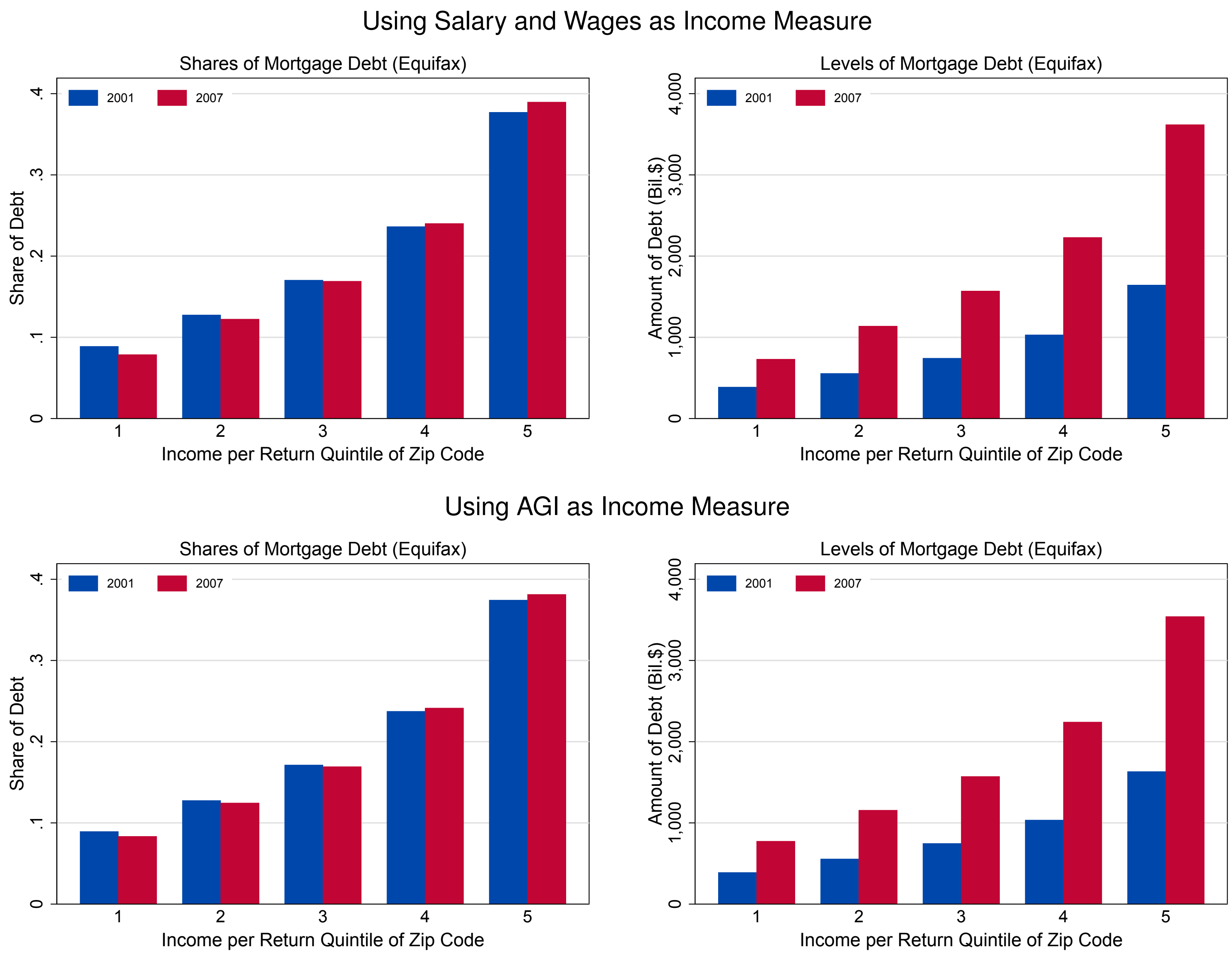


Figure A.6. Equifax/IRS Distributions of Debt for 2001 and 2007 using Alternative Income Definitions. *Note:* These graphs are analogous to the Equifax/IRS zip code-level bar charts in Figure 2, which depict distributions for 2001 and 2006, rather than 2001 and 2007. The lower panels in this figure also use AGI rather than wage and salary income. *Source:* NY Fed Consumer Credit Panel/Equifax, IRS Statistics of Income, and Survey of Consumer Finances.

Figure A.7. Distributions of Mortgage Debt and Real Estate Assets across 20 Categories of Salary and Wage Income in the SCF. *Note:* The two panels at left replicate the bar charts that use SCF data in Figure 2, but they divide households into 20 bins of wage and salary income rather than five. The two panels on the right plot the levels and shares of real estate assets held by each group. *Source:* Survey of Consumer Finances.

Poterba & Sinai (2008)		Authors' Calculation		
Household Income Category		Zip-Code Income Quintile	AGI	SW
$< \$40,000$	23.4	1	47.3	45.3
\$40–\$75,000	66.1	2	55.4	55.0
\$75–\$125,000	85.5	3	63.3	63.3
\$125–\$250,000	98.4	4	69.6	69.7
$\geq \$250,000$	99.9	5	72.8	73.7
All	63.1	All	63.8	63.8

Table A.1. Percentage of Homeowners and Mortgagors that Itemize Deductions by Income Categories. *Note:* The first two columns are from Table 1 of Poterba and Sinai (2008). These columns report the fractions of homeowners in the 2004 SCF who are predicted to have itemized their deductions, across various categories of income. These predictions are generated by comparing the value of the standard deduction to value of itemized deductions, where the latter is calculated for each homeowner in the 2004 SCF using the NBER's TAXSIM model. The remaining columns report the authors' calculations of zip code-level fractions of mortgaged households in 2007 who deducted their mortgage interest payments. Income quintiles are based on AGI in column (4) and salary and wage income in column (5). *Source:* Poterba and Sinai (2008), NY Fed Consumer Credit Panel/Equifax and IRS Statistics of Income.

Row		Bottom 95%		Top 5%	
		2001	2007	2001	2007
(1)	Share of Households	.95	.95	.05	.05
(2)	Share of Mortgage Debt	.78	.79	.23	.21
(3)	Average Mortgage Debt per Household ($)	36,348	68,270	201,178	348,084
(4)	Share of Total Dollar-Value Change in Debt: 2001–2007	.80		.20	
(5)	Average Income per Household ($)	47,317	56,062	492,450	628,213
(6)	Share of Total Household Income	.65	.63	.35	.37
(7)	Average Debt-to-Income Ratio (DTI)	.77	1.22	.41	.55
(8)	Absolute Change in DTI: 2001–2007	.45		.14	
(9)	Ln Change in DTI	.46		.30	
(10)	Ln Change in Mortgage Debt per Household	.63		.55	
(11)	Ln Change in Income per Household	.17		.24	

Table A.2. MORTGAGE DEBT AND TOTAL HOUSEHOLD INCOME BY INCOME CATEGORY IN 2001 AND 2007. Note: To facilitate comparisons with Kumhof, Rancière, and Winant (2015), income is defined as total income for the household, not salary and wages. Households with no income are omitted. *Source:* Survey of Consumer Finances.

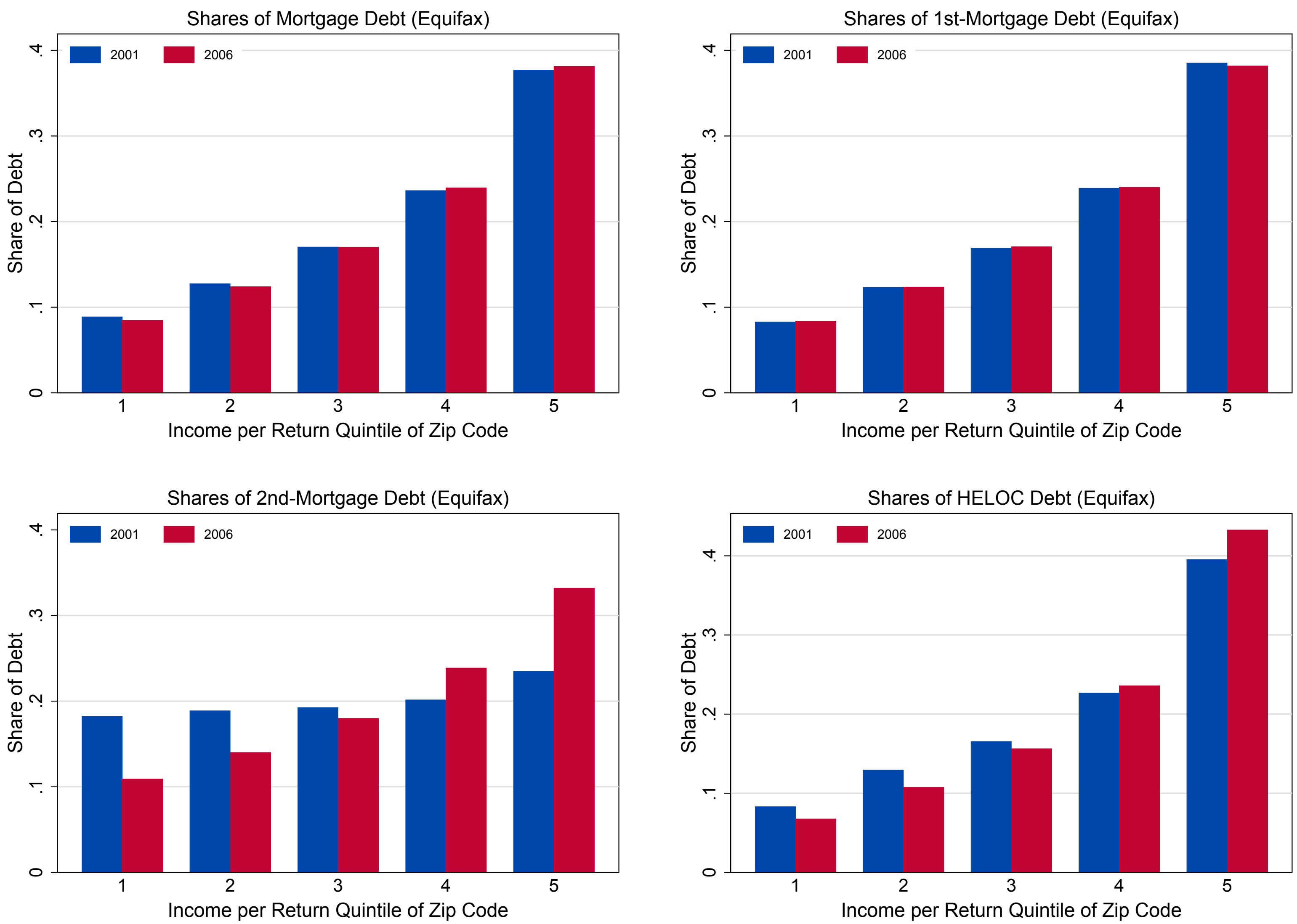


Figure A.8. Equifax/IRS Distributions of Debt by Mortgage Type, using Salary and Wages as Income Definition. *Note:* First mortgages include all purchase and refinance mortgages that are neither home equity loans nor home equity lines of credit (HELOCs). *Source:* NY Fed Consumer Credit Panel/Equifax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

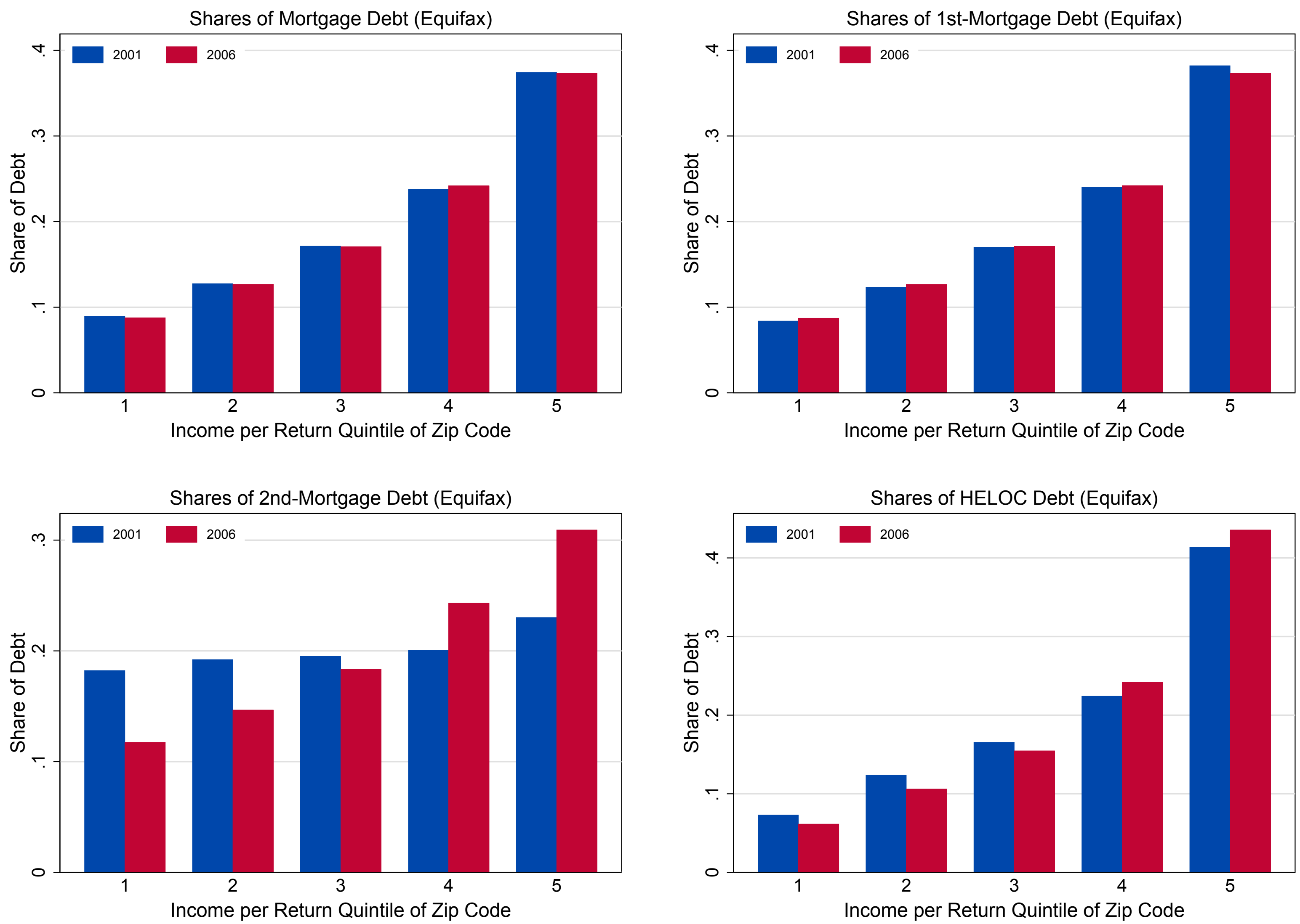


Figure A.9. Equifax/IRS Distributions of Debt by Mortgage Type, using AGI as Income Definition. *Note:* First mortgages include all purchase and refinance mortgages that are neither home equity loans nor home equity lines of credit (HELOCs). *Source:* NY Fed Consumer Credit Panel/Equifax and IRS Statistics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

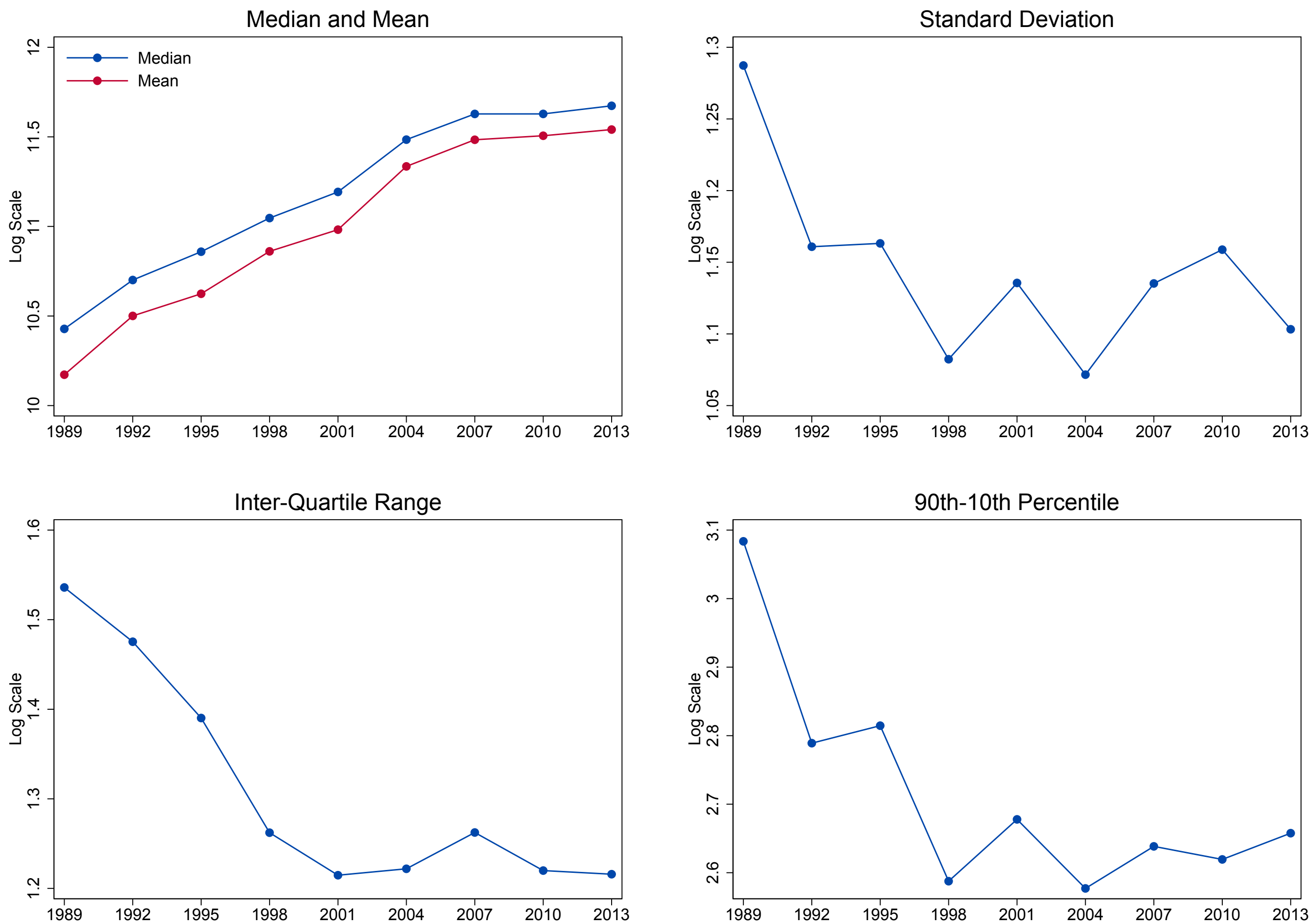


Figure A.10. Distributional Statistics for Household-Level Mortgage Debt in the Survey of Consumer Finances. *Note:* Statistics in these panels relate to the central tendency and dispersion in the distributions of household-level mortgage debt as measured in the Survey of Consumer Finances. Kernel estimates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

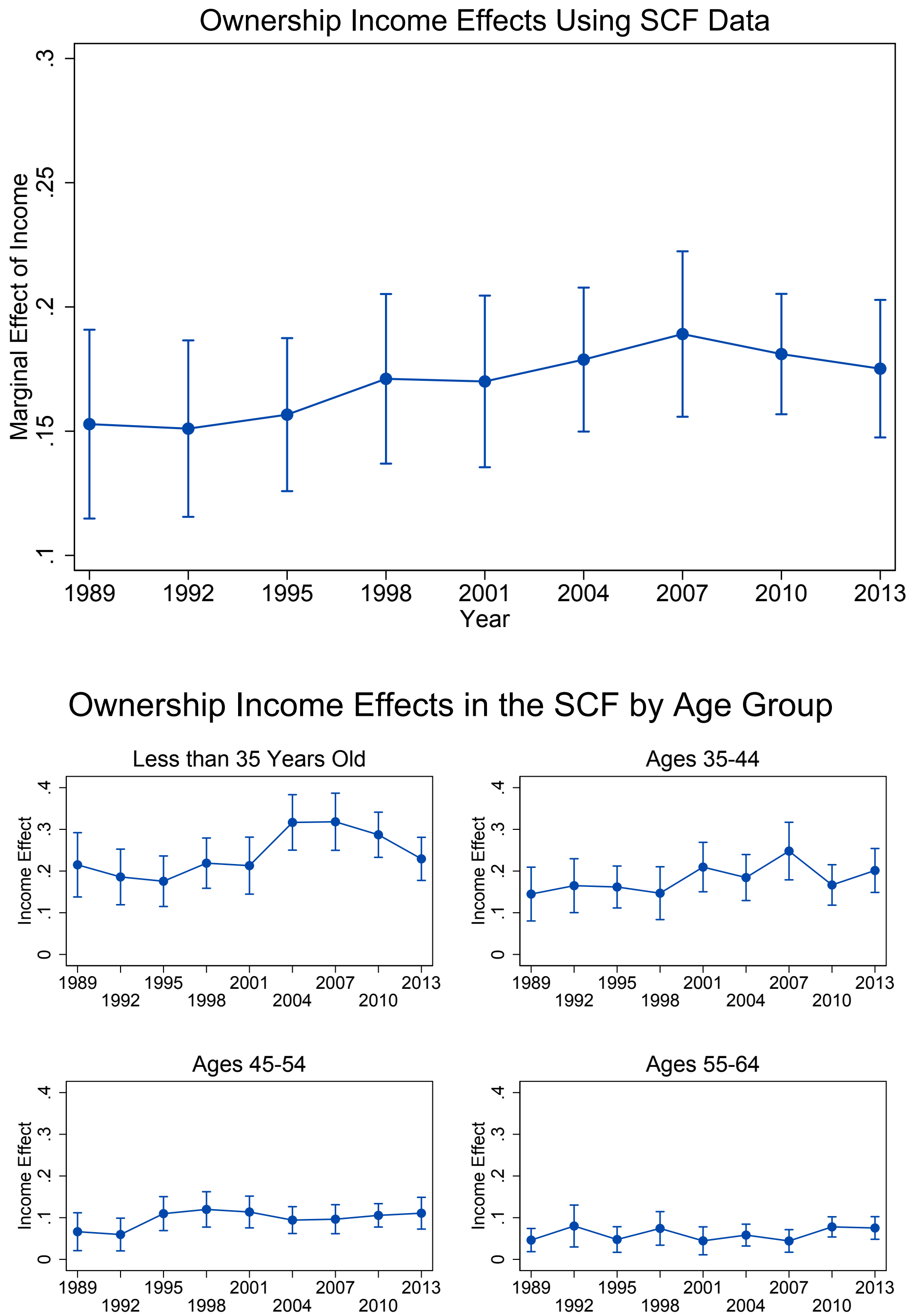


Figure A.11. Regression Evidence on the Relationship between Homeownership and Income in the Survey of Consumer Finances. *Note:* These panels are derived from logit homeownership regressions with the same right-hand-side variables and sample restrictions as those used for the Poisson regressions for total debt depicted in the bottom panel of Figure 5 and the SCF mortgageship regressions in Figure 7. All panels plot the 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.

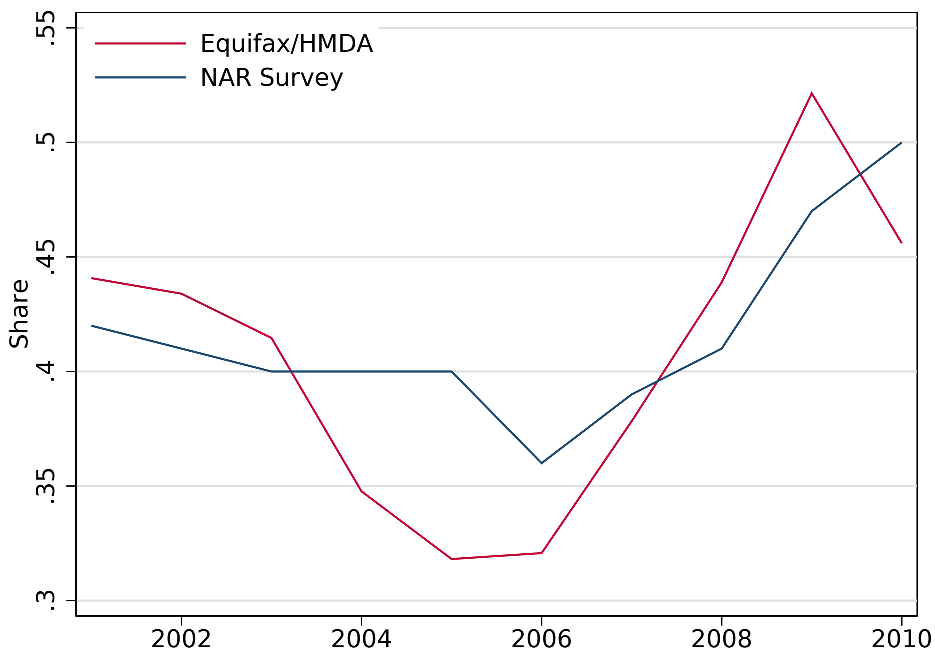


Figure A.12. Comparison of First-Time Borrower Share using Equifax and HMDA Data with First-Time Homebuyer Share Reported in the National Association of Realtors Survey. *Note:* The red line is the number of first-time mortgage borrowers in Equifax divided by the number of owner-occupied purchase mortgage 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.

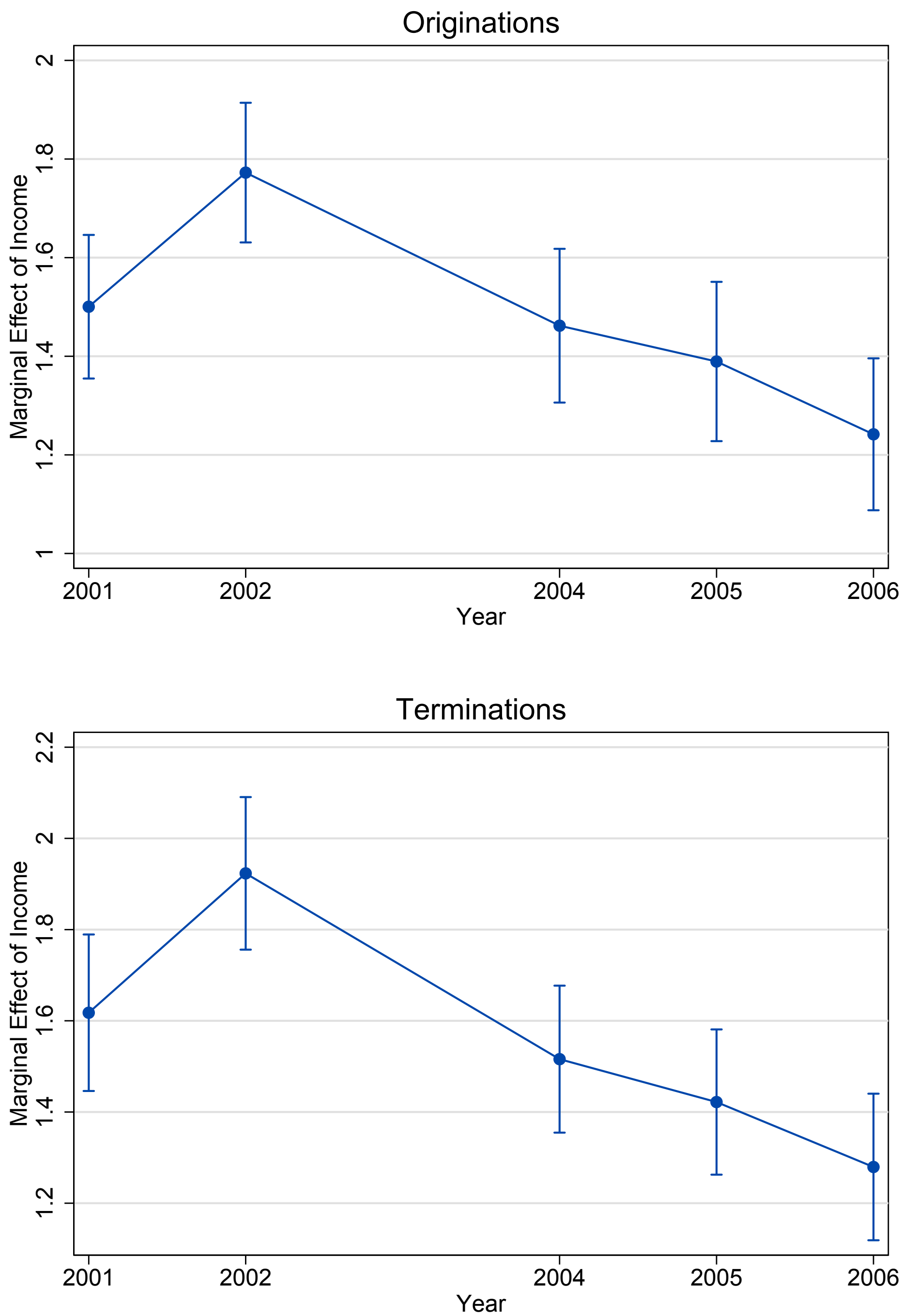


Figure A.13. Income Effects for Originations and Terminations without CBSA Fixed Effects. *Note:* Figure 10 in the main text displays income effects for originations and terminations when CBSA fixed effects are included. *Source:* NY Fed Consumer Credit Panel/Equifax and Internal Revenue Service Statistics of Income.

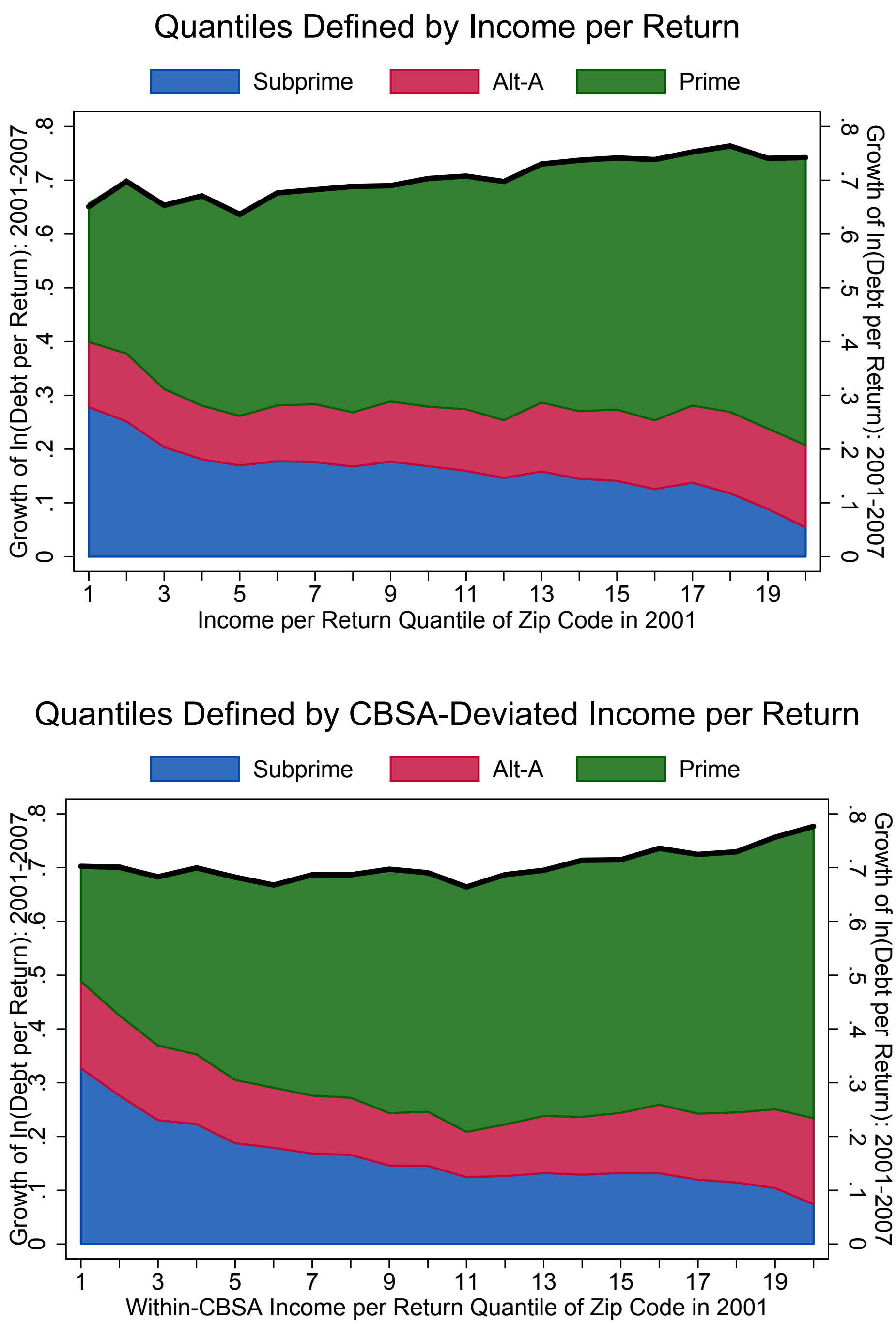


Figure A.14. Mortgage Debt Growth by Debt Type Across the Income Distribution of Zip Codes: 2001–2007. *Note:* These graphs are analogous to Figure 15, which is based on debt growth from 2001 to 2006 rather than growth from 2001 to 2007. *Source:* NY Fed Consumer Credit Panel/Equifax, CoreLogic Private Label Securities ABS Database, and IRS Statistics of Income.

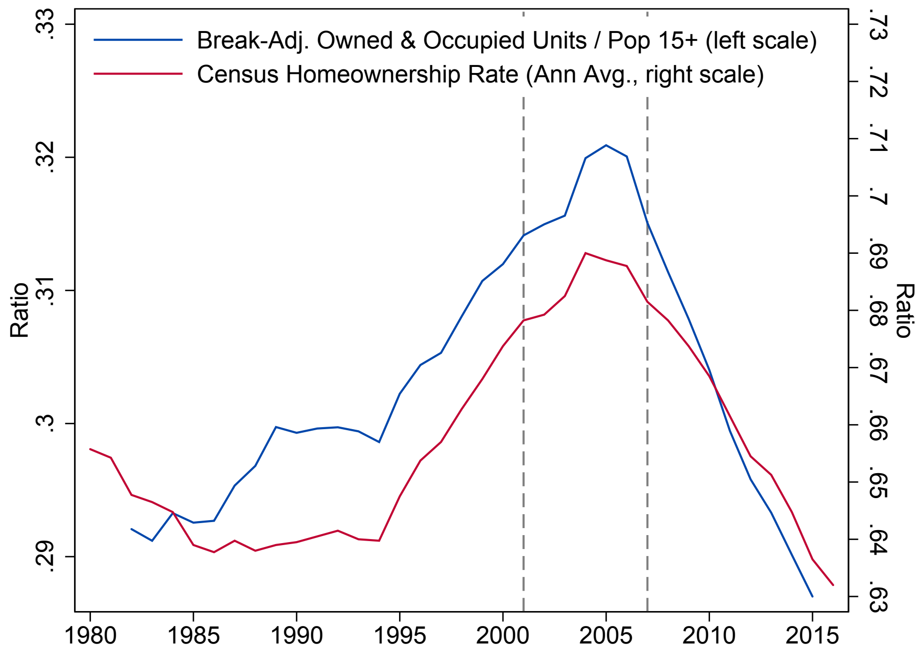


Figure A.15. Alternative Measures of Homeownwership. *Note:* The red line shows the standard homeownership rate, which is the share of occupied housing units that are occupied by owners. The blue line shows the total number of owner-occupied housing units divided by the population of adults aged 15 or older. The number of owner-occupied units is adjusted for break in 2000 using information on the total housing inventory in Table 953 of the 2004 Statistical Abstract of the United States. *Source:* Bureau of the Census and Bureau of Labor Statistics.