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Technological Innovation in Mortgage Underwriting and the Growth in Credit, 1985–2015

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Abstract:

The application of information technology to finance, or "fintech," is expected to revolutionize many aspects of borrowing and lending in the future, but technology has been reshaping consumer and mortgage lending for many years. During the 1990s, computerization allowed mortgage lenders to reduce loan-processing times and largely replace human-based assessments of credit risk with default predictions generated by sophisticated empirical models. Debt-to-income ratios at origination add little to the predictive power of these models, so the new automated underwriting systems allowed higher debt-to-income ratios than previous underwriting guidelines would have allowed. In this way, technology brought about an *exogenous* change in lending standards that was especially relevant for borrowers with low current incomes relative to their expected future incomes—in particular, young college graduates. By contrast, the data suggest that the credit expansion during the 2000s housing boom was an endogenous response to widespread expectations of higher future house prices, as average mortgage sizes rose for borrowers across the entire income distribution.

Keywords: mortgage underwriting, housing cycle, technological change, credit boom

JEL Classifications: C55, D53, G21, L85, R21, R31

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At first glance, Louise Beyler of Gainesville, GA, might appear as an unlikely candidate for a mortgage to buy a $105,500 home. Self-employed and earning $19,000 a year, Beyler would have to spend nearly 45 percent of her income to cover the mortgage payments. Given her circumstances, many lenders would deny Beyler a mortgage. Thanks to automated underwriting, however, Beyler's application was approved—in just three days.

—from Peter E. Mahoney and Peter M. Zorn
"The Promise of Automated Underwriting," (1996), p. 18.

1 Introduction

This paper studies the relationship between borrower income and mortgage debt during the past three decades. Better-off people tend to have larger homes and take out larger mortgages to pay for them, so there is a positive relationship between average mortgage sizes and household income in the data. This cross-sectional pattern is also influenced by lenders' underwriting policies: if these policies are exogenously relaxed, so that low-income households are able to take out larger loans, then the positive cross-sectional relationship between debt and income will flatten. Researchers are now debating whether an exogenous loosening of lending standards took place during the 2000s housing boom, and the main way they have studied this possibility is by measuring changes in the slope of the debt-income relationship. Unfortunately, progress in this area has been hindered by data-quality concerns. In this paper, we make some important adjustments to the data previously used in this literature, and we also develop a new data source that is well-suited to study the relationship between income and mortgage debt. These data allow us to resolve the debate over the debt-income relationship during the housing boom. Additionally, because our data encompass several years before the boom, we can shed light on how changes in financial technology, or "fintech," had already transformed the debt-income relationship before the boom began, in ways that remain relevant for borrowers and lenders today.

An important early paper on the debt-income relationship is Mian and Sufi (2009), which used data from the Home Mortgage Disclosure Act (HMDA) to claim that mortgage credit rose disproportionately for low-income borrowers during the 2000s boom. A central finding of that paper is that the total dollar value of mortgage originations rose disproportionately in low-income zip codes during the boom. Adelino, Schoar, and Severino (2016) extended this analysis by splitting the value of mortgage originations into two components: the *average size* of each mortgage in a zip code and *the total number* of mortgages originated there. This decomposition revealed that Mian and Sufi's headline finding resulted from a relative increase in the number of mortgages originated in low-income areas, not by a relative increase in the average size of new mortgages in those areas. This finding undermined Mian and Sufi's claim that looser income requirements on the part of lenders drove the housing boom. Mian and Sufi (2017) responded by raising concerns with the way that Adelino and his co-authors used the HMDA data, especially their treatment of second liens and their use of borrower-income data from HMDA, which can be overstated. Our paper addresses these two concerns, and finds that in practice they are not strong enough to overturn Adelino, Schoar, and Severino's main claim: the average size of new mortgages did rise proportionately across the income distribution during the housing boom. Along with other research highlighting the broad-based nature of the boom, the proportionate increase in average mortgage sizes suggests that the housing boom resulted from excessive optimism about future house price appreciation, not from exogenous changes in underwriting requirements.[1]

We also find, however, that the relationship between debt and income did flatten in the 1990s, a period that is recognized as one of intense technological change in mortgage lending (LaCour-Little 2000; Bogdon 2000; Colton 2002). Below we show that computer technology allowed mortgage lenders to process loans much more quickly at the end of the 1990s than at the beginning of the decade. But technology did more than speed up mortgage processing: it fundamentally transformed it by replacing human evaluation of credit risk with predictions from data-driven models. Before 1990, loan officers and originators evaluated mortgage applications by personally applying so-called knockout rules, which specified maximal cutoffs for variables such as the LTV (loan-to-value) ratio and the DTI (debt-to-income) ratio.[2] This type of rules-based system would seem to be tailor-made for replacement by computers, which have transformed the US economy due to their ability to perform routine tasks efficiently (Levy and Murnane 2004; Acemoglu and Autor 2011). In fact, during the early 1990s many mortgage lenders tried to use computers in precisely this way, by encoding their lending rules into formal algorithms that computers could follow. The resulting artificial intelligence (AI) systems would then be expected to evaluate loan applications in the same way that humans had, but at a lower cost.

The coders soon discovered that despite the rules-based nature of loan-evaluation pro-

[1]As we discuss in Section 4, HMDA covers only mortgage originations, not terminations. Consequently, HMDA data cannot be used to study a credit expansion along the *extensive* margin; that is, an increase in the number of persons approved for new mortgages. Related to this, HMDA's coverage of only one *flow* of debt (originations) means that the HMDA data cannot measure changes in *stocks* of mortgage debt. As discussed below, Foote, Loewenstein, and Willen (2019) uses data from the Equifax credit bureau and the Survey of Consumer Finances to show that—consistent with the proportionate increase in average mortgage sizes highlighted here—there were no significant cross-sectional differences in debt accumulation along the extensive margin. Stocks of debt rose proportionately across the income distribution as well.

[2]For mortgage lenders, the DTI ratio denotes the ratio of the borrower's monthly *payment* to her monthly income, and does not involve the borrower's entire stock of debt. Although it is not quite accurate, this DTI definition is so ingrained in the mortgage industry that we stick with it here.

cedures, intuitive human judgment typically came into play. Making decisions was easy for human underwriters when loan applications cleared all of the relevant hurdles. But for marginal cases the underwriters had to use their own experience and judgment. Could a high DTI ratio in a particular loan application be safely offset by a low LTV ratio, or by the applicant having a particularly strong credit history? The developers of one early AI system wrote that:

> Underwriting is considered an art that is taught from one generation of underwriters to the next. It takes years of experience to learn to judge and evaluate the loan information to make an informed decision on the risk of the loan. Underwriters do not follow a systematic, step-by-step approach to evaluate a loan. Instead, the underwriter must look at the strengths and weaknesses of the individual elements in a loan file and evaluate how all the data elements affect one another. The process is intuitive rather than scientific. The challenge for the knowledge engineers was to represent the thought process of an underwriter in a manner that could be implemented as a software system (Talebzadeh, Mandutianu, and Winner 1995, pp. 54–55).

Even if human thought processes could be codified into computer algorithms, a big problem with basing lending decisions on human judgment is that mortgage defaults are rare. Individual underwriters were therefore unlikely to accumulate enough personal experience with defaults to properly quantify the tradeoffs among the various risk characteristics that were associated with a mortgage application.

Other firms in the mortgage industry used computers differently. They pulled together large datasets of loan-level records and estimated empirical models of mortgage default, which could then be used to augment the underwriters' evaluations of loan files. The modelers soon realized that default predictions could be significantly enhanced by using consumer credit scores, such as the FICO score, which had been developed to predict defaults on unsecured loans. As credit scores worked their way into mortgage-lending decisions, the housing-finance industry was transformed by the same technologies that at the same time were revolutionizing the credit-card industry and other forms of consumer lending (Evans and Schmalensee 2005; Einav, Jenkins, and Levin 2013; Livshits, MacGee, and Tertilt 2016).

Unlike credit scores, DTI ratios added little to the new mortgage models. As we explain below, modern theories of mortgage default—which are based on income *shocks* rather than initial income *levels*—are consistent with this lack of predictive power. Indeed, the small effect that DTI ratios have on default probabilities was foreshadowed by previous, smaller-scale empirical studies, including those in *Home Mortgage Delinquency and Foreclosure*, the ur-study of loan-level default sponsored by the National Bureau of Economic Research in the late 1960s (Herzog and Earley 1970). In the 1990s, however, the unimportance of

DTIs began to influence the allocation of mortgage credit. Informed by their new computer-driven empirical models, mortgage lenders discounted the relationship between a borrower's income and her mortgage obligation by approving larger loans at the lower end of the income distribution.

By and large, we find that the effects of these exogenous changes on lending patterns are consistent with economic theory. Relaxing DTI limits should have the largest effects on individuals whose expected future incomes are high relative to their current incomes. Young college graduates have relatively steep age-earnings profiles, and we find that the increase in homeownership after 1994 was particularly large for this group.

Putting the pieces together, the technological changes of the 1990s were *exogenous* with respect to the state of the US housing market—these innovations stemmed from increases in computing power and better data-storage and modeling capabilities, not because the housing market was particularly hot or cold during that decade. Consequently, the 1990s changes in mortgage-lending standards flattened the empirical relationship between debt and income, as borrowers with steeply rising income profiles took advantage of the looser requirements on current income, and borrowers who were not previously constrained were unaffected by the changes. In the 2000s, however, the average sizes of new mortgages rose across the income distribution, a pattern that is consistent with widespread optimism concerning future house price growth. Such optimism would increase housing demand for borrowers at all income levels. It would also promote an *endogenous* loosening of lending constraints that allowed low-income borrowers to expand mortgage borrowing at the same rate as their higher-income counterparts.

The rest of the paper is organized as follows. Section 2 discusses the two main data sources that we use to study the debt-income relationship over time, and section 3 presents our results. We relate these findings to the current debate on lending standards during the boom in section 4, and we explain how patterns in the 1990s related to technical change in section 5. Section 6 traces out the effects of the technical changes on the mortgage market, and section 7 concludes.

2 Data

2.1 The Home Mortgage Disclosure Act (HMDA)

Our first dataset comes from HMDA, a 1975 law that requires US financial institutions in metropolitan areas to report individual-level information relating to mortgage applications and originations. Variables in the public-use version of HMDA include the dollar amount of each new mortgage; the reported income, race, and gender of the borrower; and the Census tract of the house that serves as collateral for the loan.

Some information is not available in HMDA on a consistent basis because of changes in reporting guidelines, including some relatively major changes that occurred in 2004.[3] For example, starting in 2004 we can distinguish between first and second liens. During the 2000s housing boom, first-lien mortgages were often supplemented by second liens at purchase ("piggyback loans"), so it is important to account for second liens consistently when making comparisons that span several years. We therefore created an algorithm to identify second liens made before 2004, and then validated this rule using the reported liens available starting in 2004. The algorithm makes use of the application and origination dates of each mortgage, which are available only in a confidential version of the HMDA data to which we gained access.[4] Even when second liens are identified in HMDA, they are not matched to their corresponding first liens. Our algorithm both identifies second liens and matches them to their first liens. We then use the sum total of the first and second liens for each borrower in our loan-level regressions.

The HMDA data also include a field that distinguishes owner-occupied properties from investment properties.[5] In the main empirical work below, we remove investors from our regressions, largely because the relationship between income and mortgage size for investors is likely to be very different than it is for owner-occupiers. For investment properties, the income backing a mortgage comes not only from the borrower's resources, but also from the rental income that the property is expected to generate.

We then clean the HMDA data along the lines suggested by Avery, Brevoort, and Canner (2007), who recommend that analysts drop loans that lack information on race and gender (as these are probably business loans) and combine home improvement loans with refinances. Additionally, because miscoded outliers can exert a strong effect in our debt-income analysis, we remove outliers with an algorithm designed to detect inaccurate loan or income entries. The algorithm calculates the implied monthly payment of each loan (assuming that it is a 30-year fixed-rate mortgage at the current interest rate), and then divides this implied payment by the borrower's income as reported on the HMDA record to generate an implied DTI ratio. We then drop loans with DTI ratios in the bottom and top 1 percent of this distribution.

Figure 1 depicts some summary statistics from data on purchase-mortgage originations in HMDA. The top panel shows the total number of purchase loans originated, along with

[3] A good summary of these changes can be found in "HMDA Changes Are On the Way; New Rules Take Effect in 2004," which appears in *Community Dividend*, an online publication of the Federal Reserve Bank of Minneapolis. It is available at https://www.minneapolisfed.org/publications/community-dividend/hmda-changes-are-on-the-way-new-rules-take-effect-in-2004.

[4] Details of the second-liens algorithm appear in Appendix A.1.

[5] This field is based on information supplied by the borrower, so someone purchasing an investment property might intentionally misreport as an owner-occupier in order to get a lower mortgage rate.

the fraction of those loans that have associated second liens. The number of purchase loans originated increases steadily from 1990 until 2005, while the use of piggyback loans grows dramatically in the mid-2000s, near the end of the housing boom. After 2007, both series drop sharply. The bottom panel displays the median total loan amount for owner-occupied purchase mortgages, with this total encompassing both first liens and any associated piggybacks. The panel also shows the share of purchase mortgages made for owner-occupied properties, which declines by almost 10 percentage points during the boom. Note also that there is a hump shape in the median loan amount at the peak of the boom, when the piggyback share and the investor share were highest.

A potential problem with using income information from HMDA is that the data reflect only what the mortgage lender verified in order to qualify the borrower for the loan, so HMDA data may not necessarily reflect the household's total income. Mortgage lenders have long favored income that can be documented and reasonably expected to continue into the future. If the borrower is purchasing a relatively inexpensive property, then the mortgage broker may not go to the trouble of documenting the stability of any income that is not needed to approve the loan.[6] Consequently, when house prices rise, the incomes reported on HMDA records may also rise, because borrowers will need to show more income to qualify for the larger mortgages. This fact makes individual-level income as reported on HMDA records potentially endogenous with respect to housing values. Additionally, as pointed out by Mian and Sufi (2017), borrowers or mortgage brokers may misrepresent income to lenders if they cannot document enough income to qualify for loans through legitimate means.[7] In light of the potential discrepancies in incomes reported to HMDA, in our main HMDA regressions we instrument for income using the median household income by tract from the decennial Census and the American Community Survey (ACS).

[6]Page D-10 of the 2013 Guide to HMDA Reporting states that: "An institution reports the gross annual income relied on in evaluating the credit worthiness of applicants. For example, if an institution relies on an applicant's salary to compute a debt-to-income ratio but also relies on the applicant's annual bonus to evaluate creditworthiness, the institution reports the salary and the bonus to the extent relied upon."

[7]Some evidence on the potential endogeneity of incomes reported in the HMDA data comes from a comparison of HMDA incomes to Census income data. The decennial US Census and the American Community Survey (ACS) include data on the incomes of homeowners with mortgages and who have recently moved. Avery et al. (2012) find that average incomes reported on HMDA records were up to 30 percent higher than incomes reported in the ACS in 2005 and 2006 in five states: California, Hawaii, Massachusetts, Nevada, and New York. By comparison, in 2000 reported incomes in HMDA were no more than 10 percent above those in the 2000 decennial census, and HMDA incomes from 2009 and 2010 were no more than 10 percent above those in the ACS. These time-series and geographical patterns are consistent with a positive relationship between house prices and reported HMDA incomes, although it is unclear how much of this correlation comes from the need to document additional income as opposed to outright fraud.

2.2 The American Housing Survey (AHS)

Another source of both income and mortgage-debt data is the American Housing Survey (AHS), which began in 1973 and has been conducted in every odd-numbered year since 1981. We use AHS data after a significant redesign in 1985.[8] The AHS is a joint project of the US Department of Housing and Urban Development (HUD) and the Census Bureau that is designed to measure the size, quality, and composition of the American housing stock. The survey also measures monthly housing costs for US residents and collects information on demographics and income of sampled households.

The AHS can be used to analyze the flow of new purchase-mortgage debt because the survey includes information about the size of any existing mortgages *at the time those mortgages were originated.* Our sample consists of homeowners who moved into their residences since the last AHS survey, for which the current mortgage is likely to be the purchase mortgage. Although the AHS includes no question asking whether the current mortgage on the house is the actual purchase mortgage, we do know whether the mortgage was taken out in the same year that the house was purchased, and we only use those mortgages. For income, the AHS includes both wage income and the household's total income. We use total income in our regressions, but our results are essentially identical when only wage income is used.[9] Because the AHS income measures come from surveys, not mortgage applications, they are much less likely to be influenced by housing prices. Indeed, Blackburn and Vermilyea (2012) use the AHS to directly measure income overstatement in HMDA from 1995 to 2007; we discuss that paper in more detail below.

As we do with the HMDA data, we take precautions regarding spurious outliers in the AHS, where problems can arise for two reasons. First, consider a new homeowner appearing in the 1991 AHS who moved into his residence in 1990, and then retired or significantly cut back his working hours in 1991. His 1991 income would be much lower than the 1990 income used to qualify for his mortgage. Some recent homeowners who report only a few thousand dollars of income in the survey year likely fit this scenario. A second problem arises from the topcoding of income and debt. Like many household surveys, the AHS reports a household's income level only if it falls below some upper limit, which changes across survey years. Mortgage debt is treated analogously, and income and debt levels above the topcode limits are replaced with allocated values.[10] By truncating the top and bottom 5 percent of

[8]For a general description of the AHS, see US Department of Housing and Urban Development (2017). For discussions of the AHS as a data source for housing-finance issues, including new mortgage debt, see Lam and Kaul (2003), Eggers (2007), and Eggers (2008).

[9]The similarity of our results using either total or wage income is not surprising in light of the exclusion of capital gains from the total-income measure. Because capital gains are rarely expected to continue year after year, this source of income is typically not used to qualify for mortgage loans.

[10]Early in the sample, the allocated values are the topcode limits themselves; later in the sample, the allocated values are the mean values of income or debt above the respective topcode limits.

the debt and income distributions, we found that we could exclude all topcoded debt and income values and also generate reasonable minimum income levels for home purchasers. As we show in the appendix, however, our results are materially unchanged (albeit somewhat noisier) when we run our regressions on the non-truncated data instead. Table 1 displays the unweighted sample counts from the AHS, with the last column showing that our baseline sample includes about 35,000 households in total.

Figure 2 compares median levels of new mortgage debt and income from HMDA and the AHS.[11] The top panel shows that the time-series patterns of median mortgage debt line up well across the two datasets, especially when we subset on metropolitan areas, where HMDA reporting is concentrated. The lower panel, however, shows that income reported to HMDA rises relative to AHS income during the height of the housing boom. The income pattern thus confirms a lesson from Avery et al. (2012), who note that income reported to HMDA potentially overstates a borrower's true income in areas or periods where house prices are rising rapidly. The pattern is also consistent with Blackburn and Vermilyea (2012), who use the AHS to measure HMDA income overstatement from 1995 to 2007. The authors compare the incomes of individual home purchasers in the AHS to local averages of reported HMDA incomes for similarly sized mortgages that have matching borrower and loan characteristics. They find income overstatement of around 15–20 percent in 2005 and 2006.

3 Income and Mortgage Debt in the 1990s and 2000s

3.1 The Canonical Debt-Income Regression

In the wake of the housing boom, the relationship between mortgage debt and income has been a focus of much empirical research, most of which is based on some variant of what can be called the canonical specification for the debt-income relationship:

$$D_{it} = \alpha_t + \beta_t I_{it} + \epsilon_{it}, \tag{1}$$

where D_{it} is the log of the value of a new mortgage originated for individual i in year t, I_{it} is log income, and the coefficients α and β have subscripts because they can change over time. Empirical estimates of β, the partial correlation between new debt and income, are positive because higher-income households tend to live in more expensive houses and take out larger mortgages. Additionally, low-income borrowers might face limits on the amount of mortgage debt they can take on, via ceilings on permissible DTI ratios. Relaxing these limits allows low-income households to take out larger mortgages, which increases the amount of debt at

[11] Because the median levels are not affected by the truncation rule, the AHS series are generated using the non-truncated sample of homeowners who recently moved into a new residence.

the bottom of the income distribution and causes a decline in the positive cross-sectional relationship between debt and income that is summarized by β.

Figure 3 motivates the regression analysis with binned scatter plots of log debt and income using individual-level data from HMDA and the AHS. In both cases, the cross-sectional relationship between income and debt is nearly linear in logs. The plots also show that for both data sources, the positive relationship between debt and income flattens from the beginning to the end of the sample periods. By running the canonical regression and examining the yearly βs that result, we can determine precisely when these declines took place.

3.2 Regression Results

We first use the canonical specification to study the data on individual-level debt and income obtained from HMDA. Some limited demographic variables are available in that dataset, and we are also able to include CBSA-year fixed effects to control for local housing market characteristics, including area-wide fluctuations in housing demand.[12] The CBSA-year fixed effects also correct for any over-reporting of income that is consistent across a local market in a given year. We modify Equation 1 to

$$D_{it} = \alpha_{ct} + \beta_t I_{it} + \gamma X_{it} + \epsilon_{it}, \tag{2}$$

where the vector X_{it} includes dummy variables denoting the borrower's race and gender, while c indexes the CBSA. Note that α_{ct} is indexed by CBSA as well as by time, so this term now represents CBSA-year fixed effects.[13] Because income reported in HMDA can potentially be overstated, as described in Section 2, we instrument for individual-level income reported to HMDA with median tract-level household income from the decennial Census and the ACS.

The top panel of Figure 4 displays the β_ts resulting from this regression, which trend downward from 1990 through the early 2000s. This trend is consistent with a steady decline in the partial correlation of income and debt until the housing boom begins, at which point there is an increase in the estimated β_ts. The bottom panel displays expected mortgage amounts, which are calculated from a regression that includes only yearly intercepts α_t rather than CBSA-fixed effects α_{ct}. The estimates of these intercepts are added to the yearly estimates of a $\beta_t \times \overline{I}_{.t}$ interaction, where $\overline{I_{.t}}$ denotes the mean of income in the entire sample. These expected amounts increase sharply after 2000, when the well-documented

[12]CBSAs, or core-based statistical areas, consist of at least one urbanized core with a population of 10,000 or more, along with adjacent counties that have a high level of social and economic integration. CBSAs have been the main way that the US government classifies metropolitan areas since 2003.

[13]In this regression, we will cluster the standard errors by CBSA, but the results remain robust when clustering by state.

increase in aggregate US mortgage debt to aggregate US income takes place.[14]

Figure 5 presents analogous results using the AHS. Recall that in this dataset, there is no need to instrument for income, which comes from survey data, not loan applications. Unfortunately, the small sample sizes in the AHS mean that we cannot run regressions with CBSA-year fixed effects.[15] The top panel in Figure 5 mimics the HMDA results, in that the debt-income relationship summarized in β_t declines throughout the 1990s and flattens out in the 2000s. The bottom panel shows the estimates of expected mortgage amounts. As with the HMDA data, these amounts increase rapidly during the housing boom.

4 Mortgage Debt and Income in the 2000s

The stability of the debt-income coefficients throughout the 2000s in both the HMDA and AHS regressions confirm a central finding in Adelino, Schoar, and Severino (2016): the debt-income relationship remained stable during the 2000s housing boom. Because we have treated second liens consistently over the sample period, and because we have addressed the possibility that individual-level income in HMDA can be overstated, our findings are immune to the criticisms of Adelino, Schoar, and Severino (2016) advanced by Mian and Sufi (2017).

The average-size finding is important because it speaks directly to what caused the 2000s housing boom. An exogenous expansion of credit would be expected to flatten the cross-sectional relationship between debt and income, because this expansion would have the largest effect on the mortgages taken out by the most-constrained borrowers, who are located at the lower end of the income distribution. The fact that no flattening occurred in the 2000s argues against this type of exogenous expansion. An alternative explanation for the housing boom is overly optimistic expectations regarding future house prices, which encouraged both high- and low-income households to increase their exposure to the housing market (Foote, Gerardi, and Willen 2012; Gennaioli and Shleifer 2018).

Yet the stability of the 2000s coefficients is only one piece of evidence regarding the source of the boom. An exogenous credit expansion can occur along the extensive margin, in which a larger number of low-income borrowers are approved for mortgages.[16] Neither the HMDA

[14] Figure A.2 in the appendix contains the results from parallel regressions that do not include CBSA-year fixed effects and that do not use Census tract-level median household income as an instrument for income reported to HMDA.

[15] We can, however, include yearly fixed effects for the United States's four Census regions: Northeast, Midwest, South and West. These results, along with additional robustness checks, are included in Figure A.3 in the appendix.

[16] Indeed, in their 2017 response paper to Adelino, Schoar, and Severino (2016), Mian and Sufi write that their original 2009 paper was focused on the extensive margin: "As a final note, it is important to note that [Mian and Sufi (2009)] focused on the extensive margin of mortgage lending, and the key argument in the study was that credit expanded on the extensive margin toward low-credit-score individuals, defined as those with a credit score below 660" (Mian and Sufi 2017, p. 1841). Although this quotation references zip codes

data nor the AHS can speak to the extensive-margin possibility, because neither dataset tells us how many mortgages were *terminated*. For example, the HMDA data shows that relatively more mortgages were originated in low-income zip codes during the boom. But the data are silent as to whether the additional mortgages resulted in new homeowners, as opposed to the new mortgages simply replacing or refinancing existing mortgages. A related question is whether a change in one flow of mortgage debt (the number of originations) resulted in a change in relative stocks of debt across the income distribution.

To answer this question, we need other data. In Foote, Loewenstein, and Willen (2019), we use information from the Equifax credit bureau and the Survey of Consumer Finances (SCF) to study both the stock of mortgage debt and the extensive margin of credit allocation.[17] In both datasets, and using several ways of distinguishing households cross-sectionally, we find that stocks of debt rose proportionately during the boom, just as the average size of new mortgages did. Stocks of debt behaved in this way because the higher number of mortgage originations in low-income zip codes was cancelled out by a higher number of mortgage terminations so that, on net, there was no relative extensive-margin expansion of credit to low-income areas.[18]

Yet the results above also show that during the 1990s, the debt-income relationship did flatten, suggesting that an exogenous credit expansion occurred during that decade. What might have caused this expansion, and what effect did it have on the US housing market? We take up those questions next.

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grouped by credit score, current research focuses on the debt-income relationship, which was also studied in Mian and Sufi's original paper. In practice, this makes little difference, because zip codes with low credit scores tend to have low-income residents as well.

[17]Adelino, Schoar, and Severino (2016) also include a graph that uses the SCF, but it displays debt-to-income ratios of borrowers in different income categories. Thus it does not shed light on the extensive margin—that is, whether the number of new borrowers expanded differently across the income distribution.

[18]In the appendix of Foote, Loewenstein, and Willen (2019), we show how these findings are consistent with the purported "negative correlation" between mortgage credit and income during the boom discussed in Mian and Sufi (2009). First, as we have noted, the mortgage credit referred to in Mian and Sufi (2009) is mortgage credit originated, not the stock of mortgage debt. Second, the regression used to show a negative correlation projects the *growth* in mortgage credit originated in a zip code on the *growth* of income. But this growth specification is appropriate only if the correlation under study remains stable across years; the proper regression to study a potential change in a correlation is in levels. Taking these two factors into account overturns the negative-correlation finding, as the zip-code level income is always positively correlated with both flows and stocks of debt. The positive correlations of income with the two flows decline during the boom, reflecting a relative increase in both mortgage originations and terminations in low-income areas. But because the increases in the two debt flows offset one another, the increases do not result in a relative increase in the stock of debt in poorer areas.

5 Mortgage Debt and Income in the 1990s

5.1 Interest Rates and Government Policy

Two related factors affecting the US mortgage market during the 1990s were the long decline in nominal interest rates and the emergence of a truly national mortgage market. The top-left panel of Figure 6 shows the mean and median nominal interest rate paid by movers in the AHS, along with the conventional 30-year rate for US mortgages published by Freddie Mac. The top-right panel shows that the dispersion in interest rates began to decline in 1985, a finding that is consistent with the increased geographic competition among lenders that took place during this period.[19] But the lower left panel shows that the β_ts estimated by our canonical regression display the same pattern even after controlling for individual-level interest rates, by allowing for yearly interest-rate effects as well as yearly income effects (the interest-rate coefficients themselves appear in the lower right panel).

The 1990s also saw a series of policy decisions intended to ensure that low-income households had access to mortgage credit (Wallison and Pinto 2012; Morgenson and Rosner 2011; Rajan 2010). Research in this area often cites the Clinton administration's National Homeownership Strategy of 1995, a policy initiative that encouraged housing-market participants from the private and public sectors to increase the number of US homeowners by 8 million by 2000. The varied nature of the 100 action items in this strategy make it difficult to assess this effort's direct effects. These items ranged from building-code reform (item 8), home mortgage loan-to-value flexibility (item 35), subsidies to reduce down payment and mortgage costs (item 36), flexible mortgage underwriting criteria (item 44), and education on alternative forms of homeownership (item 88).

Other regulations designed to increase US homeownership included the Community Reinvestment Act (CRA), which was passed in 1977 but strengthened in the 1990s, and a 1992 act that encouraged the government-sponsored enterprises (GSEs) to increase credit availability in low-income or underserved areas. Part of the GSE's efforts to expand mortgage credit to underserved borrowers were conducted through affordability programs, such as Freddie Mac's Affordable Gold program, which began in 1992. Among other things, the Affordable Gold program relaxed front-end and back-end DTI limits to 33 and 38 percent, respectively, and also allowed smaller down payments.[20]

[19]There is a long literature on the integration of the mortgage market with national capital markets, which limits the dispersion in mortgage interest rates paid by US households. A classic reference is Rudolph and Griffith (1997) and a more recent paper is Hurst et al. (2016).

[20]In some cases, the back-end ratio could rise to 42 percent. The normal limits for these ratios was 28 and 36 percent. The program also allowed borrowers to contribute less than the full 5 percent down payment from their own funds, and required participants to take a financial counseling course before purchasing a home. Fannie Mae had a similar program, called the Community Homebuyer Program, that began in 1990. See US Department of Housing and Urban Development (1996, p. 90) for details.

Could the shift in government and GSE policies during the 1990s be responsible for the decline in the debt-income coefficients we find for those years? Government policies that rewarded lenders for making loans to underserved areas have been subject to a number of empirical tests, but regression-discontinuity studies fail to show that either the CRA or the 1992 GSE act had much of an effect (Bhutta 2011, 2012; Avery and Brevoort 2015). For our part, we believe that while the GSE policy changes during the 1990s might explain some of our results, particularly in the early 1990s, the policy changes are not the whole story. The main reason why is that the debt-income coefficients from the regressions have remained low, even after the housing boom of the 2000s ended and GSE policy goals shifted. This stability points to a more fundamental and longer-lasting change in the evaluation of mortgage-credit risk during the 1990s that was separate from, but perhaps complimentary to, the GSE's goals at the time.

5.2 Decline in Mortgage-Processing Timelines

The best explanation for a longer-term change in credit allocation during the 1990s is that it stemmed from technology-augmented innovation. As noted earlier, significant technological advances in mortgage lending occurred during the 1990s (LaCour-Little 2000; Bogdon 2000; Colton 2002). We provide some new evidence on those advances by illustrating the decline in the time required to originate a new mortgage that occurred during the 1990s. Our analysis of mortgage-origination timelines is made possible by the use of the confidential HMDA data; as noted in the data section, these data include both the application date of each mortgage as well as its so-called action date, when either the application is denied or a mortgage is originated. The mortgage timeline is simply the number of business days between the application and origination dates. A number of factors determine these timelines, including the volume of applications processed by the lender, the lender's size, and whether the borrower is applying alone or with a co-applicant. To account for as many of these determinants as possible, we run loan-level regressions that project the time required to process a loan on the assets of the lender (in logs), the lender type (credit union, thrift, mortgage company, and so on), the race and gender of the borrower, whether the borrower has a co-applicant, and a concurrent measure of mortgage application volume.[21]

Figure 7 depicts the results of these regressions. Between 1995 and 1998, there is a dramatic decline in the average processing time for refinances, which then continues to drift lower until 2005. The timeline increases after 2007, but on average it remains about 10 business days faster today compared to before 1995. There is no such pattern for purchase

[21] Our measure of lending volume is the average number of mortgage applications per business day in each month using the HMDA data. To account for seasonality, we only consider loans originated in the second and third quarter of each year; other methods of accounting for seasonality give similar results.

loans. This is not surprising, because the closing dates for purchase loans are often chosen to accommodate the borrower and seller as they move to new residences. Consequently, the time between a purchase-loan application and the closing date can be lengthy, even if the borrower has been pre-approved and has provided much of the necessary documentation before making an offer on the house.

After the US housing boom ended, refinance timelines increase sharply as various lender and governmental policies changed. One of the most significant policy changes involved the repurchase policies of the GSEs. Fannie Mae and Freddie Mac occasionally require mortgage originators to repurchase loans that do not meet the agencies' underwriting guidelines. After housing prices fell, both Fannie and Freddie increased their repurchase requests to originators that had incorrectly underwritten loans. This prompted originators to follow GSE policies more carefully, which likely lengthened origination timelines. The post-crisis period also saw new disclosure rules for mortgage originators.[22] One goal of the new rules was to give borrowers more information about mortgage offers at the start of the origination process, so that they could better shop around for the best deal. Additional disclosures near the end of the process were intended to ensure that borrowers were not surprised at the loan closing about any features of the mortgages they ultimately chose.

The new disclosure regulations may well be a net plus for the housing market, because they provide potential borrowers with important information about their loans. Additionally, any effects of the new regulations or GSE practices on origination costs and timelines may fade as lenders adapt to them and the rules themselves evolve. Indeed, as discussed in Goodman (2017), the GSEs began instituting new policies for loan repurchases in September 2012; these policies include time limits on repurchase requests for newly originated loans and additional guidance on the types of defects that might prompt a repurchase.[23] Although further research is needed, our main point is that rule changes in the wake of the crisis may well explain the recent increase in origination timelines.

5.3 Credit Scores versus Artificial Intelligence (AI)

The decline in mortgage timelines during the 1990s provide a good summary statistic for the rapid technological progress then tranforming mortgage markets. But the specific technological innovation that most affected the debt-income relationship was the use of computers to evaluate credit risk. As discussed in the introduction, computerization in the

[22]The Dodd-Frank Act of 2010 instructed the new Consumer Finance Protection Bureau to propose rules that would combine and integrate mortgage disclosures under the Truth in Lending Act (TILA) and the Real Estate Settlement Procedures Act (RESPA). The final rule, called the TILA-RESPA Integrated Disclosure (TRID) Rule, became effective in 2013.

[23]See also the *Housing Wire* story titled "Fannie Mae, Freddie Mac Announce New Mortgage Buyback Rules," by Ben Lane, Oct. 7, 2015.

mortgage-lending industry was initially expected to take the form of artificial-intelligence algorithms that would replicate mortgage underwriters' decisions. But the intuitive decision rules employed by human underwriters proved difficult to code into formal algorithms, and the development of AI systems in the early 1990s eventually turned out to be a dead end. As one industry professional wrote, these algorithms "gave speed and consistency to the underwriting process, [but] by 1995 their accuracy was seriously questioned. These systems were built to reproduce manual underwriting without much consideration of whether the manual-underwriting thought process was optimal" (Makuch 1998, p. 4).

At the opposite end of the spectrum was a method that would prove much more accurate: numerical credit-scoring algorithms. An example of such an algorithm is a linear default regression that projects binary default indicators on variables derived from borrowers' credit histories and the risk characteristics of their loan applications. A more complicated algorithm to predict default risk might be estimated via machine learning, using nonlinear or hierarchical relationships among the relevant variables. In either case, the resulting default model could be used to construct predicted probabilities of default, which would then inform a mortgage lender's decision regarding whether to make a loan and the interest rate that should be charged. Credit-scoring algorithms have been used in one form or another at least since the 1970s; the first modern version of the FICO score appeared in 1989. Previous researchers have shown that the distillation of high-dimensional information from credit records into a single score had a substantial impact on many types of consumer loans, particularly credit cards (Evans and Schmalensee 2005).

Yet even as credit scoring transformed consumer lending in the 1990s, many lenders doubted that credit scores could help them predict mortgage-default risk. Unlike consumer debt, mortgages are secured loans, and the borrower's equity stake in the property plays a critical role in the default decision. In fact, the central project for academic economists studying mortgage default in the 1980s and 1990s was building the so-called frictionless option model (FOM), in which borrower-specific variables, including credit scores, play no role in the default decision. In the FOM, the borrower's default decision is fully characterized by the level of negative equity at which the borrower should "ruthlessly" or "strategically" default. This threshold equity level is a complex and time-varying function of borrower equity, house prices, and interest rates. Individual-level adverse life events such as job loss and illness do not lead to default in the FOM, because the model assumes that borrowers can ride out these problems by obtaining unsecured loans at the risk-free rate.

In reality, many borrowers are liquidity constrained, so adverse shocks can lead to default when borrowers are underwater on their mortgages. The mortgage-default literature is now attempting to blend insights from the FOM with those of the "double-trigger" model, which links default to the simultaneous occurrence of negative equity and an adverse life event.[24] In these models, borrowers who suffer adverse life events often lack the liquid funds needed to remain current on their mortgages and are unable to take take out unsecured loans to tide themselves over. Those borrowers who also have negative equity are unable to sell their homes at a price that is high enough to discharge their obligations, so default occurs.

Another relevant finding from the mortgage-default literature concerns those negative-equity borrowers who do not suffer adverse life events. For these unconstrained borrowers, most calibrations of the FOM generate optimal default triggers in the neighborhood of 10–25 percent negative equity (Kau, Keenan, and Kim 1994; Bhutta, Dokko, and Shan 2017). In empirical data, however, negative equity typically exceeds this level without the borrower defaulting. This result is relevant for mortgage-default modeling because it suggests that empirical models do not have to predict the relevant negative-equity default thresholds in a way that is consistent with the FOM.

The overall characterization of the default decision that emerges from this research suggests that initial LTV ratios and credit scores should be included in any empirical default model. Low initial LTV ratios (that is, high down payments) reduce the probability of future negative equity, so low LTV ratios reduce the probability of both double-trigger and strategic defaults. Borrowers with high credit scores should also be less likely to experience double-trigger defaults if these scores reflect low probabilities of experiencing a liquidity shock, either because the borrower has a stable job, or because he has ample liquid wealth.[25]

Although borrower income is critical in the new generation of default models, the role of future income shocks, as opposed to initial income levels, suggests that DTI ratios at origination should not affect default very much. In the double-trigger model, default occurs when an income shock raises the borrower's current DTI ratio to very high levels. Origination DTI ratios should matter only to the extent that low DTI ratios make it less likely that a borrower will experience a shock large enough to trigger default. The variance of income shocks at the individual level is so high that setting a low DTI ratio at origination may not offer the lender much insurance in that regard (Foote et al. 2009). After all, in the case of a job loss that halts income completely, the borrower's DTI rises to an infinite level no matter how low the origination DTI ratio had been.

[24]Examples of this work include Corradin (2014), Campbell and Cocco (2015), Laufer (2018), and Schelkle (2018). For a survey of recent research in this area, see Foote and Willen (2018).

[25]High credit scores may also indicate that the borrower assigns a high "stigma" cost to any type of default. This possibility also supports the inclusion of credit scores in mortgage-default models.

5.4 Integrating Credit Scores into Mortgage Lending Decisions

Empirical models estimated with individual mortgages confirm these theoretical predictions. In a very early study sponsored by the NBER, Herzog and Earley (1970) used data from 13,000 individual loans and found that initial LTV ratios were good default predictors; in the following decades, subsequent studies confirmed this result. Later researchers found that the new credit scores developed in the 1990s also entered mortgage-default regressions significantly. Mahoney and Zorn (1997) discuss Freddie Mac's modeling work in the early-to-mid 1990s, noting that borrowers with FICO scores less than 620 were found to be more than 18 times more likely to experience foreclosure than borrowers with scores greater than 660. Yet DTI ratios proved to be much weaker default predictors. An influential Federal Reserve study (Avery et al. 1996) summarized the existing consensus in both industry and academia by noting that "[p]erhaps surprisingly, after controlling for other factors, the initial ratio of debt payment to income has been found to be, at best, only weakly related to the likelihood of default" (p. 624). The Fed study also presented original research showing that credit scores were good predictors of default and could be used to improve lending decisions: "[t]he data consistently show that credit scores are useful in gauging the relative levels of risk posed by both prospective mortgage borrowers and those with existing mortgages" (p. 647).

Armed with this information, the GSEs began encouraging loan originators to use credit scores in their lending decisions. In July 1995, Freddie Mac's executive vice president for risk management, Michael K. Stamper, sent a letter to Freddie's sellers and servicers encouraging them to use credit-score cutoffs when underwriting loans. Loans with FICO scores over 660 should be underwritten with a "basic" review, while borrowers with scores between 620 and 660 should get a more "comprehensive" review. For borrowers with FICO scores below 620, underwriters should be "cautious," in that they should:

> [P]erform a particularly detailed review of all aspects of the borrower's credit history to ensure that you have satisfactorily established the borrowers' willingness to repay as agreed. Unless there are extenuating circumstances, a credit score in this range should be viewed as a strong indicator that the borrower does not show sufficient willingness to repay as agreed. (Stamper 1995, p. 2)

The letter also explicitly permitted lenders to use high credit scores to offset high DTI ratios: "A FICO bureau score of 720 or higher... will generally imply a good-to-excellent credit reputation. If your underwriter confirms that the borrower's credit reputation is indeed excellent, then it could be used a compensating factor for debt-to-income ratios that are somewhat higher than our traditional guidelines ..." (Stamper 1995, p. 13). Within a few months, Fannie Mae followed suit by encouraging lenders to use credit-score cutoffs that were identical to the ones recommended by Freddie Mac.[26]

In addition to supporting the general use of credit scores, the empirical default models were used to develop numerical scorecards that could weigh all the data in a loan application. One scorecard produced by Freddie Mac was the Gold Measure Worksheet, which was designed to assist underwriters in evaluating applications for the Affordable Gold program. This worksheet, which also appeared in Avery et al. (1996) and which we reprint as Figure 8, allocated risk units to a loan application based on the borrower's LTV ratio, DTI ratio, credit score, and other credit information. If a loan had 15 or fewer total risk units, then the loan met Freddie's underwriting standards.

The implicit weights in the worksheet reflect the lessons about the determinants of mortgage defaults that had been learned from empirical default models. Most importantly, the worksheet assigns a high importance to equity and credit scores and a low importance to origination DTIs. The table below illustrates this pattern by using the worksheet to evaluate three hypothetical loans. Loan A has an LTV of 90 percent, a FICO score of more than 790, and a DTI ratio exceeding 50.5 percent.[27] Although the DTI ratio is very high, the high FICO score offsets this penalty by enough to reduce the total risk-unit score to 14, which is one unit below Freddie's approval cutoff. The application for Loan B is generated by a hypothetical borrower with a low credit score and carries a much smaller DTI ratio. This loan turns out to be too risky, as its 17 risk units are two units above Freddie's cutoff. Finally, Loan C has very high LTV and DTI ratios (99.5 percent and 50.5 percent, respectively), as well as an adjustable interest rate. But the borrower also has a credit score of more than 790 and five months of liquid financial reserves. Because the latter factors are enough to offset the high DTI and LTV ratios, the loan just makes the risk-unit cutoff.

Although the Gold Measure Worksheet fit on a single page and took only minutes to complete, it proved to be far more accurate in predicting default than human underwriters, who also took much longer to evaluate each loan file. The superior speed and accuracy of scorecard-based evaluations were illustrated powerfully in a head-to-head comparison between human underwriters and the computer-based scorecard that is described in Straka (2000). Sometime after 1994 Freddie Mac purchased about 1,000 loans from a major lender through the Affordable Gold program. After Freddie Mac received these loans, the agency's quality-control investigators indicated that the loans' risk characteristics fell outside of Freddie Mac's guidelines, so a sample of 700 loans was scored using the Gold Measure Worksheet. This exercise, which took only a few hours, indicated that only about half of the loans were "investment quality" and thus eligible for purchase by Freddie Mac. At that point, human underwriters then re-evaluated all 1,000 mortgages, a process that took six months. The

[26]See Poon (2009, p. 663) and Dallas (1996) for details of Fannie Mae's instructions.

[27]This DTI ratio is the back-end ratio, so it encompasses not only the borrower's mortgage payment but also car loans and other regular installment payments.

	LTV Ratio	FICO Score	DTI Ratio	Months of Reserves	Fixed or Adjustable Rate	Total Risk Units
Loan A	90%	Over 790	Over 50.5%	2–3	Fixed	
Risk Unit Increment	0	–16	+30	0	0	14
Loan B	90%	640	Below 32.6%	2–3	Fixed	
Risk Unit Increment	0	+17	0	0	0	17
Loan C	99.5%	Over 790	50.5%	5	Adj.	
Risk Unit Increment	+13	–16	+18	–6	+6	15
Maximum Number of Risk Units Suggested by Freddie Mac for Loan Acceptance						**15**

Evaluating Alternative Loans Using the Gold Measure Worksheet
Note: These calculations correspond to single-family, 30-year mortgages for which no special cases apply (for example, the borrower is not self-employed). The adjustable-rate mortgage in Loan C is a rate-capped ARM (not a payment-capped ARM).
Source: Authors' calculations using the Gold Measure Worksheet in Figure 8.

underwriters also found that about half of the loans were good enough to be purchased by Freddie Mac. Yet while there was some overlap between the two assessment exercises, the underwriters and the worksheet delivered substantially different results on the set of mortgages that met Freddie Mac's standards.

By following these mortgages over time, Freddie Mac could conduct a horse race between the worksheet and human underwriters regarding their respective abilities to predict mortgage default. As Straka writes, "the race was not very close." During the first three years after origination—a period when underwriting differences tend to have the strongest effect on default outcomes—the worksheet ratings proved to be powerful predictors of mortgage distress. The foreclosure rate on loans placed in the worksheet's noninvestment category was almost three times higher than the foreclosure rate for loans in the investment category; the 30-day delinquency rate was nine times higher. But loans determined to be below investment quality by the underwriters performed almost exactly the same as the loans that the underwriters approved, despite the higher extra cost of the human evaluations: "[r]eview underwriting ratings that took six months to complete performed not much better (if better) than flipping coins" (Straka 2000, p. 219).

5.5 The Growth of Automated Underwriting

The next step was for the GSEs to leverage their central place in the US mortgage industry (and their substantial financial resources) by developing software that incorporated their default-prediction scorecards and that could be distributed directly to loan originators.[28] By 1995, both GSEs had developed automated underwriting (AU) systems: Loan Prospector at Freddie Mac and Desktop Underwriter at Fannie Mae. These proprietary software packages allowed loan originators to enter borrower and loan characteristics into a desktop computer, which would then report how the GSEs would treat the loan. For example, an "accept" rating from Loan Prospector meant that Freddie Mac would purchase the loan without conducting additional analysis. Ratings of "caution" or "refer" required the originator to perform additional screening before submitting the mortgage to the GSE for purchase.

As the GSEs gained more confidence with the ability of their AU systems to evaluate risk, they began to expand the credit box. Evidence on this point comes from data in Gates, Perry, and Zorn (2002), which we use to construct Table 2. The table reports the results of two additional horse races that also use the set of Affordable Gold mortgages referenced above. The two contests pit the human underwriters against the 1995 and 2000 calibrations of Freddie Mac's Loan Prospector AU system. The bracketed numbers in the table report the 90-day delinquency rate for each group of loans, relative to the delinquency rate for the entire sample; a rate of 1.00 indicates that the group defaulted at the same rate as the entire sample. The non-bracketed numbers in the table refer to group shares, as percentages of the entire sample of evaluated loans.

The first column reports the results from loans as they were classified by the human underwriters. As noted above, the underwriters took six months to designate about half of the loans as acceptable for purchase by Freddie Mac, although this group ultimately performed about the same as the noninvestment-quality half did.[29] The next two columns show how Freddie Mac's 1995 model evaluated the sample. The bottom row of the 1995 accept column indicates that with only 44.8 percent of the mortgages labeled as acceptable, the 1995 AU model was slightly more conservative than the human underwriters. But the 1995 AU model accepted many of the mortgages that the human underwriters rejected (a group comprising 20.8 percent of the sample), while it rejected many mortgages that the human underwriters accepted (27.5 percent). And the AU model appeared to pick the right mortgages on which to disagree, as its accepted mortgages defaulted at only about one-fifth the rate of the sample as a whole.

Gates, Perry, and Zorn (2002) observe that over time, "Freddie Mac rapidly expanded accept rates as the tool became more accurate and the company gained experience with and confidence in the new technology" (p. 380). This expansion is shown in the last two columns,

[28]Freddie Mac was generally ahead of Fannie Mae in this effort. In fact, Fannie Mae started out as a leader in developing computerized AI algorithms to mimic human decisions. But Fannie Mae officials eventually realized that it was critical to incorporate lessons from empirical default models into any computerized underwriting system. See McDonald et al. (1997) for details.

[29]Indeed, the underwriters' "accept" group had a relative default rate of 1.04, a bit higher than the default rate for rejected half (0.96).

which depict accept rates and relative performance according to the 2000 version of Loan Prospector. The model now accepts more than 87 percent of the sample, but the relative delinquency rate of this group is still better than the 51.6 percent accepted by the humans (0.70 vs. 1.04).

How much of this credit-box expansion involved an increase in permissible DTI ratios? Once lending policies have been encoded into a proprietary automated underwriting system, we can no longer evaluate them with comparisons of hypothetical loans, as we did for the Gold Measure Worksheet. But relaxed DTI standards were no doubt an important part of the credit expansion. As the use of AU systems grew in the late 1990s, some borrowers and lenders became frustrated by their black-box nature, so the GSEs provided limited information about their underlying scorecards in mid-2000. Freddie Mac, for example, reported that DTI ratios (both front-end and back-end) were one of 14 factors that its algorithm considered. But this ratio was not one of the three most important factors, which were the borrower's total equity, loan type, and credit scores. As for Fannie Mae, a well-known syndicated real estate journalist wrote in mid-2000 that the most critical component of the Desktop Underwriter system was the credit score, and the last of 10 factors listed was the "payment shock." This shock was not the DTI ratio itself, but the *difference* between the new monthly mortgage payment and the amount that the homeowner was already paying for housing. And mortgage brokers did not view this weaker income test as a "major tripper-upper."[30]

6 Consequences of the 1990s Credit Expansion

A relaxation of current-income constraints should have the largest effect on borrowers with low current incomes relative to their expected future incomes. Young college graduates have relatively steep age-earnings profiles (Tamborini, Kim, and Sakamoto 2015), so we would expect the credit expansion described above to have relatively large effects on that group. The official homeownership rate is generated by the Current Population Survey/Housing Vacancy Survey (CPS/HVS), so it is straightforward to test this prediction by disaggregating the CPS/HVS microdata by age and education. Figure 9 shows that the post-1994 increase in the homeownership rate was particularly large for younger persons with at least some years of college (that is, for college graduates and for persons with some college attendance but no degrees). The middle panel of the top row shows that among households headed by a 25–29 year-old, homeownership rates rose sharply among the more educated households, but barely moved for less-educated households. Qualitatively similar but less pronounced patterns are

[30]See "Building Blocks of Automated Underwriting," by Lew Sichelman, United Feature Syndicate, June 4, 2000.

evident for older households as well.[31] For all but the youngest age groups, homeownership rates for the college-educated are substantially higher than for the less-educated. Looking at all the evidence, we see that the credit expansion of the 1990s essentially allowed younger and better-educated households to purchase houses sooner than otherwise would have otherwise been the case. These households had expectations of relatively high permanent incomes (because of their educational attainment) but low current incomes (because of their ages).[32]

In allowing some young people to buy homes sooner than they otherwise would have, the credit expansion of the 1990s played out as a miniature version of the much larger credit expansion that took place immediately after World War II. In the 20 years after 1940, the introduction of zero-down-payment Veterans Administration loans and relaxed lending standards for mortgages insured by the Federal Housing Administration helped increase homeownership by nearly 20 percentage points.[33] Figure 10 uses data from the decennial Census and the American Community Survey (ACS) to provide a more detailed look at homeownership changes during various periods. The use of Census and ACS data rather than the CPS/HVS allows us to disaggregate these changes in homeownership rates sorted by four educational groups, rather than two, and also permits analysis by single-year-of-age rather than five-year age groups. The top panel of Figure 10 depicts ownership changes by single-year-of-age and education over the 1940–1960 period. As Fetter (2013) has shown, the main effect of underwriting changes immediately after World War II was to raise homeownership rates for younger adults, who were otherwise likely to purchase homes later in life. Eligibility for the mid-century lending programs was broadly distributed across the population with respect to education, so it is not surprising that young persons in all educational classes, except high school dropouts, saw their homeownership rates increase dramatically. Using the 1990 and 2000 Censuses and the 2005 ACS, the lower panels depict changes in ownership between 1990 and 2000 (bottom left panel) and 2000 and 2005 (lower left panel). Although the 1990–2000 panel shows little within-group increases, those in the 2000–2005 panel show that younger college graduates were most affected by the changes in mortgage-lending requirements, consistent with the above results from the HVS/CPS above. Homeownership rates for persons with no college education did not change during this period.

[31] For household heads under 25 years of age, homeownership rates rise for both higher- and lower-educated households. But ownership rates for both groups remain small throughout the sample period.

[32] The better-educated groups would also be less likely to experience income disruptions, because the probability that a worker transitions from employment to unemployment is an inverse function of his education level (Mincer 1991; Mukoyama and Şahin 2006).

[33] The homeownership rate rose from 43.9 percent in 1940 to 61.9 percent in 1960. See https://www.census.gov/hhes/www/housing/census/historic/owner.html for ownership rates based on decennial Census data.

7 Conclusion

During the last three decades, improvements in information technology have transformed numerous aspects of American life, including mortgage lending practices. During the 1990s, both mortgage and consumer lending were enhanced by technologies that not only processed data more rapidly, but could also evaluate risk more efficiently and accurately than humans could. For the mortgage industry, the new empirical models downplayed the role of current income in future mortgage default, so the 1990s saw mortgage credit expand exogenously with respect to income, a fact that makes the 1990s a particularly valuable period to consider when studying how changes in lending standards affect the housing market. By and large, the modest effects of this exogenous change on the overall US mortgage market are in line with economic theory, but the effects run counter to the claim that an exogenous change in lending standards during the 2000s was responsible for the period's aggregate housing boom.

A close look at the data and the historical record indicates that DTI ratios at origination became less important in lending decisions during the 1990s, consistent with modern theories of mortgage default as well as the debt-income analysis presented in section 3. Data also show that downplaying the importance of human judgment in default decisions improved the evaluation of credit risk, which explains why numerical methods continue to be developed today, via machine learning and other methods. To the extent that the information used in these methods is racially neutral, the models also deliver racially unbiased lending decisions, something that could not be taken for granted at the start of the 1990s (Munnell et al. 1996). The decreased cost, increased accuracy, and unbiased nature of AU systems help explain why they were embraced so quickly by mortgage lenders.

A deeper point is that the computerization of mortgage lending during the 1990s has close parallels with technological change in other industries. When the decade began, it was not clear exactly how computer technology could enhance the mortgage-lending process. Although attention initially focused on computerized AI systems designed to replicate human decisions, lenders eventually realized that information technology could bring about a more fundamental transformation of their industry by reducing the importance of human-based decision-making. There is an obvious parallel here with perhaps the best-known example in the productivity literature: the introduction of electricity into manufacturing in the early twentieth century (David 1990). US manufacturers took some time to realize that electricity could do more than simply replace the central steam-power sources in their multistory factories. Because sources of electricity could be distributed more easily throughout factories than steam power could, electricity allowed manufacturers to essentially turn their factories on their sides by constructing new single-story factories, through which materials could move more easily. As David (1990) and others have argued, computer technology also took time to translate into productivity gains, because businesses need a while to figure out the fundamental changes permitted by computerization. The transformation of mortgage lending during the 1990s provides another good example of this phenomenon, and future advances in fintech may provide additional examples in the years to come.

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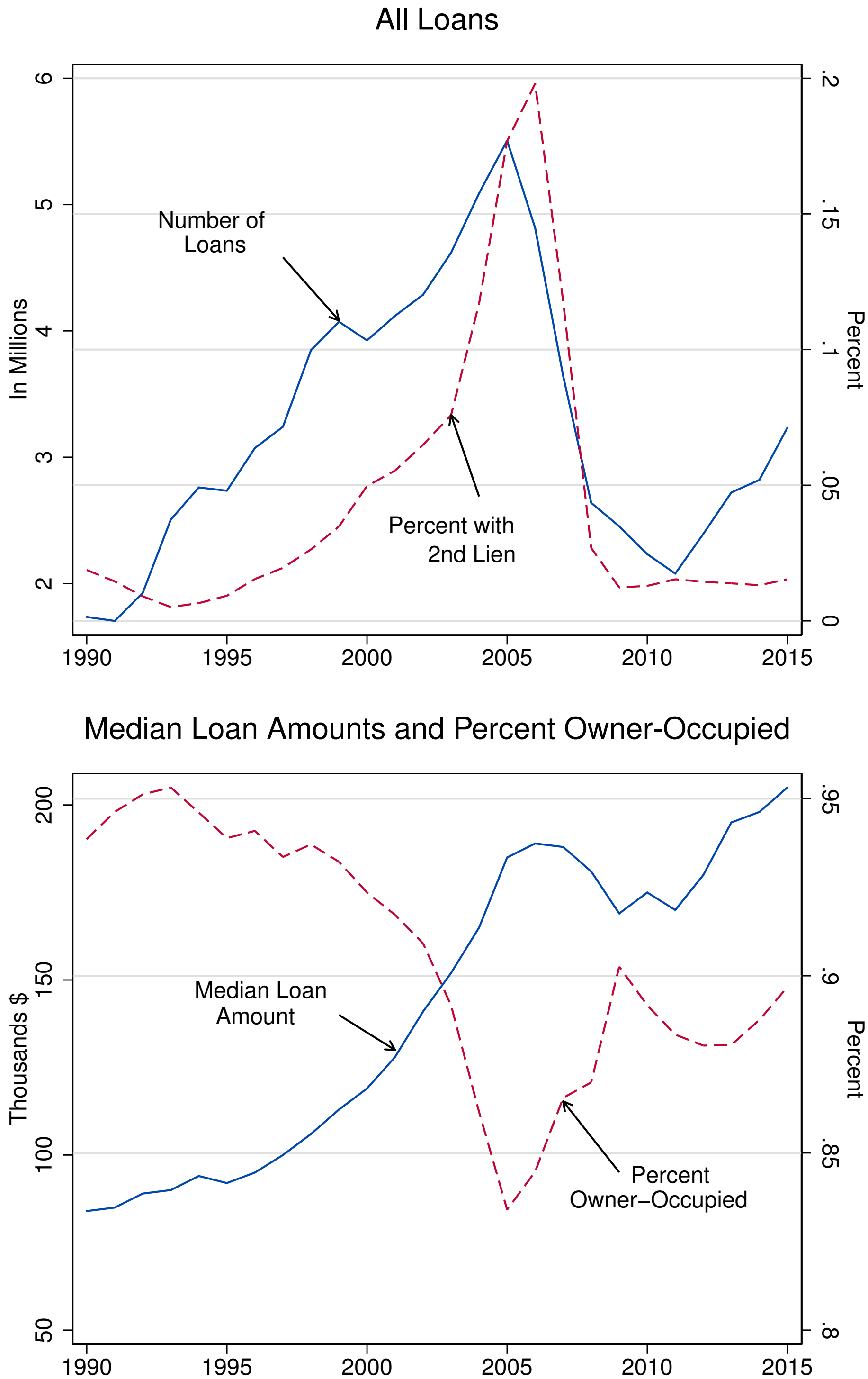


Figure 1. Summary Statistics from HMDA

Note: The total median loan amount refers to the median value of the sum of first liens and associated piggyback loans on owner-occupied properties. The percent with second lien is the share of all loans that have a piggyback loan.

Source: Microdata from the Home Mortgage Disclosure Act.

AHS Survey Year	(1) Total AHS Observations	(2) Occupied Interviews w/Nonzero Weights	(3) Homeowners	(4) Recently Moving Owners...	(5) ...with Nonzero Income & Mortgage Debt	(6) Truncate Top & Bottom 5% of Debt & Income (Baseline Sample)
1985	53,558	37,470	24,312	3,232	2,880	2,338
1987	54,052	43,436	28,857	3,184	2,740	2,259
1989	58,942	39,399	25,557	2,435	2,093	1,717
1991	59,491	44,764	29,608	2,851	2,440	2,004
1993	64,998	40,931	26,460	2,433	2,087	1,701
1995	63,143	45,675	29,384	3,436	3,424	2,742
1997	58,287	39,981	26,309	2,664	2,635	2,136
1999	67,177	46,589	30,799	3,228	3,198	2,587
2001	62,314	42,487	28,703	2,892	2,853	2,322
2003	71,170	48,197	32,586	3,209	3,174	2,589
2005	69,020	43,360	29,603	3,395	3,370	2,735
2007	65,419	39,107	26,671	2,616	2,598	2,094
2009	73,222	45,057	30,228	2,177	2,155	1,747
2011	186,448	134,918	82,418	5,372	5,313	4,252
2013	84,355	60,097	35,852	2,075	2,042	1,621
Totals					43,002	34,844

Table 1. Unweighted Sample Counts in the American Housing Survey
Source: Microdata from the American Housing Survey.

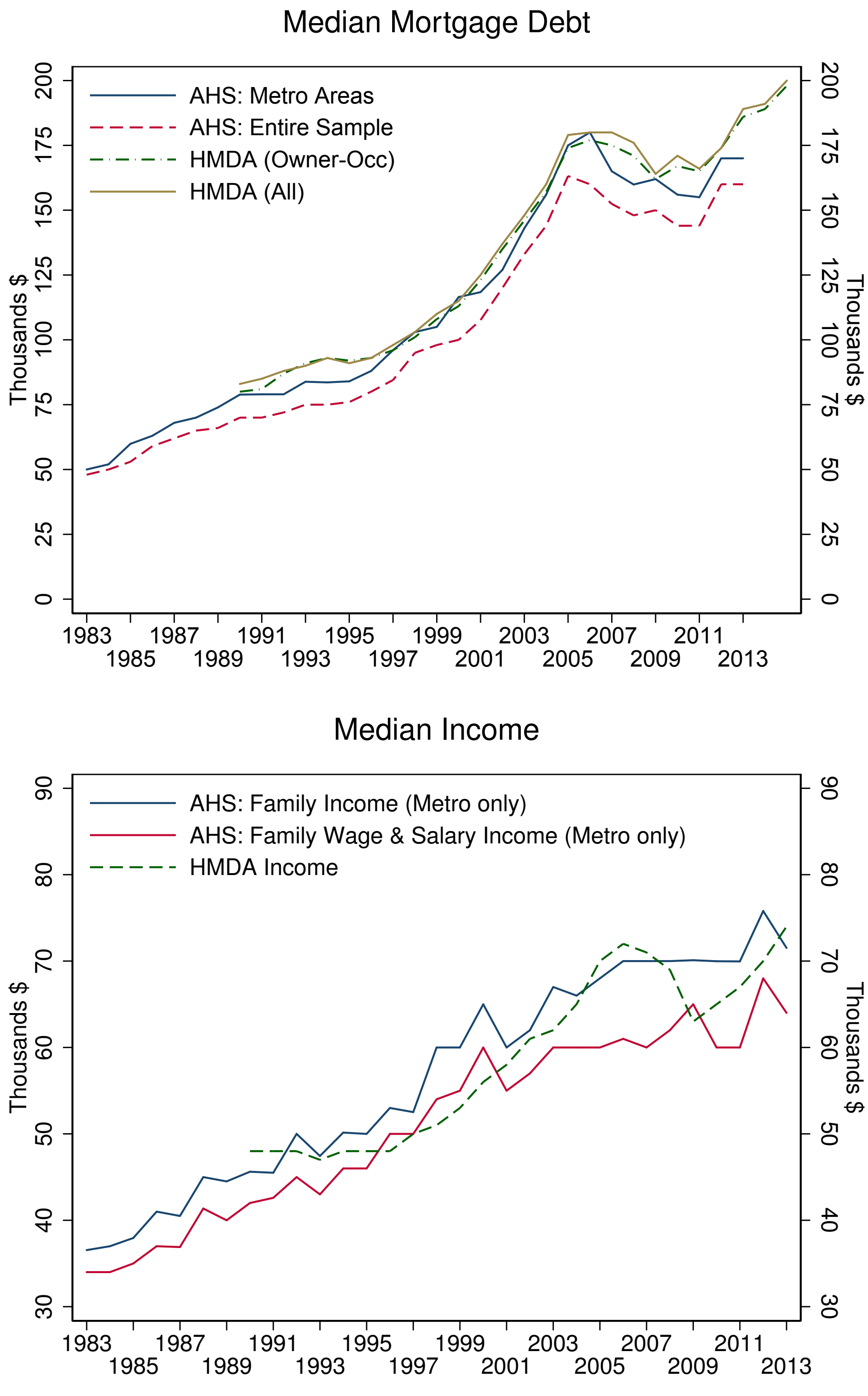


Figure 2. Comparison of Median New Mortgage Debt and Median Income from the Home Mortgage Disclosure Act and the American Housing Survey
Source: Microdata from the Home Mortgage Disclosure Act and the American Housing Survey.

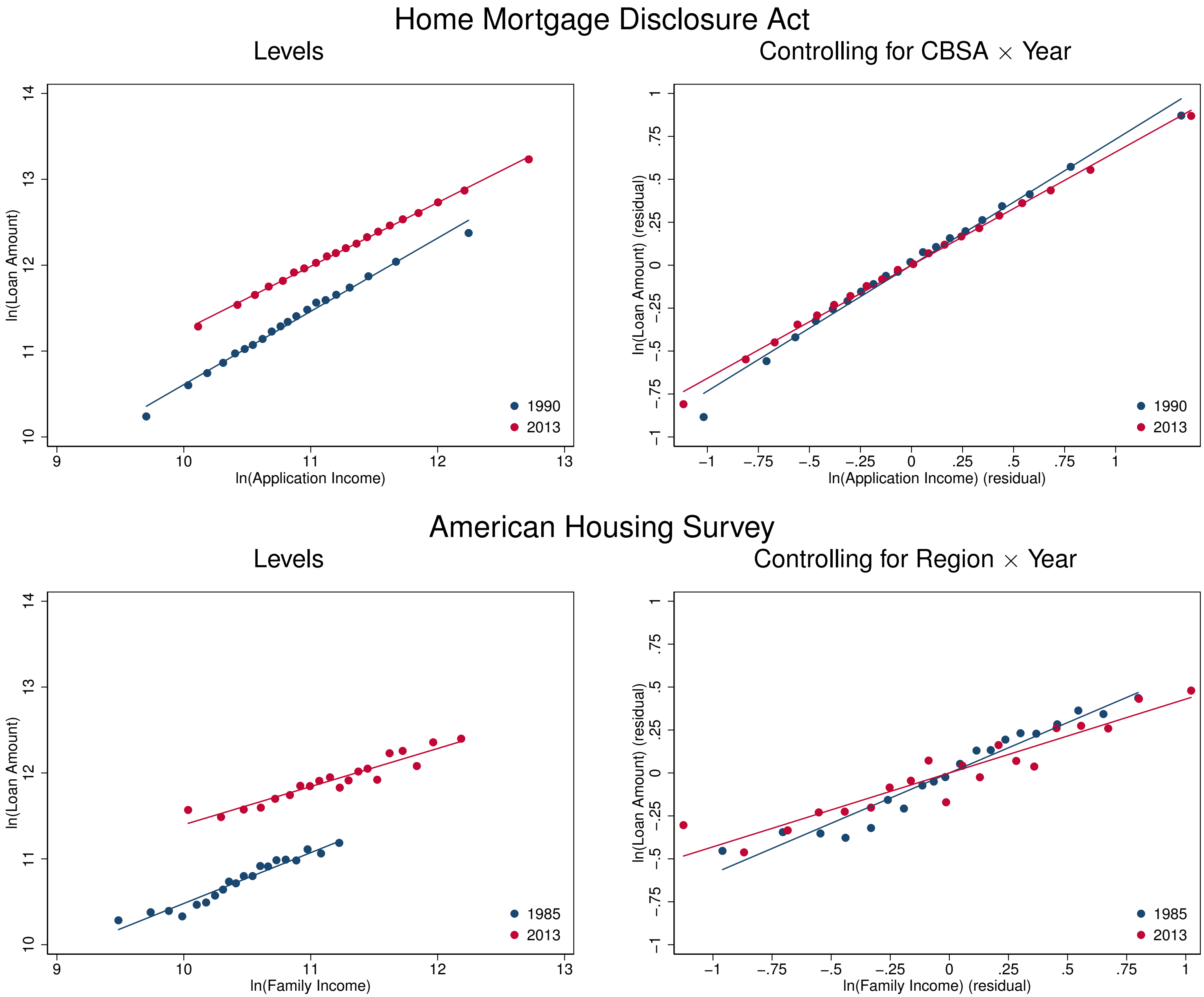
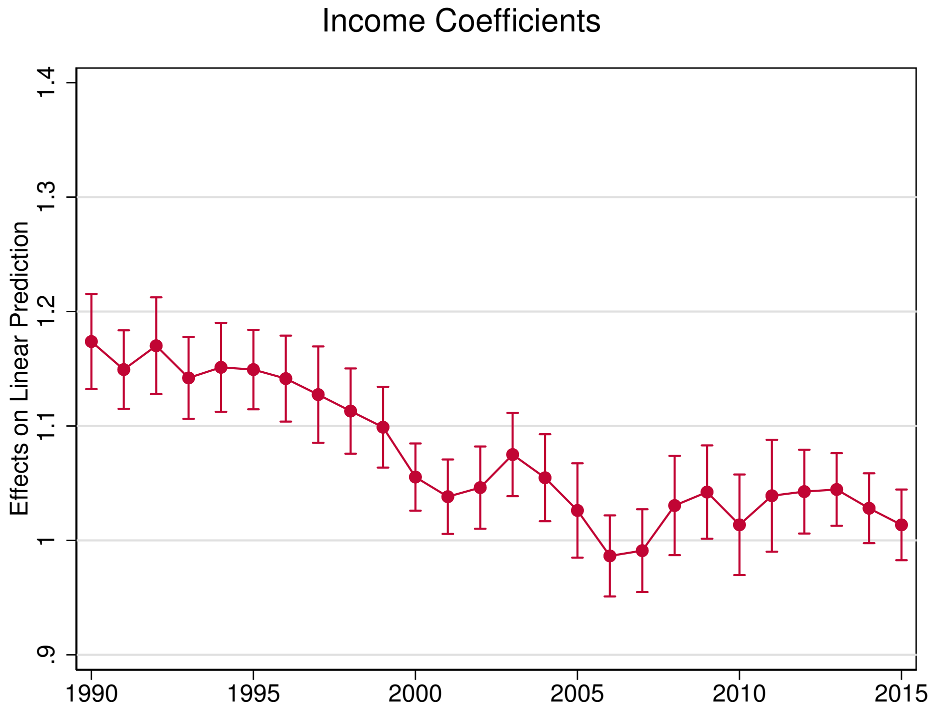


Figure 3. Binned Scatter Plots of New Mortgage Debt and Income at the Individual Level
Note: Each dot plots the average loan value for a given income quantile. The two left panels are binned scatter plots of residuals from regressions of the natural log of loan amounts and income on geographic area by year fixed effects.
Source: Microdata from the American Housing Survey and the Home Mortgage Disclosure Act.



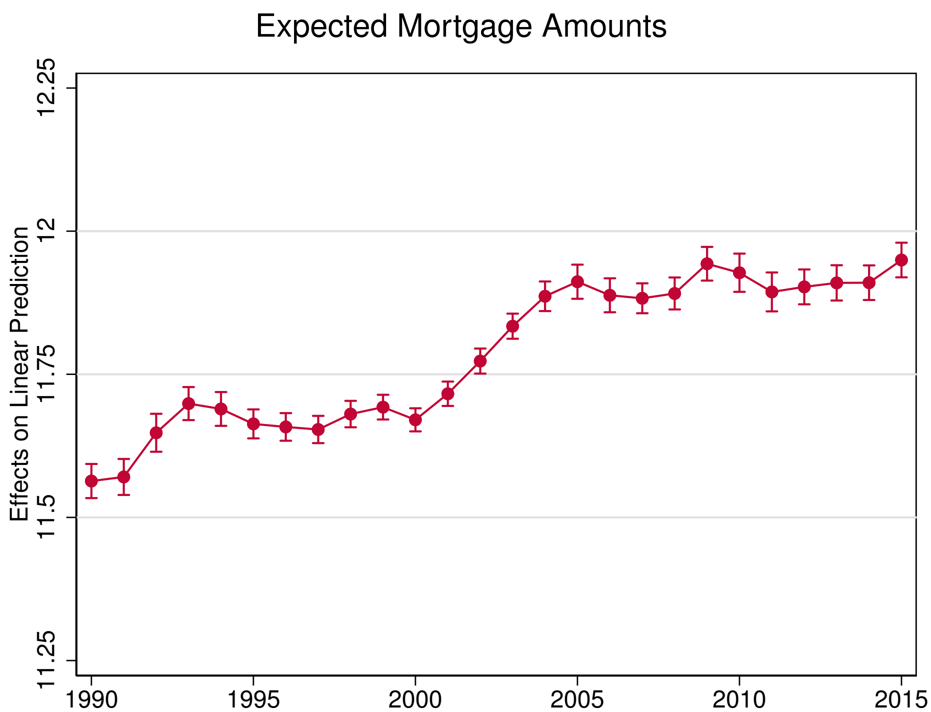


Figure 4. Regression using Individual-Level HMDA Mortgage Balances and Income Levels
Note: The top panel graphs income coefficients (and 95 percent confidence intervals) from regressions of individual purchase mortgage origination amounts from HMDA on measures of income from HMDA. The HMDA income measure is instrumented with the most recently available Census tract income from the Census and ACS. The regressions include CBSA $\times$ year fixed effects, and also control for the borrowers race and gender interacted with year. Expected mortgage amounts are predictions from an identical regression without CBSA fixed effects, holding income constant at its average value across all years.
Source: Home Mortgage Disclosure Act, US Decennial Census, and the American Community Survey.

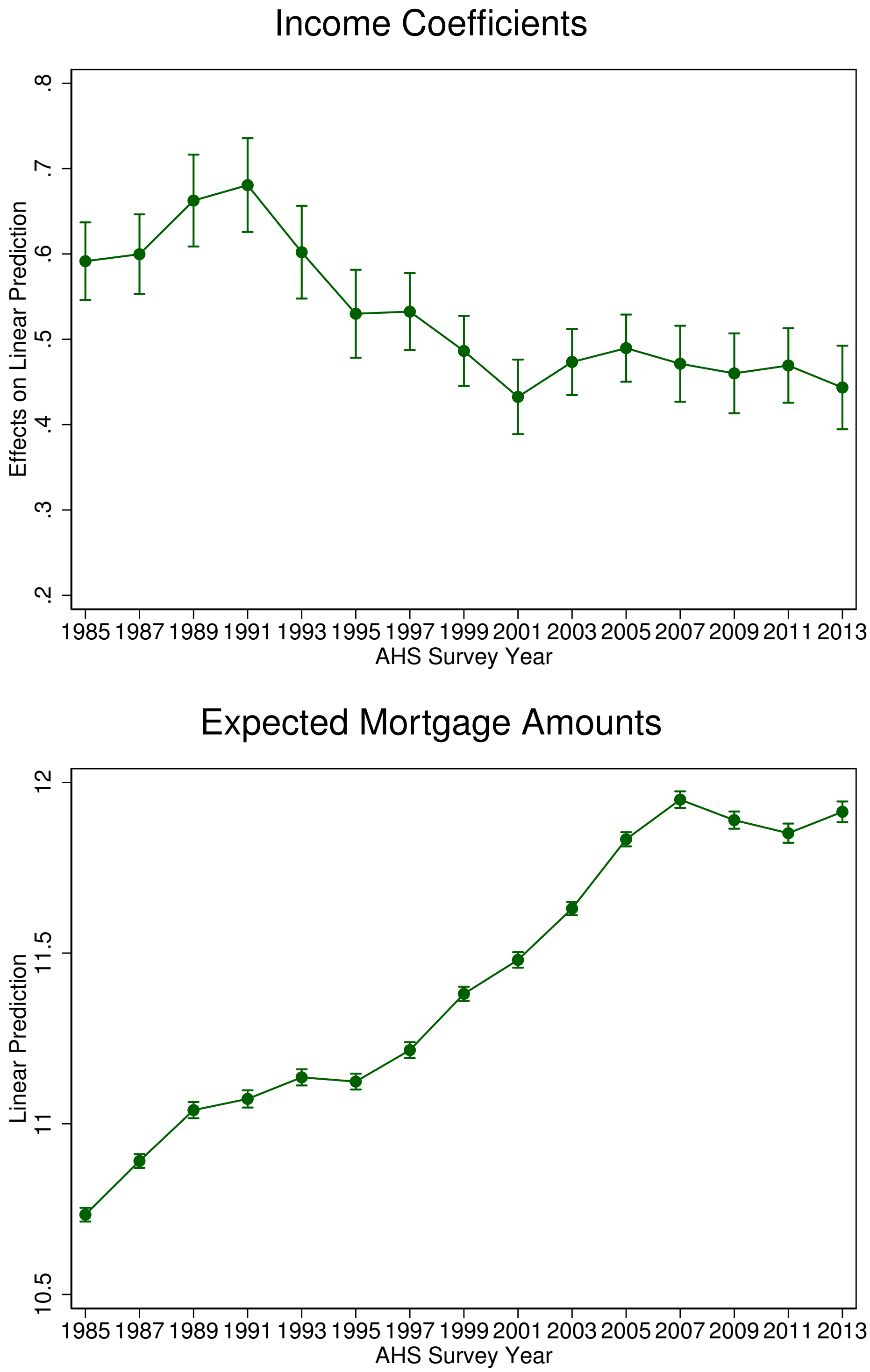


Figure 5. Regression using Individual-Level AHS Mortgage Balances and Income Levels
Note: The top panel graphs income coefficients (and 95 percent confidence intervals) from regressions of AHS mortgage amounts on AHS income at the individual level. The sample for the regressions is the baseline sample, described by the last column of Table 1. The years in the panel refer to the wave of the AHS, and the data are therefore generated by owners who move in the previous two years. The expected mortgage amounts in the lower panel are calculated as in Figure 4.
Source: Microdata from the American Housing Survey.

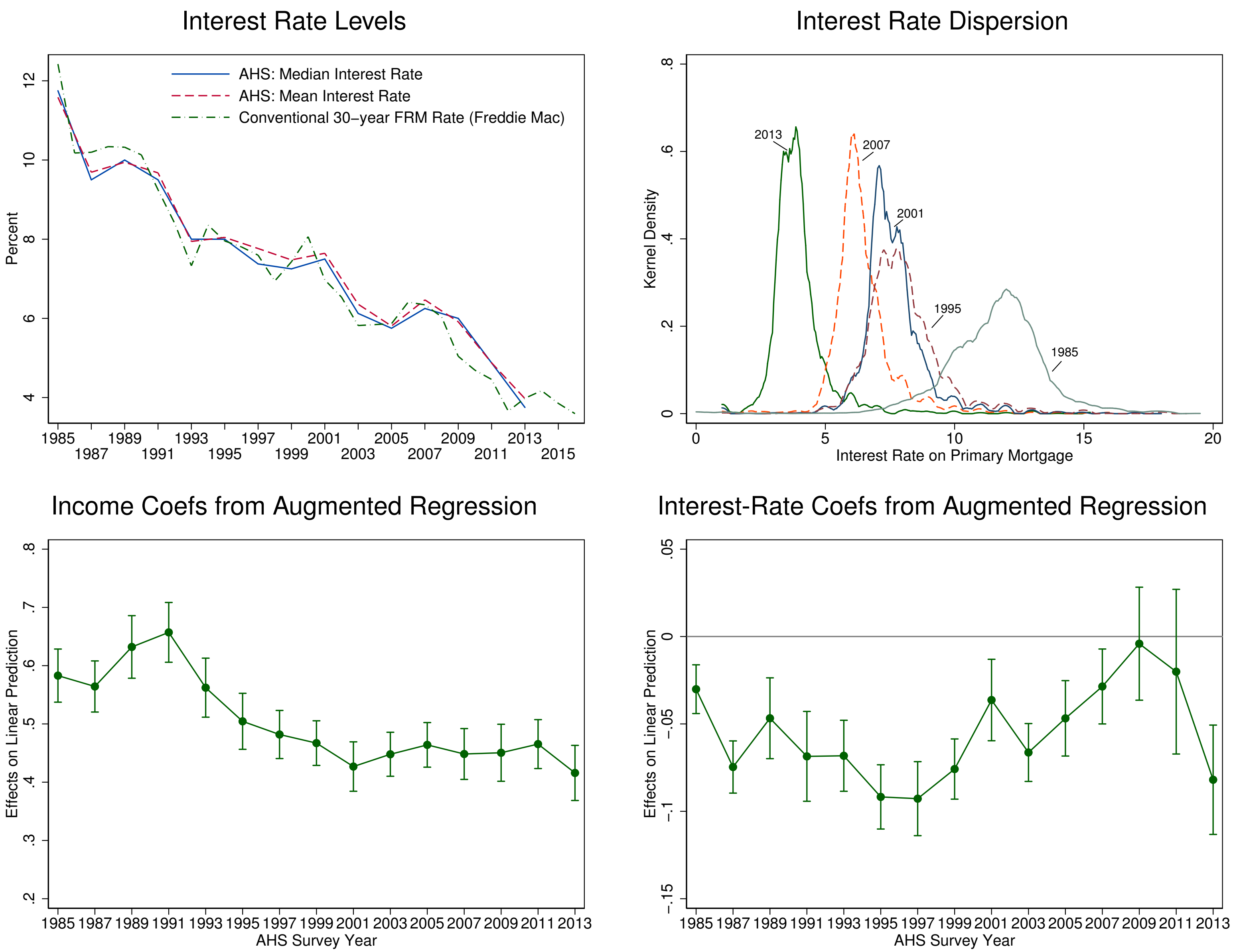


Figure 6. Interest Rates and Mortgage Lending
Source: American Housing Survey and Freddie Mac.

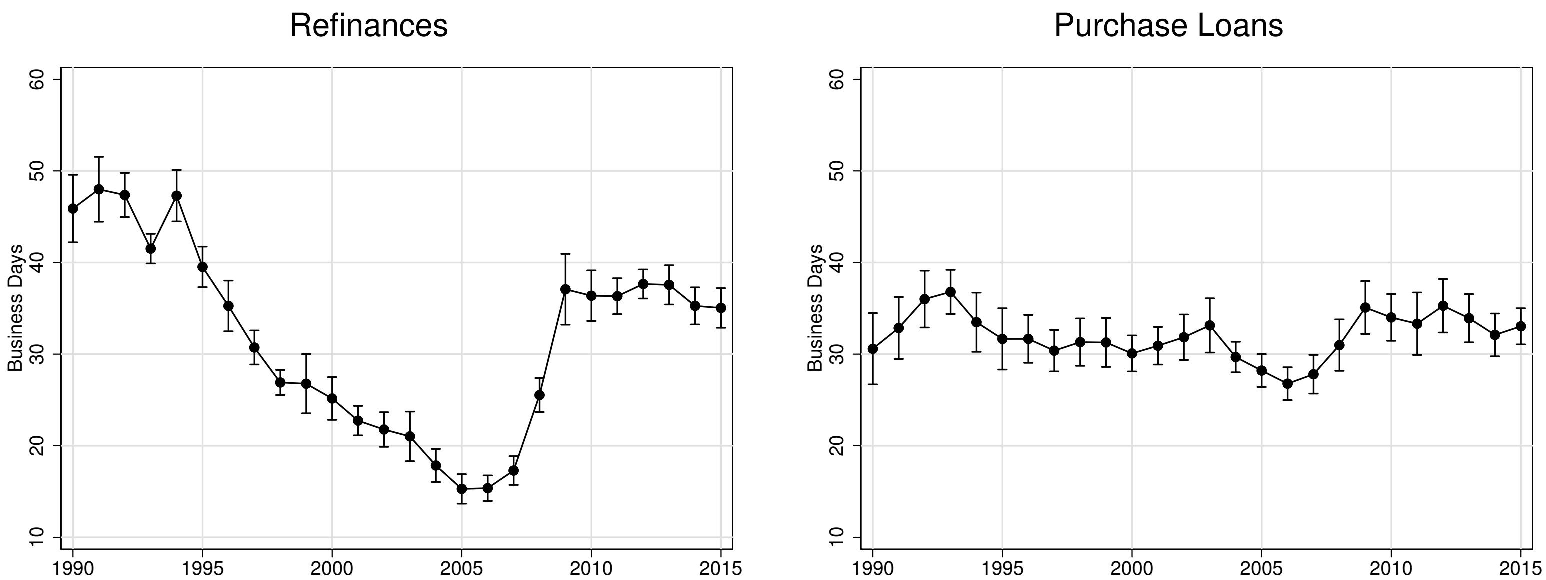


Figure 7. Time-to-Close Regressions
Note: Each panel shows a plot of the average processing time by year after stripping out any variation explained by the size of the lender, the borrower's race and gender, whether the borrower has a coapplicant, and the concurrent monthly application volume. The processing times are calculated as of the year of application and include both closed loans and denials.
Source: Microdata from the Home Mortgage Disclosure Act.

Freddie Mac

GOLD MEASURE WORKSHEET—Version 2.0

Borrower/Co-borrower Name(s) ______________________

City, State ______________________
Lender Loan Number ______________________
Origination Date ______________________
Completion Date ______________________

Seller Name ______________________
Freddie Mac Seller Number ______________________
Freddie Mac Loan Number (if available) ______________________
Branch Office/Channel ______________________
Underwriting Center ______________________
TPO Name ______________________
Underwriter ______________________

Loan Decision Approved __ Denied __ Withdrawn __ File Closed __

Directions:
- Circle the appropriate "Risk Units" (RUs) for each category. Total the RUs in each section and enter on the Subtotal line. Then combine Subtotals for each section and enter the Grand Total on the Total RUs line. Note that negative numbers such as "−2" are risk offsets.
- It is important to read the accompanying *Gold Measure Worksheet and Instructions—Version 2.0* booklet and to refer to it for additional information on completing this worksheet.
- This worksheet is an aid, not a substitute for the underwriting decision.
- Complete **either** Credit File A **or** Credit File B, but not both. Use Credit File A if 3 credit scores are requested. Use Credit File B if fewer than 3 credit scores are requested. See the *Gold Measure Worksheet and Instructions—Version 2.0* booklet for easy instructions on how to order bureau and bankruptcy scores for use with Credit File A.

I. Credit File A

Directions: When using Credit File A, complete **either** the Bureau Score **or** the Bankruptcy Score, but not both.

Bureau Score
Equifax Beacon Score, Trans Union Empirica Score and TRW-FICO Score (See instructions)

	RUs
Over 790	−16
771 – 790	−14
761 – 770	−11
731 – 760	−7
721 – 730	−5
701 – 720	0
681 – 700	6
661 – 680	8
641 – 660	12
621 – 640	17
601 – 620	20
581 – 600	23
541 – 580	25
540 or less	32
No reported Score available	20

Bankruptcy Score
Equifax DAS Score, Trans Union Delphi Score and TRW-MDS Score (See instructions)

	RUs
150 or less	−12
151 – 200	−10
201 – 240	−4
241 – 300	−3
301 – 320	−1
321 – 360	0
361 – 420	4
421 – 480	8
481 – 540	11
541 – 620	15
621 – 700	18
701 – 740	21
741 – 840	23
841 – 960	25
Over 960	29
No reported Score available	20

I. Credit File A. **Subtotal** of circled **RUs**: ______

II. Income

	RUs
Self-employed and above area median income:	5
Majority of income from commissions:	5
Employed second earner on application:	−2
Borrower's time on job is 5 years or more:	−2
Co-borrower's time on job is 2 years or more:	−1

II. Income. **Subtotal** of circled **RUs**: ______

III. Loan, Collateral, Assets

LTV/TLTV (including secondary financing*) is:

	RUs
60.5% or lower	−27
60.6 – 70.5%	−16
70.6 – 80.0%	−5
80.1 – 85.5%	−1
85.6 – 90.5%	0
90.6 – 93.5%	2
93.6 – 94.5%	5
94.6 – 95.5%	8
95.6 – 96.5%	10
96.6 – 98.5%	11
98.6 – 99.5%	13
99.6 – 99.9%	15

Property seller contributions exceed 3% of value: **RUs** 5

Reserves are:

	RUs
Less than 1 month	8
At least 1, but less than 2 months	5
At least 2, but less than 4 months	0
At least 4, but less than 5 months	−3
5 or more months	−6

Less than 5% down from borrower funds with 95% LTV (e.g. Affordable Gold with 3/2 Option): **RUs** 8

III. Loan, Collateral, Assets. **Subtotal** of circled **RUs**: ______

*When secondary financing is included, if the secondary financing provides for any amortization (payments) before maturity of the Freddie Mac loan, then add 1% to LTV for every rounded percentage point of secondary financing. Likewise, add 0.5% to LTV for every rounded percentage point of secondary financing, if there is no amortization (no payments due) before maturity of the Freddie Mac loan. Unsecured grants or gifts require no adjustments to LTV.

I. Credit File B

Directions: Use Credit File B if fewer than 3 credit scores are requested.

No delinquencies or other derogatory tradeline or derogatory public record information and number of tradelines (open or closed) is:

	RUs
11 or more	−4
6 – 10	−3
1 – 5	0

One or more revolving tradelines and **total** revolving balances are under $500: **RUs** −4

Fewer than 3 tradelines (open or closed): **RUs** 2

Percent of all tradelines (open or closed) ever delinquent or worse (30-90 days or more, collection, charge-off, etc.):

	RUs
0 – 10%	−3
11 – 15%	0
16 – 40%	4
41 – 60%	8
Over 60%	11

Worst ever derogatory credit file entry is either:
- 30–180 days delinquent: **RUs** 6

or

- Public record (bankruptcy, foreclosure, judgment, lien, garnishment, suit, certain collections) or tradeline reported as over 180 days delinquent, charge-off, repossession or collection: **RUs** 10

Number of derogatory Public records:

	RUs
0 – 1	0
2 – 3	4
Over 3	9

Number of inquiries in the past 3 months:

	RUs
0	−2
1	0
2 – 3	5
4	8
5	11
More than 5	14

Age of **oldest tradeline** (in months):

	RUs
0 (no tradelines) – 6	18
7 – 12	13
13 – 24	7
25 – 48	3
49 – 72	2
73 – 120	0
121 – 168	−1
169 or more	−2

If age of oldest tradeline is 13–48 months and **any one or more** of the following:
- More than 3 inquiries within the past 3 months
- More than 3 tradelines opened in the past year
- Total open balances exceed $10,000

RUs 6

I. Credit File B. **Subtotal** of circled **RUs**: ______

IV. Debt-Payment Burden

Debt-to-income ratio is:

	RUs
Less than 32.6%	0
32.6 – 38.5%	2
38.6 – 40.5%	4
40.6 – 42.5%	7
42.6 – 44.5%	10
44.6 – 46.5%	13
46.6 – 48.5%	15
48.6 – 50.5%	18
Over 50.5%	30

Spread between total debt and housing ratios (i.e. nonhousing debt ratio) is:

	RUs
10 to 15%	2
More than 15%	5

Proposed housing expense is less than 120% of previous housing expense: **RUs** −1

IV. Debt-Payment Burden. **Subtotal** of circled **RUs**: ______

V. Loan/Property Type

Loan type is:

		RUs
Fixed-Rate:	15-Year	−6
	20-Year	−4
	25-Year	−1
ARM:	Rate-Capped	6
	Payment-Capped	8

Property type is:

	RUs
2 Unit	5
3–4 Unit	11
Condominium	5

V. Loan/Property Type. **Subtotal** of circled **RUs**: ______

Total of sections I A or B, II, III, IV and V. **TOTAL RUs:** ______

Freddie Mac Risk Unit Guideline:	15 RUs
If pre-purchase counseling:	16 RUs
If post-purchase counseling:	17 RUs
If pre- and post-purchase counseling:	18 RUs

Refer to *Gold Measure Worksheet and Instructions—Version 2.0* booklet for more information. This worksheet is an aid, not a substitute for the underwriting decision. Call your Account Representative for additional information.

Figure 8. FREDDIE MAC'S GOLD MEASURE WORKSHEET
Source: Avery et al. (1996).

			Automated Underwriting			
			1995 Model		2000 Model	
			Accept	Caution/ Reject	Accept	Caution/ Reject
Manual Underwriting	Accept	51.6 [1.04]	24.0 [0.21]	27.5 [1.75]	44.7 [0.66]	6.9 [3.52]
	Caution/ Reject	48.4 [0.96]	20.8 [0.21]	27.7 [1.52]	42.7 [0.75]	5.8 [2.55]
	Total	100 [1]	44.8 [0.21]	55.2 [1.63]	87.3 [0.70]	12.7 [3.08]

Table 2. Comparing Manual and Automated Underwriting on a Sample of Freddie Mac Loans
Note: The non-bracketed numbers in this table refer to group shares (as percentages of the entire evaluation sample). The bracketed numbers refer to the relative default rates (relative to the sample-wide rate).
Source: Gates, Perry, and Zorn (2002).

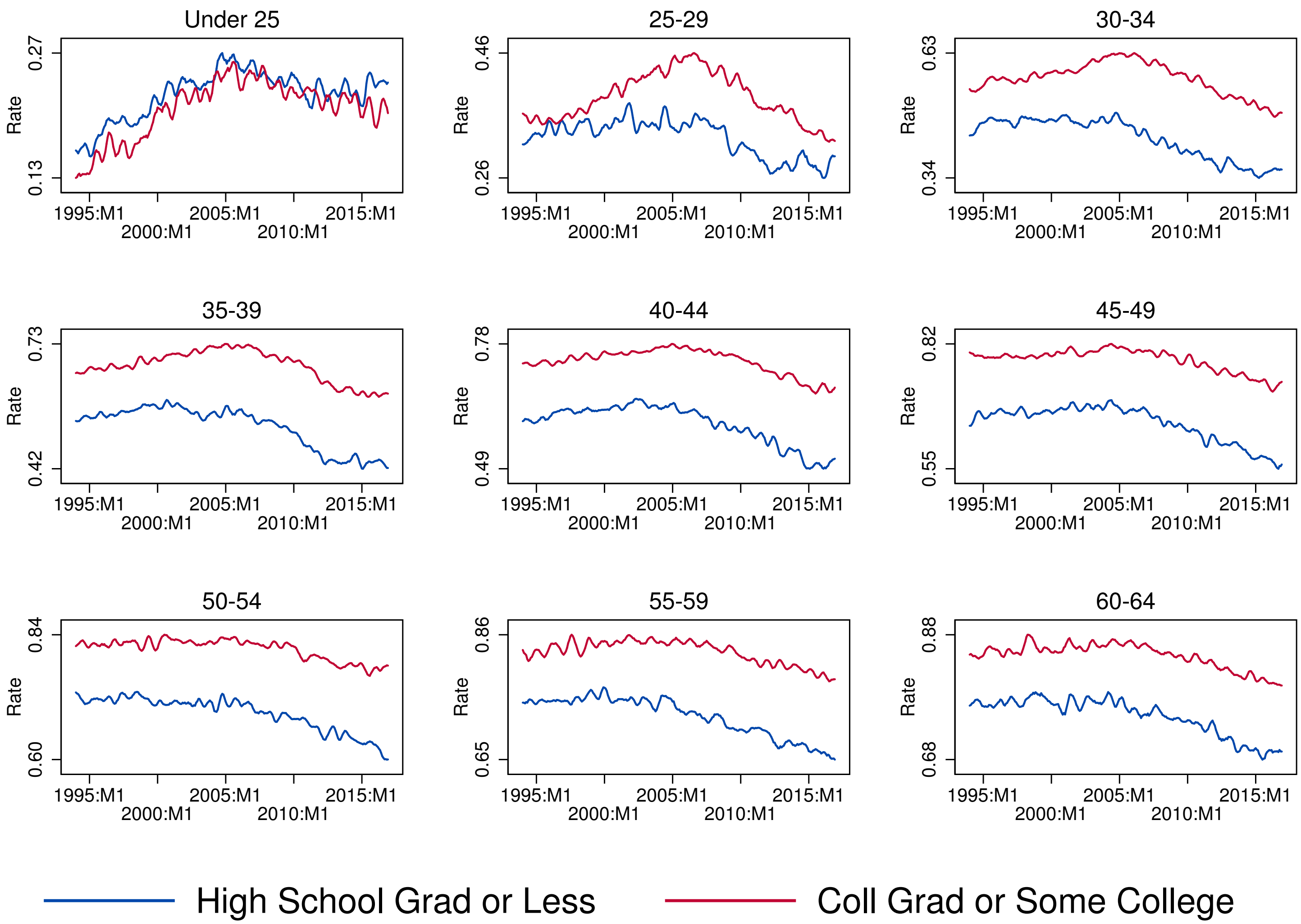


Figure 9. Homeownership Rates by Age of Householder and Education in the Current Population Survey/Housing Vacancy Survey

Note: Data are six-month moving averages of monthly rates.

Source: Microdata from the Current Population Survey/Housing Vacancy Survey.

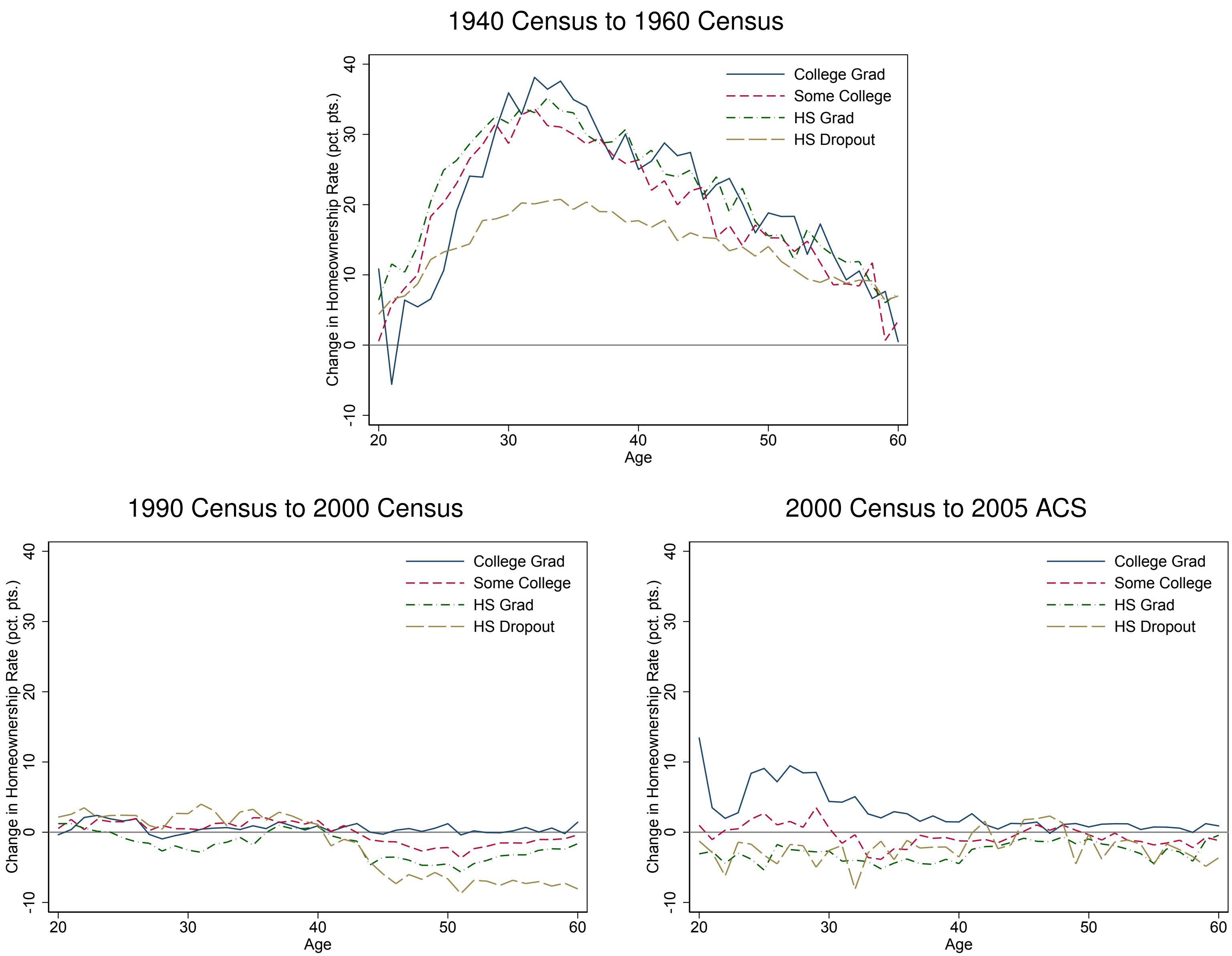


Figure 10. Changes in U.S. Homeownership in Three Historical Periods
Note: The top panel graphs the change in homeownership rates for households with heads of various ages and educational attainment from 1940 to 1960, using individual-level Census data (which are not available for 1950). The lower panels construct analogous graphs displaying homeownership changes between the 1990 and 2000 decennial Censuses (lower left panel) and the 2000 census and the 2005 ACS (lower right panel).
Source: 1940, 1960, 1990 and 2000 Decennial Censuses and 2005 ACS (from IPUMS: Ruggles et al. (2018)).

A Internet Appendix

A.1 Identifying Piggyback Loans in HMDA

The procedure for identifying piggyback loans in HMDA involves multiple stages. Each stage involves the identification of some piggyback loans, and after each stage, those piggyback loans and their associated first liens are removed from consideration.

The first stage uses loan-level characteristics available in HMDA to identify duplicate observations. Of the two observations that comprise a duplicate observation, we assume that the larger loan value is the first lien and that the smaller is the piggyback loan. The loan-level characteristics that we used to identify these duplicates are as follows:

1. The banking institution originating the loan.
2. The week that the loan was originated.
3. The month that the loan was originated.
4. The Census tract in which the property is located.
5. The loan type. Loans can be either conventional or guaranteed by the Federal Housing Administration (FHA), the Veterans Administration (VA), the Farm Service Agency (FSA) or the Rural Housing Service (RHS).
6. Whether or not the borrower will be occupying the property.
7. The income, race, and sex of the borrower.

The second identification stage is similar to the first, but in place of some of the loan-level characteristics, this stage assumes specific ratios of the origination amounts of first and second liens. First, we assume that the first lien is four times the value of the second lien (an 80–20 ratio), which is the most common ratio of first liens to their associated piggybacks. Then we assume that the ratio is 80–10, 80–5, and finally 80–15, which are also common ratios observed in the data. The loan-level characteristics used to match loans in this stage are the month of origination, the property's Census tract, and the borrower's income.

The third stage is more ad hoc and identifies piggyback loans using duplicate observations in a variety of loan-level variables:

1. The origination date; the application date; the property's Census tract; the borrower's income; and whether the borrower intends to occupy the property.

2. The origination date; the application date; the property's Census tract; the income of the borrower rounded to the nearest $10,000; whether the borrower plans to occupy the property; the borrower's sex and race; the co-applicant's sex and race; and whether the loans are conventional or guaranteed by one of the federal authorities listed above.

3. The origination date; the property's Census tract; whether the borrower is an owner-occupant; the banking institution that made the loans; and the income, race, and sex of the borrower.

4. The origination date; the banking institution that made the loans; the property's Census tract; whether the borrower intends to occupy the property; whether the loans are conventional or guaranteed by one of the federal authorities listed above; the race, sex, and income of the borrower; and the race and sex of the co-applicant.

5. The origination date; the banking institution that made the loans; the week the loans were applied for; the property's Census tract; whether the borrower intends to occupy the property; whether the loans are conventional or guaranteed by one of the federal authorities listed above; the income of the borrower rounded to the nearest $5,000; and the race and sex of the borrower and co-borrower.

6. The origination date; the week of application; the property's Census tract; whether the borrower intends to occupy the property; whether the loans are conventional or guaranteed by one of the federal authorities listed above; the income, race, and sex of the borrower; and the race of the co-borrower.

As a last step, we use county-level median house prices from Zillow, and code any loan that is less than 0.01 percent of the value of the median house price in the county as a piggyback loan. We are not able to identify the first liens associated with these piggyback loans, so they are removed from the analysis.

Starting in 2004, HMDA identifies the lien type of all reported loans, but does not link associated first and second liens. To assess the quality of our identification of piggyback loans, we compare our results to the HMDA-identified second liens in 2004. Of the loans that HMDA denotes as first liens, we identify more than 99 percent of them correctly as first liens. Of the loans that are coded in HMDA as second liens, we correctly identify 84.8 percent as second liens. Therefore, we falsely identify 15.2 percent of HMDA-coded second liens as first liens, and 0.9 percent of HMDA-coded first liens as second liens. Because there are many more first liens than piggyback loans, the number of falsely identified first liens is a little under half the number of falsely identified second liens. Unfortunately, these errors do not cancel each other out, but overall we correctly identify 97 percent of the loans. This rate holds for all years after 2004 as well. We also checked to see if our procedure was more accurate in higher or lower income areas. Using 2000 Census tract income, in 2004 we correctly identify 97.8 percent of the loans in the lowest quartile of Census tracts by median income, and 96.9 percent of the loans in the highest quartile of Census tracts.

Figure A.1 compares results from regressions that project individual loan amounts from HMDA on borrower-level incomes from HMDA. The gray line depicts the estimated income coefficients when all HMDA observations are treated equivalently; no attempt is made to distinguish observations with first liens from observations with second liens. The dataset generating the red line uses our identification algorithm to combine loan amounts from associated first and second liens into single observations. Estimates denoted by the blue line use a sample that includes only first-lien observations that are directly identified in HMDA starting in 2004. The divergence of the gray line from the red and blue lines indicates that first and second liens should not be treated as separate and equivalent observations in HMDA regressions. However, the general agreement between the red and blue lines indicates that a dataset in which first liens and piggyback loans on the same property are added together (shown by the red line) generates results that are similar to those obtained using as a dataset that omits second liens entirely (shown by the blue line).

A.2 Robustness Checks for Debt-Income Regressions

Figures A.2 and A.3 display results from alternative specifications of the debt-income regressions using either HMDA or AHS data. The dependent variable for these regressions is the loan amount, while the regressor of interest is borrower income. In our baseline specification using the HMDA data, we instrument individual-level HMDA income with tract-level income from the US Census or ACS. The baseline HMDA regressions also include CBSA-year fixed effects. The top left panel of Figure A.2 displays the income coefficients from a HMDA regression in which individual-level income is not instrumented and no CBSA-year fixed effects are included. The middle panel of the top row shows the expected mortgage amounts resulting from that regression. The top right panel of Figure A.2 displays the income coefficients from a regression is which income is not instrumented, but which includes CBSA-year fixed effects.

Each of the panels in the lower row comes from a regression for which tract-level income serves as an instrumental variable for individual-level income, as in the baseline specification. The first two panels of the lower row display the income coefficients and the expected mortgage amounts from an instrumented regression without CBSA-year fixed effects. The bottom right panel in the lower row depicts income coefficients from an IV regression that includes CBSA-year fixed effects. The last two panels of the lower row are therefore identical to the panels in Figure 4, which display our baseline results.

Figure A.3 presents alternative versions of the AHS regressions, with the top row reprinting the baseline results from Figure 5. Recall that the dataset used for the baseline results imposes a 5-percent truncation rule for income and mortgage debt; the baseline regressions also omit any geographic fixed effects. The middle row shows the effects of adding fixed effects generated by interacting Census region and year. The bottom row displays income coefficients from a regression that uses a non-truncated sample (left panel) and from a quantile regression that uses the truncated baseline sample (right panel). None of the changes made for this figure have a substantive effect on our main result: income coefficients are relatively stable in the 2000s but decline in the 1990s.

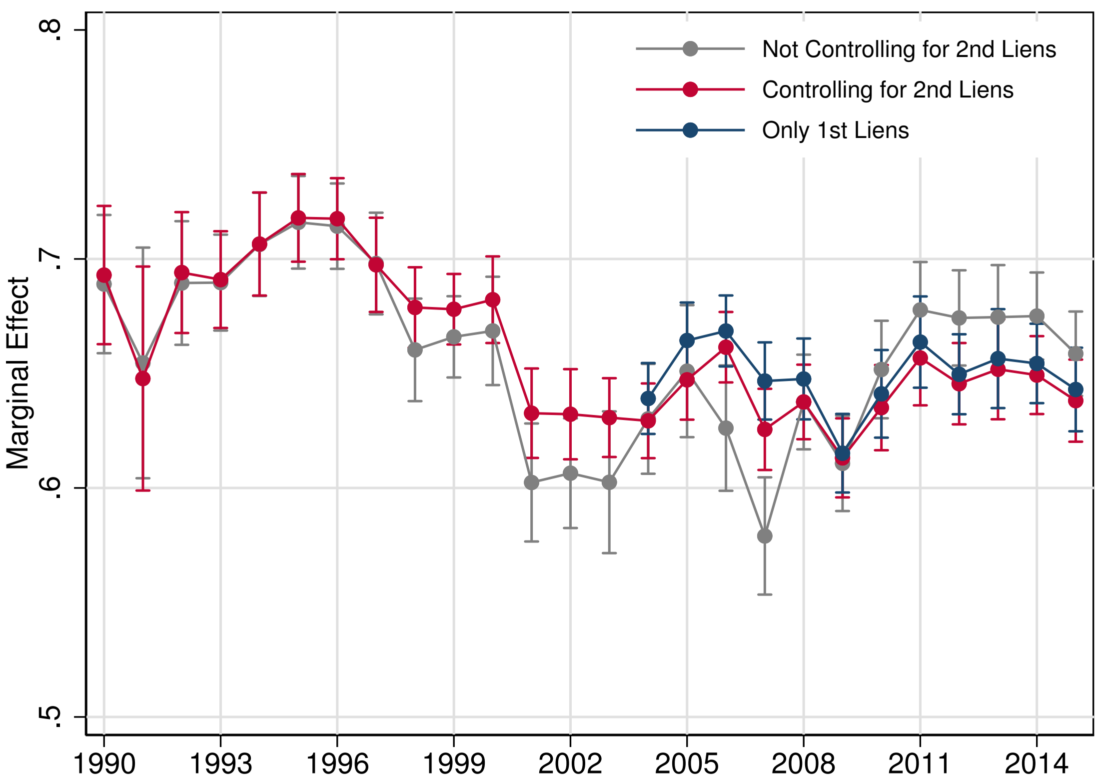


Figure A.1. Comparison of Author-Identified First Liens and those Identified by HMDA
Note: This graph plots coefficients from regressions of individual loan amounts on income and covariates from HMDA data. The blue line plots the coefficients only using first liens as identified by HMDA. The grey line does not make any correction for second liens. The red line uses the authors' algorithm to identify second liens back to 1990, and corrects the loan amount to account for both mortgages.
Source: HMDA.

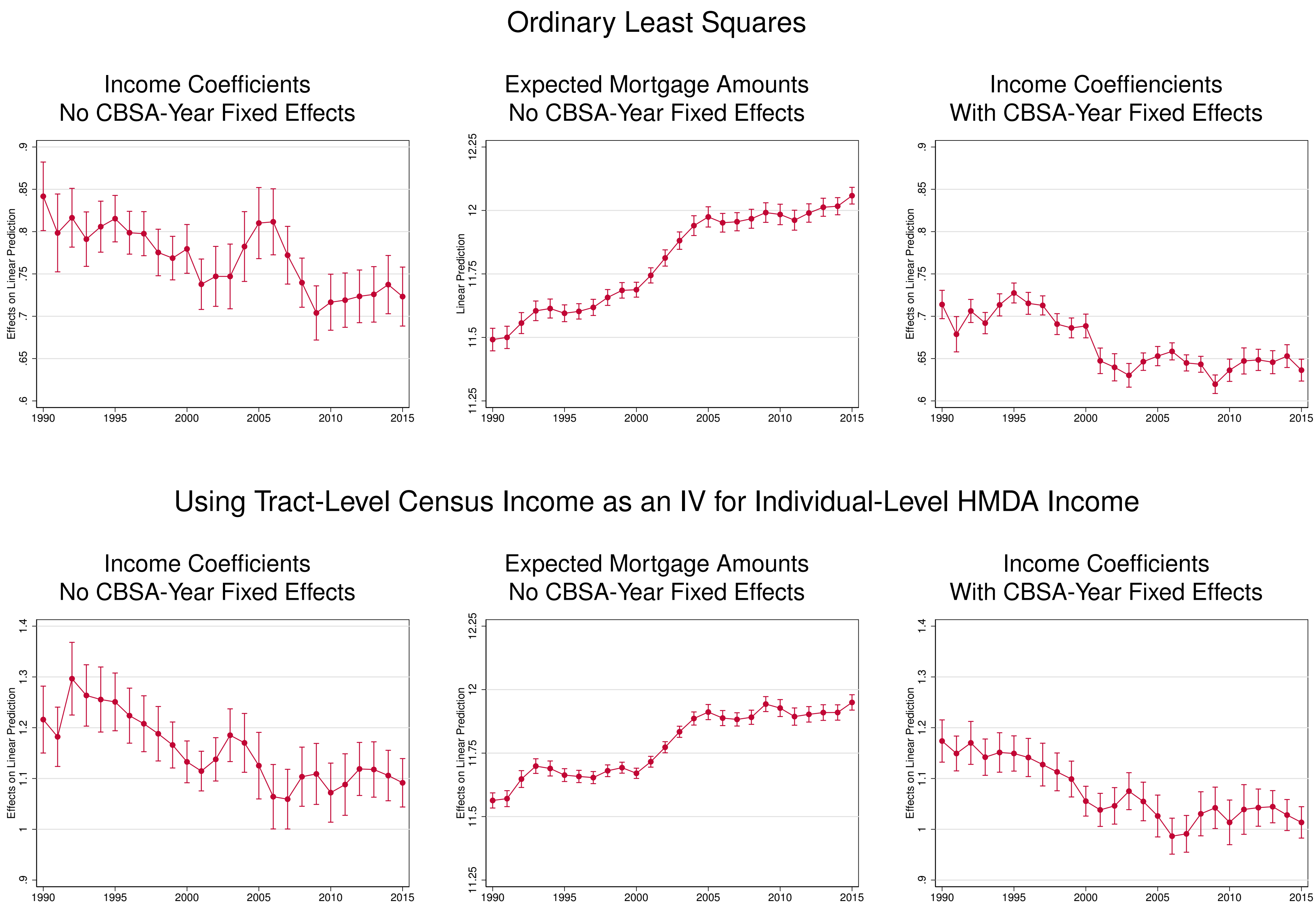


Figure A.2. Canonical Regression using Individual-Level HMDA Mortgage Balances and Income Levels

Note: These panels graph income coefficients (and 95 percent confidence intervals) from regressions of individual purchase-mortgage origination amounts determined from HMDA on measures of income. The top panels use individual income as reported in HMDA. The bottom panels instrument for HMDA income using the most recently available Census tract income from the Census and ACS. CBSA-year fixed effects are omitted in the first and second panels of each row. All specifications control for the borrower's race and gender interacted with year. Expected mortgage amounts are predictions, holding income constant at its average value across all years.

Source: HMDA, decennial Census, and the American Community Survey.

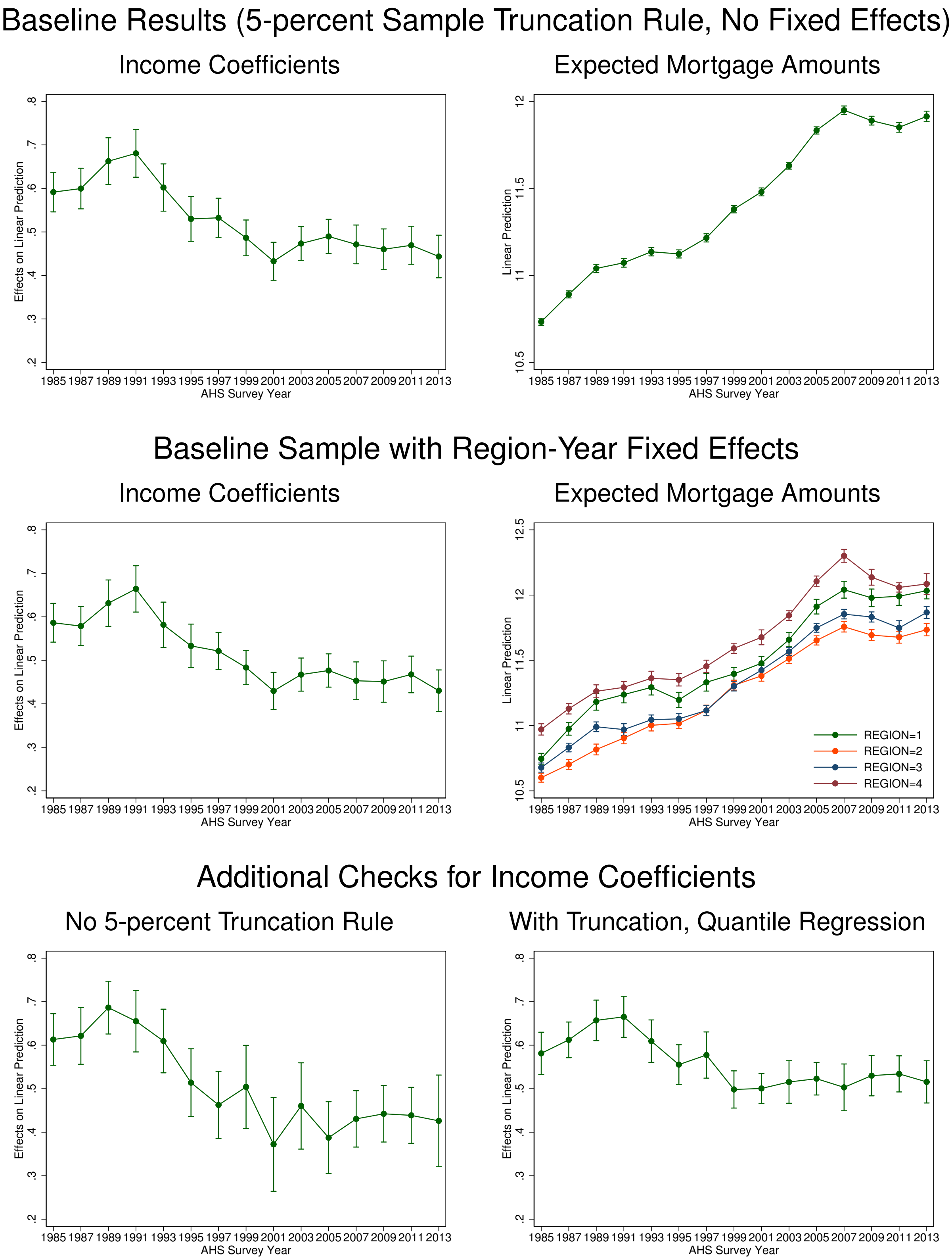


Figure A.3. Robustness Checks for AHS Regressions

Note: The top row reprints the baseline AHS results from Figure 5, which are generated by a regression run on a sample that imposes a 5-percent truncation rule for debt and income outliers. The middle row adds fixed effects that are generated by interacting Census region and year. The bottom row displays income coefficients from a regression that uses a non-truncated sample (left panel) and from a quantile regression that uses the baseline truncated sample (right panel).

Source: AHS.