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Jeffrey Thompson

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Do rising top incomes lead to increased borrowing in the rest of the distribution?

Jeffrey Thompson*
Federal Reserve Board of Governors
jeffrey.p.thompson@frb.gov

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Abstract:

One potential consequence of rising concentration of income at the top of the distribution is increased borrowing, as less affluent households attempt to maintain standards of living with less income. This paper explores the "keeping up with the Joneses" phenomenon using data from the Survey of Consumer Finances. Specifically, it examines the responsiveness of payment-to-income ratios for different debt types at different parts of the income distribution to changes in the income thresholds at the 95th and 99th percentiles. The analysis provides some evidence indicating that household debt payments are responsive to rising top incomes. Middle and upper-middle income households take on more housing-related debt and have higher housing debt payment to income ratios in places with higher top income levels. Among households at the bottom of the income distribution there is a decline in non-mortgage borrowing and debt payments in areas with rising top-income levels, consistent with restrictions in the supply of credit. The analysis also consistently shows that 95th percentile income has a greater influence on borrowing and debt payment across in the rest of the distribution than the more affluent 99th percentile level.

Key words: Inequality, Debt, Consumption

JEL Codes: D63, D14

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1. Introduction

Rising levels of income inequality have long been recognized by researchers in the US and other wealthy countries (Morelli, Smeeding, and Thompson, 2015). High-level policymakers are increasingly acknowledging the widening of the distribution of income as an area of concern. Indeed, in 2014 the head of the International Monetary Fund[1] and the Chair of the Federal Reserve Board[2] each gave important addresses on the subject of income inequality (and equality of opportunity), and in December 2013 President Obama identified income inequality and inadequate mobility as the "defining challenge of our time."[3]

This new attention by policymakers is partly a result of inequality continuing to rise, and partly due to other changes in the conversation around inequality. Commentary and research on the topic are increasingly asking about the potential consequences of inequality (Thompson and Leight, 2013). Instead of simply representing a distributional outcome which might be considered "unfair," rising income inequality itself may actually be producing potentially harmful outcomes. There is already a well-established, if unsettled, literature on the effects of inequality on overall levels of economic growth, and other potential consequences are also being explored.

One of those questions concerns the consequences of rising top income inequality on consumption and debt of households lower down the distribution. As the share of income held by households at the very top of the distribution has risen to the highest levels in generations (**Figure 1**), household borrowing has also climbed to historic high levels (**Figure 2**), and earnings across the broad middle and bottom of the distribution have experienced little growth. Several recent papers explore the link between inequality and consumption and borrowing (Bertrand and Morse, 2013; Coibion et al, 2014, and; Bricker, Ramcharan, and Krimmel, 2014).

This paper extends the budding literature on this question; it uses data from the Survey of Consumer Finances (SCF) to explore how changes in the income levels at the 95th and 99th percentiles of the distribution at the state-level have impacted borrowing and debt payments of

[1] http://wallstcheatsheet.com/politics/imf-head-inequality-will-haunt-the-21st-century.html/?a=viewall

[2] http://www.bostonfed.org/inequality2014/agenda/index.htm

[3] http://www.whitehouse.gov/the-press-office/2013/12/04/remarks-president-economic-mobility

households further down the income distribution. The contributions this paper makes to the literature include using superior data, as well improved outcome and inequality measures. Borrowing and debt payments are arguably better outcome measures than consumption in capturing an unsustainable household response to rising inequality. Changes in high-income levels, particularly at the 99th percentile, are also a better measure of the inequality signal that might influence households at various parts of the distribution than other measures such as the P90/P10 ratio or the Gini coefficient.[4]

The results from this paper indicate that household borrowing and debt payment does respond to changes in top-income levels, and that this response is primarily concentrated in housing-related debt payments and among households in the upper-middle and middle portions of the income distribution. These households are going into greater housing-related debt in places where top incomes are rising faster for reasons than cannot simply be explained by home prices; the results condition on MSA-level variation in quality-adjusted rent and elasticity of the housing supply as well as time-varying MSA-level measures of changes in average home prices, as well as length of household tenure. The findings also confirm that rising top incomes are associated with decreases in non-mortgage borrowing and payments. The paper proceeds in the next section by discussing different mechanisms by which income inequality could lead to increased consumption and debt among non-affluent households and several of the recent papers exploring this topic. Section three highlights the contribution made by this paper, the data used, and the empirical strategy. Section four discusses the findings, and section five concludes.

2. The Influence of Inequality on Consumption and Debt

There are multiple channels through which increasing inequality in the distribution of income could lead to higher consumption and greater levels of household debt. Broadly, the influence of inequality could work through the supply of credit or the demand for credit. Financial institutions could use increasing inequality of income within a region as information to help them target credit (Coibion et al, 2014). Alternatively, there are a variety of ways rising inequality could affect the demand for credit (Bertrand and Morse, 2013). If households value

[4] I also argue that residential sorting makes using very small geographic areas problematic for understanding the relationship between inequality and consumption, and that use of broader aggregates such as the state-level, as employed in this paper, is preferred.

their consumption relative to peer groups (including aspirational benchmark groups with somewhat higher incomes), rising incomes at the top of the distribution could lead to "expenditure cascades" where households further down the distribution increase their spending to maintain their relative status (Levine, Frank, and Dijk, 2010). Alternatively, rising top incomes could lead to a rising supply of "rich" goods in a market or rising prices for supply-constrained good and services, both of which could result in higher levels of consumption and debt among households across the rest of the distribution.

One recent paper addresses the way households signal status to their neighbors, and explores how changing inequality might influence signaling consumption. Bricker, Ramcharan, and Krimmel (2014) (BRK) argue that increased dispersion of incomes within a community increases the importance of using consumption to signal status to ones neighbors. They use data from the SCF and Census-tract level measures of income to explore the relationship between luxury car-buying and local income inequality. They find that census tracts with greater inequality do experience higher levels of luxury car-buying and household debt.

There are two important limitations of the analysis by BRK for understanding the implications of the rising levels of inequality in recent decades. The first is their use of a measure of inequality (Gini) that does not distinguish between changes in income at the top or bottom of the distribution. The Gini coefficient is a widely available distribution statistics, and one of the only measures available at the tract level, but it is relatively insensitive to changes in income at the top of the distribution. Compared to other distribution statistics, the Gini coefficient reveals the lowest levels of change in inequality in recent decades (**Figure 3**). The Gini coefficient does have a number of strengths, but it does a poor job of capturing the aspects of changing income – rising concentration at the top of the distribution – that has captured the public imagination in recent years.

The second limitation of BKR is their use of very small area geography, focusing on Census-tract level income in their analysis. One artifact of the way in which households sort themselves residentially, however, is that high-income communities experience the lowest levels of within-county inequality, and have seen the least change in within-county inequality over time. Figure 4 uses county-level data from the 2000 Decennial Census and shows a strong negative relationship between county-level median household income and the county-level Gini coefficient (**Figure 4A**). Between 1990 and 2006-10 counties with higher median incomes also experienced much smaller changes in their Gini coefficient, while lower-income counties had much larger increases and decreases in their Gini coefficients (**Figure 4B**). The geographic pattern of inequality depicted in Figure 4 suggests that the relatively high-income (within tract) households living in high inequality tracts that BRK find engaged in high levels of luxury car-buying actually overwhelmingly reside in low-income communities. The inequality they are exploring reflects distributional issues that are largely distinct from the dramatic increases in the top income shares seen in recent years.

Additional ways rising inequality could influence household consumption include the possibilities that consumption of high-income households influences a social standard or benchmark level that other household aspire to – regardless of neighbor status signaling – and also that the consumption behavior of high-income households could influence the prices and range of goods available to other households. Bertrand and Morse (2013) explore these mechanisms, using household income and consumption data from the Consumer Expenditure Survey (CEX) and income inequality measures from the Current Population Survey (CPS). They find that rising income at the 90th percentile of the distribution, at the state-level, does lead to higher levels of consumption, conditional on income, among households further down the distribution.

The findings of Bertrand and Morse (2013) are only an obvious concern if the higher levels of consumption they identify are not supported by higher current or future levels of household income. One important limitation of their analysis is that the CEX is a weak foundation on which to "hold income constant." The CEX has serious problems with underreporting of income at the bottom of the distribution, in addition to its problems reporting income and consumption at the top (Sabelhaus et al, 2012, Sabelhaus and Groen, 2000). An additional potential limitations of the Bertrand and Morse's (2013) findings are that, while they report rising levels of certain types of consumption, rising inequality could also be related to changes in the composition of consumption, leading them to overstate (or understate) the extent of the change in consumption.

Finally, the 90th percentile of the distribution is substantially lower than the income levels most Americans regard as "rich" and may be insufficient to capture the aspects of changes in the distribution that are capable of shaping the consumption behavior across the distribution.[5] In 2014 household taxable income at the 90th percentile was $121,000, equivalent to the family income of a married couple where one partner is a police officer ($60,000 average annual earnings) and the other is a secondary-level special education teacher ($61,000).[6] At the 99th percentile taxable income was $423,000 (Saez, 2015).

An entirely different mechanism through which rising inequality might influence consumption and debt is through the supply side of the credit market. If creditors use information on income levels and local distributions of income to identify credit risk, then rising inequality might result in less credit being made available to lower-income households in high inequality areas. Coibion et al (2014) propose this outcome and test it using data from the FRBNY Consumer Credit Panel/ Equifax Data. They find that low-income households in high-inequality areas accumulated less debt and had lower credit limits than their low-income counterparts in areas with lower inequality.

Coibion et al (2014) interpret these findings as a rejection of the “keeping up with the Joneses,” “trickle-down consumption” story, but this conclusion warrants additional caveats. Their paper focuses primarily on household in the bottom fifth of the income distribution, but low-income families are not the only – or even the primary – group presumed to be impacted by the potential consequences of rising top-end inequality. Thompson and Leight (2012) find a negative correlation between state-level top-income shares and average income levels at the middle of the distribution, but no relationship at the bottom. Bertrand and Morse (2013) only find any consumption response among households above the bottom quintile of the distribution.

Another limitation of Coibion et al (2014) is the fact that the consumer credit panel data does not include income; they have information on household borrowing, credit scores, and location but not their incomes. Instead they predict household income based on the relationship between assets, debt, and income observed in the SCF. Ultimately the income variable used to

[5] Opinions on the income level required to be “rich” vary with household income level. A 2014 yougov survey of 1,000 households found that households with income less than $25,000 felt (on average) that someone would need an income of $293,000 to be considered rich. For households with incomes between $30,000 and $60,000 the income needed to be considered “rich” was $394,000; for households between $60,001 and $120,000 rich income was $426,000, and for those with income above $120,000 it was $501,000 (Vavreck, 2014).

[6] Occupation codes 33-3050 and 25-2054 in the Bureau of Labor Statistics’ Occupational Employment Statistics data for 2014 (http://www.bls.gov/oes/current/oes_nat.htm).

identify a households location in the distribution as well as the area-level distribution statistic (P90/P10) are all based on predicted income. Biases and any other problems in these predictions could be driving the relationships identified by Coibion et al (2014).

3. Empirical Approach and Data

Each of the recent papers exploring this question has made important contributions to understanding the potential consequences of rising income inequality, but each is subject to limitations and shortcomings. This paper hopes to overcome some of those limitations by using superior data, measures of inequality that are better suited to testing the impacts of rising income at the top of the distribution, and emphasis on measures of debt over consumption. Using the SCF is an improvement over the use of the CEX data by Bertrand and Morse (2013) and an improvement over relying on extensive income imputations in Coibion et al (2014). Using debt-related outcome measures is arguably a conceptual improvement over the use of consumption outcomes by Bertrand and Morse (2013). Using the high-income threshold levels represents a conceptual improvement over the inequality measures used by both BRK and Coibion et al (2013).

This paper uses simple reduced-form OLS regressions and estimates an equation similar to Bertrand and Morse (2013). The basic specification includes regional fixed effects based on the nine Census Regions and county population density (breaking counties – within Region – into thirds based on 2000 Census level measures of population density), and is of the form:

$$\begin{aligned} \mathbf{PIR}_{ti} &= \alpha + \beta_1 \mathbf{HighIncome}_{ts} + \beta_2 \mathbf{X}_{ti} + \beta_3 X_{ts} \\ &\quad + \beta_4 X_{G(MSA,County)} + \gamma_t + \sigma_{G(Div*County\_type)} + \varepsilon_{itsG} \end{aligned} \qquad \textbf{(1)}$$

Various specifications use PIRs from different debt-types (all, mortgage, non-mortgage) as well as indicators for “high” PIR (PIR>.40) and measures of the debt level to income ratio. The measure of “high-income” varies by state and year and reflects either the 95th percentile or the 99th percentile threshold income level. In addition many specifications interact the “high income” measure with indicators for portions of the lower part of the distribution. The primary aim is to discover if there is a relationship between top-income levels, and for which income groups and which debt types it is strongest.

3.1. The Survey of Consumer Finances

We use data from the nine waves of the Federal Reserve Board's triennial Survey of Consumer Finances (SCF) conducted between 1989 and 2013. Several features of the SCF make it appropriate for addressing the questions of interest. The survey collects very detailed information about households' financial assets and liabilities, and has employed a consistent instrument and sample frame since 1989. As a survey of household finances and wealth, the SCF includes some assets that are broadly shared across the population (bank savings accounts) as well some that are held more narrowly and that are concentrated in the tails of the distribution (direct ownership of bonds).[7] To support estimates of a variety of financial characteristics as well as the overall distribution of wealth, the survey employs a dual-frame sample design.

A national area-probability (AP) sample provides good coverage of widely spread characteristics. The AP sample selects household units with equal probability from primary sampling units that are selected through a multistage selection procedure, which includes stratification by a variety of characteristics, and selection proportional to their population. Because of the concentration of assets and non-random survey response by wealth, the SCF also employs a list sample which is developed from statistical records derived from tax returns under an agreement with SOI.[8] (See Bricker et al (2014) for additional details on the SCF list sample.) This list sample consists of households with a high probability of having high net worth.[9] The SCF joins the observations from the AP and list sample through weighting.[10] The weighting design adjusts each sample separately using all the useful information that can be brought to bear

[7] It is important to emphasize that the publicly-released SCF data are cleaned of any identifying information about the responding family, including any geographic information about the family. The Federal Reserve does release summary information by Census region, though (see Bricker et al, 2014). The empirical analysis in this paper uses the internal SCF data in order to identify the household's state, MSA, and county of residence.

[8] See Wilson and William J. Smith (1983) and Internal Revenue Service (1992) for a description of the SOI file. The file used for each survey largely contains data from tax returns filed for the tax year two years before the year the survey takes place.

[9] For reasons related to cost control on the survey, the geographic distribution of the list sample is constrained to that of the area-probability sample.

[10] The evolution of the SCF weighting design is summarized in Kennickell (2000).

in creating post-strata. The final weights are adjusted so that the combined sample is nationally representative of the population and assets.[11] These weights are used in all regressions.[12]

The key outcome variables explored in this paper are debt payments, specifically "payment to income ratios" (PIRs) for three broad debt classes: total debt, mortgage-related debt, and other (primarily consumer) "non-mortgage" debt. Total debt reflects all types of debt, including credit cards, mortgage debt, student loans, business debts, and other miscellaneous types of debt, and is reported by the respondent at the time of the interview.[13] It is important to consider the different types of debt separately, as the payment to income ratios across the distribution vary considerably by debt type. The total PIR declines across the income distribution, but not monotonically (**Figure 5**). Non-mortgage debt payments as a share of household income do fall steadily over the income distribution (Figure 5, Panel C), but payments on mortgage debt rise, relative to income, over the broad middle of the distribution (Figure 5, Panel B).

The specific dependent variables used in the regressions below are payment to income ratios for overall debt payments as well as for specific debt types (mortgage debt and non-mortgage debt).[14] In a series of robustness checks, we also report some results using other dependent variables, including total debt to income ratios, indicators for "high levels" of debt (PIR>.40), and PIRs for a broader housing payment measure including rent payments for non-homeowners. In addition to household finances, the SCF also collects some basic demographic and labor market information, primarily for the household head and spouse, including race, age, educational attainment, number of children, family-type, labor force status, occupation, industry, and housing tenure. These are included in the regressions as control variables, and are summarized in **Appendix Table 1**.

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[11] The SCF weights were revised in 1998 to incorporate home ownership rates by race (Kennickel, 1999). Weights for earlier years were updated to reflect the revised methodology.

[12] Standard errors for all regressions are calculated in STATA using "scfcombo" using 999 bootstrapped replications of scf weights to reflect multiple imputation and sample design.

[13] Assets do not include – and the SCF does not collect information on the value of – defined benefit pensions or the implied annuity value behind future or current Social Security benefits of respondents.

[14] PIRs are truncated at 3.0 to restrict the impact of a limited number of extreme PIR values that are a result of very low imputed income values and households experiencing transitory income shocks. The extreme PIR value is further diminished by using "normal" income in the denominator when measuring PIR.

An important part of this analysis explores differences in the relationship between top income and PIRs at different parts of the income distribution. A families' location in the state-level income distribution is based on household-level income from the SCF and state-level information on the distribution of taxable income from the IRS (Frank, Sommeiller, Price, Saez, 2015). The income groupings we evaluate include top/bottom halves, thirds of the distribution, and a continuous measure of "relative income" which is simply family income divided by state-level average income.

Location in the distribution is calculated using the incomes families report that they "usually" receive in a "normal" year – referred to as "normal income." Specifically, when inquiring about income, the SCF asks respondents to note whether their total income is unusually high or low relative to a normal year. If income was unusually high or low then a follow-up question is asked about what the family's income is in a typical year. This "normal" family income measure, then, should be a measure of income that smooths transitory income shocks and can approximate the family's permanent income.[15]

The unit of analysis in the SCF is the "primary economic unit" (PEU) which refers to a financially-dependent related (by blood, marriage, or unmarried partners) group living together. This concept is distinct from either the household or family units employed by the Census Bureau, but is conceptually closer to the latter, and throughout this paper PEUs are referred to as "families."[16] Single individuals living alone are included and simply considered a "family" of one.

3.2 High Incomes and Other Data

The inequality measures used in the analysis are the income levels of households at the top of the distribution, specifically threshold income levels at the 95th and 99th percentiles of the

[15] See Krimmel, Moore, Sabelhaus, and Smith (2013): "The concept of 'normal' income in the SCF is conceptually and empirically close to the concept of "permanent" income that economists generally consider when they describe consumer behavior. The label "normal" stems from a question posed to SCF respondents; after they report their actual income, they are asked whether they consider the current year a 'normal' year. If respondents state it is not a normal year, they are asked to report a value for 'normal' income. Actual and normal income are the same for most respondents. However, Ackerman and Sabelhaus (2012) show that the deviations from normal for the subset who report such deviations provide a relationship between actual and permanent income consistent with estimates of transitory shocks using panel income data."

[16] A typical question in the SCF asks the respondent to consider "you and your family living here" in providing answers.

state-level distribution of income. These income levels have been produced by Frank, Sommeiller, and Price (2014) based on state-level data tabulations of taxable income made available by the Internal Revenue Service. Standard household income surveys, such as the CPS, are not able to provide estimates of the incomes of households in the upper tail of the income distribution, and the only statistics on high incomes at the state level are based on income data collected by the IRS. These data are the state-level analog of the national distribution figures made popular in the research of Emmanuel Saez and Thomas Piketty (2003) and produce similar levels and trends for top-income shares (**Figure 1**). The mean of state P90 income levels in 2013 is $110,000 (min. $86,000/max. $144,000), for state P95 it was $151,000 (min. $118,000/max. $220,000), and for state P99 it was $341,000 (min. $237,000/max. $635,000) (**Appendix Table 1**). In the analysis, these top-income threshold measure are linked to the SCF data through the respondent's state of residence.[17]

The primary focus in this paper is how changes in income at the 99th percentile influence borrowing at lower parts of the income distribution. This top-income level is closer to what is commonly regarded as "rich," and it is also the case that changes over time at the 99th percentile have been much larger and have exhibited considerably more variation across states (**Figure 6**). Between 1989 and 2013 the state-level 90th percentile income rose $21,000 on average, with a maximum increase of $43,000.[18] The 99th percentile income level rose $96,000 on average, with six states seeing increases of $200,000 or more (**Appendix Table 2**).

The analysis also includes a number of additional covariates to control for potential confounding factors. Summary statistics for these covariates are also reported in Appendix Table 1, and they include:

Income Taxes: The maximum combined state and federal marginal tax rates on wage income provided by the NBER Taxsim program (Feenberg and Couts, 1993);

Quality-adjusted Rent: An MSA-level measure of quality-adjusted rent levels (based on the analysis of the 2000 Decennial Census by Chen and Rosenthal, 2008);

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[17] As noted earlier, the respondent's state of residence (and any other geographic location information) is not included in the public-use version of the SCF.

[18] Adjusted for inflation (2013$) using the CPI-U RS all city average.

Elasticity of the supply of housing: estimated at the MSA-level by Albert Saiz (2010);

Housing Price Growth: CBSA-level growth (1, 5 and 10-year growth rates) in the repeat purchase house price index (HPI) calculated by the LPS, and[19];

FICO risk-score: County-level measures of the average consumer credit risk score (FICO measure) from the FRBNY Consumer Credit Panel/ Equifax Data for 1999.

4. Results

The simplest regressions indicate that being in a state with a higher level of 95th percentile income is positively correlated with a higher overall payment-to-income ratio. Including only fixed effects for year and region, as well as demographic and labor force covariates, a $10,000 higher level of 95th percentile income is associated with a 0.39 percentage point higher overall PIR (**Table 1, Column 1**).[20] Results for the regression showing the coefficients on the full range of demographic and labor force covariates is shown in **Appendix Table 3**. Controlling for regional real estate covariates, including MSA-level varying measures of real estate supply constraints ("elasticity") and quality-adjusted rent (**Column 2**) results in a somewhat lower coefficient on 95th percentile income. The intuition behind including these control variables concerns the clustering of affluent households in places with high cost-of-living. To live in the pricey areas, where affluent households also choose to live, may impose higher costs on households and leave them with lower disposable income and higher levels of debt, conditional on income. Conversely, areas with fewer restrictions on building (higher supply elasticity) should have lower housing costs, ceteris paribus. The inclusion of time-varying measures changes in the housing prices index at the MSA-level, on the other hand, does not affect the threshold coefficients, and the HPI variables themselves are also not statistically significant (**Column 3**).

Further controls, including the maximum combined state and local marginal tax rate on wage income, a household-level measure of tenure in the current residence, and county-level average consumer credit score ("risk score") (**Column 4**) each have the anticipate sign, but very limited effect on the relationship between state 95th percentile incomes and household PIR. Expressing

[19] Respondents not located in a CBSA are assigned the state average value for the HPI.

[20] All regressions exclude households in the top 10 percent of the income distribution (income above P90).

the 95th percentile income threshold in natural log form, a one standard deviation ($27,000 in 2013) increase in the high-income level results in a 1.4 percentage point increase in the total PIR (**Column 5**).

In the remaining regressions we continue to use the natural log of the high-income thresholds as the coefficient of interest, exploring the impacts on a variety of outcome measures, with different income concepts, and over different parts of the income distribution.

4.1. Alternative high-income thresholds and income concepts

In **Table 2** we use the continuous measure of PIR and also the natural log of the high-income threshold. We begin to explore the sensitivity of the relationship between PIR and high-income thresholds to different high-income levels and also to different income concepts to calculate the PIR measure. Much of the conversation around inequality in recent years has focused on very high income levels, and the incomes of the top 1 percent are indeed much larger than those at the 90th and 95th percentiles. In this table we start using the state-level 99th percentile income as the key independent variable. We also explore the sensitivity to using normal income as the denominator of the PIR. Normal income smooths out transitory fluctuations. Households experiencing transitory shocks may have measured PIRs are much higher what they typically face; mean total PIR using normal income is lower than PIR with actual income and has a substantially smaller standard deviation (**Appendix Table 1**). Since the "normal" income questions have only been asked since 1995, Table 2 restricts some specifications to those years.

Using normal income to calculate PIR results in a modest reduction in the measured relationship between 95th percentile incomes at PIR (**Columns 2, 3**), and suggests a 1 SD increase in the 95th percentile threshold income results in 1.6 percentage point increase in total PIR. Switching to the use of the 99th percentile income level has a more dramatic impact. Using the 99th percentile, the effect of a 1 SD ($89,000 in 2013) increase in top income levels on total PIR falls to 0.6 percentage points (**Column 6**).

That PIR – at the mean of the data – appears more responsive to changes in 95th percentile income than 99th percentile income is consistent with the idea that the benchmark income/consumption levels that household target is set by their somewhat nearer neighbors in the income distribution.

4.2. Exploring Debt Types and Impacts at Different Points of the Income Distribution

In the specifications shown in the next several tables, we begin to explore how using different debt types influences the relationship between PIR and high-incomes, and also how this relationship varies across the income distribution. **Table 3** includes the results from six different specifications using interactions between two different top-income thresholds (P95, P99) and an indicator for being in the top-half of the state-level distribution of income and three different PIR dependent variables (total PIR, mortgage PIR, and non-mortgage PIR).

Key patterns that begin to emerge in these results are that the overall relationship between PIR and high incomes is strongest for mortgage debt, that mortgage debt of higher-income households is more responsive to top-income levels, and that the non-mortgage PIR of lower-income households is negatively related to high-income thresholds.

Rising top 1 percent incomes have no statistically significant effect on overall debt PIR or mortgage debt PIR for the bottom half of households (**Columns 4, 5**). The non-mortgage debt PIRs, however, fall 0.8 percentage points with a 1 SD increase in top 1 percent income levels (**Column 6**), broadly consistent with the findings of Coibion et al (2014). In the top half of the income distribution a 1 SD increase in top 1 percent income is associated with a 1.2 percentage point increase in the mortgage PIR, but no change in non-mortgage PIR.

Compared to increases in top 1 percent incomes, rising levels of income at the 95th percentile of the income distribution are associated with similar effects on non-mortgage debt, but consistently larger effects on mortgage debt. A 1 SD increase in the top 5 percent threshold income level is associated with a 0.9 percentage point increase in mortgage PIR for households in the bottom half of the income distribution and a 1.7 percentage point increase for those in the top half (**Column 2**).

The additional covariates used in the regressions also differ in expected ways across the different dependent variables. Coefficients on the real estate covariates are typically statistically significant and of the expected sign for specifications using total PIR and mortgage PIR, but not for those using non-mortgage debt to calculate the PIR. The zip-code level risk score measure is positive and significant for mortgage PIR, but negative and significant for non-mortgage PIR, also consistent with credit supply restrictions.

In **Table 4** we explore additional income distribution interactions, reporting only the key coefficient from twelve specification. These results extend what we showed in Table 3 (using two top-income thresholds and three PIR dependent variables) to two additional types of distribution interactions. We report the key coefficients from the top-half interaction from Table 3 in **Panel A,** and also add results from specifications using thirds of the distribution (**Panel B**), and a continuous measure of "relative income" in **Panel C**.[21]

The results in Table 4 indicate that effect of rising top-income thresholds on mortgage PIR is greater the higher up the 'non-rich' distribution you go. The differences between the top and the middle thirds of the distribution, however, are modest. A 1 SD increase in the top 1 percent income level is associated with a 1.2 percentage point increase in the mortgage PIR of households in the top third and a 0.9 percentage point increase for those in the middle third (**Panel B, Column 5**). Isolating the bottom third of the distribution does, however, substantially increase the negative effect on non-mortgage PIR for low-income households. A 1SD increase in the top 1 percent income level is associated with a 1.4 percentage point decline in the non-mortgage PIR among households in the bottom third of the distribution (**Panel B, Column 6**).

Using a continuous measure of location in the state income distribution (household income relative to state average) interacted with top-income thresholds tells a consistent story (**Panel C)**. Implied reactions for different points of the income distribution, based on these coefficients, are shown in **Appendix Table 4**. At the 90th percentile of the income distribution (relative income = 2.5) a 1 SD increase in the top one percent threshold is associated with a 2.1 percentage point increase in the mortgage debt PIR. At one-half of the average income (relative income = 0.5), there is no significant effect on mortgage debt, but a 1.1 percentage point decline in the non-mortgage PIR.

[21] All specifications in Table 3 use the normal income concept to calculate PIR and to locate households in the state-level distribution of income. The top half of the state-level distribution is made-up of households with normal income above average taxable income; the middle-third of the distribution has "relative income" above 0.75 and below 1.25. "Relative income" is defined as normal income divided by state-level average taxable income.

4.3. Alternative Dependent Variables

Payment to income ratios are the preferred measure of debt as they give the best indication of how manageable the level of indebtedness is for a household. Payments, though, are also influenced by the interest charged on the debt, and we might worry that trends in interest rates might be correlated with trends in high-income thresholds and introduce bias into our PIR regressions shown above. Below in **Table 5 Panel A** we report the key coefficients from our preferred specifications, but substituting the debt level to income ratio as the dependent variable. The results are broadly similar, suggesting that interest rates or other factors affecting payments cannot account for the observed relationship between high-income thresholds and debt of households further down the income distribution. As with the PIR measures, we see that rising top incomes levels are related to increased mortgage borrowing for households in the top half of the distribution; a 1 SD increase in the 99^{th} percentile income level results in an 12 percentage point increase in the debt to income ratio among upper-income households, but has only a small and statistically insignificant effect for households in the bottom half of the distribution (**Panel A, Column 5**). Also, rising top incomes result in decreased non-mortgage borrowing among lower-income households, with a 1 SD increase in the 99^{th} percentile leading to a 4.9 percentage point decline in the debt to income ratio in the bottom half of the distribution (**Panel A, Column 6**).

4.3b. High PIR Regressions

Payment to income ratios are sometimes used to identify households with high debt levels that might be an indication of experiencing financial distress. Commonly a PIR above 0.4 is regarded as “high.” Small changes in the average PIR could potentially miss changes in the number of households experiencing high PIR, understating the implications for debt of rising top incomes. In **Table 5 Panel B** we replicate the preferred specifications using “high PIR” (by debt type) as the dependent variable. The results indicate that a 1 SD increase in the 99^{th} percentile income level leads to a 0.8 percentage point increase in the share of households in the bottom half of the income distribution experiencing a high PIR for mortgage debt (**Panel B, Column 5**), and a similarly large increase in the top half as well. There is a 0.9 percentage point decline in the share of low-income families experience high non-mortgage PIR (**Panel B, Column 6**).

4.3c. Combined Rent + Mortgage PIR Regressions

So far we have found that rising top incomes seem to have a substantial effect on mortgage-related debt payments. Many households, however, are renters and do not pay any mortgage. It is possible that the decision to own versus rent could be related to changes in top income levels, which could bias our results looking at mortgage PIRs. In **Table 5, Panel C** we report key coefficients from two additional specifications, reproducing our preferred specifications using the combined mortgage plus rent PIR as the dependent variable. When we include rent in the PIR, we see even more strongly that the effects of rising top incomes are isolated to the top half of the distribution. For both the 95th and 99th percentile thresholds, the coefficients fall sharply in the bottom half of the distribution and rise by roughly the same amount in the top half.

5. Conclusion and Discussion

This paper uses data from the Survey of Consumer Finances and state-level data from the IRS on high-income levels to explore the relationship between rising top-incomes and borrowing and debt payments among households further down the income distribution. The findings indicate the "trickle-down" consumption identified by Bertrand and Morse (2013) – the part financed through debt at least – seems to be primarily evident in housing. Payments on mortgage debt are higher in states where the high-income thresholds are higher.

The responsiveness of mortgage debt payment also appears to be largely isolated to the top half of the income distribution. This suggests that any debt-linked "expenditure cascade" in response to rising incomes at the very top – referred to as "keeping up with the slightly richer neighbors" by Freeland (2012) – does not extend to the lower portions of the income distribution.

These results are consistent with multiple explanations, including consumption benchmarking and price effects. The standard interpretation of "keeping up with the Joneses" implies that the consumption of a somewhat more affluent reference group influences the behavior of somewhat less affluent consumers. In this case, it could be that rising top incomes are fueling increased housing consumption at the top, which in turn inspires debt-financed housing consumption further down the distribution. Alternatively (or also), rising disposable income at the top of the distribution could be helping to bid up the price of land and housing in affluent neighborhoods. Since we include a variety of MSA-level real estate controls, price effects would have to be within the MSA (CBSA) level to account for our findings.

Thoughout the paper we consistently find that changes in the 95th percentile income levels are more strongly associated with debt levels and payments of non-affluent households than changes at the 99th percentile level. Income at the 95th percentile ($151,000 in 2013) is a marker of economic success for households, but it is conceptually quite different from conversations of the “top 1%” or “the rich and rest of us.” Income at the 95th percentile exhibits far less variation across states or change over time compared to the 99th percentile. The stronger impacts of 95th percentile incomes are consistent with the “expenditure cascade” (Levine, Frank, and Dijk (2014)) concept, suggesting households do respond to “upper income” levels that are closer to them in the distribution and arguably more salient.

The results are also generally supportive of the findings of Coibion et al (2014) and the negative relationship they identify between inequality and debt among low-income households. We find that non-mortage debt levels and payments are lower in the bottom half of the income distribution where top-income levels are higher. Rising top incomes could be used by lenders to target the supply of non-mortgage credit in ways which restrict access to debt among lower-income families.

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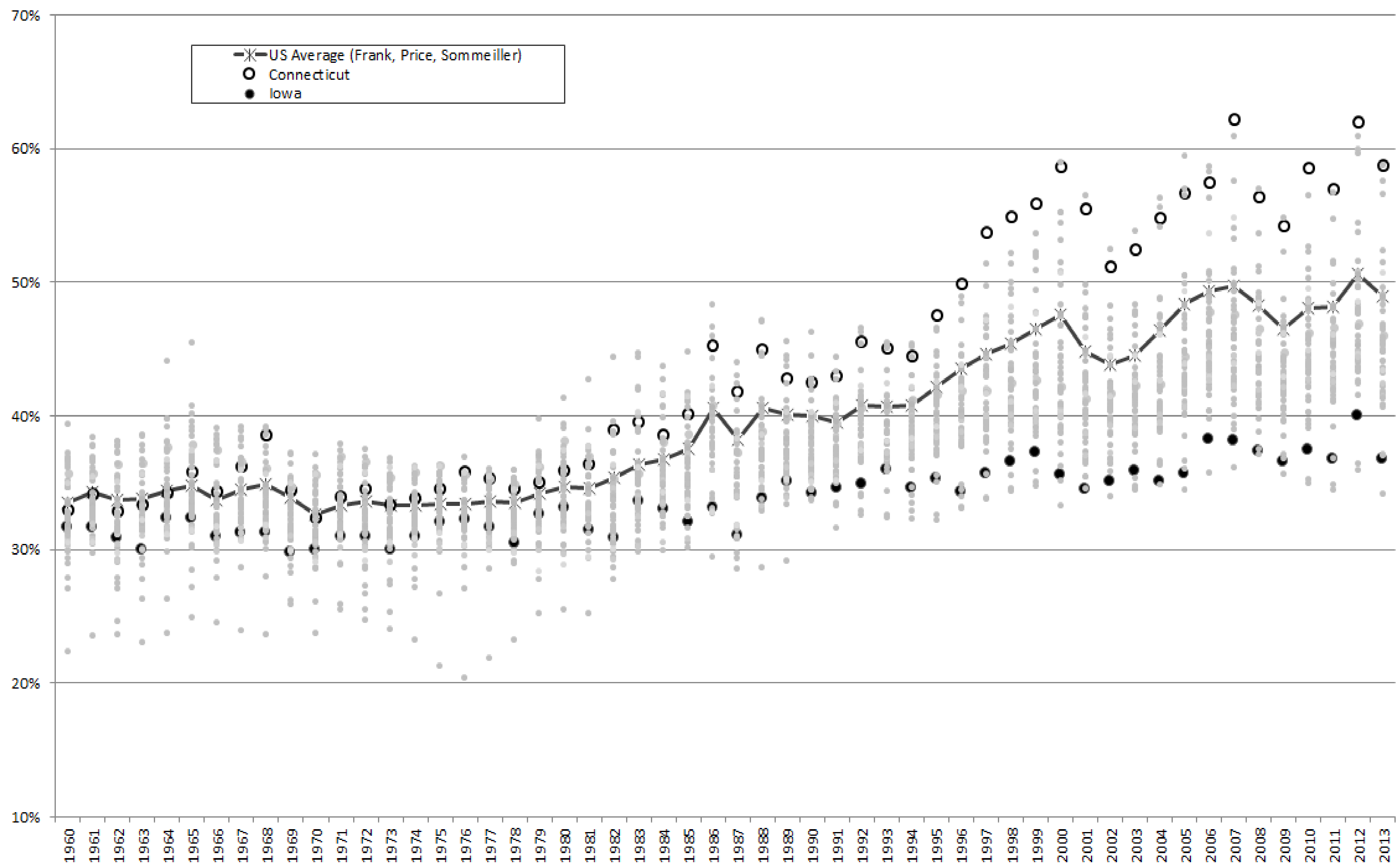
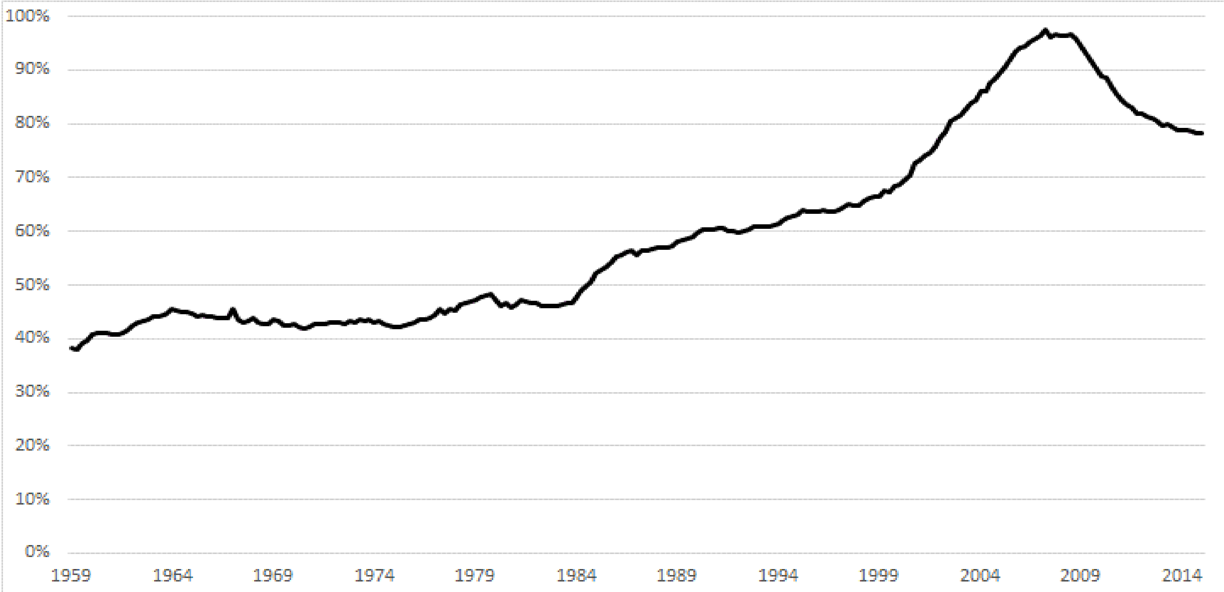
Figure 1. Top 10 Percent Share of Income (1960-2013) Using State-level Data



Note1: Each "dot" represents the top share for each state each year, with largers dots representing the highlighted states (CT & IA).

Note2: The Frank, Price, Sommeiller (2015) state-level income shares are calculated from state-level income and tax distribution tables produced by the IRS.

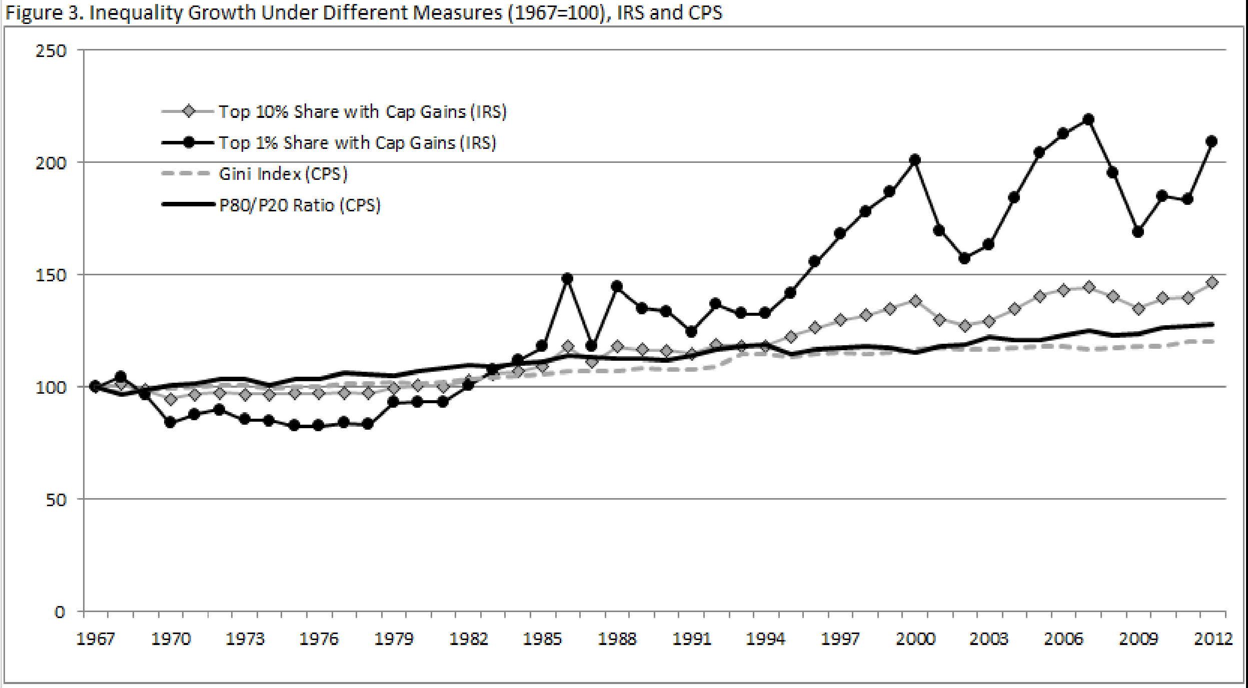
Figure 2. Household Liabilites Relative to GDP



Source:

Board of Governors of the Federal Reserve System (US), *Households and Nonprofit Organizations; Credit Market Instruments; Liability, Level* [CMDEBT], retrieved from FRED, Federal Reserve Bank of St. Louis https://research.stlouisfed.org/fred2/series/CMDEBT, May 4, 2016.
US. Bureau of Economic Analysis, *Gross Domestic Product* [GDP], retrieved from FRED, Federal Reserve Bank of St. Louis https://research.stlouisfed.org/fred2/series/GDP, May 4, 2016.

Figure 3. Inequality Growth Under Different Measures (1967=100), IRS and CPS



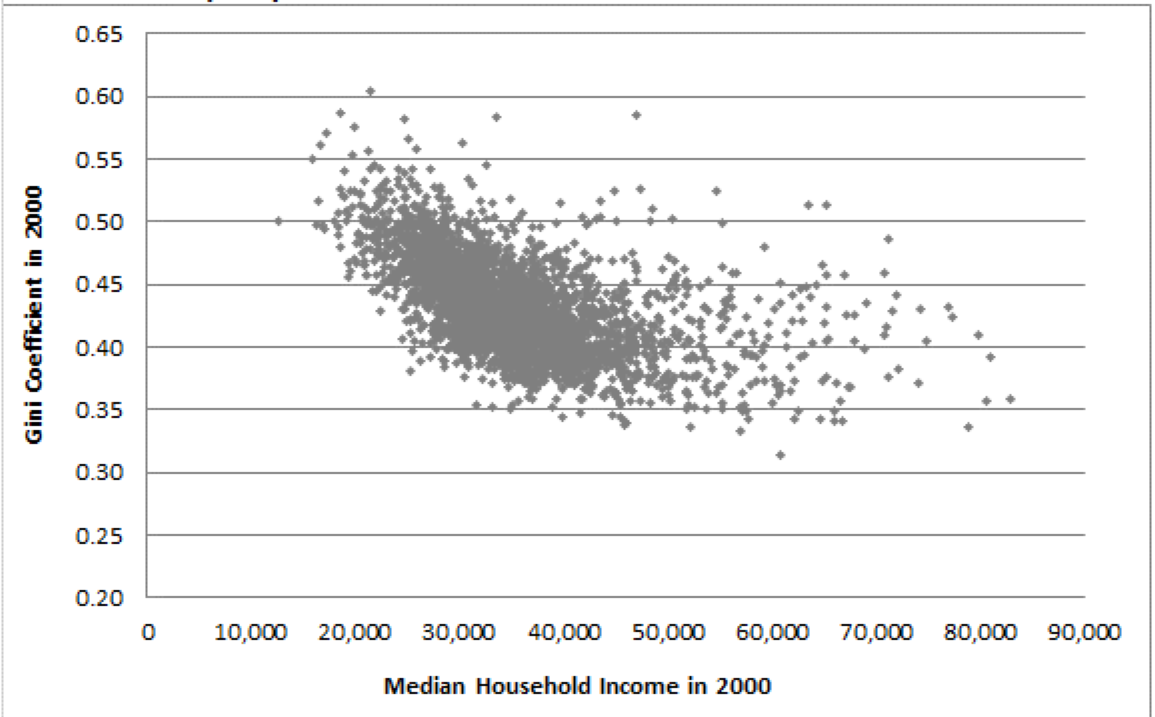
Note: Top 10% and Top 1% shares of income based on taxable income of tax-filing units. Gini Index and P80/P20 Ratio based on Census Income concept, calculated by Census Bureau using Current Population Survey.

Sources: Census Burea, Current Population Survey data analyzed in *Income and Poverty in the United States*: 2014 (P60-252)

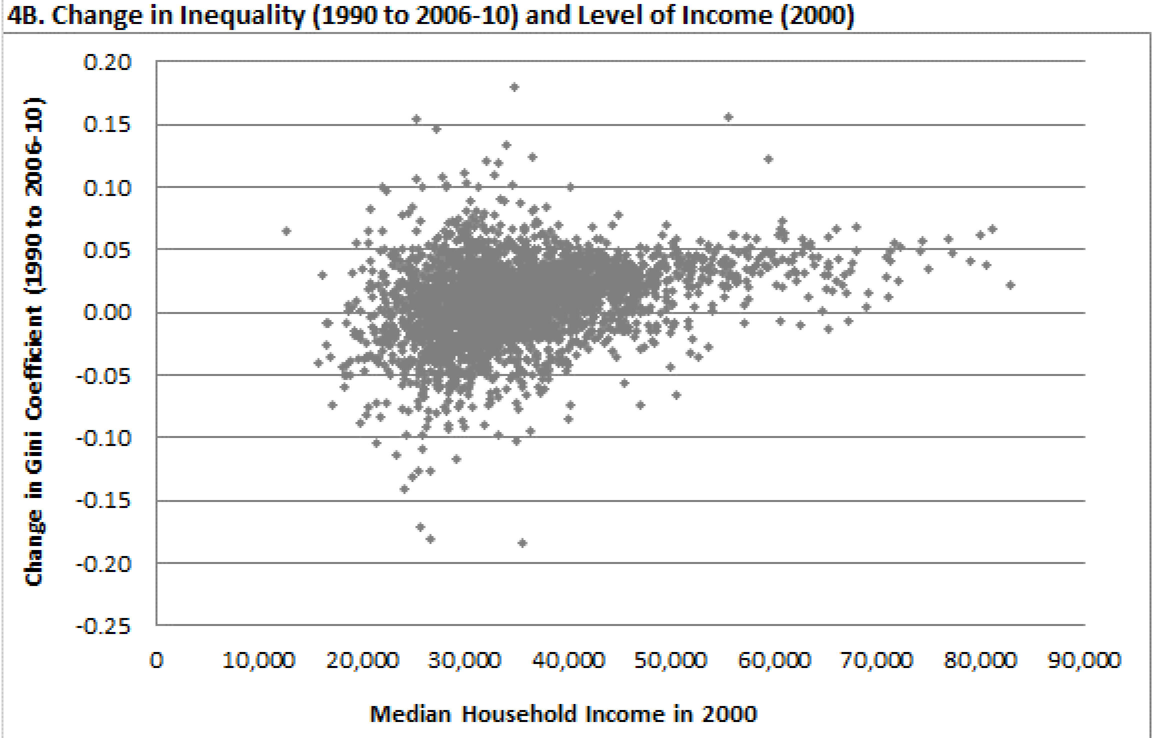
IRS Taxable Income Data analyzed in Saez (2015)

Figure 4. County-level Inequality and Household Median Income

4A. Level of Inequality and Income in 2000

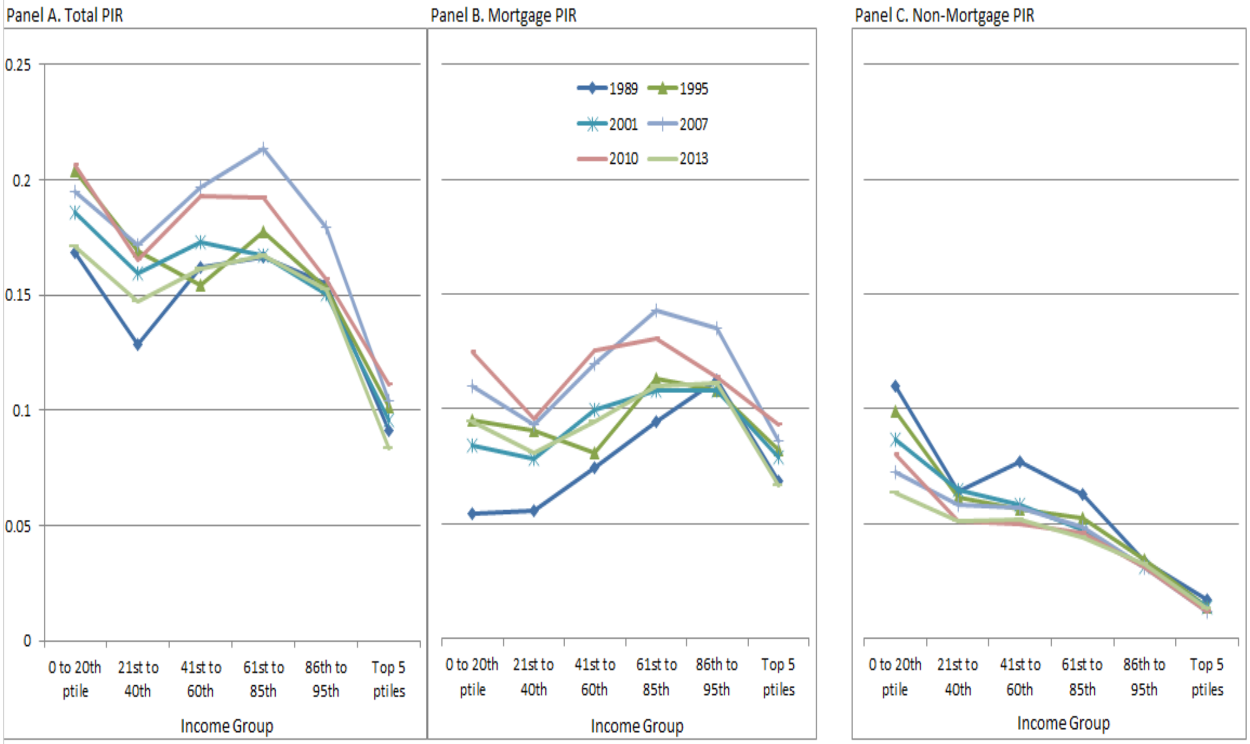


4B. Change in Inequality (1990 to 2006-10) and Level of Income (2000)



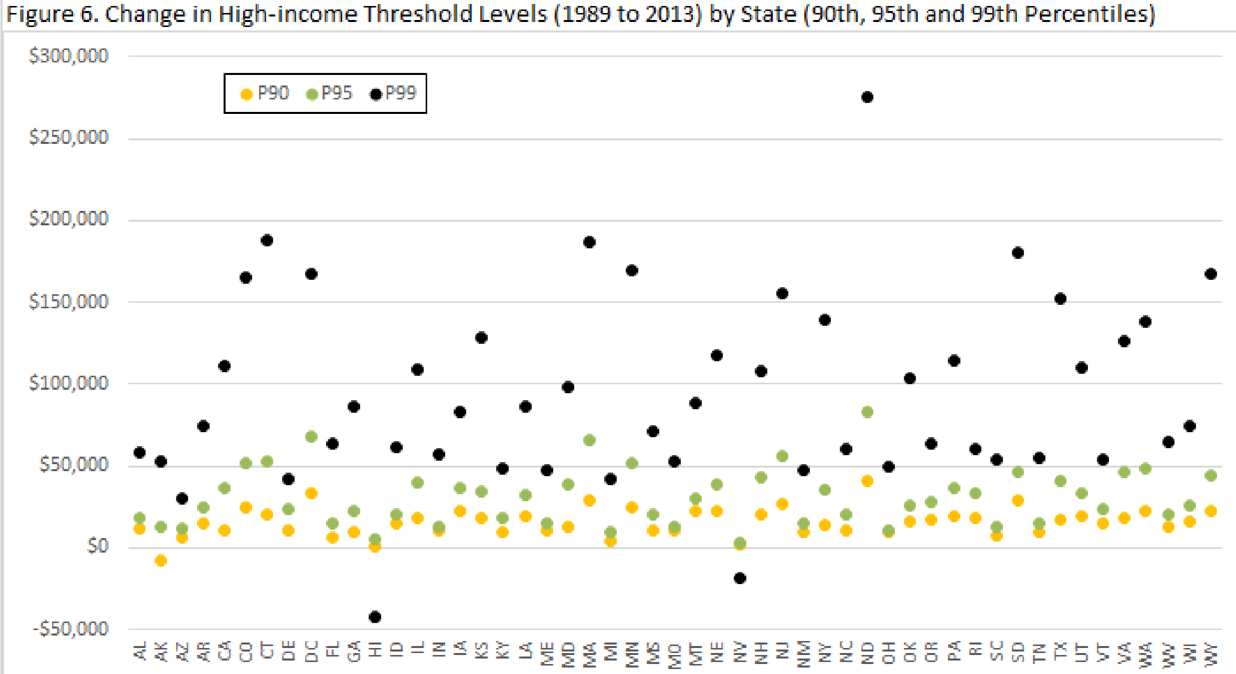
Source: County-level Gini Coefficient and Median of household income from 1990 and 2000 Decennial Census and 2006-10 ACS.

Figure 5. Payment to Income Ratio, by Debt Type, by Income Catgegory for Selected Years



Souce: Survey of Consumer Finances. Payment to income ratios calculated using "mortpay" and "tpay" variables and SCF Income.

Figure 6. Change in High-income Threshold Levels (1989 to 2013) by State (90th, 95th and 99th Percentiles)



Note: Adjusted for inflation using CPI-U RS All City Average.

Source: Author's Analysis of Frank, Price, Sommeiller (2015) state-level top-income thresholds based on IRS taxable income data.

Table 1. PIR_Total regressed on Top 5 Threshold by Covariate

	(1)	(2)	(3)	(5)	LN (6)
Top 5 Threshhold ($k)	0.000386	0.000312	0.000318	0.000315	0.0494
	(0.000111)	(0.000120)	(0.000120)	(0.000121)	(0.0164)
	***	***	***	***	***
Quality-adjusted Rent (MSA)		0.0000015	0.0000015	0.0000013	0.0000012
		(8.32e-07)	(8.45e-07)	(8.55e-07)	(8.67e-07)
		*	*		
Elasticity (MSA)		-0.00213	-0.00218	-0.00220	-0.00211
		(0.00135)	(0.00136)	(0.00138)	(0.00138)
MSA HPI one-year %change			-0.0492	-0.0488	-0.0471
			(0.0417)	(0.0416)	(0.0417)
MSA HPI 5-year %change			-0.00429	-0.00427	-0.00486
			(0.0129)	(0.0129)	(0.0130)
MSA HPI 10-year %change			0.00458	0.00451	0.00362
			(0.00699)	(0.00705)	(0.00710)
Maximum combined Federal, State MTR on Wages				0.000262	0.000392
				(0.00104)	(0.00105)
Tenure				-0.000328	-0.000326
				(0.000141)	(0.000140)
				**	**
Risk Score				0.000044	0.000048
				(0.000124)	(0.000124)
Constant	0.0945	0.0884	0.0860	0.0500	-0.486
	(0.0164)	(0.0180)	(0.0186)	(0.0954)	(0.213)
	***	***	***		**
Observations	27,397	26,730	26,730	26,730	26,730
R-squared	0.059	0.060	0.060	0.060	0.060
Demographic, Labor Covs?	yes	yes	yes	yes	yes
Census Division * County_Density_Group FE?	yes	yes	yes	yes	yes

z-statistics in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Notes: Sample includes households with SCF incomes below the 90th percentile income threshold. All regressions include year and region fixed effects. PIR_Total truncated at 3.0. Standard errors calculated using scfcombo, using 999 bootstrapped replications of scf weights to reflect multiple imputation and sample design.

Table 2. PIR_Total Regressions by Threshold Level and Income Concept

Inequality Measure	Top 5			Top 1		
Income Concept for DEPVAR and Distribution	SCF Income	SCF Income (1995+)	Normal Income	SCF Income	SCF Income (1995+)	Normal Income
	(1)	(2)	(3)	(4)	(5)	(6)
Threshold (LN)	0.0494	0.0553	0.0541	0.0159	0.0208	0.0169
	(0.0164)	(0.0163)	(0.0150)	(0.0102)	(0.00983)	(0.00877)
	***	***	***		**	*
Maximum combined Federal, State MTR on Wages	0.000392	0.000798	0.000563	0.000137	0.000547	0.000395
	(0.00105)	(0.00115)	(0.00106)	(0.000998)	(0.00111)	(0.000985)
Quality-adjusted Rent (MSA)	0.0000012	0.0000022	0.0000009	0.0000010	0.0000018	0.0000010
	(8.67e-07)	(1.01e-06)	(8.31e-07)	(7.61e-07)	(8.86e-07)	(7.65e-07)
		**			**	
Elasticity (MSA)	-0.00211	-0.00259	-0.00123	-0.00244	-0.00267	-0.00140
	(0.00138)	(0.00156)	(0.00159)	(0.00132)	(0.00148)	(0.00144)
		*		*	*	
Tenure	-0.000326	-0.000392	-0.000327	-0.000489	-0.000562	-0.000479
	(0.000140)	(0.000146)	(0.000127)	(0.000124)	(0.000128)	(0.000112)
	**	***	***	***	***	***
MSA HPI one-year %change	-0.0471	-0.0517	-0.0553	-0.0439	-0.0461	-0.0499
	(0.0417)	(0.0414)	(0.0318)	(0.0361)	(0.0353)	(0.0270)
			*			*
MSA HPI 5-year %change	-0.00486	-0.0140	0.00316	-0.00483	-0.0158	-0.00224
	(0.0130)	(0.0156)	(0.0132)	(0.0118)	(0.0138)	(0.0116)
MSA HPI 10-year %change	0.00362	0.0106	-0.00297	0.00517	0.0129	0.00205
	(0.00710)	(0.00977)	(0.00928)	(0.00643)	(0.00892)	(0.00837)
Risk Score	4.77e-05	2.13e-05	0.000158	8.72e-06	-3.57e-06	0.000127
	(0.000124)	(0.000135)	(0.000112)	(0.000112)	(0.000123)	(0.000103)
Constant	-0.486	-0.577	-0.638	-0.0784	-0.159	-0.192
	(0.213)	(0.223)	(0.182)	(0.163)	(0.178)	(0.147)
	**	***	***			
Observations	26,730	22,249	22,123	30,863	25,603	25,486
R-squared	0.060	0.061	0.060	0.053	0.054	0.056

z-statistics in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Note1: Sample includes households with income (Actual or Normal Income) below the 90th percentile income threshold. Demographic and labor force covariates, and year and region fixed effects, not shown for space.

Note2: All regressions include year fixed effects. PIR_Total truncated at 3.0. Standard errors calculated using scfcombo, using 999 bootstrapped replications of scf weights to reflect multiple imputation and sample design.

Table 3. PIR Regressions Using Top Half Distribution Interactions, by Debt Type and Threshold Level
All Specifications using Normal Income Concepts

Threshold:	Top5			Top1		
PIR-type Dependent Variable:	Total	Mortgage	Non-Mortgage	Total	Mortgage	Non-Mortgage
	(1)	(2)	(3)	(4)	(5)	(6)
Threshold (LN)	0.0110	0.0316	-0.0247	-0.00494	0.0106	-0.0209
	(0.0169)	(0.0136)	(0.00898)	(0.0110)	(0.00874)	(0.00698)
		**	***			***
Threshold X Top Half	0.0499	0.0280	0.0264	0.0390	0.0225	0.0198
	(0.0129)	(0.00901)	(0.00878)	(0.00940)	(0.00651)	(0.00651)
	***	***	***	***	***	***
Top Half	-0.613	-0.334	-0.335	-0.519	-0.289	-0.275
	(0.151)	(0.105)	(0.103)	(0.118)	(0.0816)	(0.0822)
	***	***	***	***	***	***
Maximum combined Federal, State MTR on Wages	0.000583	0.000501	0.000328	0.000680	0.000705	0.000178
	(0.00110)	(0.000913)	(0.000520)	(0.00111)	(0.000934)	(0.000516)
Quality-adjusted Rent (MSA)	2.24e-06	3.47e-06	-7.70e-07	2.46e-06	3.67e-06	-6.91e-07
	(8.46e-07)	(7.33e-07)	(4.91e-07)	(8.48e-07)	(7.37e-07)	(4.78e-07)
	***	***		***	***	
Elasticity (MSA)	-0.00156	-0.00157	-0.000432	-0.00165	-0.00165	-0.000472
	(0.00163)	(0.000894)	(0.00127)	(0.00165)	(0.000892)	(0.00128)
		*			*	
Tenure	-0.000272	-0.000236	-1.25e-06	-0.000268	-0.000231	-2.45e-06
	(0.000129)	(9.47e-05)	(9.50e-05)	(0.000129)	(9.45e-05)	(9.47e-05)
	**	**		**	**	
MSA HPI one-year %change	-0.0485	-0.0200	-0.0139	-0.0458	-0.0170	-0.0139
	(0.0316)	(0.0234)	(0.0220)	(0.0318)	(0.0237)	(0.0221)
MSA HPI 5-year %change	0.000342	-0.0109	0.00947	-0.000803	-0.0129	0.0108
	(0.0133)	(0.00938)	(0.00849)	(0.0132)	(0.00926)	(0.00841)
MSA HPI 10-year %change	0.000751	0.00875	-0.00784	0.00208	0.0102	-0.00779
	(0.00912)	(0.00621)	(0.00615)	(0.00908)	(0.00630)	(0.00611)
Risk Score	7.11e-05	0.000216	-0.000190	8.31e-05	0.000229	-0.000191
	(0.000108)	(9.43e-05)	(6.24e-05)	(0.000107)	(9.35e-05)	(6.19e-05)
		**	***		**	***
Constant	-0.0862	-0.523	0.504	0.0859	-0.311	0.483
	(0.198)	(0.164)	(0.105)	(0.165)	(0.148)	(0.0944)
		***	***		**	***

z-statistics in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Notes: Sample includes households with normal income below the state-level 90th percentile income threshold. The top half of the income distribution includes households with incomes above the state-level average. Additional covariates not shown for space. PIR_Total truncated at 3.0. Standard errors calculated using scfcombo, using 999 bootstrapped replications of scf weights to reflect multiple imputation and sample design.

Table 4. Key Coefficients from PIR Regressions by Debt Type and Alternative State-Level Distribution Interaction Terms

All Specifications using Normal Income Concepts

Panel A. By Halves of State-level Distribution

Threshold:	Top5			Top1		
PIR-type Dependent Variable:	Total	Mortgage	Non-Mortgage	Total	Mortgage	Non-Mortgage
	(1)	(2)	(3)	(4)	(5)	(6)
Threshold (LN)	0.0110	0.0316	-0.0247	-0.00494	0.0106	-0.0209
	(0.0169)	(0.0136)	(0.00898)	(0.0110)	(0.00874)	(0.00698)
		**	***			***
Threshold X Top Half	0.0499	0.0280	0.0264	0.0390	0.0225	0.0198
	(0.0129)	(0.00901)	(0.00878)	(0.00940)	(0.00651)	(0.00651)
	***	***	***	***	***	***
Top Half	-0.613	-0.334	-0.335	-0.519	-0.289	-0.275
	(0.151)	(0.105)	(0.103)	(0.118)	(0.0816)	(0.0822)
	***	***	***	***	***	***

Panel B. By Thirds of State-level Distribution

	(1)	(2)	(3)	(4)	(5)	(6)
Threshold (LN)	-0.0252	0.0117	-0.0471	-0.0356	-0.00790	-0.0377
	(0.0214)	(0.0166)	(0.0129)	(0.0148)	(0.0111)	(0.00932)
			***	**		***
Threshold X Middle Third	0.0579	0.0328	0.0340	0.0494	0.0311	0.0250
	(0.0197)	(0.0121)	(0.0154)	(0.0148)	(0.00840)	(0.0111)
	***	***	**	***	***	**
Threshold X Top Third	0.0814	0.0458	0.0449	0.0661	0.0395	0.0336
	(0.0206)	(0.0121)	(0.0159)	(0.0152)	(0.00885)	(0.0114)
	***	***	***	***	***	***
Middle Third	-0.711	-0.398	-0.426	-0.653	-0.405	-0.342
	(0.234)	(0.143)	(0.183)	(0.188)	(0.106)	(0.141)
	***	***	**	***	***	**
Top Third	-1.006	-0.553	-0.573	-0.883	-0.512	-0.469
	(0.243)	(0.142)	(0.188)	(0.193)	(0.111)	(0.146)
	***	***	***	***	***	***

Panel C. Using Continuous Distribution Interaction Term (Household Income Relative to State Average Income)

	(1)	(2)	(3)	(4)	(5)	(6)
Threshold (LN)	-0.0296	0.0120	-0.0528	-0.0377	-0.00672	-0.0415
	(0.0223)	(0.0172)	(0.0135)	(0.0150)	(0.0111)	(0.0104)
			***	**		***
Threshold X "Relative Income"	0.0570	0.0302	0.0342	0.0446	0.0258	0.0239
	(0.0165)	(0.00980)	(0.0134)	(0.0120)	(0.00711)	(0.00971)
	***	***	**	***	***	**
Relative Income	-0.718	-0.369	-0.446	-0.611	-0.340	-0.345
	(0.195)	(0.115)	(0.158)	(0.152)	(0.0893)	(0.123)
	***	***	***	***	***	***

z-statistics in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Notes: Sample includes households with normal income below the state-level 90th percentile income threshold. The top half of the income distribution (Panel A) includes households with incomes above the state-level average. The middle third of the of the income distribution (Panel B) includes households with relative income above 0.75, but below 1.25. All regressions include year and regional fixed effects. Additional covariates not shown for space. PIR_Total truncated at 3.0. Standard errors calculated using scfcombo, using 999 bootstrapped replications of scf weights to reflect multiple imputation and sample design.

Table 5. Key Coefficients from Alternative Dependent Variables, by Debt Type, Using Top Half State-Level Distribution Interaction Terms

All Specifications using Normal Income Concepts

Panel A. Debt Level to Income Ratio Dependent Variable

Threshold:	Top5			Top1		
Debt Type:	Total	Mortgage	Non-Mortgage	Total	Mortgage	Non-Mortgage
	(1)	(2)	(3)	(4)	(5)	(6)
Threshold (LN)	0.0373	0.197	-0.158	-0.0767	0.0472	-0.132
	(0.119)	(0.0981)**	(0.0479)***	(0.0845)	(0.0661)	(0.0408)***
Threshold X Top Half	0.485	0.365	0.134	0.380	0.277	0.114
	(0.0898)***	(0.0745)***	(0.0325)***	(0.0642)***	(0.0542)***	(0.0246)***
Top Half	-5.781	-4.239	-1.690	-4.876	-3.445	-1.552
	(1.046)***	(0.868)***	(0.380)***	(0.799)***	(0.675)***	(0.308)***

Panel B. High PIR (>.4) Dependent Variable

Threshold:	Top5			Top1		
Debt Type:	Total	Mortgage	Non-Mortgage	Total	Mortgage	Non-Mortgage
	(1)	(2)	(3)	(4)	(5)	(6)
Threshold (LN)	0.00187	0.0255	-0.0430	0.00111	0.0182	-0.0235
	(0.0196)	(0.0133)*	(0.00815)***	(0.0138)	(0.00944)*	(0.00567)***
Threshold X Top Half	0.0598	0.00457	0.0261	0.0484	0.00362	0.0183
	(0.0174)***	(0.00963)	(0.00867)***	(0.0131)***	(0.00720)	(0.00637)***
Top Half	-0.755	-0.0904	-0.325	-0.662	-0.0823	-0.250
	(0.204)***	(0.113)	(0.102)***	(0.165)***	(0.0899)	(0.0804)***

Panel C. Combined Rent + Mortgage PIR Dependent Variable

Threshold:	Top5	Top1
	(1)	(2)
Threshold (LN)	0.000919	0.00200
	(0.0229)	(0.0157)
Threshold X Top Half	0.0753	0.0367
	(0.0170)***	(0.0126)***
Top Half	-1.011	-0.597
	(0.200)***	(0.158)***

z-statistics in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Notes: Sample includes households with normal income below the state-level 90th percentile income threshold. The top half of the income distribution includes households with incomes above the state-level average. Additional covariates not shown for space. PIR_Total truncated at 3.0. Standard errors calculated using scfcombo, using 999 bootstrapped replications of scf weights to reflect multiple imputation and sample design.

Appendix Table 1. Summary Statistics

	Mean	Std. Dev.	Min	Max	Obs
<u>Payment to Income Ratio (truncated)</u>					
pir_total_t	0.172	0.276	0	3	41,567
pir_mort_t	0.101	0.217	0	3	41,567
pir_nonmort_t	0.073	0.179	0	3	41,567
norm_pir_total_t	0.159	0.226	0	3	34,518
norm_pir_mort_t	0.095	0.175	0	3	34,518
norm_pir_nonmort_t	0.065	0.143	0	3	34,518
<u>High PIR Variables (>.4)</u>					
hi_pir_total	0.092	0.289	0	1	41,567
hi_pir_mort	0.041	0.199	0	1	41,567
hi_pir_nonmort	0.021	0.144	0	1	41,567
hi_norm_pir_total	0.081	0.272	0	1	34,518
hi_norm_pir_mort	0.034	0.182	0	1	34,518
hi_norm_pir_nonmort	0.014	0.118	0	1	34,518
<u>Debt to Normal Income Ratios (truncated)</u>					
norm_debt_ratio	1.07	2.01	0	15	34,436
norm_mort_debt_ratio	0.76	1.57	0	10	34,436
norm_nonmort_debt_ratio	0.32	1.17	0	10	34,436
Combined Rent + Mortgage PIR (normal, truncated)	0.25	0.35	0	3	34,518
Threshold 1 (ln) (IRS, Frank-Sommeller-Price)	12.4	0.37	11.5	13.4	41,567
Threshold 5 (ln) (IRS, Frank-Sommeiller-Price)	11.6	0.29	10.8	12.3	41,567
Threshold 10 (ln) (IRS, Frank-Sommeiller-Price)	11.3	0.27	10.6	11.9	41,567
2013 Thrshld 1 (IRS, Frank-Sommeiller-Price)	341,349	88,551	237,289	634,945	51
2013 Thrshld 5 (IRS, Frank-Sommeiller-Price)	150,977	27,227	117,706	220,335	51
2013 Thrshld 10 (IRS, Frank-Sommeiller-Price)	110,438	14,102	86,189	144,150	51
Income Tax (SCF, TAXSIM)	11,782	96,673	-11,055	222,000,000	41,567
Federal Income Tax (SCF, TAXSIM)	9,650	79,641	-9,184	167,000,000	41,567
State Income Tax (SCF, TAXIM)	2,132	19,908	-7,604	54,100,000	41,567
Maximimum Combined State & Local Marginal Tax Rate on	40.17	4.47	28	49.3	41,567
Quality-Adjusted Rent (Rosenthal and Chen, MSA-level)	8,699	3,378	4,341	23,635	41,016
Riskscore (NYFRB, county-level)	681	22	607	736	41,567
hpi_growth 1 year (FHFA, CBSA)	0.044	0.070	-0.149	0.349	41,567
hpi_growth 5 years (FHFA, CBSA)	0.225	0.300	-0.554	1.373	41,567
hpi_growth 10 years (FHFA, CBSA)	0.587	0.483	-0.326	2.776	41,567
<u>Age Class</u>					
<35	0.232	0.422	0	1	41,567
35 to 44	0.208	0.406	0	1	41,567
45 to 54	0.192	0.394	0	1	41,567
55 to 64	0.151	0.358	0	1	41,567
65 to 75	0.116	0.320	0	1	41,567
>= 75	0.102	0.303	0	1	41,567

Appendix Table 1 Continued. Summary Statistics

	Mean	Std. Dev.	Min	Max	Obs
<u>Education Attainment</u>					
< High School	0.159	0.366	0	1	41,567
High School/ GED Only	0.316	0.465	0	1	41,564
Some College (AA), No BA	0.239	0.426	0	1	41,564
BA/BS Only	0.174	0.379	0	1	41,564
MA/MS (incl. nursing, but not MBA)	0.065	0.246	0	1	41,564
PhD, MD, JD, MBA	0.047	0.211	0	1	41,564
# kids	0.836	1.161	0	10	41,567
<u>Family Structure</u>					
not married/LWP + children	0.118	0.322	0	1	41,567
not married/LWP + no children + head under 55	0.152	0.359	0	1	41,567
not married/LWP + no children + head 55 or older	0.148	0.355	0	1	41,567
married/LWP+ children	0.321	0.467	0	1	41,567
married/LWP + no children	0.262	0.439	0	1	41,567
<u>Race</u>					
White	0.743	0.437	0	1	41,567
Black	0.131	0.338	0	1	41,567
Hispanic	0.086	0.280	0	1	41,567
Asian	0.024	0.154	0	1	41,567
Other	0.016	0.125	0	1	41,567
<u>Occupation Category 1</u>					
work for someone else	0.583	0.493	0	1	41,567
self-employed/partnership	0.109	0.312	0	1	41,567
retired/disabled + (student/homemaker/misc. not working and age 65 or older)	0.249	0.433	0	1	41,567
other groups not working (mainly those under 65 and out of the labor force)	0.058	0.234	0	1	41,567
<u>Occupation Category 2</u>					
managerial/professional	0.254	0.436	0	1	41,567
technical/sales/services	0.223	0.416	0	1	41,567
other (incl. production/craft/repair workers, operators, laborers, farmers, foresters, fishers)	0.215	0.411	0	1	41,567
not working	0.308	0.462	0	1	41,567
<u>Industry Category</u>					
mining + construction + manufacturing	0.185	0.388	0	1	41,567
transportation + communications + utilities and sanitary services + wholesale trade + finance, insurance and real estate	0.133	0.340	0	1	41,567
agriculture + retail trade + services + public administration	0.374	0.484	0	1	41,567
not working	0.308	0.462	0	1	41,567
2 or more properties with mortgages?	0.034	0.181	0	1	41,567

Appendix Table 2. High Income Thresholds (2013) by state 1989 to 2013 Change

	Threshold Level (2013$)			1989 to 2013 Change		
	P90	P95	P99	P90	P95	P99
US Average	118,380	168,144	398,318	12,327	28,009	102,447
AL	100,816	131,387	271,920	11,454	18,366	58,372
AK	135,294	190,753	394,266	-7,908	12,925	52,817
AZ	107,564	144,041	286,178	6,671	11,657	30,150
AR	94,778	127,260	270,625	15,000	24,585	74,418
CA	129,257	192,934	467,882	10,986	36,614	110,728
CO	130,746	190,437	436,053	24,317	51,814	165,117
CT	153,877	232,575	641,070	20,500	52,380	188,021
DE	122,895	170,499	333,886	10,787	23,784	41,905
DC	135,978	218,088	548,775	33,100	68,066	167,622
FL	105,604	148,695	392,205	6,879	14,950	64,038
GA	111,074	156,079	345,890	9,884	22,702	86,047
HI	115,621	153,600	279,433	983	4,967	-42,556
ID	104,306	131,962	281,491	14,571	20,038	61,202
IL	126,322	183,741	441,137	18,054	39,807	109,456
IN	109,195	137,371	283,698	10,721	12,555	56,699
IA	115,236	152,223	299,858	23,093	36,612	83,284
KS	118,544	164,693	369,695	18,076	34,598	128,569
KY	97,263	127,177	266,226	9,268	18,123	48,125
LA	107,228	142,491	306,146	19,800	32,367	86,167
ME	103,353	131,820	277,246	10,841	15,133	47,798
MD	138,595	199,637	438,514	12,331	38,884	98,229
MA	147,085	219,633	534,376	29,293	65,305	187,054
MI	112,239	148,581	288,963	4,130	9,900	41,614
MN	128,911	186,785	435,557	24,904	51,725	169,874
MS	89,765	122,559	254,744	10,921	20,559	71,163
MO	107,321	138,294	287,386	10,678	13,062	52,969
MT	108,026	135,546	288,396	22,413	30,277	88,227
NE	115,911	156,816	344,847	23,108	38,729	117,854
NV	106,510	139,372	311,299	1,936	2,772	-18,327
NH	132,426	189,646	403,772	20,118	43,367	107,549
NJ	156,265	228,109	548,400	26,395	55,863	155,118
NM	99,714	131,282	262,706	9,166	14,711	47,075
NY	125,571	187,467	504,588	14,242	35,279	139,313
NC	107,907	146,587	301,534	11,202	20,044	60,814
ND	128,581	190,661	485,177	40,482	83,068	275,604
OH	106,295	134,377	286,348	9,624	10,243	50,022
OK	107,053	140,984	325,387	16,487	25,466	103,872
OR	114,185	154,657	305,490	17,408	28,496	63,838
PA	118,016	165,915	374,718	19,202	36,444	114,092
RI	120,798	167,230	344,793	17,773	32,868	60,164
SC	100,244	131,778	275,705	7,963	13,374	53,557
SD	111,579	149,733	383,845	28,662	46,003	179,856
TN	100,544	133,131	288,914	9,639	15,419	55,360
TX	120,460	176,588	435,623	17,383	40,441	152,729
UT	116,188	156,258	339,999	18,924	33,701	110,305
VT	114,061	152,051	292,876	14,856	23,236	54,092
VA	137,347	200,048	432,813	18,446	45,922	126,370
WA	129,835	187,650	420,061	22,174	48,083	138,394
WV	96,328	123,729	247,111	12,663	19,995	64,884
WI	114,444	149,750	307,967	16,358	25,569	74,430
WY	121,693	167,043	392,927	22,759	44,045	167,685

Source: WTID, Frank, Sommeiller, Price, and Saez.

Appendix Table 3. PIR Total Regressed on Demographic and Labor Force Variables

	(1) Only Year, Region FE	(2) Demographic, Labor Force Covariates
Thrshld5 ($k)	0.000452	0.000386
	(0.000115)	(0.000111)
	***	***
Age_35to44		0.0320
		(0.00440)
		***
Age_45to54		0.0407
		(0.00458)
		***
Age_55to64		0.0490
		(0.00782)
		***
Age_65to74		-0.00771
		(0.00731)
Age_75+		-0.0568
		(0.00789)
		***
Ed_High School or GED		0.0135
		(0.00433)
		***
ED_Some College or Associates, No BA		0.0349
		(0.00453)
		***
ED_Bachelors		0.0488
		(0.00568)
		***
ED_MA or MS or Nursing (excluding MBA)		0.0175
		(0.00694)
		**
ED_PhD, JD, MBA, MD		0.0495
		(0.0124)
		***
# Kids		0.0311
		(0.00639)
		***
# Kids Squared		-0.00501
		(0.00104)
		***
Not married/LWP + no children + head under 55		-0.00946
		(0.00948)
Not married/LWP + no children + head 55 or older		-0.0276
		(0.00959)
		***

Appendix Table 3 CONTINUED. PIR Total Regressed on Demographic and Labor Force Variables

	(1) Only Year FE	(2) Demographic, Labor Force Covariates
Married/LWP+ children		0.0135
		(0.00551)
		**
Married/LWP + no children		0.000836
		(0.00937)
Race_African American		-0.0139
		(0.00459)
		***
Race_Hispanic		-0.0159
		(0.00694)
		**
Race_Asian		0.00819
		(0.0133)
Race_Other		-0.0225
		(0.0101)
		**
OCC1_ self-employed/partnership		0.102
		(0.00727)
		***
OCC1_ retired or student		-0.0316
		(0.0120)
		***
OCC1_ other NILF		-0.00796
		(0.00977)
OCC2_ technical/sales/services		-0.0157
		(0.00465)
		***
OCC2_ production/craft/repair/operators/laborers/farmers		-0.0271
		(0.00563)
		***
OCC2_not working		0
		(0.00747)
IND_ transportation, communication, and utilities		0.00642
		(0.00548)
IND_ wholesale trade, finance, insurance, real estate		-0.0103
		(0.00578)
		*
IND_ agriculture + retail trade + services + public administration		-0.00287
		(0.00827)
Constant	0.122	0.0945
	(0.0139)	(0.0164)
	***	***
Observations	27,399	27,397
R-squared	0.006	0.059

t-statistics in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Notes: All regressions include year fixed effects. PIR_Total truncated at 3.0. Standard errors calculated using scfcombo, using 999 boostapped replications of scf weights to reflect multiple impuation and sample design.

Appendix Table 4. Implied Effects on PIR for key points in Relative Income Distribution from 1 SD Change in Income Threshold (ln)

Based on Effects from Table 4, Panel C Continuous Distribution Interaction Term

Threshold:	Top5			Top1		
PIR-type Dependent Variable:	Total	Mortgage	Non-Mortgage	Total	Mortgage	Non-Mortgage
Points of Relative Income Distribution						
.25	-0.006	0.007	-0.016	-0.010	0.000	-0.013
0.5	0.000	0.010	-0.013	-0.006	0.002	-0.011
0.75	0.005	0.013	-0.010	-0.002	0.005	-0.009
1	0.010	0.016	-0.007	0.003	0.007	-0.007
1.5	0.021	0.021	-0.001	0.011	0.012	-0.002
2	0.031	0.027	0.006	0.019	0.017	0.002
2.5	0.042	0.032	0.012	0.027	0.021	0.007

Note: "Relative Income" is household normal income (SCF) divided by state-level average income (IRS, Frank-Sommeiller-Price). The mean value of relative-income is 2.5 at the 90th percentile income Threshold.