Debt, Inequality and House Prices: 
Explaining the Dynamics of Household 
Borrowing Prior to the Great Recession

Alessia De Stefani*
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Abstract
Growth rates of income inequality and household debt are positively corre-
lated within the US economy. Previous research explains this correlation via 
the relative income hypothesis: low and middle-income households borrow 
more when inequality increases, as they wish to emulate the consumption 
levels of richer households (Bertrand and Morse [2016]). I show instead 
that this correlation may more simply be explained by the growth of house 
prices occurring in high inequality areas. I exploit geographic variation in 
top incomes over time to show that given a 1% increase in top incomes 
relative to median incomes, homeowners in the bottom 80th percentile of the 
income distribution increased their consumption levels by 46% more than 
renters, and debt-to-income ratios by 64% more than renters. This effect 
may be explained by the fact that rising regional inequality was associated 
with rising regional house prices. A 1% increase in top incomes was corre-
lated with an increase in the self-reported value of homes close to 0.5% per 
year across US states and 0.7% per year across metropolitan areas.

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*School of Economics, University of Edinburgh. Email: a.de-stefani@sms.ed.ac.uk. I would like to thank Michele Belot, Mike Elsby and Robert Zymek for invaluable help and advice throughout this project. I would also like to thank Sam Bowles, Marianne Bertrand, Sergi Cutillas, Vanessa Ferdinand, Martin Guzman, Ed Hopkins, Aline Souza Menezes, Adair Morse the participants in the Royal Economics Society Junior Researchers Symposium, the participants in the INET-IMK Berlin Workshop on Inequality and in the Edinburgh School of Economics PhD Reading Group for useful comments. Financial support from the Economic and Social Research Council is gratefully acknowledged.
1 Introduction

A growing body of literature suggests that rising income inequality was at the root of the recent financial crisis (Van Treeck [2014]). This literature highlights the correlation between two prominent trends affecting household balance sheets over the past three decades: the growth of income inequality and the growth of household debt levels (Figure 1). The saving rates of American low and middle-income consumers, in particular, began declining as soon as inequality started to soar, in the middle 1980s (Rajan [2010]). This has led some authors to argue that poor and middle-income American consumers borrowed beyond their own capacity to repay in order to sustain consumption levels despite stagnating real incomes, generating fragility in the financial system (Rajan [2010]; Kumhof Ranciere Winant [2015]).

This paper attempts to ascertain whether rising income inequality can be considered a direct driver of the consumption choices of low and middle-income American consumers in the run-up to the 2007-2008 financial crisis. I focus in particular on testing the relative income hypothesis (Duesenberry [1949]), which received substantial attention in the public discourse as well as in academic circles (Frank, Levine and Dijk [2014]; Bertrand and Morse [2016]; Carr and Jayadev [2015]; De Giorgi Fredriksen and Pistaferri [2016]). This theory suggests that an increase in income at the top of the distribution could directly drive consumption choices at the bottom. If individuals are concerned with status, rising income inequality within a given social group will lead its relatively poorer members to consume a larger proportion of their resources, due to a desire to emulate the consumption levels of richer individuals. Low and middle-income consumers might therefore accumulate higher debt despite no real income change. Recent empirical literature finds support for this hypothesis, suggesting that inequality might have been a direct driver of household debt accumulation in the US prior to the 2007 financial crisis (Bertrand and Morse [2016]; Carr and Jayadev [2015]).

The results I present in this paper challenge this particular understanding of consumer behaviour during the 2000s credit boom. First of all, I show that between the mid-1990s and 2007 there is no significant empirical relationship between the growth in income inequality and the growth in consumption or debt levels of low and middle-income American households. On the other hand, exploiting household-level heterogeneity in the data allows me to identify one particular

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1. The decade before the crisis is the time frame in US history when, for the first time since before the Great Depression, the top decile income share increased beyond 45% (Piketty Saez [2014]). During the same time frame, US households accumulated almost half of the debt outstanding at the onset of the crisis (Figure 1.2).
2. For a complete survey of the recent literature on this topic see Van Treeck [2014].
social group that reacted strongly to changes in income inequality within this time frame: low and middle-income homeowners. Homeowners living in geographical areas where inequality increased at the fastest rates displayed a positive growth in consumption and debt levels, while renters living in the same state did not. My results also show that the growth in within-region income inequality was associated with a higher-than-average growth in house prices, in the same region. Therefore, the empirical relationship between inequality and household debt in the context of the pre-crisis US might be simply explained by the wealth and collateral effects experienced by homeowners living in high inequality areas.

My empirical approach relies on the use of state-level variation in top incomes over time to analyze how the consumption and debt levels of all households falling in the bottom eight deciles of the income distribution respond to changes in income levels of richer households living in the same state, while controlling for a wide set of household-level covariates that might affect consumption.

Using the Consumer Expenditure Survey (CEX), I show that given a 10% increase in top incomes relative to median incomes, homeowners in the bottom eight deciles of the income distribution increase their consumption of non-durable goods (unrelated to housing expenditure) by 4.6 percentage points more than the comparable group of renters. Since the net effect of top incomes on renters’ consumption is negative, this estimation implies that a 10% increase in top-incomes relative to median incomes is correlated with an absolute increase in low and middle-income homeowners’ non-housing consumption worth 0.7 percentage points. Using the Panel Study of Income Dynamics (PSID) I also show that inequality has a positive effect on homeowners’ debt-to-income ratios. Given a 10% increase in top incomes, the debt-to-income ratios of homeowners rise by 6.4 percentage points more than those of the comparable group of renters, or 1.8 percentage points in absolute terms. This effect is not explained by a change in credit conditions, as the interest rates charged on mortgages were not significantly affected by changes in income at the top of the distribution.

This evidence might instead be explained by the fact that the within-region growth in income inequality was positively correlated with the growth in house prices. Using the PSID and the American Housing Survey (AHS), I show that a 10% increase in top incomes relative to median incomes, between 1994 and 2007, was correlated with an average yearly increase in the self-reported value of homes worth about 0.5% per year across US states and close to 0.7% per year across the main metropolitan areas.
These findings are relevant for the interpretation of the demand-side mechanisms behind the 2000s credit boom. Earlier research has shown that, during this time frame, homeowners have exploited the collateral effects arising from housing wealth (Aron et al. [2010]; DeFusco [2015]) and that home-equity loans were used to finance consumption (Mian and Sufi [2009;2011]). While my results do not necessarily discount the psychological driver at the heart of the relative income hypothesis, they show that the empirical results in support of such a theory could be substantially understating the role of a reduction in borrowing constraints based on the increase in housing wealth.

It should be emphasized that I do not attempt to address causality concerns, since finding convincing instruments in this context proves difficult. Nevertheless, my results indicate that house prices played a major role in the inequality-debt cycle during the decade that preceded the 2007 financial crisis, providing an alternative explanation for the empirical relationship between inequality and household debt, which insofar has been based on two major theories.

The first line of thought is that inequality has historically led towards an easing of the credit conditions applied to poor borrowers (Rajan [2010]). During the decade preceding the 2007-2008 financial crisis, the average interest rate on household debt fell considerably (Figure 4). This is also the decade during which income inequality in the US grew at the fastest rates since before the Great Depression (Piketty and Saez [2014]). Inequality might be therefore associated with particularly low interest rates. This theory is formally developed by Kumhof et al. [2015], in a DSGE model which establishes a link between inequality, private debt, and financial crises. Assuming a decreasing marginal propensity to consume over the income ladder, top earners might be induced to invest (or lend) proportionally more of their resources, as their income increases. The influx of savings in the market lowers the real interest rate, inducing higher borrowing on the side of the most credit-constrained consumers and endogenously leading to widespread defaults. Kumhof et al. [2015] present results that are able to replicate the long term dynamics of the US economy (both for the Great Depression and the Great Recession). However, the empirical evidence in Coibion et al. [2014] challenges this hypothesis; using microdata on bank credit origination, they find that inequality actually reduced credit provision to poor applicants across the US. They interpret their results as indicative that inequality functions as a screening device for lenders, who choose to lend to richer applicants whenever possible. I test whether the price of debt is driving my results, and find no evidence that changing top incomes affect mortgage interest rates in any significant way.
The second line of thought is related to the relative income hypothesis, originally developed by Duesenberry [1949] and most recently formalized by Frank, Levine and Dijk [2014]. This paper is mainly a contribution to this second strand of literature. According to the theory of relative income, consumers compare their standard of living with those of their reference group of peers. If inequality increases within a reference group, individuals may consume more, given constant real income, in order to keep up with the consumption levels of richer individuals. The desire for positional goods might therefore explain why debt arises even in absence of a real income change.

This hypothesis has been tested empirically mostly on aggregate data: Christen and Morgan [2005] find a strong effect of inequality on debt levels in the US pre-2000. Bowles and Park [2005] find that higher inequality is associated with longer working hours. More recently, Carr and Jayadev [2013] and Bertrand and Morse [2016] use microdata on the American economy of the past two decades to test the relative income hypothesis, finding evidence in its support. All else held equal, when low and middle-income Americans have been exposed to higher levels inequality, they have been saving less and consuming more, especially on visible goods. I borrow extensively from Bertrand and Morse’s [2016] methodology. I however extend their analysis by addressing the role of wealth effects in greater detail, by looking at debt originations and by analysing the relationship between inequality and house prices.

Bertrand and Morse [2016] explicitly address whether their results might be driven by an increase in house prices, and they dismiss this potential confounding factor via two empirical tests. In particular, they show that splitting the sample between homeowners and renters does not indicate evidence of a statistically different effect of inequality between the two groups. Also, they show that homeowners were reacting more strongly to increases in inequality prior to the start of the housing boom. The discrepancy between my results and theirs is explained by the fact that Bertrand and Morse [2016] do not explicitly address whether homeownership is driving their results during the housing boom. However, this is the time frame when the majority of US household debt was accumulated.

In order to identify the trends between inequality, consumption, debt and house prices, I rely on three different household surveys. Section 2 describes each of them in detail. Section 3 presents the first part of the empirical analysis, or the relationship between inequality and consumption/debt accumulation. Section 4 provides evidence of the empirical link between inequality and house prices.
Section 5 briefly summarizes.

2 Data Sources

The empirical analysis in sections 3 and 4 of this paper requires disaggregated data on consumption, wealth and income of a representative sample of American households over a relatively long span of time. For this reason, I gather data from several population surveys: the Consumer Expenditure Survey, the Panel Study of Income Dynamics and the American Housing Survey. These are well-known but complex data sources, which require some discretionary choices. This section describes these choices in detail.

2.1 Consumer Expenditure Survey (CEX)

The Consumer Expenditure Survey is the most comprehensive American household survey on consumer behavior. As Bertrand and Morse [2013] use this dataset in their estimations, this is a natural starting point for my analysis. The public dataset has data from 1996 onwards (although the Bureau of Labor Statistics is slowly releasing earlier cohorts). The sample has a cross-sectional structure and is composed by about 6000 households per year, with the aim to be nationally representative. It consists of two main documents for each interview in any given year (each household is required to respond to four interviews per year).

The CEX is composed of two main questionnaires, the Diary survey and the Interview survey. The Diary survey collects data on weekly expenditures of frequently purchased items such as food at home, food away from home, alcoholic beverages, smoking supplies, personal care products and services, and nonprescription drugs. The Interview collects data on monthly expenditures for housing, apparel and services, transportation, health care, entertainment, personal care, reading, education, food, tobacco, cash contributions, personal insurance and pensions, as well as income and characteristics data. Both surveys therefore collect data on non-durables expenditure, which is the less volatile part of consumption and the most relevant for macroeconomic models (Kaplan, Mittman and Violante [2016]). I use the Interview Survey as it provides a vast range of information on households’ consumption behaviour, and it allows me to discriminate between housing and non-housing expenditure. In order to be consistent with Bertrand and Morse [2016] I exclude families who fail to respond to all four interviews and families with zero total consumption. The exclusion of families that do not respond to all surveys takes a large toll on the sample size: I am left with about 1000 families per given year. This however needed in order to construct a yearly
measure of expenditure, and it is standard procedure when working with the CEX.\textsuperscript{3} In order to facilitate comparison with the PSID, I only collect data from years when the PSID was also collected (intervals of two) starting with 1996.

I rely on the aggregate consumption categories reported in the summary expenditure variables of the Interview report: total expenditure and housing expenditure. I do so for simplicity, and to allow for an easier replication of my results.

2.2 The Panel Study of Income Dynamics (PSID)

I analyze debt and housing wealth with the PSID because it provides information over households’ wealth and financial liabilities, unlike the CEX. While other surveys provide this information (such as the Survey of Consumer Finances, for example), the PSID is the only source that also grants access to information about the geographical area of residence of respondents, a crucial part of my methodology. The PSID grew substantially over the years, and from an original sample in 1968 of about 6000 households, it now stands at about 8500 American families being continuously interviewed. I only take into account families reporting both a positive level of income and of consumption in a given year. My sample is restricted to 1997-2011. Overall I am left with a sample of about 14000 household heads observed over time. The discrepancy between the panel of families in each cohort and of household heads is due to family spin-offs and drop outs (the PSID is structured to followed individuals, rather than families).

2.3 American Housing Survey

The main advantage of the American Housing Survey (AHS) over other surveys describing self-reported home values (such as the PSID) is the combination its panel structure and how it provides a vast array of information on housing quality. Families are asked detailed information about their homes, including square-foot size, number of bedrooms/bathrooms and recent renovations. This is very valuable information when trying to describe the change in value of a particular house’s over time, as it allows to take into account renovations. The AHS surveys around 60000 families per year, and alternates the year when it samples National data with years when it samples a subset of Metropolitan Statistical Areas (MSAs). However, the lowest geographical level identifiable in the National survey is the macro region (NE, NW, SE, SW), and this impedes a direct comparison with the CEX and PSID.

\textsuperscript{3} Also Blundell Pistaferri and Preston [2008] apply the same criteria, and are left with about 8\% of the original CEX sample.
The Metropolitan survey, on the other hand, captures more fine-grained geographical information. It cycles through a set of 21 metropolitan areas, surveying each one about once every six years. Like the national survey, the metro survey is longitudinal. However, metro survey samples have been redrawn more often than the national samples, and this reduces the time spans where the longitudinal dimension applies. During 1996-2008, the metro surveys were conducted four times.

This allows me to identify two sets of information on family-level home value change. The first set is composed by MSAs surveyed in 1996 and 2004 respectively: Atlanta, Cleveland, Hartford, Indianapolis, Memphis, Oklahoma City, St. Louis, Seattle. The second panel was collected in 1998 and 2007, and comprises Boston, Baltimore, Houston, Minneapolis, Tampa and Washington DC. My dataset is therefore composed of 14 MSAs, and two panels: the sample between 1996 and 2004 and the sample between 1998 and 2007.

The metro survey also samples about 60000 individuals per year; however about 45% of these are not homeowners, but renters, and are therefore dropped from the analysis. I also exclude families that report negative or zero income. Moreover, not all these families respond to both waves of the survey, and those who don’t are naturally dropped from the analysis (as my main dependent variable is the change in value of their primary residence). I also exclude families who changed residence between t and t-1 to avoid confounding the results; and families who changed the size of their houses through additions (measured as the change in the number of rooms). Overall, I work on a sample of about 9000 families over the time span 1996-2007.

3 Empirical Analysis: Consumption and Debt

This paper is composed of two empirical sections: the first links inequality to household saving behaviour and the second looks at the relationship between inequality and house prices. This section focuses on whether changes in the distribution of income between the mid 1990s and the 2007 crisis were related to American households’ propensity to consume and borrow. I will use two data

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4. The AHS sample also includes Sacramento (CA), but these observations are excluded from the empirical analysis since I have no information on some of the covariates (for example, the elasticity of housing supply) for this MSA.
sources for this purpose: the Consumer Expenditure Survey and the Panel Study of Income Dynamics.

3.1 Methodology and Descriptive Statistics

Figure 3 shows that the distribution of income became more unequal over time: in real terms the bottom 60% of American households experienced a real income loss between 1999 and 2007. Nevertheless, their propensity to consume increased. In particular, the bottom 40% of the income distribution experienced a real expenditure to income ratio on average 15% higher, despite the real income loss. Debt-to-income ratios increased disproportionately at the bottom of the income distribution. The change in debt to income ratios for the bottom quintile is close to 200% in eight years, while the second quintile experienced a 100% increase. Surprisingly, this effect is not due to higher access of lower income households to homeownership; if anything, the home ownership rate for the bottom 40% of the distribution decreased by an average 10% over this time span. This suggests that if these households increased their debt to income ratios, over this time frame, this was at the intensive, rather than extensive, margin.

The change in income by decile shown in Figure 3 implies that inequality increased between the mid 1990s and the late 2000s. This was the effect of both a shrinking in real income at the bottom of the distribution, and of an increase in real income at the top. There is no evidence of a shrinking in expenditure, as a result, however: all quintiles increased expenditure and debt levels, and poorer households even more so. In this section I study the relationship between poor households’ debt and consumption levels and inequality levels in their geographical area of residence.

To do so, I will follow closely the empirical methodology suggested in Bertrand and Morse [2013] which is based on the following equation:

$$\log Y_{ist} = \alpha + \beta_1 X_{ist}^I + \beta_2 \log(80\text{th Percentile Income})_{ist} + \beta_3 Z_{ist}^I + \chi_s + \psi_t + \varepsilon_{ist},$$

where $\log Y_{ist}$ is either yearly household expenditure or outstanding debt for family $i$ in state $s$ at year $t$. Consumption is measured by the CEX, while financial liabilities are measured in the PSID. $X_{ist}^I$ is a vector of family specific characteristics, namely: total family income, number of adults and children in

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5. Income and expenditure variables are expressed in real terms. The CPI measure is local (state-level) as computed by Carrillo, Early, Olsen (2014).
household, age race sex and educational attainment of household head, and home ownership status.\textsuperscript{6}

The inequality measure \( \log(80\text{th Percentile Income}_{st}) \) is defined at the state/year level; following Bertrand and Morse [2013] it is the average annual income of the top 20% of the state/year income distribution as defined by the Current Population Survey (CPS).\textsuperscript{7}

Crucially, the CPS also permits the identification PSID and CEX households falling in top 20% of their state/year cell; these are excluded from the analysis, to avoid obvious endogeneity concerns. All remaining families (those below the 80th percentile of the state/year cell) will be collectively defined “non-rich” households throughout the paper. \( Z_{st}^I \) is a vector of controls for state-level time-varying characteristics which might be correlated both with inequality and consumption or debt. The models include sample weights, and the residuals are clustered at the state level, to account for the presence of a common random effect within states across families.\textsuperscript{89}

Equation (1) uses state-level variation in top incomes over time to test whether non-rich households’ increase their consumption and debt levels when exposed to rising to rising top incomes. In other words, I assume that the top 20% of households constitute a reference group for the bottom 80%.

Exploiting both regional and time variation across the sample, the estimation strategy in (1) constructs an empirical framework that is akin to a “difference-in-difference” model. US-wide time trends, assumed to affect all states equally, at the same point in time are taken into account by time fixed-effects; and so are the time-invariant characteristics of each state, given the inclusion of state fixed-effect. The coefficient \( \beta_2 \) measures the average effect of the within-state growth in income inequality while controlling for a wide set of individual characteristics that might affect consumption (family composition, individual income, age, gender, etc.).

\textsuperscript{6} While Bertrand & Morse [2013] control for family income by including categories for income thresholds every 2000$, I instead control for the actual measure of family income.

\textsuperscript{7} While I could compute income distribution based on the CEX or on the PSID, the CPS is more reliable when it comes to income distribution analysis, thanks to its much larger sample size (about 60000 surveys per year). The CPS on the other hand does not collect data on assets, liabilities or consumption.

\textsuperscript{8} A discussion of the opportunity of including sample weights in regression analysis of survey data is included in Appendix A2.

\textsuperscript{9} Following Bertrand, Duflo and Mullainathan [2004]. A discussion of the clusterization of standard errors in this context is provided in Appendix A3.
3.2 Consumption: Baseline

I study consumption as a function of inequality using the Consumer Expenditure Survey from 1997 to 2011. Table 1 attempts at replicating Bertrand and Morse [2016] baseline results, on a different time frame. My dataset spans from 1996 to 2011, in gaps of two years; theirs, from 1980 to 2008 on a yearly basis. The reason for my sample choice is that the majority of US household borrowing occurred well after the 1980s; actually, almost a half was accumulated between 1996 and 2008. This is also the time frame when inequality grew at the fastest rate since the decade preceding the Great Depression (Piketty and Saez [2014]).

In Table 1 I find that, post 1999, inequality had no statistically significant effect on non-rich households’ consumption, as seen in Column (1). The coefficient is positive (+0.19), but not statistically different from zero. This coefficient is an important baseline, because it replicates almost exactly Bertrand and Morse’s results for the years post 1999. While in general they find strong evidence of the relationship between inequality and higher consumption in the bottom deciles of the distribution, they also find that this relationship is weaker, and not statistically significant, during the 2000s.

I columns 2 and 3 of Table 1, I move to the analysis of potential differential effects of inequality on consumption levels of homeowners and renters, respectively. Bertrand and Morse [2016] control for wealth effects on consumption by splitting the sample between homeowners and renters and evaluate differentials in consumption levels throughout their sample. In columns (2) and (3) of Table 1, I run the same test: in the subset of sample between 2000 and 2011, owners do not seem to react to increasing inequality more than renters. If anything, splitting the sample between homeowners and renters seems to indicate that the second group responds more to changes in inequality (elasticity of +0.67, Column 3). However, the statistical relevance of the difference in the coefficient in top income levels between Columns (2) and (3) cannot be evaluated by a simple comparison of the two coefficients. This is because, by allowing all coefficients (including time and state dummies) to differ across the two models, one cannot easily test whether the

11. See Figure 2.
12. Bertrand and Morse [2016], in Column 1, Appendix A3, find an elasticity of +0.21 in the time frame 2000-2008.
13. Bertrand and Morse [2016], Table 5, Panel A, Columns 1 and 2; Bertrand and Morse [2016] Section IV.c
difference in the specific coefficient associated with top incomes between owners and renters is significant.\textsuperscript{14}

I run a more precise test of whether the two coefficients are statistically different from each other, by interacting the inequality measure with homeownership (Column 4). This model constraints all coefficients to be the same, across the two groups. Column (4) provides therefore a direct comparison of the differential effect of inequality on owners’ and renters’ consumption levels, and of the statistical significance of this difference. The test shows that the higher effect of inequality on renters’ consumption levels, albeit positive (+0.209) is not statistically different from zero. It also shows that there is no statistically significant difference in the effects of inequality between owners and renters; the coefficient for the interaction term is small and negative, but not statistically significant.

3.3 Consumption: The Role of Homeownership

Table 1 has the main purpose of confirming that I can broadly replicate Bertrand and Morse’s [2016] main results, albeit I am using a different time frame and a slightly different definition of variables. However, Table 1 has also the purpose of showing the importance of constructing a correct framework of analysis for the differential effects of inequality on owners and renters. The fact that the difference between owners and renters is insignificant could not have been figured out by a simple comparison of the coefficients on inequality in Columns (2) and (3) of Table 1.

Since the interactive model instead allows an estimation of the statistical significance in the similarity (or difference) of effects between owners and renters, I will is use this model, rather than a split of the sample, in the following estimations. This is the first way in which the analysis, in Table 2 will differ from Table 1 and from Bertrand and Morse’s [2015]. The second difference is that I only focus on the years immediately preceding the 2007 financial crisis.

Table 2 replicates the analysis above focusing on the pre-crisis years: it is the same model as in Table 1, except for the fact that the estimation includes the late 1990s and excludes the years after 2008. The sample includes exactly ten years: 1997 to 2007. Column (1) shows that, for the overall population, the relationship between top incomes and non-rich consumption is not significantly different from zero: the overall coefficient is (+0.07), but it is not significant.

\textsuperscript{14} A discussion on the matter of sample-split VS interaction terms, and type II errors in this context, can be found in Appendix A1.
In Column (2), I run the same model with the addition of an interaction term between top incomes homeownership status. The first important result of this section is that the interaction between inequality and the ownership status term is positive and strongly significant. During this time frame, non-rich homeowners responded to rising inequality with a much higher increase in consumption than renters did. Specifically, the elasticity of response was +0.35; for every 1% increase in the income of top earners in a given state/year, non-rich homeowners’ real consumption increased by 35% more than renters.

The increase in consumption on the side of homeowners was not due to higher expenditure in housing: Column (3) shows that expenditure for shelter is not significantly affected by top incomes, and that in this respect owners and renters do not differ from each other. On the other hand Column (4) shows that the elasticity of non-housing consumption to rising inequality is about 49% higher for non-rich homeowners versus renters. This effect does not capture aggregate income trends, as the effect is robust to the inclusion of controls for median at the state level (Column 5).

Another concern might be that owners, on average, are richer than renters, so they might be closer (socially/geographically) to the richest people in their states of residence. Column (6) addresses this concern by including dummies for each different decile of the income distribution non-rich households fall into (ranging from decile 1 to decile 7, as the top two deciles are excluded from the estimations). This barely affects the coefficient of the interaction term and doesn’t change its significance. Overall, Column 6 suggests that the a 1% rise in inequality was associated with a rise in non-housing consumption for homeowners about 46% larger than for renters.

Observing the relationship between top incomes and non-rich consumption between 1996 and the financial crisis, one pattern clearly emerges: homeowners changed their consumption patterns much more than renters as a result of the increase in inequality in their state of residence.

### 3.4 Household Debt

I study the relationship between top income and non-rich households’ debt accumulation using the PSID, as it contains better measures than the CEX when it comes to financial liabilities, and allows me to exploit the panel structure of the data.
Column (1) of Table 3 shows that there is no significant relationship between the average of non-rich households’ debt levels and changes in top incomes during this time frame.

However, non-rich *homeowners* strongly and significantly increased their debt to income ratios as a result of the increase in inequality in their state of residence; the elasticity of response is about 64% higher than renters’ response (Column 2). This result is robust to controls for median incomes and for the average state-level mortgage interest rate charged to families below the 80th percentile of the income distribution. The overall effect on the population can be estimated in about 0.18% increase in debt-to-income ratios per percentage increase in inequality.

The differential effect of inequality on homeowners’ debt-to-income ratios is mostly due to mortgage debt: Column (3) shows that inequality has no significant differential effect on consumer debt levels, between the two groups.

If, as suggested by Kumhof, Ranciere and Winant [2015] changes in inequality affect the interest rate, these results might however be driven by the price of mortgage debt: interest rates fell considerably in the US during the housing boom (Figure 4). Column (4) shows that individual-level interest rates on first mortgages are not significantly affected by inequality levels, however.\(^{15}\)

Interestingly, leverage ratios (measured as outstanding mortgages to house value) seem to be negatively affected by changes in top incomes (Column 5). A 1% increase in inequality reduces non-rich homeowners leverage ratios by 0.07%. This latter evidence suggests that if mortgages were the main component of the increase in the debt-income ratio of poor home owners, as it seems to be the case, they were more than offset by an increase in house prices.

Table 4 provides further evidence that the effect of recent home value increase dominates the effect of income distribution, when looking at homeowners’ debt levels. Table 4 regresses different measures of homeowners’ financial liabilities on past home value increases (as contemporaneous house price increase pose an obvious reverse causality concern). Column 1 shows that a 1% increase in home value between t-2 and t-1 increases debt-to-income ratios by 0.05%, between t-
1 and t. Top incomes, as well as average interest rates charged at the state level, have negative and non-significant coefficients. This is true after controlling for the usual state and year fixed effects, family-level controls and the lagged \((t-1)\) realization of the dependent variable. Column 2 reproduces the same model of Column 1, but adding family-level fixed effects; the results are robust to this specification, even if the coefficient is smaller \((+0.03)\).\(^{16}\) Again, the effect of past home appreciation is relevant only to mortgage originations: Column 3 shows that the effect on consumer debt is negative. Presumably, this is because people tend to prefer a cheaper form of credit, if available to them (interest rates on mortgages and home-equity loans are generally lower than those charged on non-collateralized loans). This last point is confirmed when looking at leverage, in Column 4. A 1\% increase in home value at \(t-1\) increases leverage (loan to value ratio at time \(t\)) by 0.025\%, after controlling for past realizations of leverage and the price of debt. Also, the price families pay on their mortgages is not affected by changes in house prices. Overall, Table 4 suggests that as people witness the value of their house increasing, they leverage against it, confirming the intuition suggested by Table 3.

The overall evidence in this section points to a relationship between homeownership and consumption, during the boom years. Therefore, the relationship between inequality and higher consumption might be concealing a correlation between inequality and house prices increase.

4 Inequality and House Prices

Section 3 shows that the relationship between inequality and consumption is likely to have been mediated by homeownership status, prior to 2008. In particular, only non-rich homeowners were responding to increases in inequality in their state of residence by increasing their consumption and mortgage levels. An implication of this evidence is that rising inequality might have been correlated with a wealth effect experienced by non-rich homeowners, in the form of rising house prices.

\(^{16}\) The family fixed-effects model doesn’t allow the introduction of sample weights, as fixed-effects estimation requires the weights to be constant along the panel. This affects the results considerably. Moreover as panels are not nested within clusters (families move across states over time), the cluster robust fixed-effect estimator requires a full degrees of freedom (very restrictive) adjustment of the cluster-robust covariance estimator (to allow for errors of families residing within the same state to be correlated). For both reasons, I prefer to use the model without family fixed-effects when analyzing the PSID.
In this section, I test to what extent inequality has been related to the change in house prices across the US after 1996. I analyse this by means of two different data sources: the PSID, to evaluate the effects at the level of states, and the American Housing Survey, to analyze the effect at the level of metropolitan areas.

4.1 Methodology and Descriptive Statistics

Prior to 2008, the average family reported an increase in the value of their main residence between 5 and 10 percentage points every two years (Figure 5). The wealth increase suddenly stopped after 2008. Overall the average American household perceived a compound 37% increase in the value of their housing assets between 1996 and 2007 and a 25% drop between 2008 and 2011. However, this change in house prices was not homogenous across the US territory. The most striking differences can be found between metropolitan areas: as Figure 6 shows, the Washington DC metropolitan area experienced a real increase in house prices of about 60% between 1998 and 2007, almost double the national average. On the other hand, the average change in prices in Memphis (TN) between 1996 and 2004 was below 2%. Obviously, this discrepancy cannot be explained by changes in income distribution; other factors, such as location, housing supply regulation, geography and population growth have a prominent role.

In order to estimate the relationship between inequality and the increase in housing wealth, I estimate the following model:

$$\Delta \log p_{igt} = a + \beta_1 \Delta \log (80\text{th Percentile Income})_{gt} + \beta_2 X_{igt} + \beta_3 Z_{igt} + \chi_g + \psi_t + \varepsilon_{igt},$$

(2)

where $\Delta p_{igt}$ is the change in the self-reported value of housing assets of family $i$, in geographical area $g$, between year $t-1$ and year $t$. This model, unlike equation (1), is expressed in first-difference, as I have panel data in both my data sources. My dependent variable is the change in home valuation at the family-level between two time periods. For internal consistency, all other regressors are also expressed in first-differences. Using a model in changes, rather than levels, also prevents me from capturing spurious correlation between variables. This is especially a concern since I am treating variables which are highly likely to suffer from non-stationarity and cointegration (house prices and income inequality).\textsuperscript{17}

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\textsuperscript{17} The CEX is structured as a repeated cross-section, and as such does not allow first-differencing. The PSID would allow first-differencing, in principle; however, as my identification strategy in Section 3 relies on the interaction term between state-level top incomes and homeownership status. Homeownership status is very often a constant within households over a ten-year time span. For this reason,
I make sure I exclude from my sample new buyers; families who changed residence in this time span; families who didn’t move but changed the size of their house (measured as the number of rooms). This is because $\Delta p_{igt}$ needs to reflect the change in wealth experienced by homeowners on the same house (which didn’t go through major improvements which might have substantially affected its value). $\Delta(80\text{thPercentileIncome})_{igt}$ is the change in inequality measures in the given geographical area of residence between $t - 1$ and $t$. The inequality measure is the same as for other specifications (average value of top incomes in the state/year cell) when controlling also for median income. I also run some robustness checks using a more standard measure of inequality as Gini coefficients at the state level (also computed from the March CPS).

$X_{igt}$ is a vector of family-specific characteristics which include the log of levels of income at the family level; the change in income between $t - 1$ and $t$; age, race, educational attainment, marriage status and sex of the household head; number of children in the household. $Z_{igt}$ is a vector of geographical area-specific characteristics which might affect house prices, namely: changes in median incomes; changes in the elasticity of housing supply, measured by Saiz [2010]; change in homeownership rates measured by the CPS; 10-year change in population size measured by the census; average change in interest rate on mortgages reported by PSID respondents between $t - 1$ and $t$. All geographical-area specific measures (including inequality) are expressed at the state level in PSID estimations and at the metro area level in the AHS estimations.

All regressions are weighted with the sample weights provided in the surveys, and errors are clustered at the level of geographical areas (states in section 4.2 and metropolitan areas in section 4.3).

### 4.2 Results: States

Table 5 studies the relationship between changes in inequality and changes in house values at the level of US states between 1999 and 2011 using the PSID. The dependent variable is the year-on-year change in the value of housing assets.

---

18. The measure for the number of rooms is only available for the American Housing Survey, and not for the PSID. Obviously, I exclude from the analysis also families who changed homeownership status between $t - 1$ and $t$.

19. The panel starts in 1999 rather than 1997 because I rely on changes in house prices, rather than their levels. So the first change I can observe is the one occurring between 1997 and 1999.
for homeowners who did not change residence (or homeownership status) between \(t-1\) and \(t\).

At an aggregate level, a 1% increase in top incomes versus median income was correlated with an average house price increase of about 0.03% between 1999 and 2011 (Column 1). When looking at this result in the pre-crisis period, however, the correlation is higher (0.07%, Column 2).

Columns (3)-(6) provide evidence that this effect is robust to the micro-level estimation with family-level controls and that the effects are stronger than in the aggregate-level regressions.

Column (3) shows that between 1999 and 2007, a 1% increase in top incomes was associated with an increase in the value of a family’s main residence worth about 0.10% over two years (significant at 5% level). This implies a yearly change of about 0.048% per percentage increase in top incomes (all else held equal). Column (4) shows that this relationship is robust to the use of a more conventional measure of inequality, the Gini coefficient; a 1% change in Gini coefficients has an effect on the increase in house values of about 0.23%. Both regressions take into account time-trends in income, by controlling for the change in median incomes at the state level.

However, the American public was already perceiving the burst of the housing bubble in 2007, as reported by Case Shiller and Thompson [2012]. Their expectations on future house price growth was rapidly changing for the worst, and consequently house price increase was coming to an halt before the crisis erupted in late 2007 (Figure 4). Columns (5) and (6) provide a robustness check, by focusing on the four reported changes in house value reported by the PSID sample between 1997 and 2005. The effect of inequality during this time span is even stronger: a 1% increase in top incomes is related a change in house prices worth about 0.16% in two years, or 0.077% a year (Column 5). This effect is robust to the inclusion of family level fixed-effects, to take into account household-specific time invariant characteristics (Column 6). Here, too, the coefficient is very close to the weighted OLS regression (0.15%).

The elasticity of housing supply, as expected, has mostly a negative effect on the change in house prices, although this is not always significant. The change in mortgage interest rates displays the expected negative coefficient, even if it is only significant at the aggregate level (Columns 1 and 2). Likewise, changes in the homeownership rates are never significant in the micro-level estimations.
4.3 Results: Metropolitan Areas

Table 6 shows that changes in top incomes was strongly correlated with housing appreciation also across US metropolitan areas between 1996 and 2008. The American Housing survey rotates its panels across metro areas every 8 years, on average. Therefore each family during this time period reports a change in house value at most once: between 1994 and 2006 for the first group of SMSAs and between 1998 and 2007 for the second group. Column 1 shows the macro-level effect for all MSAs: on average, the correlation between an increase in top incomes and an increase in house prices is 96%. Elasticity of housing supply has a negative coefficient, while positive changes in population display an elasticity of 0.15% on house price increase. Higher median incomes (in levels) are also positively correlated with house price increase (elasticity 0.3).

Columns 2-6 estimates the micro-level effect, in the usual semi-DiD framework. The estimated effect of a 1% increase in top income VS median incomes is 0.7% in eight years, or 0.068% per year (Column 2).

Columns (3) and (4) split the sample between the two waves of MSAs; the first (families interviewed in 1996 and in 2004) and the second (interviewed in 1998 and in 2007). The estimated effect of inequality on house prices differs substantially between the two columns. The first wave of MSAs (Column 3) displays an elasticity of 2.4, implying that a change in top incomes versus median incomes had a more than proportional effect on house prices during this time frame: a 1% increase in top incomes, for this group of MSAs, was associated with a yearly increase in prices worth 0.11%.

The estimated coefficient on top incomes, for the second wave of MSAs (Column 4), is however only 0.08%, or 0.001% per year. The positive effects of changes in inequality on house price increase is confirmed when using Gini coefficients at the MSA level in Columns 5 and 6. Again, the difference between the two waves is substantial: a 1% increase in Gini coefficients was associated with a house price increase of about 0.8% (0.076% per year) between 1996 and 2004, and only 0.12% (0.03% per year) between 1998 and 2007.

The two waves in Columns (3)-(5) and (4)-(6), respectively, are however composed of different metropolitan areas. In particular, the second group has an outlier in Houston (TX), which experienced house price increases well below the US average in this time frame, and is widely regarded to have been a peculiar case among US metro areas during the boom. Moreover, this second wave of
interviews was conducted when the price slowdown had already started (end of 2007).

Overall, these results indicate that inequality increase was strongly correlated with higher than average increases in house prices across US metropolitan areas, with an average estimated effect across metro areas of about 0.7% in eight years (0.068% per year) per percentage increase in top income. The estimated effect is therefore slightly larger for US metro areas than for US states (+0.048% per year).

5 Conclusions

The relative income hypothesis states that income inequality should be negatively correlated with the saving rates of low and middle-income households (Frank Levine and Dijk [2014]). This is because income inequality might shift the preferences of “non-rich” consumers, who will attempt to emulate the consumption levels of richer individuals and accumulate more debts in the process. Recent literature provides empirical evidence in support of this hypothesis, suggesting that income inequality might have been a direct driver of US household debt accumulation ahead of the 2007 financial crisis (Bertrand and Morse [2016]; Carr and Jayadev [2015]).

I test this theory on the years when the majority of US household debt was accumulated, between the mid 1990s and 2007. I find that the relationship between inequality and consumption holds only for a particular category of consumers: poor and middle-income homeowners. This group exhibited a positive expenditure reaction to increases in income inequality within their states of residence, especially with respect to non-housing expenditure. Non-rich homeowners also accumulated more mortgage debt, in response to increasing top incomes. However, their leverage ratios (mortgage to house value) did not increase, nor did the interest rates they paid on their debt. This evidence points to a relationship between income concentration and house price growth across the US. I find empirical support in favour of this hypothesis. Exploiting both geographical and time variation across US states and metropolitan areas, I present evidence of a positive within-region correlation between inequality and the increase in house prices in the decade preceding the financial crisis of 2007-2008.

20. Houston, thanks to its large supply of land and permissive regulations, reacted to demand growth through higher construction, not price increase, largely avoiding the boom and bust dynamic which other cities experienced (FED, 2008).
These results shed some light on the demand-side mechanism driving the 2000s credit boom. The relative income mechanism seems empirically indistinguishable from a more canonical wealth effect, against which households might have decided to borrow (Mian and Sufi [2009;2011]). An alternative and complementary interpretation is that households were subject to an increase in collateral availability, as suggested by Aron et. al [2010] and DeFusco [2015].

Overall my results suggest that the effect of inequality on consumer credit in the decade preceding the 2007 crisis was mediated by the role of house prices. In other words, what has largely been considered imprudent behaviour on the side of the weakest American consumers (borrowing beyond their own capacity to repay) might as well have been the result of a widespread illusion: the belief that the value of real estate would keep on growing (or at least hold its value indefinitely).  

This changes the narrative, shifting the blame for the post-2008 recession from “poor” consumers to poor regulators. It suggests that if house prices were not to reach unsustainable levels, as a result of better urban planning and more regulated credit markets, it might have been possible to mitigate the effects of the Recession which followed the housing boom.

References


Figures

Figure 1: Year-on-year change in household debt to GDP ratio VS top 1% income share. OECD economies, 1978-2011. Sources: Piketty Saez (2014) and BIS statistics.

Figure 2: Household debt to GDP ratio, United States, 1978-2011. Source: BIS statistics.
Figure 3: Average % Changes in selected statistics by quintile of the income distribution, 1999 to 2007. Sources: PSID and March CPS.

Figure 4: Average interest rate on first mortgages paid by households below the 80th Percentile of the State/year income distribution. Sources: PSID and March CPS.
Figure 5: Average US house price increase from previous year, as reported by PSID respondents, 1996-2011.

Average Change in House Value by SMSA

1996 to 2004

1998 to 2007

Figure 5: Average change in house value (price per bedroom) in selected metro areas over 8 years. Source: American Housing Survey, 1996-2004 and 1998-2007 waves.
### Tables

**Table 1. Top income levels and bottom 80th percentile’s consumption: 2001-2011**

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>Consumption Owner</th>
<th>Consumption Renter</th>
<th>Consumption</th>
<th>Consumption</th>
</tr>
</thead>
<tbody>
<tr>
<td>Top 20% Income</td>
<td>0.194</td>
<td>-0.035</td>
<td>0.674*</td>
<td>0.209</td>
</tr>
<tr>
<td>Owner</td>
<td>(0.170)</td>
<td>(0.178)</td>
<td>(0.339)</td>
<td>(0.224)</td>
</tr>
<tr>
<td>Top20*Owner</td>
<td>0.195***</td>
<td>0.449</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.026)</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>(1.998)</td>
<td>(2.057)</td>
<td>(4.035)</td>
<td>(2.652)</td>
</tr>
<tr>
<td>Observations</td>
<td>4,471</td>
<td>3,056</td>
<td>1,415</td>
<td>4,471</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.337</td>
<td>0.308</td>
<td>0.351</td>
<td>0.337</td>
</tr>
</tbody>
</table>

Source: Consumer Expenditure Survey, 2001 to 2011. OLS regression. The sample is restricted to households below the 80th percentile of the state/year cell. The dependent variable is the logarithm of yearly total expenditure at the family level. All variables are in real terms, with CPI scaled at the State level (1996=1). Top 20% Income is the average income of families falling in the top 20% of the income distribution in a given state/year, computed from the March CPS. Family controls include a logarithm of income; age of head and its squared; sex, marital status, race and educational attainment of head; number of children in HH. Sample weights from the CEX are included. Errors are clustered at the State level. *** p<0.01, ** p<0.05, * p<0.1
Table 2. Top income levels and bottom 80th percentile’s consumption: 1997 to 2007.

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1) Consumption</th>
<th>(2) Consumption</th>
<th>(3) Consumption</th>
<th>(4) Consumption</th>
<th>(5) Consumption</th>
<th>(6) Consumption</th>
</tr>
</thead>
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<tr>
<td>Top 20 Income</td>
<td>0.074</td>
<td>-0.185</td>
<td>-0.139</td>
<td>-0.203</td>
<td>-0.290</td>
<td>-0.387*</td>
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<tr>
<td></td>
<td>(0.170)</td>
<td>(0.181)</td>
<td>(0.232)</td>
<td>(0.198)</td>
<td>(0.201)</td>
<td>(0.222)</td>
</tr>
<tr>
<td>Median Income</td>
<td></td>
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<td>0.485</td>
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<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.312)</td>
<td>(0.325)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Top20*owner</td>
<td>0.359***</td>
<td>0.099</td>
<td>0.492***</td>
<td>0.497***</td>
<td>0.459***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.119)</td>
<td>(0.125)</td>
<td>(0.121)</td>
<td>(0.120)</td>
<td>(0.133)</td>
<td></td>
</tr>
<tr>
<td>Owner</td>
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<td>-3.971***</td>
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<td>-5.449***</td>
<td>-5.501***</td>
<td>-5.095***</td>
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<tr>
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<td>(0.021)</td>
<td>(1.389)</td>
<td>(1.459)</td>
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<td>(1.406)</td>
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<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Year FE</td>
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<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Family Controls</td>
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<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Decile FE</td>
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<td>no</td>
<td>no</td>
<td>no</td>
<td>no</td>
<td>yes</td>
</tr>
<tr>
<td>Observations</td>
<td>5,528</td>
<td>5,528</td>
<td>5,528</td>
<td>5,528</td>
<td>5,528</td>
<td>5,528</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.329</td>
<td>0.330</td>
<td>0.239</td>
<td>0.353</td>
<td>0.353</td>
<td>0.369</td>
</tr>
</tbody>
</table>

Source: Consumer Expenditure Survey, 1997 to 2007. OLS regression. The sample is restricted to households below the 80th percentile of the state/year cell. The dependent variable is the logarithm of yearly total expenditure at the family level in columns 1-2; the log of housing expenditure in column 3; the log of non-housing expenditure (calculated as a residual) in cols 4-6. All variables are in real terms, with CPI scaled at the State level (1996=1). Top 20% Income is the average income of families falling in the top 20% of the income distribution in a given state/year, computed from the March CPS. Family controls include a logarithm of income; age of head and its squared; sex, marital status, race and educational attainment of head; number of children in HH. Sample weights from the CEX are included. Errors are clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1
Table 3. Top income levels and bottom 80th percentile’s financial liabilities.

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1) Debt/Income</th>
<th>(2) Debt/Income</th>
<th>(3) Consumer Debt/Income</th>
<th>(4) Interest rate</th>
<th>(5) Leverage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Top20income*Owner</td>
<td>0.646***</td>
<td>0.771</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.215)</td>
<td>(0.852)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Top 20 Income</td>
<td>-0.098</td>
<td>-0.464***</td>
<td>-0.766</td>
<td>0.037</td>
<td>-0.071*</td>
</tr>
<tr>
<td></td>
<td>(0.075)</td>
<td>(0.113)</td>
<td>(0.698)</td>
<td>(0.057)</td>
<td>(0.041)</td>
</tr>
<tr>
<td>Owner</td>
<td>0.596***</td>
<td>-7.007***</td>
<td>-10.277</td>
<td></td>
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</tr>
<tr>
<td></td>
<td>(0.039)</td>
<td>(2.513)</td>
<td>(10.008)</td>
<td></td>
<td></td>
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<td>Median Income</td>
<td>0.045</td>
<td>0.030</td>
<td>-0.620</td>
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<td>-0.123***</td>
</tr>
<tr>
<td></td>
<td>(0.091)</td>
<td>(0.092)</td>
<td>(0.578)</td>
<td>(0.064)</td>
<td>(0.040)</td>
</tr>
<tr>
<td>Average Interest</td>
<td>0.001</td>
<td>0.003</td>
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<td></td>
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<tr>
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<td>(0.436)</td>
<td></td>
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</tr>
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<td>Constant</td>
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<td>12.414</td>
<td>1.544**</td>
<td>2.596***</td>
</tr>
<tr>
<td></td>
<td>(0.993)</td>
<td>(1.659)</td>
<td>(9.509)</td>
<td>(0.752)</td>
<td>(0.582)</td>
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</tbody>
</table>

State FE            yes                           yes                           yes                           yes                           yes
Year FE             yes                           yes                           yes                           yes                           yes
Family Controls     yes                           yes                           yes                           yes                           yes

Observations        41,742                       41,742                       41,743                       15,678                       24,878
R-squared           0.276                        0.277                        0.113                        0.333                        0.383

Source: Panel study of Income Dynamics, 1996-2011. OLS regression. The sample is restricted to households below the 80th percentile of the state/year cell. The dependent variable in columns 1-2 is outstanding debt to income ratio; in column 3 is non-mortgage debt; in column 4 is interest rate charged on the main mortgage; in column 5 is leverage (mortgage outstanding/house value). All variables are expressed in logs and are in real terms, with CPI scaled at the State level (1996=1). Top 20% Income is the average income of families falling in the top 20% of the income distribution in a given state/year, computed from the March CPS. Family controls include age of head and its squared; sex, marital status, race and educational attainment of head; number of children in HH. Sample weights are included in all columns. Errors are clustered at the state level.

*** p<0.01, ** p<0.05, * p<0.1
Table 4. Recent home value increase and bottom 80th percentile’s financial liabilities.

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1) Debt/Income</th>
<th>(2) Debt/Income</th>
<th>(3) Consumer Debt/Income</th>
<th>(4) Leverage</th>
<th>(5) Interest Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>∆ Home Value t-1</td>
<td>0.055**</td>
<td>0.033**</td>
<td>-0.200**</td>
<td>-0.025***</td>
<td>-0.006</td>
</tr>
<tr>
<td></td>
<td>(0.022)</td>
<td>(0.021)</td>
<td>(0.097)</td>
<td>(0.005)</td>
<td>(0.012)</td>
</tr>
<tr>
<td>Top 20 Income</td>
<td>-0.032**</td>
<td>-0.186</td>
<td>0.454</td>
<td>0.084</td>
<td>0.078**</td>
</tr>
<tr>
<td></td>
<td>(0.123)</td>
<td>(0.140)</td>
<td>(0.658)</td>
<td>(0.052)</td>
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</tr>
<tr>
<td>Average Interest Rate</td>
<td>-0.038</td>
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<td>-0.263</td>
<td>-0.003</td>
<td>0.655***</td>
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<td>(0.076)</td>
<td>(0.062)</td>
<td>(0.547)</td>
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<td>(0.049)</td>
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<tr>
<td>Year FE</td>
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<td>Yes</td>
<td>Yes</td>
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<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
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<tr>
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<td>No</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
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<td>-1.136</td>
</tr>
<tr>
<td></td>
<td>(1.319)</td>
<td>(2.247)</td>
<td>(8.025)</td>
<td>(0.633)</td>
<td>(0.735)</td>
</tr>
<tr>
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<td>12,084</td>
<td>11,989</td>
<td>13,760</td>
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</tr>
<tr>
<td>R-squared</td>
<td>0.642</td>
<td>0.018</td>
<td>0.200</td>
<td>0.759</td>
<td>0.466</td>
</tr>
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<td>Number of familyID</td>
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<td></td>
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</tbody>
</table>

Source: Panel study of Income Dynamics, 1996-2011. OLS regression. The sample is restricted to households below the 80th percentile of the state/year cell. The dependent variable in columns 1-2 is outstanding debt to income ratio; in column 3 is non-mortgage debt; in column 4 leverage (mortgage outstanding/house value); in column 5 is interest rate charged on the main mortgage. All variables are expressed in logs and are in real terms, with CPI scaled at the State level (1996=1). Top 20% Income is the average income of families falling in the top 20% of the income distribution in a given state/year, computed from the March CPS. ∆ Home Value t-1 is the variation in the value of housing wealth of the family between t-2 and t-1. All regressions include a lag (t-1) of the dependent variable. Family controls include age of head and its squared; sex, marital status, race and educational attainment of head; number of children in HH. Sample weights are included in all columns. Errors are clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1
Table 5. Top income levels and house prices: US states.

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average Delta Price 1999-2011</td>
<td>0.030***</td>
<td>0.069***</td>
<td>0.107**</td>
<td>0.161***</td>
<td>0.152***</td>
<td></td>
</tr>
<tr>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.052)</td>
<td>(0.051)</td>
<td>(0.045)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Δ Top Income</td>
<td>0.135***</td>
<td>0.031***</td>
<td>0.121</td>
<td>0.211**</td>
<td>0.141</td>
<td>0.088</td>
</tr>
<tr>
<td>(0.005)</td>
<td>(0.005)</td>
<td>(0.079)</td>
<td>(0.087)</td>
<td>(0.099)</td>
<td>(0.100)</td>
<td></td>
</tr>
<tr>
<td>Δ Median Inc</td>
<td>-0.004</td>
<td>0.002</td>
<td>-0.019***</td>
<td>-0.019***</td>
<td>0.006**</td>
<td>0.105</td>
</tr>
<tr>
<td>(0.008)</td>
<td>(0.009)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.003)</td>
<td>(0.173)</td>
<td></td>
</tr>
<tr>
<td>Δ Interest rate</td>
<td>-0.093***</td>
<td>-0.078***</td>
<td>-0.060</td>
<td>-0.070</td>
<td>-0.043</td>
<td>-0.040</td>
</tr>
<tr>
<td>(0.005)</td>
<td>(0.005)</td>
<td>(0.070)</td>
<td>(0.072)</td>
<td>(0.079)</td>
<td>(0.086)</td>
<td></td>
</tr>
<tr>
<td>Δ Ownership</td>
<td>0.022***</td>
<td>-0.039***</td>
<td>-0.103</td>
<td>-0.098</td>
<td>-0.099</td>
<td>-0.067</td>
</tr>
<tr>
<td>(0.008)</td>
<td>(0.008)</td>
<td>(0.099)</td>
<td>(0.097)</td>
<td>(0.101)</td>
<td>(0.132)</td>
<td></td>
</tr>
<tr>
<td>Δ Gini</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.235**</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.092)</td>
<td></td>
</tr>
</tbody>
</table>

State and Year FE: Yes, Yes, Yes, Yes, Yes, Yes
Family Controls: No, No, Yes, Yes, Yes, Yes
Family FE: No, No, No, No, No, Yes

Observations: 52,067, 37,428, 13,273, 13,273, 10,876, 11,038
R-squared: 0.565, 0.427, 0.045, 0.045, 0.053, 0.022
Number of familyID: 4,223

Source: PSID, 1999 to 2011. OLS regression. The sample is restricted to households below the 80th percentile of the State/year cell. House Price levels are in real terms, with CPI expressed at the State area level. Delta house price is the year-on-year change in the value of house. Top incomes and median incomes and Gini coefficients (in changes) are calculated from the March CPS. Elasticity is the measure of elasticity of housing supply available from Saiz (2010). The change in mortgage interest rates is calculated at the state/year level from the PSID. Ownership rates for families falling in the bottom 80th percentile of the income distributions are also calculated from the PSID. Family level controls include age, education, race, sex, marriage status of the household head; also log of income and number of children at the family level. Sample weights from the PSID included in columns 3-5, col 6 includes family fixed-effects. The dependent variable in col. 1-2 is the average change in house prices at the State level; in columns 3-5 is the family-level change in house prices. Errors are clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1
Table 6. Top Income levels and house prices: US metro areas

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Average</td>
<td>Delta Price</td>
<td>Delta House Price</td>
<td>Delta House Price</td>
<td>Delta House Price</td>
<td>Delta House Price</td>
</tr>
<tr>
<td>Δ Top Income</td>
<td>0.961*** (0.012)</td>
<td>0.703* (0.388)</td>
<td>2.432*** (0.075)</td>
<td>0.084* (0.038)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Δ Median Income</td>
<td>0.647*** (0.013)</td>
<td>0.751*** (0.208)</td>
<td>-1.696*** (0.131)</td>
<td>-2.316*** (0.057)</td>
<td>1.078*** (0.136)</td>
<td>-2.253*** (0.034)</td>
</tr>
<tr>
<td>Elasticity</td>
<td>-0.036*** (0.002)</td>
<td>-0.098 (0.062)</td>
<td>0.253*** (0.011)</td>
<td>-0.905*** (0.009)</td>
<td>-0.076*** (0.008)</td>
<td>-0.905*** (0.009)</td>
</tr>
<tr>
<td>Δ Population</td>
<td>0.150*** (0.003)</td>
<td>0.219** (0.076)</td>
<td>0.059*** (0.008)</td>
<td>0.546*** (0.008)</td>
<td>0.100*** (0.008)</td>
<td>0.551*** (0.009)</td>
</tr>
<tr>
<td>Log Median Inc.</td>
<td>0.300*** (0.019)</td>
<td>-0.118 (0.382)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Δ Gini</td>
<td></td>
<td></td>
<td>0.808*** (0.025)</td>
<td>0.126* (0.057)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Area and Year FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Family controls</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>17,601</td>
<td>6,657</td>
<td>4,929</td>
<td>1,728</td>
<td>4,929</td>
<td>1,728</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.925</td>
<td>0.133</td>
<td>0.019</td>
<td>0.109</td>
<td>0.019</td>
<td>0.109</td>
</tr>
</tbody>
</table>

Source: American Housing Survey, 1996 to 2007. WLS regression. The sample is restricted to households below the 80th percentile of the sma/year cell. House Price levels are in real terms, with CPI expressed at the Metro area level. Delta house price is the change in the value per room reported by a panel of families interviewed between 1996-2004 and 1998-2007 in 14 metro areas. Top incomes and median incomes and Gini coefficients (in changes) are calculated from the March CPS. Elasticity is the measure of elasticity of housing supply available from Saiz(2010). Family level controls include age, education, race, sex, marriage status of the household head; also log of income and number of children at the family level. The variation in population is calculated as the 10 year average from Census. Area Fixed effects include a dummy for macro geographical areas: northeast (Baltimore, Boston, Hartford, Washington DC); South (Atlanta, Memphis, Oklahoma City, Tampa, Houston TX); Midwest (Cleveland, Indianapolis, Minneapolis, St.Louis). The dependent variable in column 1 is the average change in house prices at the MSA level; in columns 2-6 is the family-level change in house prices. Column 1 and 2 take into account both waves (change between 1996-2004 and 1998-2007) and all SMSAs. Columns 3 and 5 only restrict the analysis to the change occurring between 1996 and 2004 for the first wave of MSAs: Atlanta, Cleveland, Hartford, Indianapolis, Memphis, Oklahoma City, Seattle, St.Louis. Columns 4 and 6 restrict the analysis to the second wave, between 1998 and 2007: Baltimore, Boston, Houston, Minneapolis, Tampa and Washington DC. Each observation is weighted using the sample weights included in the AHS survey. Errors are clustered at the MSA level. *** p<0.01, ** p<0.05, * p<0.1
Appendix A1. Sample Weights and Inference

The use of sample weights in descriptive analysis is necessary, in order to obtain statistics that are relevant to the population of interest. This is because the probability of selection within a given sample is not random, but rather sometimes oversamples particular subgroups, leading to potentially heavily biased estimates if the representativeness of the sample is not taken into account. Therefore, if the way the sample is unrepresentative is known, the population statistic can be consistently estimated by reweighting the sample statistic with the inverse of the probability of selection. The use of sample weights to analyze causal questions is however more controversial.

Solon, Haider and Woolridge [2013] discuss in detail the necessity and opportunity of using sample weights when attempting to address causal questions. They report three instances in which is opportune to use sample weights in regression analysis:

(1) To correct for heteroskedasticity;

(2) To correct for endogenous sampling;

(3) To identify average partial effects.

The most problematic of these issues in the context at hand is (1). The correction for heteroskedasticity is generally used to achieve a more precise estimation of the coefficients. The rationale is generally based on research that uses spatial variation, and samples of different sizes. If the group-average error term equals

\[ V_{i} = \sum_{j=1}^{J_{i}} V_{ij} \]

where \( V_{ij} \) is the error term for observation \( ij \) in group \( i \) and \( J_{i} \) is the number of individuals in a group (for example, US states). If \( J \) varies across groups (because the population is much larger in California than Arizona, for example) then the term \( V_{i} \) is highly heteroskedastic. The weighted least squares estimator applies the weight \( J_{i} \) to all terms in the regression, solving this problem.

However, in situations where the individual \( V_{ij} \) are not independent from each other, the individual error term structure resembles \( V_{ij} = n_{i} + u_{ij} \), where \( n_{i} \) is idiosyncratic, and \( u_{ij} \) is common to all individuals in a given group. So the variance of the group-level error term is homoskedastic for the idiosyncratic part, and can be highly heteroskedastic for the group-level part:

\[ \text{Var}(v_{i}) = \sigma_{n}^{2} + (\sigma_{u}^{2} / J_{i}). \]
If the idiosyncratic part is large and J is sufficient in every group, this group-level variance can be approximated by $\sigma^2_n$, which is homoskedastic. Therefore, using WLS rather than OLS could reduce efficiency, rather than improving it. While endogenous sampling (2) is less of a concern in this context and differential effects of treatment along one or more covariates (3) is hard to evaluate (given the number of covariates included in the regressions) a similar reasoning applies also in these settings: WLS might reduce efficiency, and increase the standard errors. As good empirical practice, Solon, Haider and Woolridge [2013] therefore suggest to check the difference in estimates between weighted and un-weighted models; to report both sets of estimates; and to use robust standard errors.

Therefore, table A1 presents some of the results discussed in the paper estimated without the use of sample weights (but maintaining the robust errors, clustered at the state level).

**Table A1. Comparison of standard errors between OLS and WLS**

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1)</th>
<th>(2)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Consumption</td>
<td>WLS</td>
<td>OLS</td>
<td>WLS</td>
<td>OLS</td>
<td>Delta House Price</td>
<td>WLS</td>
</tr>
<tr>
<td>Top20*Owner</td>
<td>0.359***</td>
<td>0.350**</td>
<td>0.646***</td>
<td>0.784***</td>
<td>0.703*</td>
<td>1.090**</td>
</tr>
<tr>
<td></td>
<td>(0.119)</td>
<td>(0.143)</td>
<td>(0.212)</td>
<td>(0.240)</td>
<td>(0.388)</td>
<td>(0.381)</td>
</tr>
<tr>
<td>DeltaTop20</td>
<td>8.810***</td>
<td>9.629***</td>
<td>5.527***</td>
<td>5.238***</td>
<td>1.080</td>
<td>-1.805</td>
</tr>
<tr>
<td></td>
<td>(2.077)</td>
<td>(2.239)</td>
<td>(1.655)</td>
<td>(1.502)</td>
<td>(3.867)</td>
<td>(4.672)</td>
</tr>
<tr>
<td>Constant</td>
<td>5,528</td>
<td>5,528</td>
<td>41,742</td>
<td>42,224</td>
<td>6,657</td>
<td>6,657</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.330</td>
<td>0.332</td>
<td>0.280</td>
<td>0.306</td>
<td>0.133</td>
<td>0.099</td>
</tr>
</tbody>
</table>

Columns (1)-(2) report the results of the same model estimated in Table 2., col (2) using and omitting sample weights, respectively. Cols. (3)-(4) do the same with the estimates in Table 3, Column (2); Cols. (6)-(7) estimate col. (2) of Table 6. Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Cols. (1)-(2) show that in the case of the CEX, using weights improves the efficiency of the estimate of the main coefficient of interest (the other coefficients are excluded for brevity). The standard errors are smaller in WLS than when using OLS; the same can be said of the PSID, as seen in Cols. (3)-(4). This suggests either that $\sigma^2_n$ is small, or that $J_i$ is highly variables (small in some groups and very large in others). In this context, the use of WLS somewhat improves the precision of the estimation. The use of sample weights in the American Housing Survey, instead, seems to induce lower efficiency in model. Nevertheless, the
baseline result is not affected, and the WLS estimate reported in Column (5) seems to be on the conservative side.

Appendix A2: Clusterization of Standard Errors

In equation (1) I define a model that of the type:\textsuperscript{22}

\begin{equation}
Y_{ist} = \gamma_s + \lambda_t + \beta X_{st} + \epsilon_{ist}
\end{equation}

Since the error term in (A7) reflects the idiosyncratic variation in potential outcomes that varies across people, states and time, some of this variation is likely to be common to all individuals residing in the same state at the same time (due to unobserved state-time shocks). The model (A7) can be written more precisely as:

\begin{equation}
Y_{ist} = \gamma_s + \lambda_t + \beta X_{st} + v_{st} + \eta_{ist}
\end{equation}

Where $v_{st}$ are state-year time shocks. With only two states and two time periods, there would be no way to distinguish the effect of X from the state-year shocks (such as for example regional business cycle). Fortunately in our case we can rely on estimations based on 51 states and multiple time periods, and therefore assume that $v_{st}$ will average out to zero as the number of groups (state/years) increases. However in (A8) the problem is not just cross-sectional, but has also a time dimension: $v_{st}$ and $\tilde{v}_s$ are likely to be serially correlated (as regional shocks extend their influence over time).

The simplest method adopted to take this problem into account is to cluster errors at the state level (rather than at the state/year level, as it would be appropriate if we only had a problem with cross-sectional dependence). This is because clustering at the state, rather than the state/year level, allows for residual correlation within clusters, including the time series correlation $v_{st} - \tilde{v}_s$.

Angrist and Pischke [2008] suggest that to assume that the correlation between $\tilde{v}_s$ and $v_{st}$ can be estimated reasonably well there needs to be a minimum number of clusters (they cite 42). Most of the estimations proposed here have 51 clusters (states); an exception are those in Table 6 which have 13. It is not clear how to correct for the problem in this context however. Angrist and Pischke [2008] suggest that at the minimum, one would want to show that the conclusions are consistent with the inferences that arise from group-level averages since this is a conservative approach. This is what I do in Column (1) of Table 6.

\textsuperscript{22} This section draws heavily from Angrist and Pischke [2008], pp.236-240

35