Edinburgh School of Economics

Discussion Paper Series

Number 259

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

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Date
September 2015

Published by
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http://edin.ac/16ja6A6

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

Alessia De Stefani*

September 2015

Abstract

Growth rates of income inequality and household debt levels are strongly correlated within OECD economies. I explain this evidence through the role of collateral capacity and mortgage lending. My analysis of disaggregated US data in the decade preceding the 2007/2008 financial crisis shows how the rise in income inequality across US regions was associated with a higher than average increase in house prices. Exploiting geographical variation across US regions, I apply a methodology which can be considered similar to a diff-in-diff approach. I show that between 1997 and 2007 a 1% increase in inequality, measured as the ratio of top incomes to median incomes, determined an increase in the self-reported value of homes of about 0.6% across US states and 0.7% across metro areas. Inequality therefore induced a wealth effect in homeowners. I also show that the increase in housing wealth was associated with higher consumption, despite constant real income. A 1% increase in top incomes induced a 0.46% increase in "non-rich" homeowners' consumption, and a 0.18% increase in mortgage debt. The wealth effect experienced by homeowners living in high-inequality regions can therefore explain the link between inequality and household debt without recourse to behavioral explanations such as the "conspicuous consumption" hypothesis.

JEL Classification Codes: D12, D14, D31, G21

Keywords: Consumption Behaviour, Credit, Inequality, Veblen Effects, House Prices.

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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, Adair Morse, Aline Souza Menezes, 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

The household balance sheets of OECD economies experienced two major trends since the late 1980s: a strong increase in income and wealth inequality[1] and an unprecedented rise in household debt accumulation. Figure 1 shows the substantial correlation between these two measures: changes in inequality are positively correlated with changes in housheold debt to GDP ratios, within country. US households, in particular, accumulated almost half of today's outstanding debt between 2000 and 2007 (Figure 2). This amount of private debt is far greater than what can be explained with the standard permanent income model (Barnes and Young, 2003); and while its macroeconomic consequences became clear after the 2007 financial crisis, the academic literature has only recently started focusing on explaining *why* households decided to borrow so extensively.

This paper studies the link between inequality and household debt in the US economy, by focusing on the role of collateral capacity and mortgage lending. In particular, I show that homeowners living in US areas where inequality was rapidly increasing experienced a wealth effect in the form of a steeper increase in the value of their houses. This effect, coupled with the reduction in lending constraints in the form of lower mortgage interest rates, led them to borrow against the increase in housing wealth in order to sustain consumption levels, in a mechanism already described by Mian and Sufi (2011) and Adelino, Schoar and Severino (2015). This mechanism explains the correlation between inequality and household debt without the need for a more behavioural explanation, such as the 'conspicuous consumption' hypothesis (Frank, Levine and Dijk, 2007; Bertrand and Morse, 2014).

An important contribution of this paper is to show that the wealth effect was not uniform across the US: households living in high inequality regions experienced a steeper rise in home value between the mid 1990s and 2007. A 1% increase in the 20:50 income ratio increased the value of houses by 0.6% more across states and 0.7% across metro areas, between 1999 and 2007.[2]

The existing literature has been trying to establish a systematic link between rising inequality and rising debt levels, based on two major theories.

1. Piketty,Saez (2014)

2. The link between inequality and house prices has so far received little attention in the literature. On the theoretical side, Maattanen and Tervio(2014) in a partial equilibrium model find negative effects of inequality on house prices, except in a segment of housing very close to the top of the distribution. Their model however is based on matching approach: each household holds one house, and there is no migration/foreign investment/speculation on the housing market. From an empirical standpoint, they focus on six metropolitan areas, without really controlling for other factors deemed relevant by the literature (such as the elasticity of housing supply, or changes in population). Matlack &Vigdor (2008) provide an analysis of rental prices in the US between 1970 and 2000, using census microdata. They find that in markets with low vacancy rates, increases in top incomes relative to the median imply a significant increase in the rental price per room paid by families at the bottom of the distribution.

The first line of thought is that inequality has changed, historically, the propensity to lend to poor borrowers. More formally, inequality functions as a reduction in the lending constraint faced by lenders: as rich people get richer, they are willing to lend more of their resources, therefore lowering the real interest rate with an influx of savings in the market. This theory was first proposed by Rajan (2010), and is formally developed by Kumhof, Ranciere, Winant (2015), in a DSGE model where default is endogenous: by these means, they establish a link between inequality, private debt, and financial crises, by calibrating their model on 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 theory; using original data on bank credit originations, they find that inequality actually reduced credit provision to poor applicants across the US.

The second line of thought is based on the behavioral hypothesis of 'conspicuous consumption', originally developed by Veblen (1899) and more recently revived by Frank, Levine and Dijk(2007). According to this theory, consumers compare their standard of living with those of their reference group of peers. If inequality within their reference group rises, individuals below the very top of the income distribution will desire to consume more, despite no real income gain. The desire for positional goods might therefore explain why debt arises even in absence of a real income loss.

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 work hours. More recently, Carr and Jayadev (2014) and Bertrand and Morse (2014) extend the empirical test of conspicuous consumption using micro data on the American economy of the past two decades. Both papers find evidence of "trickle down consumption", consistent with the latest Frank hypothesis. All else held equal, when poor Americans have been exposed to higher levels inequality, they have been saving less and consuming more, especially when it comes to 'visible' goods (Bertrand and Morse, 2014).

This paper is a contribution to this second strand of literature. I suggest that house prices played a major role in the circle of inequality-credit. In absence of rising house prices, there may not have been a trickle-down effect of inequality on consumption and household debt between the mid 1990s and 2007. This happens to be the decade when a vast amount of US household debt was accumulated: therefore, it constitutes an important time frame to study the drivers of households' saving behaviour. Bertrand and Morse (2014) explicitly address whether their results might be driven by house prices increase, and they dismiss this potential confounding factor via several empirical tests. However, they do not specifically address whether a wealth effect might have been a major driver of households' consumption behaviour in the decade preceding the 2007 financial crisis. My results indicate that increasing house prices, and the resulting wealth effect experienced by low and middle-income homeowners, were indeed an important determinant of household consumption and saving decisions during this time span. This result does not necessarily discount the psychological explanation at the heart of the Veblen hypothesis. However, it does provide evidence that the substantial increase in US household borrowing prior to the 2007 financial crisis might not have been primarily motivated by a status-seeking behavioural mechanism. In fact, this behavioural mechanism may not have held in absence of a reduction in borrowing constraints based on the increase in housing wealth. In other words, what has largely been considered myopic behaviour from the weakest American consumers (borrowing beyond their own capacity to repay) might well have been the result of a generalized illusion: the expectation that the value of real estate would keep on growing (or at least hold its value indefinitely).[3]

In order to identify the trends between inequality, consumption, debt and house prices over a decade, I rely on three different household surveys. Section 2 describes each of them in detail. Section 3 presents the first half of the empirical analysis on the relationship between inequality and consumption/debt accumulation. Here I first attempt at replicating the Bertrand and Morse (2014) result on a different time span, and subsequently show that the only group of people for which inequality had been causing a rise in consumption/debt between 1995 and 2007 are middle-income homeowners. Section 4 provides evidence of the empirical link between inequality and house prices. The relationship is strongly positive both at the level of US states and of metro areas, and it is robust to the inclusion of two different measures of income inequality. Section 5 briefly summarizes my findings.

3. On the role of expectations in the house price-credit cycle see Adelino, Schoar and Severino (2015).

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.

2.1 Consumer Expenditure Survey (CEX)

The Consumer Expenditure Survey is the most comprehensive American survey on consumer behavior at a family level. As Bertrand and Morse (2014) use this dataset in their estimations, this is a natural starting point for the analysis. The public dataset has data from 1996 onwards (although the BLS is slowly releasing earlier cohorts). It samples about 6000 households, and through sample weights it is 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 diary survey is about daily consumption items and it is very detailed; the interview survey has aggregate data for daily consumption items (such as food) and also reports more long term expenditures, such as housing, utilities, outflows for loans, schooling and so on. The interview survey also contains aggregate consumption categories, such as food and housing. In order to be consistent with Bertrand and Morse (2014) I exclude families who fail to respond to all four interviews and families with zero total consumption. I however do not construct my measures of consumption, and rely instead on the aggregate consumption categories reported in the summary expenditure variables of the interview report: total expenditure and housing expenditure. This is also the section of the CEX survey reporting income before tax (FINCBTAX), my measure of income.

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. In order to make the CEX analysis comparable with the PSID, I only collect data from years when the PSID was also collected (intervals of two) starting with 1996.

2.2 The Panel Study of Income Dynamics (PSID)

I analyze debt and housing wealth with the PSID because it presents the advantage, over the CEX, of being organized as a long-term panel: the same family (and its spin-offs) are interviewed every two years, allowing the identification of changes in home ownership and debt originations at the family level. 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.

As standard in the household consumption literature, I only take into account families reporting both a positive level of income and of consumption in a given year. 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 (AHS)

The main advantage of the American Housing Survey is its panel structure and how it provides a vast array of information on housing quality across the US. 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 construct a measure of a single house's value increase over time, and I use it as a robustness test for the PSID results. It 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. 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 longitudinality 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.[4] 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 periods of price change: those occurring in the first sample between 1996 and 2004 and those occurring in the second 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). On top of this, I need to exclude families who changed residence between t and t-1; and families whom carried out substantial changes in the size of their houses (measured as the change in the number of rooms). This is to avoid confounding the results. Overall, I work on a sample of about 9000 families over the time span 1996-2007.

4. The AHS sample also includes Sacramento (CA), but I have no information on the elasticity of housing supply for this MSA.

3 Empirical Analysis: Consumption and Debt

The empirical strategy of this paper is composed of two parts: the first links inequality to household saving behaviour and the second looks at the relationship between inequality and house prices. This section focuses how changes in the distribution of income between the mid 90s and the 2007 crisis changed American households' propensity to consume and borrow. I will use two data 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 home ownership; if anything, the home ownership rate for the bottom 40% of the distribution decreased by an average 10% over this time span.

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 did so even more.

My analysis aims at showing whether there is a link between the rise in inequality and the rise in debt/consumption from poorer households. In this section I study to what extent in the years preceding the 2007 financial crisis (when the majority of US household debt was accumulated), I can find evidence of 'conspicuous consumption'. That is to say, to what extent I find a positive relationship between poor households' debt and consumption levels and inequality levels in their geographical area of residence.

I will follow closely the empirical methodology suggested in Bertrand and Morse (2014), which is very similar to the estimation strategy proposed by Coibion et al. (2014), and is based on the following equation:

$$Y_{\text{ist}} = a + \beta_1 X^I_{\text{ist}} + \beta \text{Ineq}_{\text{st}} + \chi_s + \psi_t + \varepsilon_{\text{ist}} \tag{1}$$

Where Y_{ist} is either yearly household expenditure or outstanding debt for family i in state s at year t.[5] X^I_{ist} is a vector of family specific characteristics, namely: total family income, number of adults and children in household, age race sex and educational attainment of household head, and home ownership status.[6] The inequality measure (Ineq_{st}) is defined at the state level; following Bertrand and Morse, it is the average annual income of the top 20% of the State/year income distribution as defined by the Continuous Population Survey (CPS).[7] This procedure also identifies the minimum income threshold required for a PSID family to fall into the top 20% of their state/year cell; if the family falls into this category, it is dropped from the sample. All remaining families (those below the 80th percentile of the State/year cell) are defined as "non-rich" households; and they are the sample upon which I run the estimations.

The model in equation 1 simply tries to answer the following question: if in a given state/year average top incomes rise, do 'poorer' families in the same state/year spend more? The rationale of such an analysis is based on the conspicuous consumption theory, which predicts that people will try to keep up with the behaviour (consumption levels) of their reference group. A reference group is defined as the people a given family is more likely to know and/or interact with. The rationale for measuring inequality at the state level is therefore to define inequality within the reference groups at the finest level of detail which the publicly available data allows to reach.[8] One could, of course, think about other (and probably more relevant) reference groups: for example along the lines of gender, occupation, educational attainment, or race. Both the PSID as the CEX contain detailed information at the household level, and would allow for a subdivision of households along these lines. However, while some research has studied conspicuous consumption using precisely these subgroups within states (for example Carr and Jayadev, 2014) it is important to notice that the CEX and the PSID are not designed to be representative within states, but only at a national level. The state-level measure of inequality is therefore the finest level of detail I can reach while respecting the structure of the data and its sampling design.

Given the inclusion of state and year fixed effects, the estimation strategy in (1) is similar to a difference-in-differences approach. US wide time trends (for example federal economic policy) are taken into account; so are the time-invariant characteristics of each state. In this setting, families with a similar vector X^I_{ist} of family-specific characteristics are akin to 'treatment' and 'control' groups for each other. I am then able to observe what happens to consumption and debt of a given 'treatment' family when inequality within its residence state increases, versus debt and consumption of its 'control' family, living in a state where inequality doesn't change.[9]

5. Income and expenditure variables are expressed in real terms. The CPI measure is local (state-level) as computed by Carrillo, Early, Olsen (2014).

6. While B&M control for family income by including fixed effects for income thresholds every 2000$, I instead control for the actual measure of family income.

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.

8. The publicly available CEX and PSID datasets do not report any level of geographic detail other than the state of residence.

3.2 Results: Consumption

I study consumption as a function of inequality using the Consumer Expenditure Survey from 1997 to 2011. Table 1 shows the relationship between top income levels in a given state and non-rich families' consumption in the years post 1999. Here I replicate Bertrand and Morse(2014) 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.[10] However, the aim of this paper is to establish whether the credit boom was due to 'conspicuous consumption' or wealth effects; and the majority of US household borrowing occurred well after the 1980s. Actually, almost a half was accumulated between 1996 and 2008.[11] Therefore, studying the years between the mid 1990s and the late 2000s is the natural starting point for this analysis. In Table 1 I find that post 1999 inequality had no effect on non-rich consumption (column 1). The coefficient is positive, but not statistically different from zero. This insignificant coefficient is very important for the rest of the analysis, because it replicates almost exactly Bertrand and Morse's results for the 2000s.[12] They use this insignificant coefficient, together with a split of the sample between homeowners and renters[13] to suggest that wealth effects caused by house prices increase were not a main driver of the relationship between top incomes and non-rich consumption.[14] The rationale is that if renters also responded to an increase in top incomes increase with an increase in consumption, then the consumption effect cannot be due to an increase in house prices; furthermore, if during the years when the majority of the housing boom occurred (post 1995) they find a lesser evidence of 'conspicuous consumption', then their finding cannot be due to a generalized wealth effect.

Also consistent with their result[15], the effect of top incomes on homeowners and renters in the 2000s is not statistically different from zero. If anything, splitting the sample between homeowners and renters seems to indicate that the second group responds more to inequality. However, by allowing all coefficients to differ, columns 2 and 3 are not directly comparable; a more conservative model with an interaction term (column 4) confirms that the effect of inequality on consumption levels does not differ between homeowners and renters. Table 1 therefore confirms that I can replicate Bertrand and Morse results using a slightly different dataset. I move on from this evidence, using the same data and methodology, to show instead that wealth effects were an important driver of the increase in consumption as a result of the increase in inequality before the 2007/2008 financial crisis.

9. The regressions include CEX and PSID sample weights, respectively, and the residuals are clustered at the state level, to account for the presence of a common random effect within states across families following Betrand and Duflo (2004).

10. The CEX is collected yearly; however, to facilitate comparison with the PSID, I only study the years for which also the PSID sample is available, namely 1996, 1997, 1999, 2001, 2003, 2005, 2007, 2009, 2011.

11. See Figure 2.

12. Betrand and Morse(2014), Column 1, Appendix A3.

13. Betrand and Morse (2014), Table 5, Panel A, Columns 1 and 2

14. Betrand and Morse (2014) Section IV.c

15. Also Betrand and Morse (2014), Table 5, Panel A, Columns 1 and 2.

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 1990s and excludes the years after 2008. Column 1 shows that, for the overall population, the relationship between top incomes and non-rich consumption is not significantly different from zero. In order to check whether this effect differs between homeowners and renters, I test an interaction term between top incomes and non-rich ownership status in Column 2. The first important result of this section is that the interaction between inequality and the ownership status term is positive and strongly significant. Between 1997 and the start of the financial crisis, only non-rich homeowners responded to rising inequality with an increase in consumption. Specifically, the elasticity of response was 0.36; for every 1% increase in the income of top earners in a given state/year, non-rich homeowners' real consumption increased by 0.36% 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 unaffected by top incomes, and that in this respect owners and renters do not differ from each other. If anything, non-rich homeowners increased non-housing consumption as a response to rising inequality; column 4 shows that the elasticity of non-housing consumption to rising inequality is about 0.49 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). This barely affects the coefficient of the interaction term and doesn't change its significance.

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

3.3 Results: Household Debt

The conspicuous consumption theory also predicts that poor people should accumulate more debt as a result of the increase in inequality. I study the relationship between top income and non-rich households' debt accumulation using the PSID between 1997 and 2011. Table 3 shows that, consistent with the results on consumption provided in Table 1 and 2, there is no direct relationship between non-rich households' debt levels and top incomes during this time frame (Column 1). 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 0.64 higher than renters (Column 2). As the interaction term is dichotomous (1 if owner, 0 if renter). Column 2 also allows the identification of the effect of inequality on debt income ratios of non-rich renters, which is significantly negative with a coefficient of -0.46. Overall, this implies that the effect of a 1% increase in top income with respect to median incomes leads to a 0.18% increase in the debt to income ratios of non-rich homeowners. This is robust to controlling for median incomes and for the average state-level mortgage interest rate charged to families below the 80th percentile of the income distribution (Column 2). The effect of inequality on homeowners' debt to income ratios is mostly due to mortgage debt: column 3 shows that inequality has no significant effect on non-mortgage debt for either group. Also, the effect of top incomes on mortgage debt is not due to a reduction in mortgage interest rates in states where inequality was increasing: column 4 shows that interest rates on first mortgages are unaffected by inequality levels.[16] Interestingly, leverage ratios (measured as outstanding mortgages to house value) are also not affected by 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. In sum, higher inequality implies higher consumption and debt-to-income ratios for non-rich households. However, this effect is only identifiable for homeowners, and not for renters; moreover the debt effect is only visible on mortgages, precisely in the years when the housing boom was occurring. The overall evidence in this section points to a relationship between inequality and housing wealth.

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 inequality might have had a wealth effect on non-rich homeowners, by increasing house prices.

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 suddendly stopped after 2008. Overall the average American household

16. Also, Figure 4 shows that the relative dispersion in mortgage interest rates across US States is relatively low. The lending market is mostly influenced by the FED rates: in column 5 year fixed effects, which are the common trend across the US, are by far the most important variable, together with family income levels, in explaining the variation in mortgage interest rates.

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 rise in prices of about 60% between 1998 and 2007, almost double the national average. On the other hand, the average reported change in prices in Memphis (TN) between 1996 and 2004 was below 2%. Obviously, this discrepancy cannot be explained solely by changes in income distribution, and other factors, such as location, housing supply regulation, geography and population growth have a very important role. I take this into account in my estimation.

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

$$\Delta p_{\mathrm{igt}} = a + \beta_1 \Delta \mathrm{Ineq}_{\mathrm{gt}} + \beta_2 X^I_{\mathrm{igt}} + \beta_3 Z^I_{\mathrm{gt}} + \chi_g + \psi_t + \varepsilon_{i_{\mathrm{igt}}} \tag{2}$$

Where Δp_{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.[17] I make sure I exclude new buyers, families who changed residence in this time span and families who didn't move but changed the size of their house (measured in the number of room).[18] This measure reflects the change in perceived wealth from 'old' homeowners, on a house which they already possessed, and which didn't go though major improvements which might have substantially affected its value. $\Delta\mathrm{Ineq}_{\mathrm{gt}}$ 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^I_{igt} is a vector of family-specific characteristics which include the log of income at the family level; 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^I_{gt} is a vector of geographical area-specific characteristics which might affect house prices, namely 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.

17. While these are self-reported values, recent evidence shows how American homeowners were generally well-informed, and their short-run expectations on house prices reflected the actual year-on year changes in their reference market (Case, Shiller, Thompson 2012). In any case, wealth effects occurr even if perception is detached from reality; and this paper does not try to discriminate between the two.

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.

Finally, geographic and year fixed effects, as usual, assimilate this estimation framework to a DiD approach. I am able to measure to what extent the variation of house prices for families with similar characteristics across geographical areas is affected by variations in factors that are not specific to the State and constant over time or due to time trends affecting all states at the same time. 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). First differencing solves the potential spurious correlation problem; however, it does leave the estimations with very low explanatory power. This is explained by the fact that in highly non-stationary series the sample variance of the levels of Y is going to be much larger than the sample variance of ΔY. Therefore, the residual variance is larger in the levels than the differences (Plosser Schwert 1978).

4.2 Results: States

Table 4 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.[19] The dependent variable is the year-on-year change in the value of housing assets 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 2-6 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 generated an increase in the value of a family's main residence worth about 0.10% over two years. Both regressions take into account time-trends in income, by controlling for the change in median incomes at the state level. 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%.

However, the American public was already perceiving the burst of the housing bubble in 2007.[20] Their expectations on future house price growth was rapidly changing for the worst, and consequently house price increase was coming to an alt 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 implied a change in house prices worth about 0.16% (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%).

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.

20. See Case, Shiller and Thompson (2012), or Bricker, Krimmel, Sahm (2015).

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, homeownership rates are never significant in the micro-level estimations.

4.3 Results: Metropolitan Areas

Table 5 shows that changes in top incomes had a strong effect on 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. These results can be considered closer to a causal mechanism. The micro-level overall effect on both waves is 0.7% (Column 2). Columns 3 and 4 split the sample between the two waves of MSAs; the first (families interviewed in 1996 and 2004) and the second (1998 and 2007). The estimated effect of inequality on house prices differs substantially between the two columns. While the first wave of MSAs has an elasticity of 2.4, implying that a change in top incomes versus median incomes had a more than proportional effect on house prices, the estimated coefficient for the second wave is only 0.8. 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 implied a house price increase of about 0.8% between 1996 and 2004, and 'only' 0.12% between 1998 and 2007. The two waves, however, are 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.[21] 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% for each 1% increase in top incomes.[22]

21. 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 (Dallas FED, 2008).

22. The effect is not substantially different from the one identified across US states over the time span 1999-2007. Since there the 2-year elasticity was about 0.1, and I observe five changes in reported house prices in the PSID over this time period, the average elasticity over ten years can be estimated in about 0.61 for US states and 0.7 for metro areas.

5 Conclusions

This paper started by empirically testing the theory of 'trickle-down consumption', which predicts a negative relationship between income inequality and average saving rates of non-rich households. Previous research has established strong empirical evidence of this effect (Bertrand and Morse, 2014; Carr and Jayadev, 2014).

I test this theory on the years when the majority of US household debt was accumulated, between the mid 1990s and 2008. I find the relationship between inequality and consumption to hold only for a category of consumers: poor and middle-income homeowners. This group exhibited a strong expenditure reaction to increases in inequality, 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 change significantly. Since a 'trickle-down' effect can only be identified for homeowners, and their leverage ratios were unaffected by increases in inequality, my evidence points to a relationship between income concentration and house prices increase. I find strong support for this hypothesis. Exploiting both geographical and time variation across US states and metropolitan areas, I establish a close relationship between inequality and the increase in house prices in the decade preceding the financial crisis of 2007-2008.

My evidence suggests that if a 'trickle-down' consumption mechanism existed during the credit-boom years, it was mediated by the increase in house prices. In other words, the 'conspicuous consumption' hypothesis is empirically indistinguishable from a more canonical 'wealth effect'; it could also be interpreted as an increase in collateral availability, as suggested by DeFusco (2015).

This is a complementary, rather than opposing, view to the "conspicuous consumption" or "Veblen effects" theory. However, it shows that ascribing the American credit boom of the early 2000s to pure consumer myopia can be deceiving. The credit bubble was more strongly related to the housing bubble, than to a status-comparison behavioural mechanism.

This also shifts the blame for the post 2008 recession from "poor" consumers to poor regulators. It suggests that if house prices were not to increase as much, as a result better urban planning and more regulated credit markets, we might have been able to mitigate the effects of the Recession which followed the credit boom (Mian and Sufi, 2014).

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Figures

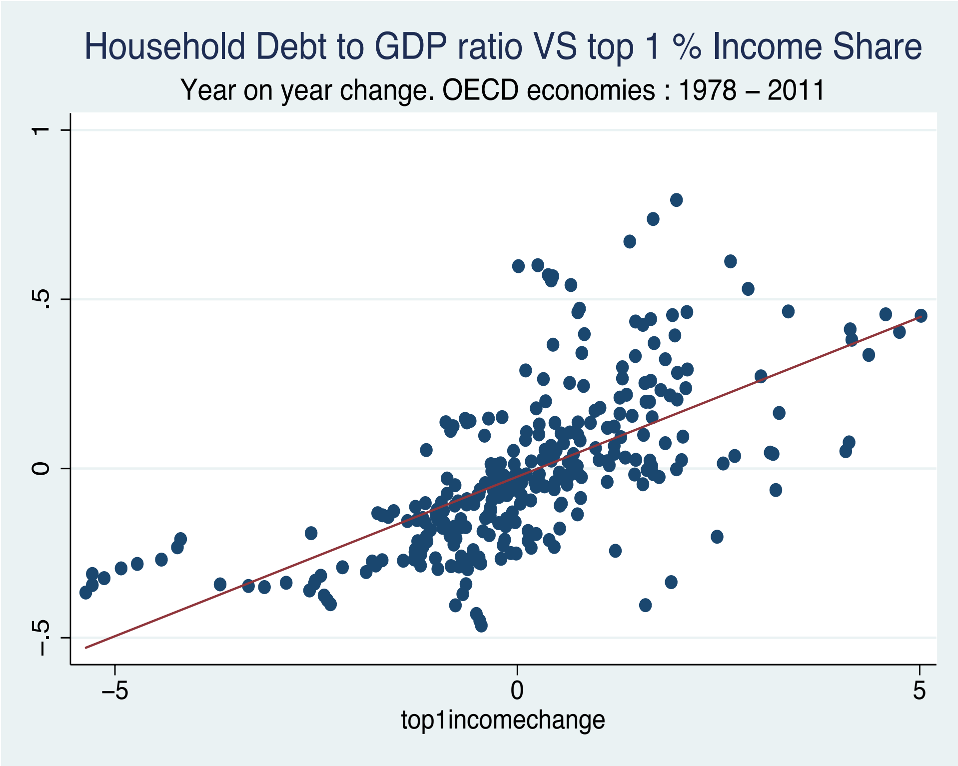

Figure 1: Year-on-year change in household debt to GDP ratio VS top 1% income share. OECD economies, 1978-2011. Sources: Piketty Saez(2014) and BIS statistics.

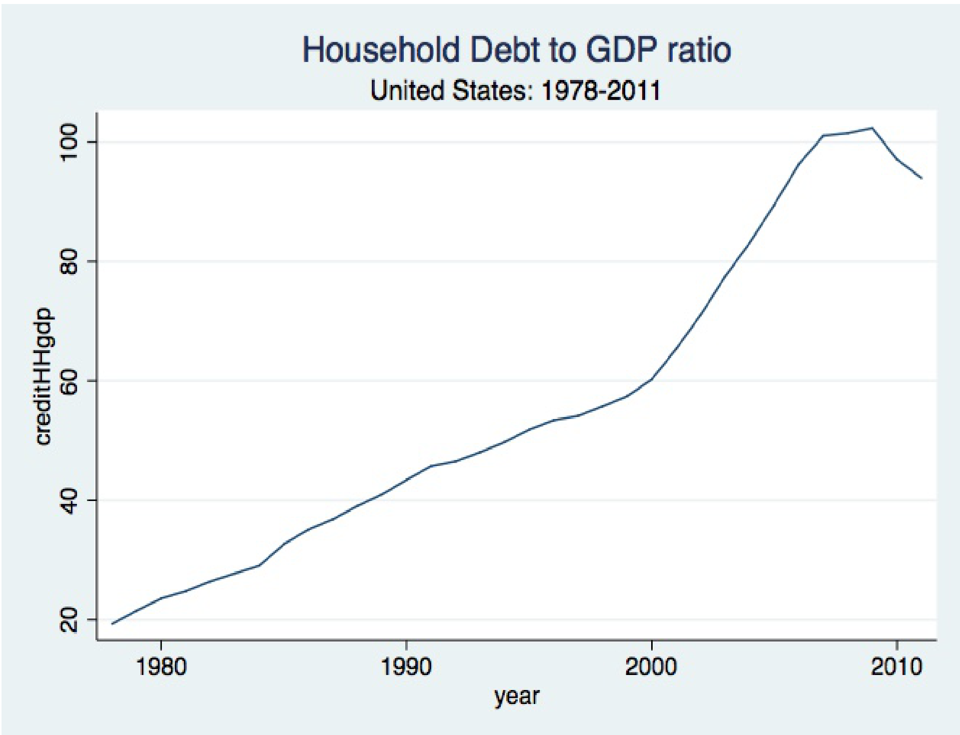

Figure 2: Household debt to GDP ratiio, United States, 1978-2011. Source: BIS statistics.

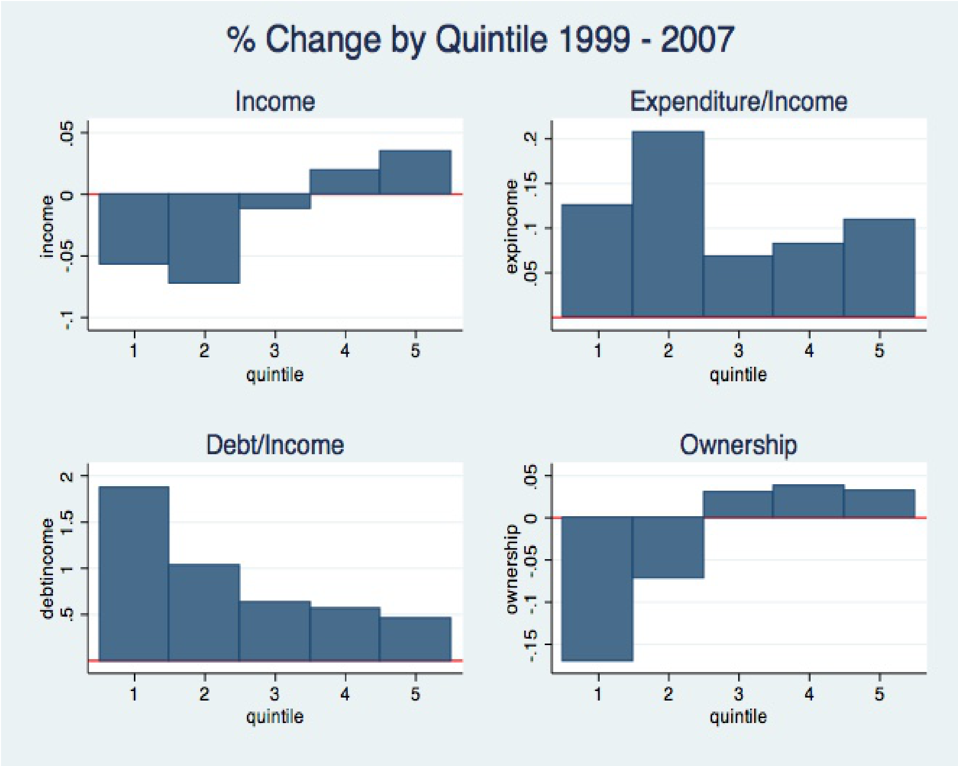

Figure 3: Average % Changes in selected statistics by quintile of the income distribution, 1999 to 2007. Sources: PSID and March CPS.

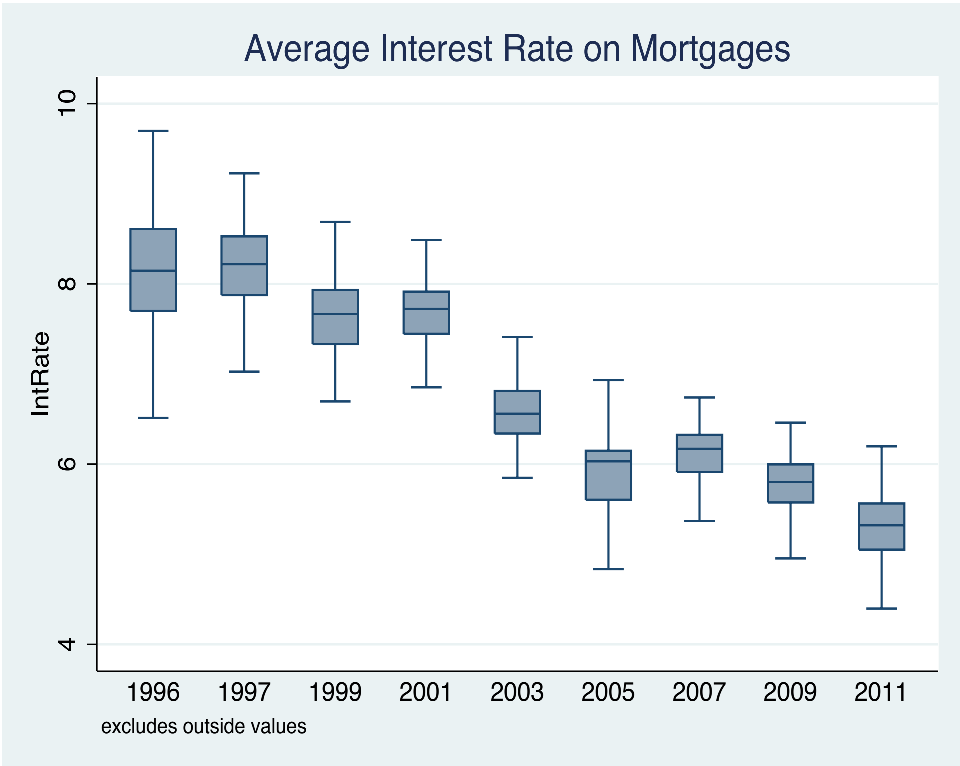

Figure 4: Average interest rate on first mortgages paid by households below the 80th Percentile of the State/year income distribution. Sources: PSID and March CPS.

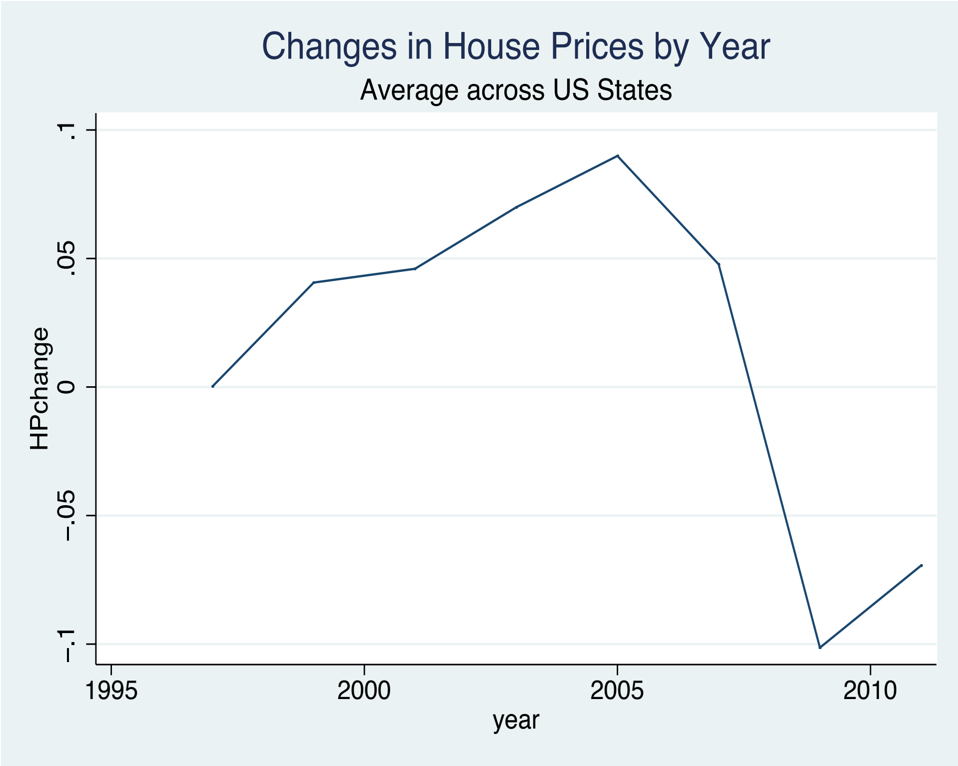

Figure 5: Average US house price increase from previous year, as reported by PSID respondents,1996-2011
Source: PSID

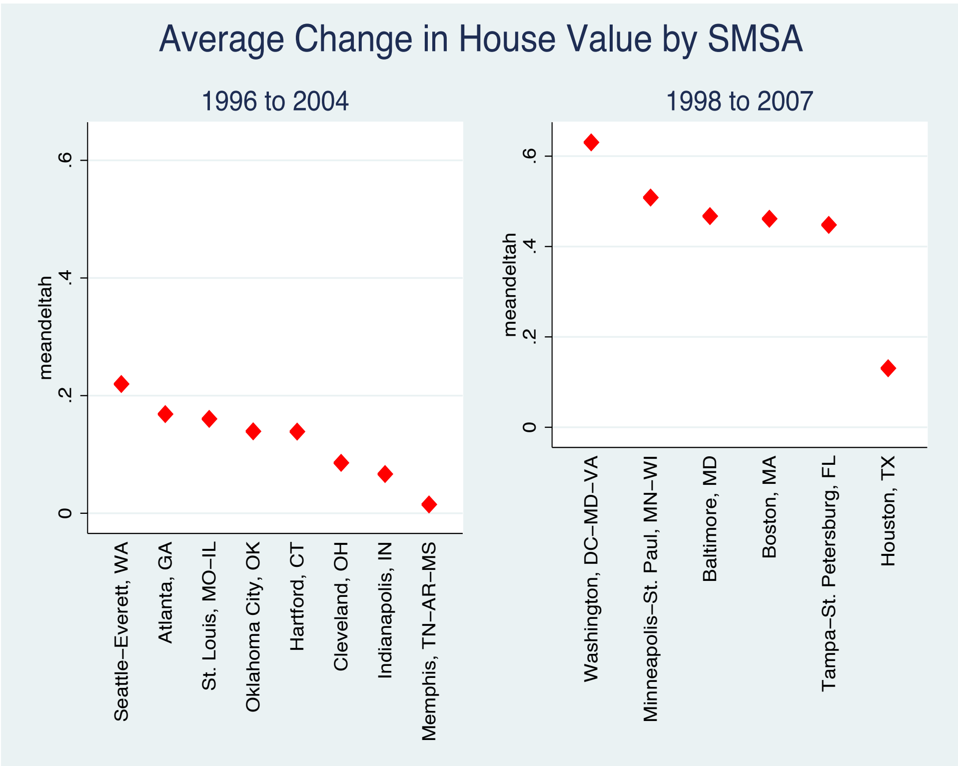

Figure 5: Average change in house value (price per bedroom) in selected metro areas over 8 years.
Source: American Housing Survey, 1996-2004 and 1998-2007 waves.

Tables

Table 1. Top Income levels and non-rich consumption. Year>1999

VARIABLES	(1) Consumption	(2) Consumption Owner	(3) Consumption Renter	(4) Consumption
Top 20% Income	0.194	-0.035	0.674*	0.209
	(0.170)	(0.178)	(0.339)	(0.224)
Owner	0.195***			0.449
	(0.026)			(2.473)
Top20*Owner				-0.022
				(0.211)
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Family Controls	Yes	Yes	Yes	Yes
Constant	3.671*	6.624***	-2.389	3.502
	(1.998)	(2.057)	(4.035)	(2.652)
Observations	4,471	3,056	1,415	4,471
R-squared	0.337	0.308	0.351	0.337

Source: Consumer Expenditure Survey, 2001 to 2011. OLS regression. The sample is restricted to households below the 80^{th} 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 level and non-rich consumption. <2009

VARIABLES	(1) Consumption	(2) Consumption	(3) Consumption Housing	(4) Consumption Non Housing	(5) Consumption Non Housing	(6) Consumption Non Housing
Top 20 Income	0.074	-0.185	-0.139	-0.203	-0.290	-0.387*
	(0.170)	(0.181)	(0.232)	(0.198)	(0.201)	(0.222)
Median Income					0.430	0.485
					(0.312)	(0.325)
Top20*owner		0.359***	0.099	0.492***	0.497***	0.459***
		(0.119)	(0.125)	(0.121)	(0.120)	(0.133)
Owner	0.225***	-3.971***	-1.078	-5.449***	-5.501***	-5.095***
	(0.021)	(1.389)	(1.459)	(1.424)	(1.406)	(1.565)
State FE	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes
Family Controls	yes	yes	yes	yes	yes	yes
Decile FE	no	no	no	no	no	yes
Observations	5,528	5,528	5,528	5,528	5,528	5,528
R-squared	0.329	0.330	0.239	0.353	0.353	0.369

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 Debt.

VARIABLES	(1) Debt/Income	(2) Debt/Income	(3) Consumer Debt/Income	(4) Interest rate	(5) Leverage
Top20income*Owner		0.646***	0.771		
		(0.215)	(0.852)		
Top 20 Income	-0.098	-0.464***	-0.766	0.037	-0.071*
	(0.075)	(0.113)	(0.698)	(0.057)	(0.041)
Owner	0.596***	-7.007***	-10.277		
	(0.039)	(2.513)	(10.008)		
Median Income	0.045	0.030	-0.620	0.030	-0.123***
	(0.091)	(0.092)	(0.578)	(0.064)	(0.040)
Average Interest rate	0.001	0.003	-0.019		
	(0.049)	(0.049)	(0.436)		
Constant	1.016	5.473***	12.414	1.544**	2.596***
	(0.993)	(1.659)	(9.509)	(0.752)	(0.582)
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 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 are included in all columns. Errors are clustered at the state level.
*** p<0.01, ** p<0.05, * p<0.1

Table 4 Top Income Levels and House Prices (US States)

VARIABLES	(1) Average Delta Price 1999- 2011	(2) Average Delta Price 1999-2007	(3) Delta House Price 1999-2007	(4) Delta House Price 1999-2007	(5) Delta House Price 1999-2005	(6) Delta House Price 1999-2005
Δ Top Income	0.030***	0.069***	0.107**		0.161***	0.152***
	(0.004)	(0.004)	(0.052)		(0.051)	(0.045)
Δ Median Inc	0.135***	0.031***	0.121	0.211**	0.141	0.088
	(0.005)	(0.005)	(0.079)	(0.087)	(0.099)	(0.100)
Elasticity	-0.004	0.002	-0.019***	-0.019***	0.006**	0.105
	(0.008)	(0.009)	(0.002)	(0.002)	(0.003)	(0.173)
Δ Interest rate	-0.093***	-0.078***	-0.069	-0.070	-0.043	-0.040
	(0.005)	(0.005)	(0.070)	(0.072)	(0.079)	(0.086)
Δ Ownership	0.022***	-0.039***	-0.103	-0.098	-0.099	-0.067
	(0.008)	(0.008)	(0.099)	(0.097)	(0.101)	(0.132)
Δ Gini				0.235**		
				(0.092)		
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 5: Top Income Levels and House Prices (Metro Areas)

VARIABLES	(1) Average Delta Price	(2) Delta House Price	(3) Delta House Price 1996-2004	(4) Delta House Price 1998-2007	(5) Delta House Price 1996-2004	(6) Delta House Price 1998-2007
Δ Top Income	0.961***	0.703*	2.432***	0.084*		
	(0.012)	(0.388)	(0.075)	(0.038)		
Δ Median Income	0.647***	0.751***	-1.696***	-2.316***	1.078***	-2.253***
	(0.013)	(0.208)	(0.131)	(0.057)	(0.136)	(0.034)
Elasticity	-0.036***	-0.098	0.253***	-0.905***	-0.076***	-0.905***
	(0.002)	(0.062)	(0.011)	(0.009)	(0.008)	(0.009)
Δ Population	0.150***	0.219**	0.059***	0.546***	0.100***	0.551***
	(0.003)	(0.076)	(0.008)	(0.008)	(0.008)	(0.009)
Log Median Inc.	0.300***	-0.118				
	(0.019)	(0.382)				
Δ Gini					0.808***	0.126*
					(0.025)	(0.057)
Area and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Family controls	No	Yes	Yes	Yes	Yes	Yes
Observations	17,601	6,657	4,929	1,728	4,929	1,728
R-squared	0.925	0.133	0.019	0.109	0.019	0.109

Source: American Housing Survey, 1996 to 2007. WLS regression. The sample is restricted to households below the 80^{th} percentile of the smsa/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. *** $p<0.01$, ** $p<0.05$, * $p<0.1$