US Household Sector Borrowing in the Long Run: Structural Change and Causality

Jan Behringer* and Rafael Wildauer**

May 2018

Unfinished Draft

*Macroeconomic Policy Institute (IMK). Düsseldorf, Germany.

**University of Greenwich and Greenwich Political Economy Research Centre (GPERC). London, UK.

1 Introduction

One of the key lessons from the 2007/2008 financial crisis is the crucial role the financial sector in general and debt in particular plays for macroeconomic outcomes. Nevertheless, a decade after the crisis many open questions remain and there is no consensus among economists about the main aspects of financial-real interactions and how to incorporate them in macroeconomic models and theories. Despite a decade of post-crisis research, major international economic policy institutions like the ECB call for more progress on the issue, special journal issues on "Rebuilding Macroeconomics" are written (Oxford Review of Economic Policy, Vol. 34, Numbers 1-2) and prominent macroeconomists argue that the discipline needs to address the theoretical shortcomings laid bare by the crisis, most importantly a more adequate treatment of debt and the financial sector (Bezemer 2016, Blanchard 2018, Stiglitz 2018, Stockhammer 2009, Wren-Lewis 2018).

We seek to contribute to these important debates by providing an analysis of US household sector indebtedness over the long run. A focus on private debt is justified not only by the events of the recent crisis but by a broad set of historic (the US banking crises in the (long) 19th century in: the 1830s, 1857, 1873, 1893, 1907), theoretical (Bernanke et al. 1998, Fisher 1933, Koo 2011, Minsky 1978) as well as empirical (Bezemer and Zhang 2014, Borio 2014, Eichengreen & Mitchener 2003, Mian and Sufi 2009, Schularick and Taylor 2012) evidence which suggests that rapid accumulation of liabilities in the private sector make economic crises more likely and that recessions which are preceded by household sector debt accumulation tend to be more severe and are followed by more sluggish recoveries compared to recessions without an overindebted household sector (Mian and Sufi 2010). As a result, it is not surprising that economic policy makers began to closely monitor variables like household sector debt-to-income ratios, house prices and debt service payments. The BIS for example began to compile and publish a dataset on private sector debt. The European Commission included house prices, private sector debt stocks and flows as well as the total liabilities of the financial sector as key indicators in the Macroeconomic Imbalance Procedure (European Commission 2018).

It is against this background that this paper aims to contribute to a better understanding of household sector debt accumulation. And while there is a growing body of research which demonstrates the serious adverse effects an overindebted household sector can have on the economy, much less research is available which seeks to understand and explain what drives households to take on excessive debt in the first place. We address this question by estimating a household sector debt accumulation function for the United States based on annual data from 1945 to 2006. The goal is to assess the relative importance of four different explanations of household borrowing:

The first is the income explanation, which considers that as disposable income rises over time, households can achieve higher living standards by increasing their liabilities along with their available income. After all, higher incomes do not only allow to directly finance more expenditures but also allow to service a larger mortgage or a second car loan. The key question with respect to the income explanation becomes whether households expand liabilities proportionally or disproportionally to rising incomes. The second is the income distribution explanation, which acknowledges the massive shifts in the distribution of income which occurred in the US over the last 70 years. These shifts are important for household sector debt accumulation if households are slow or reluctant to adjust their borrowing activities to changes in long term income growth rates. In that sense shifts of the income distribution can change what is perceived by society as a "normal" or "acceptable" level of indebtedness, relative to disposable income. In addition, the distribution of income can play an important role for debt accumulation if households spend to signal social status and if status comparisons work in an upward looking manner. In such a scenario, households would compare themselves with richer peers and in a situation of growing income inequality these richer peers would enjoy higher income growth. In an attempt to keep up with them, status spending needs to be debt-financed. The group which orients themselves towards this richer group of households is enjoying even lower income growth and thus engages in even more debt financed status spending. The overall result is a cascade of debt-financed spending down the income distribution. The third explanation represents the number one reason why US households take on debt: to buy real estate. If real estate transactions are heavily debt-financed, then changes in real estate prices will have a strong and direct impact on household sector debt accumulation. Rising property prices boost household debt accumulation for various reasons; from eased credit constraints over potential changes in mental accounting structures and wealth target norms to implicit or explicit speculative behaviour fuelled by the expectation of further price increases. The fourth is the interest rate explanation and represents the argument that the price of loans has an important impact on how much people borrow.

We think that while understanding the immediate pre-crisis period is important, there is value in searching for stable macroeconomic relationships over longer periods of time. However, estimating a debt accumulation function to analyse the impact of the outlined explanations on household debt accumulation is complicated by the fact that the underlying relationships are very likely to change over time. While the income explanation almost surely has changed in the face of massive shifts of the income distribution, the fact that information about these shifts is available makes it possible to explicitly include this source of change in our analysis. Other important aspects of household sector borrowing subject to structural change over time such as the weight financial institutions put on collateral relative to income when assessing creditworthiness, changes in mental accounting norms or the proportion of people using a standard US 30-year fixed rate mortgage contract rather than flexible rate contracts are difficult or impossible to measure. However, ignoring them would bias our analysis.

We seek to tackle this problem in two ways. First, we saturate our regression with step-indicators (Castle et al. 2015, Hendry and Mizon 2014, Marczak and Proietti 2016) to detect mean shifts occurring over time. Step indicator saturation can be understood as a special case of a Markow-switching model which allows model parameters to vary over time. In our case the only parameter which can switch is the intercept. As our analysis will show, allowing for such switches is an important and powerful tool. While it might seem simplistic and of limited use in detecting structural change, step indicator saturation is a compromise between the requirement of simple and concise models due to the curse of dimensionality in macroeconometrics and the acknowledgement that economic relationships are likely to change over time. The experience of applied forecasters is encouraging insofar as that in practice the most common and most important problems are indeed intercept shifts (Bardsen et al. 2005). The second measure we undertake to detect and take structural change in household sector debt accumulation into account, is to use recursive estimations to find model specifications which remain stable over long sample periods and thus indicate that they are not affected by omitted structural factors. Recursive estimation serves two purposes: On the one hand it helps us to determine the start of our sample period by transparently investigating how different sample starts impact our analysis (we call these varying-sample-start regressions: VSS). This is fundamentally different than just using the longest sample available in a naïve quest for a large sample size. The second purpose of recursive estimation is to check whether results are robust to the variation of the sample end (we call these varying-sample-end regressions: VSE) and thus assess whether a chosen model yields a stable summary of the data. In that sense we use VSS as a model and sample selection tool and VSE as a diagnostic test. This latter interpretation of VSE as a diagnostic test provides an indirect test of weak- and super-exogeneity along the lines of Engle et al. (1983) and Hendry (1995; p. 162).

One last word on our methodological approach of estimating a single debt accumulation function combined with step indicator saturation and recursive estimation as model selection tools: We are aware that our approach suffers from important limitations, most importantly that a single equation approach is not able to consider the mutual feedback among the economic variables we study. However, we think this is not the only problem empirical macroeconomics should pay attention to. More specifically, we think that in the current applied literature the issue of model and parameter stability is under-appreciated. If we want to draw relevant conclusions from an empirical investigation it is important to ensure that the uncovered relationships remain stable over the sample period and potentially even into the future. Therefore, we think step indicator saturation and recursive estimations are important tools for applied macroeconometric research. Unfortunately, it is not realistic to apply these tools in combination with a systems approach to estimation simply because of the lack of degrees of freedom. What this means is that there can't be one modelling approach which addresses all issues but different approaches which complement and inform each other.

The main findings can be summarised as follows: Firstly, our results strongly suggest that property prices are the predictor with the most explanatory power of the evolution of outstanding household sector liabilities over the period 1964 to 2006. This is an important contribution especially relevant for the theoretical literature which aims at incorporating private and household sector debt in macro models because it fundamentally questions the dominant association of household sector borrowing with consumption motives. Secondly, the long run income elasticity we estimate is very close to and not statistically different from 1. This indicates that household liabilities do evolve in proportion with disposable income growth holding other factors, most importantly house prices, constant. Put differently, economic expansions on their own do not lead to rising debt to income ratios. Thirdly, the relationships between the time series under investigation change over the full sample period of 1951 to 2006. Some of these changes can be modelled by means of step indicator saturation and some cannot which forced us to choose a later sample start to obtain a specification which exhibits stable parameters. This demonstrates that paying attention to parameter stability and structural change is of fundamental importance despite its current underappreciation in current macroeconometric practice. Fourth, the pronounced changes of the income distribution over the sample period had a significant impact on the accumulation of liabilities in the household sector over the sample period. While the power to explain the increase in debt-to-income ratios of the top 1% income share is clearly second to the evolution of house prices, our results show that the increasingly polarised distribution of income positively contributed to household sector debt accumulation.

The remainder of the paper is structured as follows: The next section discusses how household sector debt is currently looked at in macroeconomic models and research. Section 3 introduces the dataset and the methodology, most importantly our combination of Autoregressive Distributed Lag (ARDL) models with step indicator saturation and recursive estimations. Section 4 and 5 present the recursive estimation results. Section 6 presents effect size computations and section 7 concludes.

2 Household Sector Debt in Macroeconomics

This section discusses the different explanations of household debt accumulation we are seeking to investigate in detail. Let us begin with the income explanation. If households have more income at their disposal, their standard of living rises as well. With growing income, households want to enjoy a larger house, a larger or second car and more expensive holidays. If living standards grow in relation to income, some of the related expenses will be debt financed. Thus, at the aggregate level there will be a positive relationship between disposable household income and household sector debt. This might sound odd at first. If household income increases, a rational consumer could run down her liabilities, pay less interest and improve her net-worth position. However, the more households value current consumption over future consumption, the more they will use additional income to service accordingly larger liabilities. While there will be a natural degree of heterogeneity among individual consumers in how they react to income increases over time, at the aggregate level, desired living standards are likely to increase over time, at least this is what happened over extended periods of time in the US and European countries. With respect to the question of household sector indebtedness the key issue becomes whether living standard expectations grow in line with, slower or faster than disposable income. Holding other factors constant, aggregate debt-to-income ratios would remain stable, decline or increase, respectively. Since we are looking at sectoral aggregates one factor which can also contribute to aggregate debt growing at a faster rate than aggregate income is if the proportion of households who hold debt increases.

The second is the income distribution explanation. In the US the disposable income share of the bottom 90% increased from 66% in 1945 to 70% in 1969, remained flat around 70% until 1980 and then began to fall from 70% to 60% in 2006 and continue to fall thereafter. For the 40% of US households between the 51st and 90th percentile of the income distribution their share of aggregate disposable income fell from 45.4% in 1962 to 41.6% in 2006 (Piketty et al. 2018)[1]. This means large parts of the US population experienced stable and even above average income growth up to the 1980s and declining growth rates thereafter[2]. If households are reluctant or unable to adjust their expenses in the face of declining income growth rates, this will lead to different income elasticities of household credit across income groups. Another argument why the distribution of income is important for household borrowing decisions is related to how households form their expenditure decisions. There is a large body of literature (Frank et al. 2014, Kapeller and Schütz 2014, Ryoo and Kim 2014, Behringer and Treeck 2013) which argues that households consume not only for their own direct satisfaction but also to signal their social status to their peers. In addition, if social status is related to income and wealth, households will look to (slightly) richer peers or peers whom they perceive as richer based on their status display, when deciding on their own expenditures. Under these circumstances rapidly growing top incomes can lead to a cascade of status driven and debt financed expenditures down the income distribution. So, based on both arguments we expect a positive relationship between top

---

[1] These figures are coming from the Distributional National Accounts (DINA) project and are based on a cash-measure of disposable income which excludes in-kind transfers and collective expenditures from the definition of disposable income. See Piketty et al. (2018) section 3 for details.

[2] Piketty et al. (2018, p. 41) document an interesting fact in their breakdown of disposable income by sex. They show that median pre-tax labour income remained flat for men over the 1960 to 2014 period, whereas due to increased labour force participation female median labour income increased from less than $5000 in 1962 to more than $20,000 in 2014. Increasing female labour force participation helped to maintain increasing overall household incomes for couples.

income shares and household sector indebtedness (and a negative relationship between bottom and middle income shares and household debt).

The third explanation under investigation is the housing or real estate explanation. Its importance is demonstrated by the fact that mortgages are by far the dominant class of household sector debt. The share of mortgage debt was roughly stable around 66% in the US until the mid-1980s. The end of non-mortgage interest payment tax deductibility as part of the Tax Reform Act of 1986 led to substitution of consumer loans in favour of mortgages. Together with a booming housing market the mortgage share climbed and peaked at 78% in 2006. House prices can have an impact on household borrowing for several reasons. First, rising house prices ease credit constraints by providing additional collateral against which households can secure loans. Second, there is evidence that mental accounts (Thaler 1990) play an important role how households plan and organize their finances. Thaler (1990) argues that for large parts of the 20th century most US citizens did not perceive home equity as a form of wealth which can be readily spent or borrowed against for consumption purposes. However, if rapidly increasing property prices change this perception, then people will become more comfortable with borrowing against their home equity. Thaler (2015) does not argue that the structure of mental accounts changed due to house prices but points out that it became much more normal to borrow against home equity for consumption purposes. Third, the literature on stock-flow-consistent macro models (Godley and Lavoie 2007) argues that household behaviour is anchored by so-called stock-flow norms which act as target for household behaviour. For example, if households follow an implicit net-wealth-to-income target due to precautionary reasons, an increase in house prices and thus real estate wealth would push them above their target value. One way to get back to their target would be to consume part of the excess wealth due to the higher level of real estate wealth and thus to borrow against that asset. Fourth, in the face of rising house prices, those home buyers who are not willing to postpone their purchase to save for a bigger deposit will take on a larger mortgage, especially if they expect home prices to increase in the future and even more so if they expect home prices to increase at a faster rate than they can save up their deposit. If in addition banks focus primarily on loan-to-value ratios instead of loan-to-income ratios when assessing customers, households will accumulate debt in the face of rising property prices, holding other factors constant.

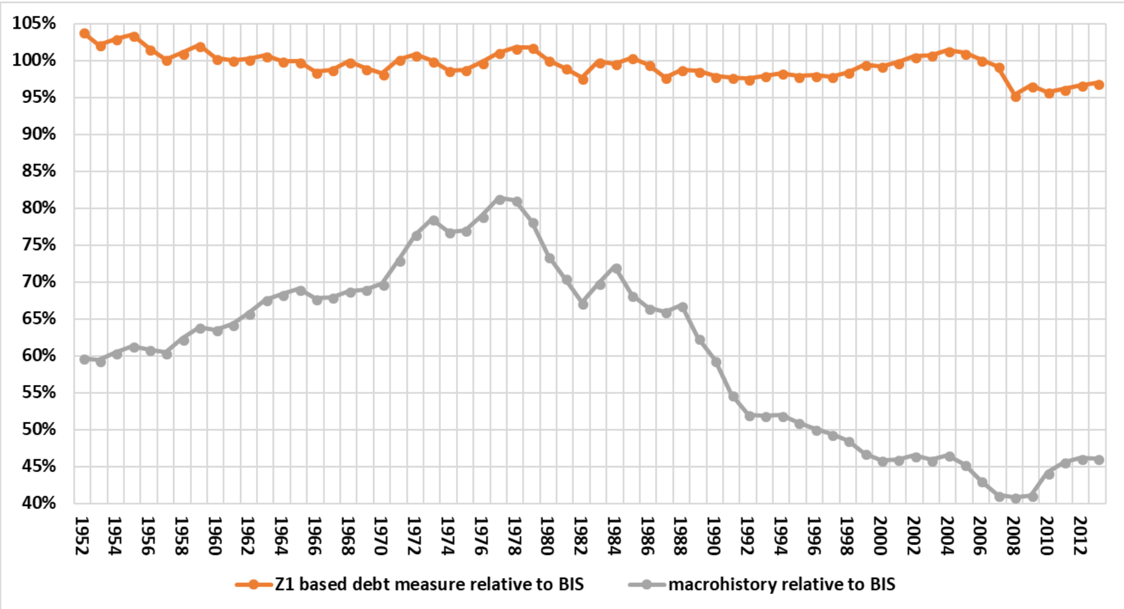
The final explanation is the interest rate explanation. The arguments are straight forward: low interest rates encourage borrowing as debt service payments are low. In contrast high interest payments limit the amount of debt, households can take on as debt service payments take up too much of household disposable income. There is some literature (Taylor 2009, Sinn 2014, Sinn and Valentinyi 2013) which argues that excessively low interest rates after the economic slowdown in the early 2000s led encouraged excessive debt accumulation and thus playing an important role in the development of the 2007/2008 crisis.

3 Data and Method

3.1 Data

We compiled a macroeconomic database of the United States which goes back to 1945 for most variables. The reason why we did not choose to compile a much longer dataset was the availability of our main variable of interest: outstanding liabilities of the household sector. While more and more long macroeconomic time series (especially for the US) going back to the beginning of the 20th century or longer, are being compiled by researchers we decided to stick with a shorter sample in favour of data consistency. The longest time series on US household debt to our knowledge is supplied by the microhistory database (Jordà et al. 2017). It contains a series of total loans to households (starting in 1945) and two series of total (mortgage) loans to non-financial private sector (both starting in 1880). While the long debt series are not restricted to the household sector the total loans to households time series only represents between 41% (2008) and 81% (1977) of total outstanding household sector (including NPISH) liabilities as presented by the BIS database on private credit (BIS 2018). Figure 1 below presents the total household debt measure from the macrohistory database and our own Flow of Funds based measure of household sector debt[3] relative to the BIS measure of credit to the household sector (Q:US:H:A:M:USD:A). Due do these substantial discrepancies we stick to the official Flow of Funds statistics as the main source for our financial variables. This allows us to exclude the non-profit institutions serving households (NPISH) from our measure of outstanding aggregate household debt.

Figure 1: US household liabilities - macrohistory database and own Flow of Funds based measure



The main variables used in this paper are the following: Total household sector liabilities (D_t) are defined as the sum of home mortgages (FL153165105.A), consumer credit (FL153166000.A) and other loans and advances (FL153169005.A). It is important to note that student debt is classified as

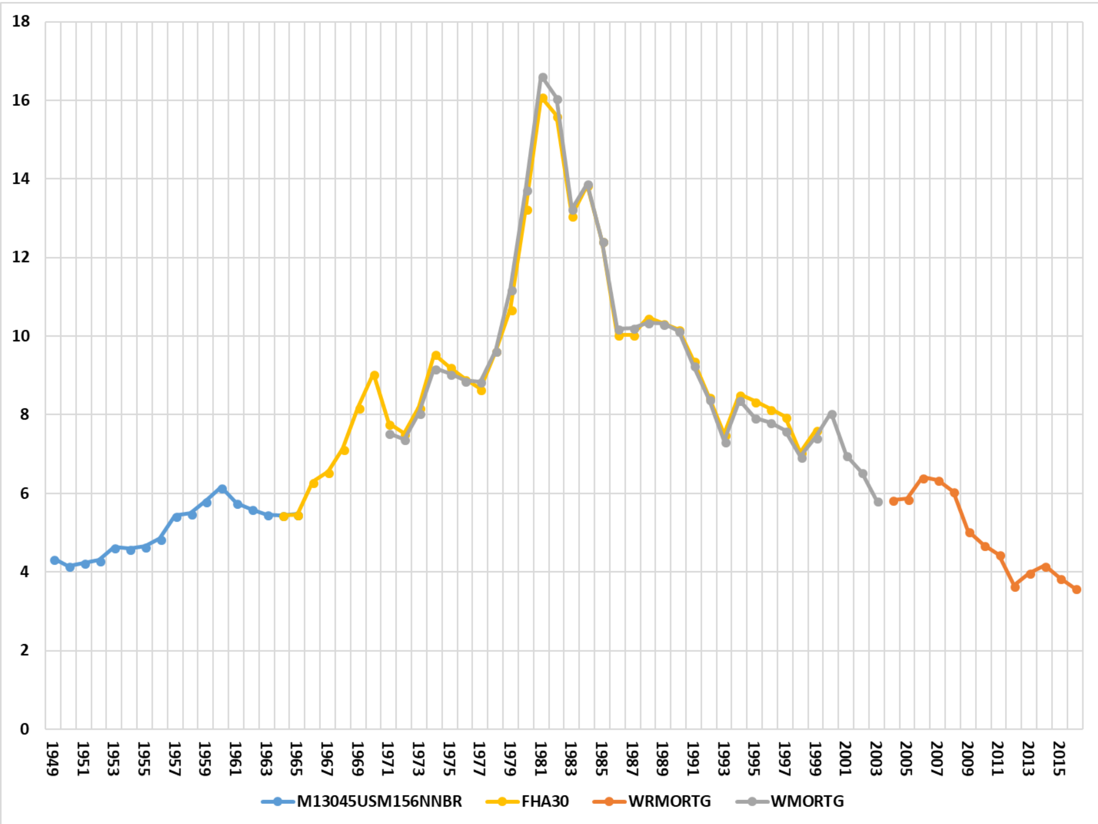
---

[3] The household debt aggregate used in this paper consists of home mortgages (FL153165105.A), consumer credit (FL153166000.A) and other loans and advances (FL153169005.A). This was the best approximation to total outstanding liabilities of the household sector excluding NPISH the authors could construct.

consumer credit in the Flow of Funds. A separate series only starts in 2006. Other loans include government loans, overdrafts, loans on life insurance policies and non-mortgage loans from government sponsored enterprises.

Our household disposable income (Y_t^D) measure and the top 1% income share are taken from Piketty et al. (2018) and the World Inequality Database, making use of the latest contributions to the Distributional National Accounts (DINA) project (Alvaredo et al. 2016). What this means is that our disposable income variable and the income series which was used to construct the top 1% income share are fully consistent and are coming from the same source. This was not possible in the past, especially with disposable household income. We use net personal disposable income (Y_t^D), to which Piketty et al. (2018) refer as a "cash" measure because it does not include transfers in-kind which are normally counted as income in standard national accounts income measures. In addition, contributions towards and benefits from pension plans are handled on a cash-flow basis instead of an accrual basis. The latter point becomes clear if one starts from the concept of disposable income as it is recorded in national accounts (NIPA in the US case but the SNA treats it in the same way). Contributions towards pension plans are immediately treated as disposable income of the household sector, even though the beneficiaries of these contributions have no or only very limited access to these funds. This is what accounting on an accrual basis means. Consistently pension benefit payments are not treated as income since they have been recorded already as contributions in the past. The approach Piketty et al. (2018) adopt (like Cynamon and Fazzari 2017) is to count pensions only as income when they are paid out to pensioners but not when they are paid as contributions into pension schemes. The series of top 1% income ($TOP1_r$) is the distributional share based on this income variable.

Figure 2: Interest rate on 30-year Federal Housing Administration mortgages



Our property price index (PP_t) is the US home price index from the online appendix to Shiller (2015) which is the national level Shiller/Case repeat sales index. The interest rate time series ($R30_t$) we are using is a mixture of four interest rate time series and is the longest possible time series on 30-year-mortgages the authors could construct. It starts in 1949 and even though it is a mixture of 4 time series overall the series does not exhibit major breaks (Figure 2). All four series are based on rates of Federal Housing Administration mortgages and the data is extracted from the FRED database, Figure 2 uses the identifiers from the FRED database as labels for each series.

3.2 Recursive Estimation of Autoregressive Distributed Lag Models with Step Indicator Saturation

In order to assess the long-term importance of the four different modes of household debt accumulation while taking into account the likely structural changes which occur over our sample period stretching from 1952 to 2006 we use a Autoregressive Distributed Lag (ARDL) models in combination with step indicator saturation (Castle et al. 2015, Hendry and Mizon 2014, Marczak and Proietti 2016). We use this approach to estimate a debt accumulation function of the following form:

$$\log(D_t) = \mu + \sum_{i=1}^{p} \lambda_i \log(D_{t-i}) + \sum\nolimits_{i=1}^{k} \sum_{j=0}^{m} \delta_{i,j} \boldsymbol{X}_{i,t-j} + \varepsilon_t \tag{1}$$

where D_t is our measure of outstanding household sector debt in billion US Dollars, and $\boldsymbol{X}_{i,t}$ is a $4m \times T$ regressor matrix which contains household disposable income ($\log(Y_t^D)$), the top 1% income share ($TOP1_t$), the Shiller home price index ($\log(PP_t)$) and our series of interest rates on 30-year mortgages ($R30_t$). We use a maximum lag order of $p = 2$ and $m = 1$.

In addition, we define a set of step indicators $S = \{S_{1952}, \ldots, S_{2006}\}$ one for each year in our sample (except the first) such that:

$$S_y = \begin{cases} 0 \ \forall \ t \leq y \\ 1 \ \forall \ t > y \end{cases} \tag{2}$$

Thus, the step indicator for 1986 (S_{1986}) is equal to 0 from years 1951 to 1986 and equal to 1 from 1987 onwards. Following the literature (Castle et al. 2015) we split our set of $T - 1$ step indicators into four equally large subsets where the first set contains the first quarter of step indicators, the second set the second quarter etc. Then we estimate equation (1) containing the first subset of step indicators. Then we add the next set of step indicators (and remove the first) and estimate equation again and repeat the procedure for sets three and four. From these four regressions we retain those step indicators with a p-value $p \leq \frac{1}{T-1}$ which ensures that we include at most 1 step indicator wrongly due to type I error. The final step is to estimate equation (1) again but now only including those step indicators which passed the p-value threshold in the previous four steps.

Step indicator saturation allows us to detect mean shifts in our model of the marginal probability distribution. Ignoring them can severely bias the estimates of the remaining coefficients in the model. While we are not engaging in a forecasting exercise it is the forecasting literature and community which on the one hand had argued for a long time that such mean shifts are the most important forms of structural breaks one has to deal with in macroeconometrics and especially in forecasting (Bardsen 2005). It is obvious why forecasters are interested in stable parameter values over their sample period.

Variation in parameters makes forecasts based on such parameters useless. From a theoretical point of view Engle et al. (1983) argue that parameter stability is a condition not only for forecasting but also for super exogeneity. They define a variable z_t is said to be super-exogenous in a regression model if: "… changes in the values of z_t or its generating function will not affect the conditional relation between y_t and z_t." (Engle et al. 1983, p. 278) and interpret super-exogeneity as a crucial requirement for a causal interpretation of an estimated coefficient in a regression model. Hendry (1995, p: 34) points out that parameter constancy refers to invariance with respect to changes of the sample period and invariance over the sample period and in addition parameters need to be invariant with respect to changes in the specification (thus inclusion or exclusion of variables), for a structural or causal interpretation.

This is where recursive estimation comes into play: We will rely on recursive estimations of equation (1) as a test of parameter stability and thus a test of a crucial condition of super-exogeneity. Recursive estimation can be performed in different ways. One can bring the sample start closer to the sample end and thus test whether the estimated parameters are sensitive to the information added at the beginning of the sample. We will refer to estimations of this kind as VSS (varying sample start). Alternatively, one can re-estimate the model for consecutively smaller samples by eliminating observations at the sample end. We will refer to estimations of this kind as VSE (varying sample end). Finally, one can define a window containing a certain proportion of the entire sample and move that window over the sample. This latter procedure often referred to as rolling regression compares specifications of equal sample length but faces the problem that the number of windows which can be calculated is negatively related with the window length and thus subsample size. Since we are interested in the accumulation of liabilities in the household sector prior to the 2007/2008 financial crisis, the end of our sample is given through our research question and is the year 2006. In 2007 the downturn of the US housing market already began and thus we do not consider it in our "pre-crisis" sample. However, the choice of the sample start is less obvious. If one follows common practice in the applied macroeconometrics literature and just uses the longest available, implicitly assuming stability of model parameters, one runs the risk of drawing conclusions based on the results from a specific subperiod which cannot be generalized. In contrast we transparently test the implicit assumption of stable parameters by running VSE regressions. In general, we think that current practice in macroeconometrics is overly concerned with sample size at the expense of testing and ensuring model stability.

After deciding which step indicators should enter the final specification and estimating equation (1) we reparameterize the ARDL model into its error correction form:

$$\Delta \log(D_t) = -\left(1-\sum_{i=1}^{p}\lambda_i\right)\left[\log(D_{t-1}) - \frac{\mu}{1-\sum_{i=1}^{p}\lambda_i} - \frac{\sum_{i=1}^{k}\sum_{j=0}^{m_k}\delta_{i,j}}{1-\sum_{i=1}^{p}\lambda_i}\boldsymbol{X}_{i,t-1}\right] - \sum_{i=2}^{p}\lambda_i^{*}\,\Delta\log(D_{t-1}) - \sum_{i=1}^{k}\sum_{j=0}^{m_k-1}\boldsymbol{\delta}_{i,j}^{*}\,\Delta\boldsymbol{X}_{t-j} + \upsilon_t \tag{2}$$

$$\log(D_{t-1}) = \mu^{*} + \boldsymbol{\theta}\boldsymbol{X}_{i,t-1} \tag{3}$$

The subsequent analysis will focus on the coefficients of the long run relationship expressed by equation (3) and the adjustment parameter $\phi = 1-\sum_{i=1}^{p}\lambda_i$. Specifically we apply the bounds testing procedure of Pesaran et al. (2001) and test $H_0: \lambda_i = \delta_{i,j} = 0$ in order to see whether there is a statistically significant long run relationship.

We will estimate equation (1) in nominal terms, meaning we will use household liabilities and household disposable income in current prices and the nominal mortgage interest rate described in the previous section. There are two reasons why we chose this approach. First, households must repay and service their liabilities out of their nominal income. From a financial stability perspective, it is nominal liabilities or nominal debt service payments in relation to nominal income which provide information about the likelihood of defaults and the vulnerability of the aggregate household sector balance sheet. Second, the choice of deflators if one would be interested in estimating equation (1) in real terms is not trivial. While consumption expenditures are primarily financed out of disposable income and thus consumer price index or the aggregate consumption deflator could be a valid choice for disposable household income, liabilities are primarily used to finance real estate purchases. However, if we deflate income and liabilities differently the interpretation of the results becomes very difficult. In addition, we are interested in the impact of increasing real estate prices on household sector liabilities. Using real estate prices or a mixture of real estate prices and the aggregate consumption deflator as a deflator for household sector liabilities would eliminate the variation in the data associated with changes in real estate prices. By choosing a purely nominal specification we are implicitly assuming that inflation is not an important factor which influences the borrowing decisions of the household sector. Put differently, whether changes in disposable income are due to inflation or due to volume changes have the same impact on household sector indebtedness. We interpret this as a simplifying assumption which allows us to keep the model concise and will test the robustness of this assumption in the next section. Furthermore, it can be shown that deflating all monetary series with the same deflator (for example the US CPI) is equivalent to a nominal specification if there is a unity income elasticity. Specifying equation (3) in real terms:

$$\log\left(\frac{D_t}{P_t}\right) = \mu^* + \theta_1 \log\left(\frac{Y_t}{P_t}\right) + \theta_2 \log(PP_t) + \theta_3(R_t - \Delta\log(P_t)) + \theta_4 TOP1 \tag{4.1}$$

$$\begin{gathered} \log(D_t) = \mu^* + \theta_1 \log(Y_t) + \theta_2 \log(PP_t) + \theta_3 R_t + \theta_4 TOP1 - \\ \theta_1 \log(P_t) - \theta_3 \Delta \log(P_t) + \log(P_t) \end{gathered} \tag{4.2}$$

If $\theta_1 \log(P_t) - \theta_3 \Delta \log(P_t) + \log(P_t) = 0$, then the real-terms specification of equation (4.1) is equivalent to a specification in nominal terms only.

$$(\theta_1 - \theta_3 + 1) \log(P_t) + \theta_3 \log(P_{t-1}) = 0 \tag{4.3}$$

In the steady state where $\log(P_t) = \log(P_{t-1})$ holds we have:

$$\theta_1 = 1 \tag{4.4}$$

So, if there is a unity income elasticity of household liabilities, a specification in real terms is a special case of a purely nominal specification. Based on that result we can start from a nominal specification and then test whether adding a price index (P_t) yields a statistically significant coefficient. If it does not, then we have shown that estimating equation (1) in nominal terms does not impose any restrictions which are rejected by the data and is a valid specification.

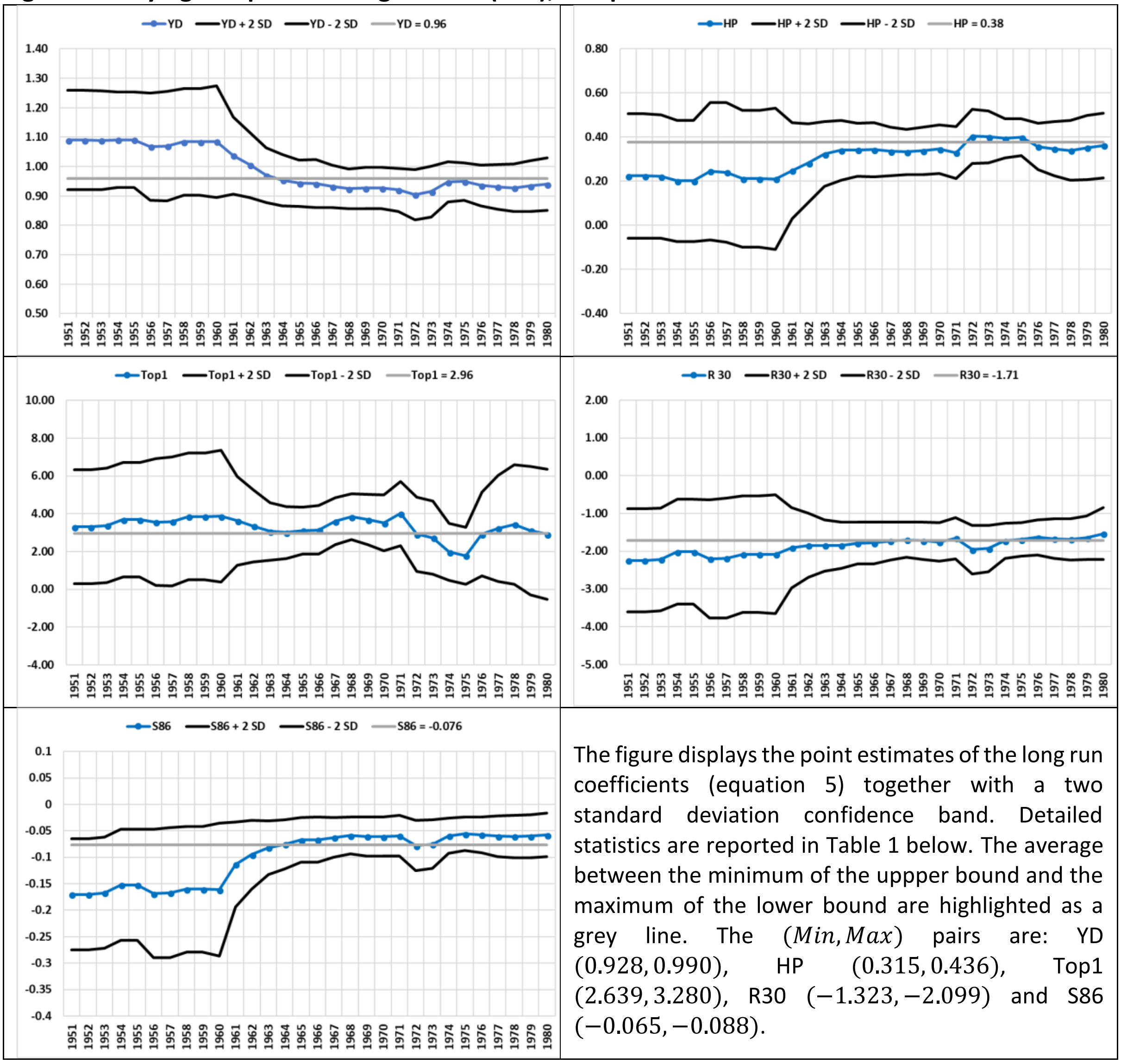
4 Assessing Model Stability: Varying Sample Starts

We are interested in the relative importance of the four explanations identified above in the pre-2006 accumulation of household sector liabilities. The focus on the pre-crisis period defines the end-point of the sample. Holding the sample end fixed, we start by estimating equation (1) with the longest available sample: 1951 to 2006. Equation (1) is estimated 30 times by moving the sample start one year ahead in each step up to 1980 (varying sample start, VSS). Figure 3 summarises the results by plotting the obtained long run coefficients $\{\theta_1, \theta_2, \theta_3, \theta_4\}$ of the error correction mechanism for all the 31 regressions:

$$\log(D_{t-1}) = \mu^* + \theta_1 \log(Y_{t-1}^D) + \theta_2 \log(HP_{t-1}) + \theta_3 R30_{t-1} + \theta_4 TOP1_{t-1} + \theta_5 S86 \qquad (5)$$

In addition, Figure 3 also plots the transformed long run coefficient of a step indicator for the year 1986 which was included in the baseline specification after it was retained by the automated search procedure in about half of all regressions. Table 1 presents the details for the obtained long run relationships for every second regression (sample starts 1950 to 1980).

Figure 3: Varying Sample Start Regressions (VSS); Sample ends in 2006



The figure displays the point estimates of the long run coefficients (equation 5) together with a two standard deviation confidence band. Detailed statistics are reported in Table 1 below. The average between the minimum of the uppper bound and the maximum of the lower bound are highlighted as a grey line. The (Min, Max) pairs are: YD $(0.928, 0.990)$, HP $(0.315, 0.436)$, Top1 $(2.639, 3.280)$, R30 $(-1.323, -2.099)$ and S86 $(-0.065, -0.088)$.

Figure 3 and Table 1 contain several important results. The first, which is demonstrated by Figure 3, is that the estimated long run coefficients are statistically significand and exhibit an extraordinary degree of stability, especially for specifications based on sample starts after the mid-1960s. The range of values which is contained within the two standard deviation confidence band across all specifications is the interval $(0.928, 0.990)$ in the case of disposable income, $(0.315, 0.436)$ in the case of house prices, $(2.639, 3.280)$ in the case of the Top 1% income share and $(-1.323, -2.099)$ in the case of the 30-year mortgage rate. The averages between these bounds are 0.96, 0.38, 2.96 and -1.71, respectively and are highlighted in grey in Figure 3. Therefore, these results provide support for the hypothesis that the estimated model exhibits parameter stability across different sample starting points and thus is a first demonstration of the reliability of the obtained results.

Secondly, the interpretation of the estimated long run (semi)elasticities: The income elasticity is very close to unity and for most specifications not statistically different from 1[4]. This means that that household debt expands proportionally to disposable household income, holding other factors constant. Thus, an economic expansion on its own does not lead to rising debt to income ratios. In addition, a unity income elasticity was the required condition to demonstrate that a nominal specification of equation (1) and a specification in real terms are equivalent. This means that our results are not driven by a common inflation trend in household liabilities and disposable income. The long run house price elasticity is close to 0.38 for most of the specifications, implying that a 1% increase in real estate prices lead to an 0.38% increase in outstanding household liabilities, confirming the relevance of the housing explanation. Interestingly this house price elasticity only becomes statistically different from 0 in specifications with sample starts after 1961. The top 1% income share semi-elasticity is positive and statistically different from 0 for all specifications except for the regression starting in 1980. While the estimated long run coefficient exhibits considerable variation, the results indicate that there is a positive relationship between increasing income inequality and household sector debt accumulation. The 30-year mortgage rate exhibits a statistically significant semi-elasticity around -1.7 which confirms the notion that higher interest rates are associated with less borrowing. Finally, the coefficient of the 1986 step indicator is statistically different from 0 in all specifications. The negative coefficient of the 1986 step indicator represents a permanent reduction in household debt levels after 1986, holding all other factors constant. So, the question becomes what happened in the US in the mid-1980s which had a statistically significant and permanent effect on household sector debt accumulation? We think two events are especially relevant. The first is the savings and loans crisis which was hitting the US at that time. While it might have had a long standing negative effect on the appetite of households to take on debt, it is not entirely clear why such a precautionary motive would not die out eventually. The second event is the Tax Reform Act of 1986 (TRA86) which represented the biggest change of the US federal income tax since the second world war. There is a vast literature which used this tax reform as a natural experiment in order to identify the effect of tax policy on the economy (Auerbach and Slemrod 1997). The most relevant change in relation to household debt was that the TRA86 terminated tax deductibility of non-mortgage interest payments. This meant that non-mortgage borrowing suddenly became much more expensive because an indirect subsidy via the tax code was abolished. While there is evidence that households reacted by substituting consumer debt for mortgage debt, it is unlikely that households fully substituted

[4] A t-test for the specification with the upper confidence band of 0.99 (sample start 1972) yields a p-value of the null hypothesis of a unity long run income elasticity of 3.57%. For most other sample starts this hypothesis is not rejected and never rejected at a 1% confidence level.

consumer loans with mortgages. Maki (2001) for example argues that substitution effects reduced the expected tax revenue effects only by half relative to a “no substation” counterfactual. Thus, we conclude that the TRA86 led to a permanent reduction of consumer debt which is picked up by the 86 step indicator.

Thirdly, while the estimated long run coefficients exhibit a high degree of stability over time, there is visible variation especially for specifications which start in the early 1960s. The estimated long run income elasticities seem to be higher around 1.1 for specifications with sample starts prior to 1960, the house price elasticity seems to be lower around 0.2 in these same specifications and similar statements hold for the top income share and the mortgage rate semi elasticities. Similarly, the coefficient of the 1986 step indicator seems to be substantially smaller before 1960. While none of these shifts are statistically significant in the sense that the mid-point between the minimum and maximum of the confidence bands lies still within the confidence bands also for these specifications, we will check whether specifications with sample starts in the 50s will yield qualitatively different conclusions compared to specifications relying on later sample starts. Thus, for the next steps of our analysis we will pick three main specifications with sample starts in 1951, 1964 and 1980. The rationale is that for all three specifications the null of normally distributed residuals and the null of first, second and third order autocorrelation cannot be rejected even at the 10% level of significance. In addition, the specification starting in 1951 represents the longest sample available and therefor acts as a benchmark representing a naïve sample selection approach based on the maximum of available observations, the 1964 specification represents the preferred specification as it is a compromise between securing a large number of observations and choosing a starting point such that estimated parameters exhibit minimal variation for later starting points. Finally, the 1980 specification minimizes the chances for any structural breaks and parameter instability at the expense of a very small sample. The problems of small samples for dynamic time series regressions are not limited to large standard errors on the estimated coefficients. In addition, coefficients from a dynamic regression are biased in finite samples but normally one ignores this problem since the bias declines quickly as the sample size increases (Hendry 1995: 220, 727). Thus choosing smaller and smaller samples is not necessarily a good idea.

This section established the stability of the estimated long run (semi)elasticities with respect to changing the start of the sample. The next section will investigate whether the results are sensitive to variations in the sample end.

Table 1: Moving Sample Starts

specification	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
ARDL	(2,1)	(2,1)	(2,1)	(2,1)	(2,1)	(2,1)	(2,1)	(2,1)	(2,1)	(2,1)	(1,1)	(1,1)	(1,1)	(1,1)	(1,1)
sample start	1952	1954	1956	1958	1960	1962	1964	1966	1968	1970	1972	1974	1976	1978	1980
adjustment	0.29***	0.31***	0.27***	0.28***	0.27***	0.45***	0.61***	0.68***	0.74***	0.74***	0.64***	0.75***	0.75***	0.71***	0.72***
	0.05	0.06	0.06	0.06	0.07	0.09	0.11	0.13	0.12	0.13	0.14	0.13	0.16	0.18	0.19
LOG(Y^D(-1))	1.09***	1.09***	1.06***	1.08***	1.08***	1.00***	0.95***	0.94***	0.92***	0.92***	0.90***	0.94***	0.93***	0.92***	0.94***
	0.08	0.08	0.09	0.09	0.10	0.06	0.04	0.04	0.03	0.04	0.04	0.03	0.03	0.04	0.04
LOG(HP)	0.22	0.20	0.24	0.21	0.20	0.28***	0.33***	0.34***	0.33***	0.34***	0.40***	0.39***	0.35***	0.33***	0.36***
	0.14	0.14	0.16	0.15	0.16	0.09	0.07	0.06	0.05	0.05	0.06	0.04	0.05	0.07	0.07
TOP1	3.30**	3.69**	3.55**	3.85**	3.86**	3.35***	3.01***	3.14***	3.84***	3.51***	2.92***	1.97**	2.91**	3.43**	2.91
	1.51	1.51	1.67	1.67	1.74	0.95	0.69	0.64	0.60	0.73	0.98	0.75	1.11	1.57	1.72
R30(-1)	-2.24***	-2.01***	-2.20***	-2.08**	-2.08**	-1.84***	-1.84***	-1.78***	-1.69***	-1.75***	-1.95***	-1.72***	-1.63***	-1.68***	-1.53***
	0.68	0.69	0.78	0.77	0.79	0.43	0.31	0.28	0.23	0.25	0.32	0.23	0.23	0.27	0.34
C	-2.12***	-2.09***	-1.91***	-1.90***	-1.74***	-1.46***	-1.27***	-1.22***	-1.14***	-1.17***	-1.13***	-1.37***	-1.21***	-1.11***	-1.27***
	0.22	0.21	0.24	0.23	0.27	0.16	0.13	0.12	0.10	0.11	0.16	0.14	0.18	0.27	0.34
normality	0.65	0.58	0.53	0.57	0.56	0.90	0.94	0.90	0.67	0.63	0.20	0.95	0.67	0.66	0.69
AR1	0.62	0.60	0.53	0.24	0.23	0.16	0.32	0.53	0.07	0.15	0.80	0.75	0.96	0.93	0.99
AR2	0.12	0.11	0.14	0.03	0.09	0.05	0.21	0.36	0.09	0.29	0.92	0.28	0.43	0.32	0.44
AR3	0.14	0.16	0.20	0.02	0.04	0.03	0.26	0.30	0.11	0.08	0.12	0.09	0.14	0.13	0.13
SIC	-4.78	-4.79	-4.82	-4.85	-4.90	-5.03	-5.14	-5.15	-5.25	-5.24	-5.25	-5.08	-5.36	-5.40	-5.29
SE of regression	0.015	0.015	0.015	0.015	0.015	0.014	0.013	0.013	0.012	0.012	0.012	0.013	0.011	0.011	0.011
N	56	54	52	50	48	46	44	42	40	38	36	34	32	30	28
step indicators	S1954 S1958 S1986	S1954 S1958 S1986	S1958 S1986	S1958 S1986	S1986	S1986	S1986	S1986	S1986	S1986	S1986	S1986	S1986	S1986	S1986

Dependent variable: LOG(D). Specifications 1 to 10 are estimated as ARDLs with 2 lags of the dependent variable and 1 lag of each regressor. Specifications 11 to 15 are estimated as ARDLs with 1 lag of the dependent variable and 1 lag of each regressor. All specifications estimated by OLS. Normality represents the p-value of the Jarque-Bera test on the residuals, AR1-AR3 are the p-values of the Breusch-Godfrey LM test. SIC is the Schwarz Information Criterion.

5 Assessing Model Stability: Varying Sample Ends

Figures 2, 3 and 4 present the stability analysis of the specifications based on sample starts in 1951, 1964 and 1980, respectively. The choice of these three specifications is because 1951 and 1980 are the longest and the shortest samples possible[5] and thus act as important benchmarks. In addition, the 1964 specification is a compromise between securing a decent sample length and choosing a start point after which parameters only exhibit minimal variability.

Figure 2 presents the results of repeatedly estimating equation (1) when holding the sample start fixed at 1951 and reducing the sample end by 1 year in each step, starting in 2006. The years on the horizontal axis in Figure 2 represent the sample end of the regression for which the long run parameter is reported together with a two standard error confidence band.

Figure 4: Varying Sample End Regressions (VSE); Sample starts in 1951

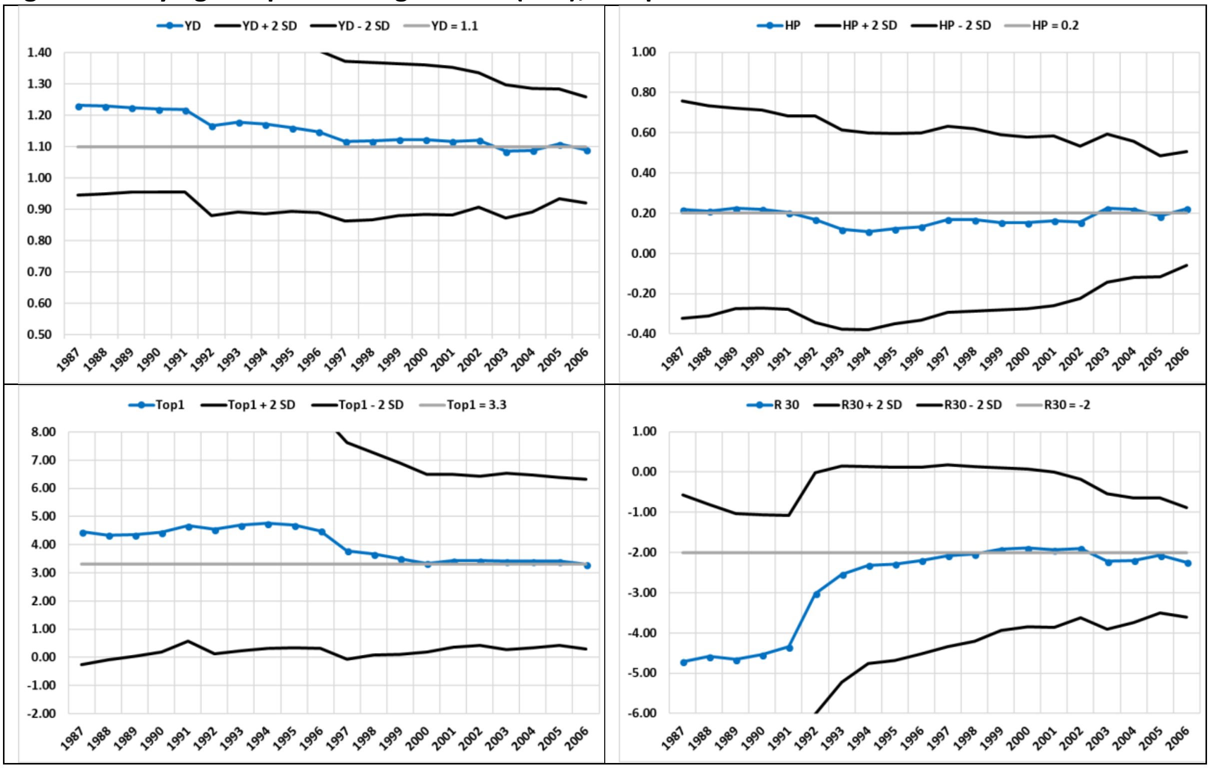


Figure 4 shows that the long run income elasticity declines as the sample end point moves closer from 1987 to 2006. The value towards which it converges eventually is around 1.1 and the case of a unit income elasticity is contained in the two standard error confidence bands across all sample ends. The house price elasticity is stable around 0.2 but remains statistically insignificant across all specifications. The top 1% income share semi-elasticity stabilizes around 3.3 for sample end points of 200 and afterwards. The lower limit of the confidence band remains barely above zero across most specifications. Finally, the 30-year mortgage rate semi-elasticity converges towards a value of -2 and remains very close to that value for all specifications with end points in 1994 and later.

[5] Strictly speaking it is not clear that 1980 is the latest sample starting point. However, because the available number of observations between 1980 and 2006 is only 27 anymore, we abstained from estimating the model for even shorter sample even though this might be possible.

We repeat the exercise of re-estimating equation (1) with different sample ends, while holding the starting point constant at 1964. Results are reported in Figure 5 below. For this specification the estimated long run income elasticity is very close to unity and in the last four regressions stabilizes around 0.95 and thus confirms the previous results that the long run income elasticity is not statistically different from unity and potentially only marginally below it. Next, the long run house price elasticity is very close to 0.32 in all specifications. Standard errors are large. However, the lower confidence band remains above zero in all except two specifications (sample ends 1987 and 1989). The top 1% income share long run semi-elasticity remains firmly around 3 from 1996 onwards and the lower confidence band remains above zero in all except the first three specifications. The 30-year mortgage rate semi-elasticity remains very close to -1.7 across all specifications. The upper confidence band remains below 0 from 1991 onwards.

Figure 5: Varying Sample End Regressions (VSE); Sample starts in 1964

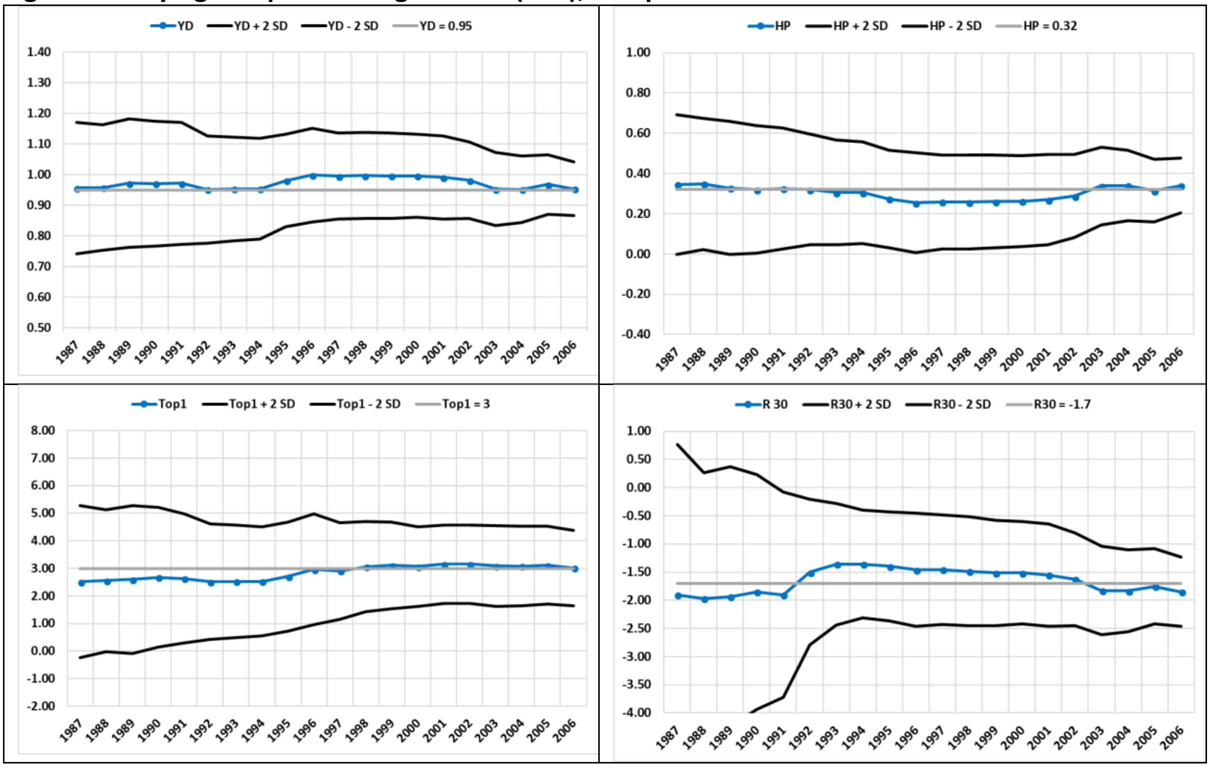
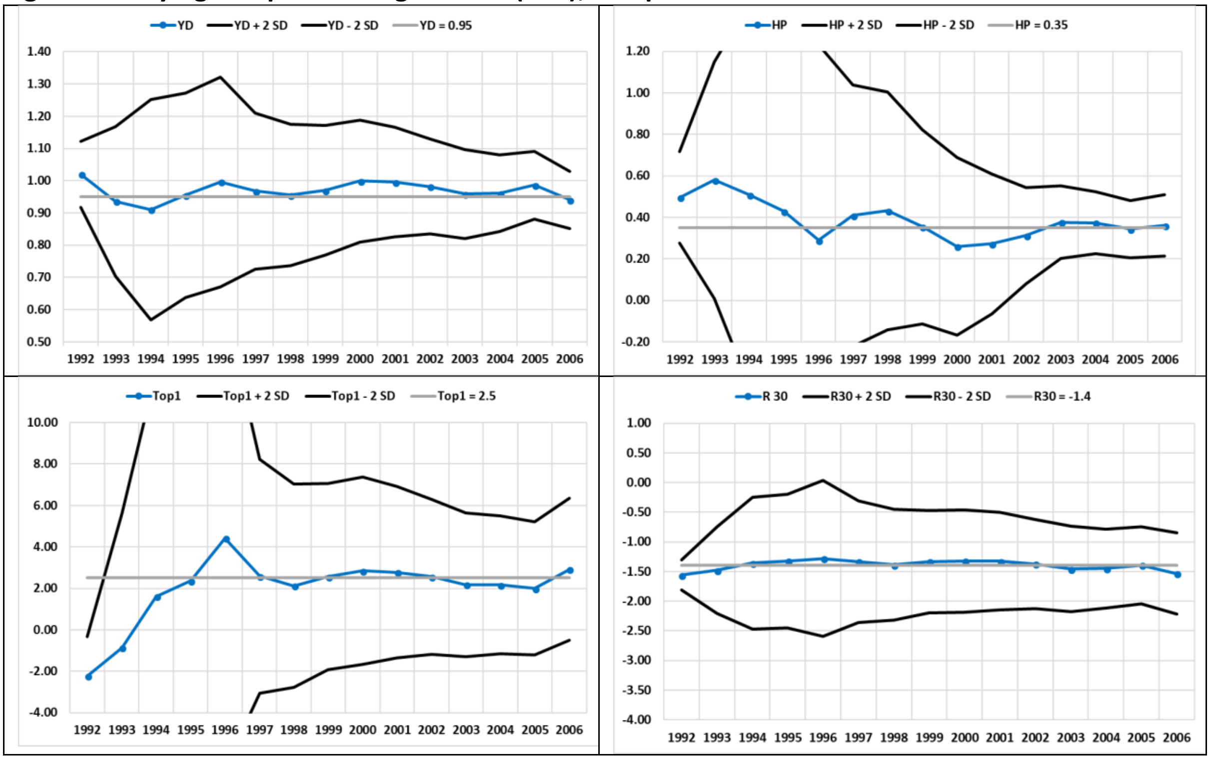


Figure 6 presents the results of re-estimating equation (1) for different sample end points and a fixed sample start in 1980. The long run income elasticity remains firmly between 0.95 and unity and is highly statistically significant across all specifications. The two standard error confidence band is wider due the smaller sample size. The long run house price elasticity exhibits more variation compared to the specification which starts in 1964 (Figure 5) but stays close to a value of 0.35 especially in the last 5 regressions (2002-2006) which is when the confidence band moves above zero. The long run top income semi-elasticity is stable around 2.5 which is lower compared to the value of 3.3 in the specification which starts in 1964. The lower confidence bound remains below zero across all specifications. The 30-year mortgage rate semi-elasticity is stable around -1.4 and hence is higher compared to 1964 specification where it converged towards -1.7.

Figure 6: Varying Sample End Regressions (VSE); Sample starts in 1980



Altogether we draw two conclusions from this assessment of model stability with respect to changing the sample end-points. The first is that the long sample which starts in 1951 is less table than the baseline specification which starts in 1964. The estimated long run income elasticity steadily declines in the 1951 model from 1.23 to 1.1 when moving the sample end from 1987 to 2006. In comparison with the 1964 specification the estimated long run income elasticity only fluctuates across a value of 0.95 but does not persistently increase or decrease as one adds data points to the end of the sample. The same is true for the 30-year mortgage rate semi-elasticity. With the 1951 model it increases from -4.7 to -2 when the sample end is extended from 1987 to 2006. In comparison with the 1964 model the estimated semi-elasticity changes from -1.9 to -1.85 over the same period. We interpret this as an important indication that there are structural changes occurring over the period 1951 to 2006 which the 1951 model is not able to adequately capture despite the use of step indicators. This is not entirely surprising given the simple nature of the step indicator approach and the vast changes which happed over this almost 6 decades. This finding demonstrates that simply choosing the longest sample possible is not a viable strategy for obtaining specifications with stable parameters. Second, while the specification using the short sample starting in 1980, does not exhibit persistent trends in the estimated parameters as data points are added at the sample end, the results obtained from additional observations are more volatile compared to the specification starting in 1964.

6 Effect Size Computation and Robustness of Specification

After testing the stability of the long run elasticities when estimating equation (1) for different sample starting and end points, the next step is to quantify the relative importance and explanatory power of the four different explanations under investigation. For this purpose, Table 2 presents effect size computations for each of the regressors in equation (1) based on the estimated long run coefficients from the specification starting in 1964 (for details see Appendix A). Over the entire sample period the debt-to-income ratio increased by 140%: From 64% in 1964 to 154% in 2006. This is an increase of 140% and 90 percentage points respectively. The estimated model predicts an increase of the debt to income ratio by 139% percent and thus fits the data very well. Since the long run income elasticity in the 1964 specification is less than unity (0.95), it means that household debt expands slightly slower than household income. Accordingly, there is a negative contribution of disposable income to the debt to income ratio over the entire sample period of 12% as can be seen from line (1) of Table 2. The contribution of the house price index is 130% and thus house prices alone account for almost all of the increase in the debt to income ratio over the sample period. This is a strong indicator that purely consumption-based explanations of household sector borrowing are very much out of line with the available data. The top 1% income share exhibits a contribution of 21% over the sample period. While this is a non-trivial contribution it is clearly a secondary factor compared to the explanatory power of the house price index. Finally, the 30-year mortgage rate does not contain any substantial explanatory power for the long-term increase of debt to income ratios between 1964 and 2006. It is important to realize that these are multiplicative contribution factors and hence: $2.39 \approx 0.88 * 2.3 * 1.21 * 0.98$, ignoring rounding errors. In the decade directly leading up to the financial crisis the picture remains roughly the same (line (2) of Table 2). The contribution of house prices is three times as large as the contribution of the top income share and disposable income and the 30-year mortgage rate do not exhibit explanatory power of a significant degree.

Overall based on the 1964 specification we draw the following conclusions: The close to unity long run income elasticity of household debt implies that debt to income ratios remain stable and even decline slightly in the light of economic growth and disposable income growth in particular. House price dynamics are the single most important factor to understand household sector debt accumulation. This finding casts doubt on primarily consumption-based explanations of household indebtedness. Top income shares play a significant role in household sector debt accumulation, although their importance is clearly secondary in comparison to house prices.

Table 2: Effect size computation; Sample starts in 1964

line	period	actual change D/Y	explained change D/Y	YD	HP	Top1	R30
(1)	1964-2006	140%	139%	-12%	130%	21%	-2%
(2)	1997-2006	48%	43%	-2%	30%	10%	2%
(3)	1987-1996	15%	16%	-2%	8%	6%	5%
(4)	1977-1986	29%	23%	-3%	26%	4%	-2%

Results based on specification 7 in Table 1. For details see Appendix A.

Table 3 presents the same effect size computations as in Table 2 but using the estimated long run coefficients from the specification which starts in 1980 instead of 1964. For the ease of comparison, effect sizes are compute for the same timer periods even though the specification does not include observations prior to 1980. Upon comparison of the first two lines of Table 2 and 3 we draw the same conclusions: House prices exhibit by far most explanatory power and shifts in the top 1% income share are the second most important factor in explaining rising debt to income shares. Line (2) contains the decade prior to the financial crisis and thus is based on data points which are used in both specifications. Again, the results obtained from both specifications are effectively identical.

Table 3: Effect size computation; Sample starts in 1980

line	period	actual change D/Y	explained change D/Y	YD	HP	Top1	R30
(1)	1964-2006	140%	141%	-16%	142%	20%	-1%
(2)	1997-2006	48%	44%	-3%	32%	10%	2%
(3)	1987-1996	15%	15%	-3%	8%	5%	4%
(4)	1977-1986	29%	24%	-4%	28%	4%	-2%

Results based on specification 15 in Table 1. For details see Appendix A.

We argued in section 4.2 that we deliberately choose a purely nominal specification and that this approach is equivalent to deflating the time series measured in monetary terms and the interest rate prior to estimation with the same price index, like the CPI. The necessary condition for the claim of equivalence was that the model exhibits a unity long run income elasticity. While we could not reject the null hypothesis of a unity income elasticity of the point estimates for the 1964 as well as the 1980 specifications a more direct test of the hypothesis that consumer price inflation is an important missing variable is to include the CPI as an additional variable in equation (1) and re-estimate the model. The results are presented in Table 5 and the corresponding effect size calculations are presented in Table 4. Table 5 reveals that the consumer price index exhibits a statistically significant long run coefficient in the specifications up the sample start in 1966. Thus, also our baseline specification which starts in 1964 exhibits a statistically significant long run CPI elasticity. Table 4 presents the impact of the inclusion of the CPI into the model on the effect size computations. The first line depicts the results for the entire sample period: 1964-2006. If one compares it to line (1) in Table 3, it becomes clear that the conclusions we have drawn so far do not change: The key explanatory variable is the house price index with a significant but secondary role of the top income share. The combined contribution of disposable income and the CPI are displayed in the last column of table 4 and amount to -17%. This is almost identical to the contribution of disposable income in Table 3. Thus we conclude that the results presented so far are not driven by the fact that we do not explicitly include the CPI in our model. In contrast doing so, shows that the main conclusions do not change.

Table 4: Effect size computation; Sample starts in 1964; CPI-augmented specification

line	period	actual change D/Y	explained change D/Y	YD	HP	Top1	R30	CPI	YD*CPI
(1)	1964-2006	140%	139%	44%	161%	12%	-1%	-42%	-17%
(2)	1987-1996	15%	13%	7%	9%	3%	3%	-9%	-3%
(3)	1977-1986	29%	20%	10%	30%	2%	-2%	-16%	-8%
(4)	1997-2006	48%	45%	6%	35%	6%	2%	-6%	-1%

Results based on specification 7 in Table 5. For details see Appendix A.

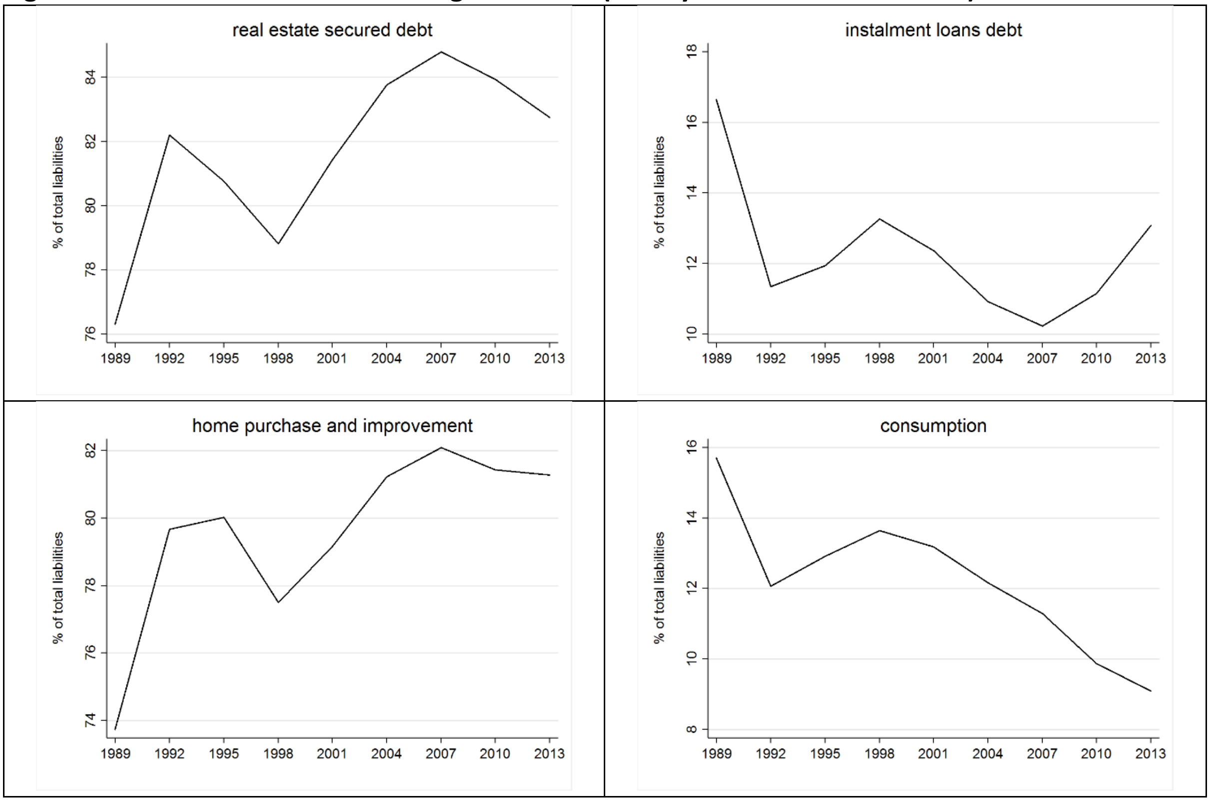
Table 5: Moving Sample Starts; CPI-augmented specifications

specification	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
ARDL	(2,1)	(2,1)	(2,1)	(2,1)	(2,1)	(2,1)	(2,1)	(2,1)	(2,1)	(2,1)	(1,1)	(1,1)	(1,1)	(1,1)	(1,1)
sample start	1952	1954	1956	1958	1960	1962	1964	1966	1968	1970	1972	1974	1976	1978	1980
adjustment	0.41***	0.40***	0.35***	0.37***	0.39***	0.61***	0.70***	0.74***	0.75***	0.76***	0.65***	0.76***	0.78***	0.72***	0.69***
	0.06	0.07	0.08	0.08	0.09	0.10	0.10	0.11	0.11	0.11	0.15	0.15	0.17	0.18	0.17
LOG(YD_N)	1.34***	1.35***	1.32***	1.34***	1.34***	1.21***	1.12***	1.11***	0.94***	1.06***	0.97***	1.04***	1.04***	1.14***	1.51***
	0.09	0.10	0.12	0.11	0.11	0.07	0.07	0.09	0.11	0.12	0.22	0.18	0.18	0.21	0.31
LOG(HP_N)	0.34***	0.36***	0.39***	0.34***	0.34***	0.36***	0.39***	0.38***	0.40***	0.42***	0.48***	0.42***	0.38***	0.36***	0.31***
	0.10	0.11	0.13	0.12	0.12	0.06	0.06	0.05	0.05	0.05	0.07	0.06	0.07	0.08	0.08
TOP1	1.59	1.29	0.97	1.46	1.50	1.89**	1.82**	1.89**	2.54***	1.52*	1.28	1.09	1.96	2.44	3.21*
	1.27	1.50	1.72	1.63	1.61	0.83	0.70	0.68	0.66	0.83	1.40	1.09	1.30	1.48	1.63
R30_N	-1.22**	-1.23*	-1.47*	-1.26*	-1.25*	-1.22***	-1.41***	-1.40***	-1.83***	-1.63***	-1.98***	-1.61***	-1.47***	-1.46**	-1.72***
	0.60	0.63	0.76	0.71	0.70	0.36	0.33	0.35	0.37	0.36	0.60	0.49	0.48	0.52	0.55
C	-2.10***	-2.09***	-1.90***	-1.92***	-1.79***	-1.56***	-1.40***	-1.38***	-1.07***	-1.32***	-1.16**	-1.47***	-1.38***	-1.26***	-0.72
	0.15	0.16	0.19	0.18	0.19	0.12	0.13	0.16	0.19	0.22	0.45	0.38	0.37	0.42	0.57
S1986	-0.09**	-0.09**	-0.10**	-0.09**	-0.09**	-0.05**	-0.05***	-0.04***	-0.05***	-0.05***	-0.07***	-0.05***	-0.05***	-0.05**	-0.06**
	0.04	0.04	0.05	0.04	0.04	0.02	0.02	0.02	0.02	0.02	0.03	0.02	0.02	0.02	0.02
LOG(CPI)	-0.52***	-0.54***	-0.51***	-0.52***	-0.52***	-0.38***	-0.29***	-0.28**	-0.06	-0.22	-0.14	-0.15	-0.15	-0.34	-1.02*
	0.14	0.15	0.18	0.17	0.17	0.09	0.09	0.11	0.13	0.15	0.27	0.22	0.22	0.27	0.50
normality	0.39	0.43	0.43	0.36	0.33	0.80	0.97	0.90	0.75	0.74	0.58	0.66	0.80	0.91	0.67
AR1	0.89	0.89	0.64	0.51	0.45	0.09	0.10	0.20	0.01	0.06	0.14	0.85	0.59	0.57	0.46
AR2	0.35	0.38	0.18	0.51	0.34	0.07	0.11	0.23	0.02	0.16	0.26	0.65	0.35	0.52	0.31
AR3	0.54	0.53	0.16	0.47	0.29	0.13	0.21	0.31	0.05	0.28	0.04	0.21	0.09	0.11	0.02
SIC	-4.95	-4.90	-4.95	-4.93	-4.94	-5.31	-5.37	-5.31	-5.45	-5.50	-5.10	-5.26	-5.29	-5.30	-5.38
SE of regression	0.013	0.014	0.014	0.014	0.014	0.011	0.011	0.011	0.010	0.010	0.012	0.011	0.011	0.011	0.010
N	55	53	51	49	47	45	43	41	39	37	35	33	31	29	27
step indicators	S1954	S1954	S1958	S1958	S1986	S1986	S1986	S1986	S1986	S1986	S1986	S1986	S1986	S1986	S1986
	S1958	S1958	S1986	S1986											
	S1986	S1986													

7 Conclusion

The results we presented in the previous sections, make us sceptical about consumption-based borrowing interpretations of household sector debt accumulation in general and the 2007 crisis in particular. The data clearly shows that property prices are the most relevant predictor of household sector liabilities. While this finding does not rule out real estate secured borrowing we are not convinced of such an interpretation. The reason is that it is not consistent with available micro data. The Survey of Consumer Finances for example asks households about their outstanding real estate secured liabilities. In addition, it also asks how these liabilities were used, whether it was for consumption purposes or to buy or improve a property. Figure 7 presents the aggregate answers to these questions.

Figure 7: Household Sector Borrowing Behaviour (Survey of Consumer Finances)



Source: Authors' calculations based on SCF waves 1989-2013.

The upper row presents the proportion of total reported liabilities which is secured by real estate and instalment loans which are mainly auto-loans and are the largest type of non-mortgage loans ahead of credit card balances. The top left panel suggests that in the immediate run-up to the 2007/2008 crisis the proportion of real estate secured debt increased from 79% in 1998 to 85% in 2007. However, the left panel in the lower row shows that over the same time the proportion of liabilities used for home purchases and improvements also rose from 78% of total liabilities in 1998 to 82% in 2007. This means a growing proportion of real estate secured debt was used for consumption purposes. In 1998 this amounted to $90 billion and increased to $341 billion in 2007 and thus an increase of $251 billion (all figures in 2013 Dollars). However, over the same time total household sector liabilities reported in the SCF rose from $6,886 billion to $12,656 billion which is by $5,770 billion. Our claim that borrowing consumption-based borrowing was not central to the accumulation of household debt between 1998 and 2007 is supported further by the declining share of instalment loans and the proportion of loans used for consumption purposes, according to the Survey of Consumer Finances.

The empirical evidence is very clear: To predict outstanding household sector liabilities house prices (together with disposable income) are by far the two most important factors. While this might sound obvious to some readers we think it is an important contribution which too often is forgotten in theoretical macroeconomic modelling. What it means is that if one wants to meaningfully incorporate private and especially household sector liabilities into a macroeconomic model, one needs to link this stock of liabilities to the housing market. Overall: assuming that household liabilities are driven by consumption decisions is inconsistent with the available data.

Literature

Alvaredo, F., Atkinson, A., Chancel, L., Piketty, T., Saez, E. and Zucman, G. (2016). Distributional National Accounts (DINA) Guidelines: Concepts and Methods used in WID.world. WID.world working paper series, No. 2016/1. Available at: [http://wid.world/document/dinaguidelines-v1/].

Auerbach, A. and Slemrod, J. (1997). The Economic Effects of the Tax Reform Act of 1986. *Journal of Economic Literature*. Vol. 35(2), 589-632.

Banerjee, A., Dolado, J. and Mestre, R. (1998). Error-Correction Mechanism Tests for Cointegration in a Single-Equation Framework. *Journal of Time Series Analysis,* Vol. 19(3), 267-283.

Bank for International Settlements (2018). Credit to the non-financial sector. Available at: [https://www.bis.org/statistics/totcredit.htm].

Bardsen, G. Eitrheim, O., Jansen, E. and Nymoen, R. (2005). The Econometrics of Macroeconomic Modelling. Oxford University Press. Oxford.

Behringer, J. and Treeck, T. van, (2013). Income distribution and current account: A sectoral perspective. *IMK Working Paper No 125*, (November).

Bernanke, B., Gertler, M. and Gilchrist, S., 1998. The Financial Accelerator in a Quantitative Business Cycle Framework. NBER working paper, (6455).

Bezemer, D. (2016). Towards an 'accounting view' on money, banking and the macroeconomy: history, empirics, theory. *Cambridge Journal of Economics,* Vol. 40(5), 1275-1295.

Bezemer, D. & Zhang, L., 2014. From Boom to Bust in the Credit Cycle: The Role of Mortgage Credit. SOM Research Reports, 14025–GEM

Blanchard, O. (2018). On the future of macroeconomic models. *Oxford Review of Economic Policy,* Vol. 34(1), 43-54.

Borio, C., 2014. The financial cycle and macroeconomics: What have we learnt? *Journal of Banking and Finance*, 45(1), pp.182–198.

Castle, J., Doornik, J., Hendry, D. and Pretis, F. (2015). Detecting Location Shifts during Model Selection by Step-Indicator Saturation. *Econometrics,* Vol. 3, 240-264.

Cynamon, B. and Fazzari, S. (2017). Household Income, Demand, and Saving: Deriving Macro Data With Micro Data Concepts. *Review of Income and Wealth,* Vol. 63(1), 53-69.

European Commission (2018). Macroeconomic imbalance procedure. https://ec.europa.eu/info/business-economy-euro/economic-and-fiscal-policy-coordination/eu-economic-governance-monitoring-prevention-correction/macroeconomic-imbalance-procedure_en [Accessed: May 2018].

Eichengreen, B. and Mitchener, K., 2003. The Great Depression as a Credit Boom Gone Wrong. *BIS Working Papers*, (137).

Engle, R., Hendry, D. and Richard, J. (1983). Exogeneity. *Econometrica*, Vol. 51(2), 277-304.

Fisher, I., 1933. The Debt-Deflation Theory of Great Depressions. *Econometrica*, 1(4), pp.337–357.

Frank, R.H., Levine, A.S. and Dijk, O., (2014). Expenditure Cascades. *Review of Behavioral Economics*, Vol. 1(1–2), 55–73.

Godley, W. and Lavoie, M., (2007). Monetary Economics, New York: Palgrave Macmillan.

Hendry, D. (1995). Dynamic Econometrics. Oxford University Press. Oxford.

Hendry, D. and Mizon, G. (2014). Unpredictability in economic analysis, econometric modelling and forecasting. *Journal of Econometrics,* Vol. 182, 186-195.

Jordà, Ò., Schularick, M. and Taylor, A. (2017). Macrofinancial History and the New Business Cycle Facts. NBER Macroeconomics Annual 2016, Vol. 31. ed. Martin Eichenbaum and Joathan A. Parkger. University of Chicago Press. Chicago. [accessed January 2018]

Kapeller, J. and Schütz, B., (2014). Debt, boom, bust: a theory of Minsky-Veblen cycles. *Journal of Post Keynesian Economics*, 36(4), 781–814.

Koo, R., 2011. The world in balance sheet recession: causes, cure, and politics. *Real World Economics Review*, (58), pp.19–37.

Maki, D. (2001). Household Debt and the Tax Reform Act of 1986. *The American Economic Review*. Vol. 91(1), 305-319.

Marczak, M. and Proietti, T. (2016). Outlier detection in structural time series models: The indicator saturation approach. *International Journal of Forecasting.* Vol. 32, 180-202.

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

Mian, Atif R., and Amir Sufi (2010). Household Leverage and the Recession of 2007 to 2009. Available at: [https://www.imf.org/external/np/res/seminars/2009/arc/pdf/mian.pdf].

Minsky, H.P., 1978. The Financial Instability Hypothesis: A Restatement. Hyman P. Minsky Archive Paper 180.

Piketty, T., Saez, E. and Zucman, G. (2018). Distributional National Accounts: Methods and Estimates for the United States. *Quarterly Journal of Economics,* Advance Access publication October 2017.

Ryoo, S. and Kim, Y.K., (2014). Income Distribution, Consumer Debt and Keeping up with the Joneses. *Metroeconomica*, Vol. 65(4), 585–618.

Schularick, M. and Taylor, A.M., 2012. Credit booms gone bust: Monetary policy, leverage cycles, and financial crises, 1870-2008. *American Economic Review*, 102(2), pp.1029–1061.

Shiller, R. J. (2015). Irrational Exuberance. 3rd edition. Princeton University Press.

Sinn, H.W. (2014). The Euro Trap - On Bursting Bubbles, Budgets and Believes, Oxford: Oxford University Press.

Sinn, H.W. and Valentinyi, A., (2013). European Imbalances. voxeu.org. Available at: www.voxeu.org/article/european-imbalances [Accessed March 9, 2017].

Stiglitz, J. (2018). Where modern macroeconomics went wrong. *Oxford Review of Economic Policy,* Vol. 34(1), 43-54.

Stockhammer, E., 2009. The finance-dominated accumulation regime, income distribution and the present crisis. *Papeles de Europa*, 19, pp.58–81.

Taylor, J.B. (2009). The Financial Crisis and the Policy Responses: An Empirical Analysis of What Went Wrong. *NBER Working Paper* No 14631, 1–30.

Thaler, R. (1990). Anomalies. Saving, Fungibility, and Mental Accounts. *Journal of Economic Perspectives,* Vol. 4(1), 193-205.

Thaler, R. (2015). Misbehaving. The Making of Behavioural Economics. Allen Lane.

Wren-Lewis, S. (2018). Ending the microfoundations hegemony. *Oxford Review of Economic Policy,* Vol. 34(1), 43-54.

Appendix A: Deriving effect size computations

This appendix describes how the results for Tables 2 and 3 are obtained. These effect size computations are based on the estimated long run elasticities. Taking the difference of the predicted dependent variable between 2006 and 1997 for example gives the predicted growth rate in that period. Equivalently the difference can also be expressed in terms of the independent variables according to the following equation:

$$\log\left(\frac{\widehat{D}_{2006}}{\widehat{D}_{1997}}\right) = \hat{\theta}_1 \log\left(\frac{Y^D_{2006}}{Y^D_{1997}}\right) + \hat{\theta}_2 \log\left(\frac{HP_{2006}}{HP_{1997}}\right) + \hat{\theta}_3(TOP1_{2006} - TOP1_{1997}) + \hat{\theta}_4(R_{2006} - R_{1997}) \quad \text{(A1)}$$

$\widehat{D}_{2006}$ and $\widehat{D}_{1997}$ represent the predicted long run debt levels in 2006 and 1997 based on the estimated long run coefficients. After some manipulation equation (A1) becomes:

$$\frac{\widehat{D}_{2006}}{\widehat{D}_{1997}} = \left(\frac{Y^D_{2006}}{Y^D_{1997}}\right)^{\widehat{\theta}_1} \left(\frac{HP_{2006}}{HP_{1997}}\right)^{\widehat{\theta}_2} e^{\widehat{\theta}_3(TOP1_{2006}-TOP1_{1997})} e^{\widehat{\theta}_4(R_{2006}-R_{1997})} \quad \text{(A2)}$$

In order to obtain a change in debt to income ratios equation A2 can be transformed:

$$\frac{\frac{\widehat{D}_{2006}}{Y^D_{2006}}}{\frac{\widehat{D}_{1997}}{Y^D_{1997}}} = \left(\frac{Y^D_{2006}}{Y^D_{1997}}\right)^{(\widehat{\theta}_1-1)} \left(\frac{HP_{2006}}{HP_{1997}}\right)^{\widehat{\theta}_2} e^{\widehat{\theta}_3(TOP1_{2006}-TOP1_{1997})} e^{\widehat{\theta}_4(R_{2006}-R_{1997})} \quad \text{(A3)}$$

From equation (A3) each variable's contribution to the predicted change in household debt to income ratios between 1997 and 2006 can be defined. For example, in the case of disposable household income itself as well as property prices these contributions are:

$$\frac{\widehat{D}_{2006}}{Y^D_{2006}} \Bigg/ \frac{\widehat{D}_{1997}}{Y^D_{1997}} = \left(\frac{Y^D_{2006}}{Y^D_{1997}}\right)^{(\widehat{\theta}_1-1)} \quad \text{(A4)}$$

$$\frac{\widehat{D}_{2006}}{Y^D_{2006}} \Bigg/ \frac{\widehat{D}_{1997}}{Y^D_{1997}} = \left(\frac{PP_{2006}}{PP_{1997}}\right)^{\widehat{\theta}_2} \quad \text{(A5)}$$